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Spatial disparities in human development

Spatial disparities in human development: Perspectives from Asia

Edited by Ravi Kanbur, Anthony J. Venables and Guanghua Wan

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Foreword

Anthony Shorrocks

Amidst a general and growing concern about global inequalities, considerable policy interest has begun to be directed at regional disparities within developing and transition economies. Spatial variations in living standards – as reflected in average incomes, the incidence and depth of poverty, health indicators, and education status – are particularly pronounced in large nations such as Brazil, China, Russia and South Africa; but marked regional differences are also evident in many smaller countries, especially in Africa. Although spatial inequality is of interest in its own right, the topic takes on added significance when spatial and regional divisions align with political and ethnic tensions to undermine social and political stability.

Variations in living standards within countries have a number of underlying causes. They may reflect historical differences in the pace of development (São Paulo versus north-east Brazil), the uneven impact of economic reform (Guangdong versus Qinghai), discrimination in the provision of economic and social infrastructure (South Africa during apartheid), and impediments to labour migration (China and Russia). Unfavourable agricultural conditions and geographical remoteness from principal markets also play a role. Whatever the original source, there is a widespread perception that spatial disparities in human development have recently become more visible and that they are increasing over time. Furthermore, increasing spatial variations are very often thought to be linked in some way to greater openness of economies, and to globalization in general.

Despite the significance of the problem, little systematic scholarly analysis has been devoted to the causes of growing inequalities within countries and their cumulative detrimental impact on human development. The UNU-WIDER project on ''Spatial Disparities in Human Development'', directed by Ravi Kanbur and Tony Venables in collaboration with Guanghua Wan, set out to rectify this neglect by drawing together expertise from all regions of the globe in order to better understand the incidence, significance and causes of spatial variations within countries, and to contribute to the global policy debate.

Separate meetings were convened to focus on the experiences within Africa, Latin America and Asia. This book is a collection of studies on Asia first presented at a conference at the United Nations University in Tokyo in March 2003. Seven of the chapters are minor revisions of papers published in a special issue of the *Review of Development Economics* in February 2005. The volume is the first serious attempt to examine spatial inequality in Asia from multiple perspectives, and it contains valuable information and advice for both policy makers and policy takers. It will be essential reading for academics and students interested in this research area and a useful reference source for others wishing to know more about a topic of growing national and international significance.

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Abbreviations

ASI	Annual Survey of Industries (India)
AVHRR	Advanced Very High Resolution Radiometer
CARP	Comprehensive Agrarian Reform Program (the Philippines)
CASS	Chinese Academy of Social Sciences
CET	constant elasticity of transformation
CGE	computable general equilibrium
CMIE	Center for Monitoring the Indian Economy
CSES	Cambodian socio-economic surveys
DFID	Department for International Development (UK)
FAO	Food and Agriculture Organization of the United Nations
FDI	foreign direct investment
FGT	Foster–Greer–Thorbecke
FIES	Family Income and Expenditure Survey (the Philippines)
GAIOV	gross agricultural and industrial output value
GDP	gross domestic product
GE	generalized entropy
GIS	geographical information system
GLS	generalized least squares
GSO	General Statistics Office (Viet Nam)
HDI	human development index
NASA	National Aeronautics and Space Administration
NDVI	normalized differential vegetation index
NEG	new economic geography
NGO	non-governmental organization
NSS	National Sample Survey (India)
OLS	ordinary least squares

PPP	purchasing power parity
RNA	Royal Nepalese Army
SAM	social accounting matrix
SSB	State Statistical Bureau (China)
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UNU	United Nations University
VLSS	Vietnam Living Standards Survey
VSAM	Vietnam Social Accounting Matrix
WFP	World Food Programme
WIDER	World Institute for Development Economics Research
WTO	World Trade Organization

1

Spatial disparities in human development: An overview of the Asian evidence

Ravi Kanbur, Anthony J. Venables and Guanghua Wan

Overview of Asian evidence

Asia is the most populous continent on earth. Changes in inequality or poverty in this region alter the corresponding global picture. Owing to its remarkable economic growth and catch-up in living standards, Asia has been an equalizing force in international inequality. However, within-country inequalities in Asia are rising fast, retarding poverty reduction in the world. The rising inequality within individual countries is a cause of concern since Asia, particularly East Asia, has until recently been considered to be a good example of growth without worsening distribution.

It is known that a large proportion of the world's poor – 67 per cent in 1998 – are living in Asia, especially southern and rural parts. Although economic development has benefited the poor in some countries, this has not happened in all. On the contrary, poverty increased in Indonesia, Mongolia, Pakistan and Thailand during the 1990s. At the same time, poverty reduction slowed down in China, Bangladesh, India, the Philippines and South Korea and stagnated in Nepal, Sri Lanka and Mongolia. These changes are not unrelated to the rising inequality in Asian countries.

The recent rises in inequality in some Asian countries are in contrast to the historically stable levels of inequality in much of Asia. One possible explanation is the role of economic reforms. However, the Asian experience is mixed. For example, China and Viet Nam are two successful tran-

sition economies and have followed a similar reform path. However, inequality has been fairly stable in Viet Nam but increased substantially in China. Interestingly, inequality in China declined in the early years of reform, before starting to climb in 1985. Mongolia has seen inequality increase significantly without economic growth. Inequality has also gone up in non-transition but reforming economies such as India, the Philippines and Pakistan. It seems that the increasing inequalities have little to do with the economic or political system, be it democratic (India), dictatorship (China), market economy (Philippines), transition economy (Mongolia), reforming economy (Pakistan), or mixed combinations of political and economic systems.

Spatial inequality refers to the uneven distribution of income or other variables across different locations. It is a component of overall inequality between individuals. Measuring spatial inequality usually involves calculating interpersonal inequality when each income recipient is assumed to receive the mean income of their location group. When the Theil measure is used, total inequality can be conveniently broken down into two components: spatial inequality, or the so-called between-group component, and the within-group component. When spatial inequality dominates total inequality, policy measures can be targeted towards particular groups and/or locations. Dominance of the within-group component calls for policies targeting finer units within groups.

The between-group component is typically small except in the case of urban–rural divisions. However, what may be more important is the change in this component; although small in terms of levels, the contribution of spatial inequality to changes in inequality may be significant. Moreover, when spatial inequality coincides with divisions between socioeconomic groups such as migrants and natives, different ethnicities, different religions and so on, it is not the numerical value but its mere existence that is important. Such spatial inequality can have severe consequences such as discontent, conflict and even war.

The chapters in this volume

Given the unique features and importance of the subject, the World Institute for Development Economics Research of the United Nations University (UNU-WIDER) launched a major research project on spatial inequality in 2002. As one of the project activities, a conference was held at the United Nations University Centre in Tokyo in March 2003, focusing on spatial inequality and development in Asia. Out of some 100 submissions, 18 papers were presented at the conference, and the chapters in this book were further selected, subject to the customary process of peer

review and revision. The chapters highlight a range of theoretical, empirical and policy issues in the evolution of spatial disparities in Asia. In doing so, they also contribute to the general literature on spatial inequality and development.

Part I of the volume consists of three methodologically oriented papers. A major problem with examining the structure of spatial inequality is a lack of disaggregated data. Most household sample surveys do not allow a disaggregation below the province level because of sample size, whereas censuses do not collect sufficiently detailed information on household income and expenditure. Recent methods attempt to combine the strengths of these two approaches by first estimating an income or expenditure equation from household surveys and then applying it to census data to generate distributions at highly disaggregated levels spatially. Minot and Baulch (Chapter 2) examine the loss in precision when aggregated census data are employed in this manner to measure poverty. They show analytically that such aggregation will result in poverty rates that are biased downward (upward) if the rate is below (above) 50 per cent and that the bias approaches zero as the poverty rate approaches zero, 50 per cent, and 100 per cent. Relying on data from Viet Nam, it is found that the average absolute error in estimating provincial poverty rates is about 2 percentage points if the data are aggregated to the enumeration area level and 3–4 percentage points if the data are aggregated to the provincial level. In ranking the 61 provinces by the incidence of poverty, even data aggregated to the provincial level perform reasonably well: the average absolute error in ranking is only 0.92.

Chapter 3, by Kolenikov and Shorrocks, is the second methodology-oriented study. They propose a new analytical framework for poverty decomposition, namely the Shapley value decomposition, which is based on cooperative game theory. Empirical results for Russia (whose land mass and many of whose poorer regions are mainly in Asia) suggest that the regional poverty variations are the result more of differences in inequality across regions than of those in real income per capita. When real income is split into nominal income and price components, differences in nominal income per capita emerge as more important than either inequality or price effects for the majority of regions.

The use of a computable general equilibrium (CGE) model to analyse poverty and inequality is a recent development. Relying on Vietnamese data, Jensen and Tarp in Chapter 4 calibrate two static CGE models with, respectively, 16 and 5,999 representative households. Aggregated and disaggregated household categories are consistently embedded in a social accounting matrix (SAM), and they map on a one-to-one basis to each other. Distinct differences in poverty assessments emerge when the impact of trade liberalization is analysed in the two models. This high-

lights the importance of modelling micro household behaviour and related income and expenditure distributions endogenously within a static CGE model framework. Simulations indicate that poverty will rise following a revenue-neutral lowering of trade taxes. This is interpreted as a worst-case scenario, which suggests that government should be proactive in combining trade liberalization measures with a pro-poor fiscal response to avoid increasing poverty in the short to medium term.

Part II focuses on case studies of inequality. It starts with China – considered to be the most dynamic and fast-growing economy in the world. Kanbur and Zhang (Chapter 5) compile a time series data set for China, which is used to construct a time profile of China's regional inequality for the period 1952–2000. They identify three peaks of inequality, coinciding with the Great Famine of the late 1950s, the Cultural Revolution of the late 1960s and 1970s, and finally the period of openness and global integration in the late 1990s. The authors then employ econometric analysis to establish that regional inequality is mainly caused by three key policy variables: the ratio of heavy industry to gross output, the degree of decentralization, and the degree of openness.

A considerable literature exists on the measurement of income inequality in China and its increasing trend. Much less is known, however, about the driving forces of this trend and their quantitative contributions. Chapter 6 by Wan and Zhou represents an attempt to apply the regression-based decomposition framework to the study of inequality accounting in rural China using household-level data. It is found that geography has been the dominating factor but is becoming less important in explaining total inequality. Capital input emerges as a most crucial determinant of income inequality. Farming structure is more important than labour and other inputs in contributing to income inequality across households.

Complementary to the Wan and Zhou study on rural China is Chapter 7 by Knight, Li and Zhao, which explores income inequality and its changes between 1988 and 1995, mainly for urban China. Although intra-province inequalities in income and wages increased everywhere except Gansu, and more for coastal provinces, the gaps in inequality are closing over time, particularly when city-level data are used. Convergence in inequality also appears when total income is broken down into factor components, with the sole exception of pensions. Conversely, mean incomes across provinces (cities) are found to be diverging (converging), primarily driven by the wage component. Labour mobility is claimed to be responsible for these conflicting findings. The earning gaps across location and over time are completely due to differences in returns to resources, particularly education, not in the level of resources.

The causes of spatial inequality in Asia's, indeed the world's, second

most populous economy come next in this volume. The study by Lall and Chakravorty (Chapter 8) argues that spatial inequality of industry location is a primary cause of spatial income inequality. It identifies spatial factors that have cost implications for firms, and factors that influence the location decisions of new industrial units. By examining the contribution of economic geography factors to the cost structure of firms in eight industry sectors, the authors show that local industrial diversity is the one factor with significant and substantial cost-reducing effects. Further, new private sector industrial investments in India are found to be biased toward existing industrial and coastal districts, whereas state industrial investments (in deep decline after structural reforms) are far less biased toward such districts. It is concluded that structural reforms lead to increased spatial inequality in industrialization, and therefore in income.

Chapter 9 by Murshed and Gates analyses a case in which spatial inequalities were a contributory factor in social breakdown. Spatial inequality amidst ethnic and caste divisions can be counted as a main cause of the Nepalese civil war, which is most intense in the mid and far western regions of Nepal. These regions are the most disadvantaged in terms of human development indicators (HDI) and asset (land) holdings. Using the number of deaths as the dependent variable and HDI and landlessness as control variables, a Poisson regression analysis indicates that the deaths across the districts of Nepal are most significantly explained by the degree of inequalities.

The case of the Philippines is taken up by Balisacan and Fuwa in Chapter 10. Although the Philippines is more unequal than other Asian countries, expenditure inequality in the Philippines experienced little change during 1988–2000. The high inequality is largely owing to within-sector non-spatial factors. Gaps between regions contribute no more than 15 per cent to the total inequality; the urban–rural divide constitutes only 5 per cent. The remaining 80 per cent is attributable to household characteristics, particularly the educational attainment of the household head. Further, average income across 72 provinces is found to converge at a speed of 10.7 per cent unconditionally, and 8.5 per cent conditionally.

Ethnic and sub-ethnic ties are strong in Central Asian countries, making spatial inequality particularly inflammatory. Focusing on inequality in five countries of Central Asia, Chapter 11 by Anderson and Pomfret documents the impact of political, social and economic institutions on inequality in private and public resources (education, health care and other services). Although the degree of spatial inequality differs from country to country, the provision of public goods reinforces expenditure inequality because their distributions seem to favour the wealthy and the Slavic communities. The inter-region gaps in expenditure and public resources are large and growing, not always as a result of the urban–rural divide.

In contrast to Knight, Li and Zhao's findings, labour mobility is found not to reduce spatial inequality because of strong family ties.

Part III comprises two chapters, both built on methodologies developed in Part I of this volume. Following the methodology developed in Chapter 4, Dhongde in Chapter 12 decomposes the poverty rate into income and distribution components for India for the period 1999–2000, taking all-India as the benchmark. It is found that differences in poverty rates across states are largely the result of income differences. Inequality is lower in less developed areas than elsewhere, highlighting the importance of growth in reducing poverty in less developed areas.

Complementary to Chapter 2, Chapter 13 by Fujii presents poverty mapping for Cambodia at the commune level. To this end, the author utilizes 1999 survey data with 1998 census data. An interesting feature is the extensive use of health, soil, location and climatological data to obtain better-fitted models. Finally, school meals programmes are used to illustrate how other maps may be combined with poverty maps to identify the target areas for social sector intervention programmes.

The volume contains both theoretical and empirical contributions to the study of poverty and inequality. Although restricted to the Asian region, many of the findings and approaches are applicable to other areas. In particular, policy implications drawn from these studies could be used by Asian and other governments in fighting poverty and working to curb rising inequality.

Clearly, limitations of space allow only a small selection of papers to be included here and many issues remain unexplored. It is our hope that this collection will bring about more interest in spatial inequality in Asia, particularly its causes, consequences and policy implications.

Part I

Methodological issues

2

Poverty mapping with aggregate census data: What is the loss in precision?

Nicholas Minot and Bob Baulch

1. Introduction

Policy makers and researchers are interested in the geographical distribution of poverty for several reasons. First, knowledge of these patterns facilitates the targeting of programmes designed, at least in part, to reduce poverty. Many countries use some form of geographical targeting in government programmes such as credit, food aid, input distribution, health care and education. Second, this information is useful in monitoring progress in addressing poverty and regional disparities. Third, it may provide some insight regarding the geographical factors associated with poverty, such as access to markets, climate or topography.

In a growing number of countries, high-resolution poverty maps are now being produced using a relatively new two-stage approach. In the first stage, household survey data are used to estimate econometrically the relationship between poverty (or household expenditure) and a series of household characteristics, including household size and composition, education, occupation, housing characteristics, access to utilities, and ownership of consumer goods such as radios and bicycles. In the second stage, this relationship is applied to census data on the same household characteristics to calculate an estimate of the poverty rate[1] for some small geographical unit. Other poverty measures and indicators of income inequality can also be calculated, as well as standard errors of the estimates.

In an early application of this approach, Minot (1998, 2000) combined

a probit regression on data from the 1993 Vietnam Living Standards Survey (VLSS) and district-level means of the household characteristics from the agricultural census in 1994 to estimate the ranking of the incidence of poverty across 543 rural districts. Hentschel et al. (1998, 2000) use household survey data and household-level census data to estimate disaggregated poverty rates for Ecuador. They show that with household-level census data it is possible to generate unbiased estimates of the poverty rate as well as estimates of the standard error of the poverty rates. In the first stage of this approach, the logarithm of per capita expenditure is regressed on household characteristics from a household survey. In the second stage, data on the same household characteristics from the census are used to predict per capita expenditures and derive various poverty (and inequality) measures. This method, further developed by Elbers et al. (2003), has been used to construct poverty maps for Cambodia, Guatemala, Mozambique, Malawi, Nicaragua, Panama, Peru, South Africa and Viet Nam (see Henninger and Snel 2002).

Researchers, however, do not always have access to household-level census data. The national statistics agencies in many countries are reluctant to release household-level census data to researchers and international organizations, in part because of the issue of the confidentiality of the data. For example, China conducted a census in 2000 and India carried one out in 2001, but only district/county-level results are available to outside researchers. This means that household-level census data are not available to produce disaggregated poverty maps for 55 per cent of the people who are living in extreme poverty worldwide.[2] In addition, the computational burden of processing census data, which may contain tens or even hundreds of millions of records, can be a challenge for even the most powerful desktop computers. When access to household census data or the computational burden of processing such data are constraining factors, one alternative is to use census data that have been aggregated to a higher level (such as the commune, district or province).[3] In this case, the researcher uses a database consisting of (for example) the district-level means of all the household characteristics for the second stage of the approach described above. An important question, however, arises: how much precision is lost in generating poverty maps from aggregate census data? If the errors are small, then reliable poverty maps can be produced for a wider range of developing countries. If the errors are large, then the use of aggregated data is not advisable and researchers should focus on getting access to household-level data.

This study uses recent household survey and census data from Viet Nam to assess the loss in accuracy associated with the use of aggregated census data to estimate poverty instead of the original household-level data. The results of this analysis suggest that errors from using aggre-

gated census data in the second stage of poverty mapping are, in the case of Viet Nam, about 2–3 percentage points on average, if the level of aggregation is low. Furthermore, the chapter shows analytically and empirically that the error is close to zero when the incidence of poverty is close to zero, close to 50 per cent, or close to 100 per cent. Results from using aggregated census data must be interpreted with caution, however, because this approach tends exaggerate differences between poor and less poor regions. We also propose a method to adjust for the aggregation bias and show that it can cut the mean errors by 75 per cent.

The chapter is divided into four sections. Section 2 describes the data and methods used to compare alternative measures of the incidence of poverty using household survey data and census data from Viet Nam. Section 3 presents four types of results. First, we present an updated district-level map of poverty in Viet Nam based on the best available data and methods. Then we derive analytical results regarding the factors that affect the sign and relative magnitude of errors from the use of aggregate data. Next, we generate poverty estimates using Vietnamese census data that have been aggregated to different levels and compare the results with those obtained from the household-level census data. Finally, we propose and test a method for reducing the size of the errors associated with using aggregated census data. Section 4 summarizes the results and draws some implications for future research in poverty mapping.

2. Data and methods

2.1. Data

In this study, we use the 1998 VLSS and the 1999 Population and Housing Census. The VLSS was carried out by the General Statistics Office (GSO) of Viet Nam with funding from the Swedish International Development Agency and the United Nations Development Programme (UNDP), and with technical assistance from the World Bank. The survey was based on a stratified random cluster sample of 6,000 households, comprising 4,270 rural households and 1,730 urban households. The VLSS sample was based on 10 strata: the rural areas of the seven regions and three urban strata (Hanoi and Ho Chi Minh City, other cities, and towns). For this analysis, we merge ‘‘other cities’’ and ‘‘towns’’ because the census data do not distinguish between these two strata.

The 1999 census was carried out by the GSO and refers to the situation as of 1 April 1999. It was conducted with the financial and technical support of the United Nations Family Planning Association and UNDP. Unit record data from the full census are not available, but a 33 per cent

sample was obtained from the GSO. The 33 per cent sample was selected by the GSO using systematic sampling of every third household, yielding a sample of 5.55 million households.

The VLSS and the census have a number of household variables in common: household size and composition, education of the head and spouse, housing characteristics, source of water, type of sanitation facility, ownership of three consumer goods (radios, televisions and bicycles), and location of residence.

2.2. *Methods*

We begin with a description of the poverty mapping method when household-level census data are available. As mentioned above, the first step in implementing this approach is to use household survey data to estimate per capita expenditure as a function of a variety of household characteristics.[4] This typically takes the following semi-log form:

$$\ln(y_i) = X_i\beta + e_i, \tag{2.1}$$

where y_i is the per capita expenditure of household i, X_i is a $1 \times k$ vector of characteristics of household i from the survey, β is a $k \times 1$ vector of estimated coefficients, and e_i is the residual term.[5] To implement the regression analysis, we use the svyreg command in Stata, which takes into account the clustering, stratification and other features of the sampling design. This command generates Huber/White/sandwich estimates of the standard error of the regression coefficients. We estimate separate models for rural and urban areas.[6]

The second step is to apply the regression equation to census data on the same household characteristics. If we are using household-level census data, this generates estimates of per capita expenditure for each household in the census. Hentschel et al. (2000) show that the expected value of the probability that household i is poor (P_i) can be described as follows:

$$E(P_i \mid X_i^{\mathrm{C}}, \beta, \sigma) = \Phi\left[\frac{\ln(z) - X_i^{\mathrm{C}}\beta}{\sigma}\right], \tag{2.2}$$

where $\Phi(\ )$ is the cumulative standard normal function, X_i^{C} is a vector of the same household characteristics taken from the census, β is a vector of the coefficients estimated in the first stage, z is the poverty line, and σ is the standard error of the regression from the first stage. If the region contains N households labelled $i = 1, \ldots, N$, the expected value of the poverty rate for the region, P, is simply the weighted average of the prob-

abilities that the individual households are poor, where the weights are the share of the population in each household (m_i/M):

$$E(P \mid X_i^{\mathrm{C}}, \beta, \sigma) = \sum_i \frac{m_i}{M} P_i = \sum_i \frac{m_i}{M} \Phi\left[\frac{\ln(z) - X_i^{\mathrm{C}}\beta}{\sigma}\right]. \tag{2.3}$$

In some cases, however, the statistics bureau of the government is not willing to release household-level census data but is willing to release aggregated data, such as the mean values of household characteristics for each district or village. The two studies of this type have used probit or logit regression models instead of the semi-log model to predict whether households are poor or not (Minot 1998, 2000; Astrup and Dessus 2001). The mean values of the household characteristics in the census data are then inserted into the estimated probit/logit equation to estimate poverty for each aggregation unit in the census data (for example, for each district). This is not an unbiased estimate of poverty because the probit equation is non-linear. Using aggregate data ignores the variation in the household characteristics within each aggregation unit. For this reason, Minot (2000) used the results to rank districts by the incidence of poverty rather than reporting the estimated poverty rates. Even if we adopted the semi-log functional form in the first stage, the non-linearity of the cumulative standard normal function in equation (2.3) would make it impossible to get an unbiased poverty estimate using aggregated census data.

In section 3.1, we present the semi-log and probit regression models to "predict" expenditure and poverty, respectively, based on household characteristics. Then we use the semi-log model and household-level census data to generate district-level estimates of the incidence of poverty in Viet Nam. In section 3.2, we use a second-order Taylor series expansion to provide an analytical expression for the error associated with using aggregate census data instead of household-level census data. This provides some information on the factors that influence the sign and relative magnitude of the error. In section 3.3, we use data from Viet Nam to examine the sensitivity of the poverty estimates to the choice of functional form in the first stage of the procedure and to the use of aggregate census data in the second stage. With regard to the functional form, we compare the results obtained from using a probit model and the semi-log model. With regard to the level of aggregation of the census data, we compare the estimates of the incidence of poverty (denoted by P_0) from the original household-level census data (considered the most accurate estimate) with estimates obtained from census data aggregated to the level of (a) the enumeration area, (b) the commune, (c) the district, (d) the province, and (e) the region.[7] The poverty estimates are calculated at four levels (district, provincial, regional and national), though, of course, the poverty

Table 2.1 Summary of alternative methods to be compared

Level of aggregation of the census data	Level of aggregation of poverty estimates		
	District	Province	Region
Household	Semi-log model (underlined)	Semi-log model (underlined)	Semi-log model (underlined)
	Probit model	Probit model	Probit model
Enumeration area	Semi-log model	Semi-log model	Semi-log model
	Probit model	Probit model	Probit model
Commune	Semi-log model	Semi-log model	Semi-log model
	Probit model	Probit model	Probit model
District		Semi-log model	Semi-log model
		Probit model	Probit model
Province		Semi-log model	Semi-log model
		Probit model	Probit model
Region			Semi-log model
			Probit model

Note: The underlined item represents the standard of comparison.

estimates cannot be more disaggregated than the census data on which they are based.

Table 2.1 provides a summary of the methods being compared in this chapter. The upper rows represent the (presumably) more accurate measures of poverty that use more disaggregated census data. The underlining indicates the standard of comparison used for each type of poverty estimate. The lower rows represent cruder approaches to estimating the incidence of poverty. For example, the third pair in the first column refer to the estimation of district-level poverty rates using commune averages of the indicators.

3. Results

3.1. District-level estimates of poverty in Viet Nam

As described above, the first step in the poverty mapping procedure is to use household expenditure data to estimate per capita expenditure (or poverty) as a function of household characteristics. Table 2.2 provides the semi-log models of per capita expenditure in rural and urban areas using the VLSS. Table 2.3 presents the rural and urban probit models to predict which households are poor based on the same household characteristics. The second step is to apply the regression model to census data on the same household characteristics.

Table 2.2 Semi-log regression models of per capita expenditure

Variable	Rural model Coefficient	Rural model t	Urban model Coefficient	Urban model t
Household size	−0.0772	−19.5***	−0.0785	−8.1***
Percent elderly	−0.0831	−2.4**	−0.1026	−1.6
Percent children	−0.3353	−9.4***	−0.2368	−3.6***
Percent female	−0.1177	−3.5***	0.0386	0.5
Ethnic minority	−0.0765	−1.9*	0.0142	0.2
Head finished primary	0.0585	3.4***	0.0616	1.7*
Head lower secondary	0.0883	4.5***	0.0338	1.3
Head upper secondary	0.0884	3.3***	0.1368	3.2***
Head adv. tech. training	0.1355	4.2***	0.1603	3.5***
Head post-secondary education	0.2552	4.9***	0.1843	3.7***
No spouse	0.0173	1.0	0.0344	0.8
Spouse finished primary	0.0049	0.3	0.0642	1.9*
Spouse lower secondary	0.0132	0.6	0.0987	2.6***
Spouse upper secondary	0.0107	0.3	0.1912	2.7***
Spouse adv. tech. training	0.0921	2.3**	0.1285	3.2***
Spouse post-secondary education	0.1571	2.7***	0.1752	3.1***
Manager/leader	0.1414	3.5***	0.2312	3.0***
Professional/technician	0.1350	3.3***	0.0576	1.2
Clerk/service worker	0.1362	3.4***	0.0357	0.9
Agriculture/forest/fish	−0.0163	−0.6	−0.0093	−0.2
Skilled labourer	0.0701	1.9*	0.0071	0.2
Unskilled labourer	−0.0586	−1.7*	−0.1599	−2.9***
Permanent house	−0.9228	−4.3***	−0.5194	−3.4***
Semi-permanent house	−0.3120	−3.6***	−0.4001	−3.8***
Area of permanent house	0.2958	5.7***	0.2001	5.4***
Area of semi-permanent house	0.1180	5.2***	0.1403	4.6***
Electricity	0.0765	2.7***	−0.0026	0.0
Tap water	0.0828	1.4	0.2289	5.3***
Other clean water source	0.1157	4.4***	0.0340	0.6
Flush toilet	0.2700	5.5***	0.1311	2.2**
Latrine	0.0556	2.6**	0.0049	0.1
Owns television	0.2124	15.1***	0.2167	5.5***
Owns radio	0.1009	7.0***	0.1599	6.2***
Red River Delta	0.0314	0.6	0.0693	0.7
North Central Coast	0.0485	0.8	0.0445	0.6
South Central Coast	0.1373	2.2**	0.1460	1.9*
Central Highlands	0.1708	2.1**	[a]	
South-east	0.5424	9.4***	0.4151	5.5***
Mekong River Delta	0.3011	5.1***	0.1895	2.1**
Constant	7.5327	108.7***	7.7538	64.7***
N	4,269		1,730	
R^2	.536		.550	

Notes: Dependent variable is the log of per capita expenditure. Regression analysis uses the ‘‘svyreg’’ command in Stata, taking into account sample design effects. The standard errors are the Huber/White/sandwich estimators.

[a] Variable omitted because there are no urban Central Highland households in the VLSS sample.

* Indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Source: Semi-log regression analysis of 1998 Vietnam Living Standards Survey.

Table 2.3 Probit regression models of poverty

	Rural model		Urban model	
Variable	Coefficient	*t*	Coefficient	*t*
Household size	0.2646	14.3***	0.2016	5.2***
Percent elderly	0.2960	2.0*	0.6555	1.6
Percent children	1.1654	8.3***	1.9540	4.8***
Percent female	0.2654	1.8*	0.6060	1.8*
Ethnic minority	0.3480	2.5**	−1.4063	−2.7***
Head finished primary	−0.1838	−2.7***	0.0492	0.3
Head lower secondary	−0.2715	−3.0***	−0.1834	−0.7
Head upper secondary	−0.2188	−1.9*	−0.9618	−2.1**
Head adv. tech. training	−0.1901	−1.3	−0.1838	−0.8
Head post-secondary education	−0.9608	−2.9***	–[a]	
No spouse	0.0570	0.7	−0.0772	−0.4
Spouse finished primary	−0.0304	−0.4	−0.3579	−1.6
Spouse lower secondary	0.0401	0.4	−0.1744	−0.8
Spouse upper secondary	0.0946	0.6	−0.4886	−1.4
Spouse adv. tech. training	−0.3949	−1.9*	−0.9367	−2.8***
Spouse post-secondary education	−1.2828	−3.3***	[a]	
Manager/leader	−0.7908	−3.2***	[a]	
Professional/technician	−0.5138	−2.6***	−0.6283	−1.2
Clerk/service worker	−0.4315	−2.4**	0.2873	1.2
Agriculture/forest/fish	−0.0490	−0.4	0.0570	0.3
Skilled labourer	−0.2490	−1.7*	0.0747	0.3
Unskilled labourer	0.0926	0.7	0.6134	3.2***
Permanent house	2.0174	2.3**	1.1957	0.8
Semi-permanent house	0.7057	1.8*	0.5558	0.9
Area of permanent house	−0.6689	−2.9***	−0.4698	−1.2
Area of semi-permanent house	−0.2889	−2.7***	−0.2922	−1.7*
Electricity	−0.1990	−1.9*	−0.0948	−0.2
Tap water	−0.1337	−0.4	−0.4582	−2.2**
Other clean water source	−0.3644	−3.4***	0.2702	1.2
Flush toilet	−0.6064	−2.7***	−0.4153	−1.5
Latrine	−0.0802	−1.1	−0.1649	−1.0
Owns television	−0.6760	−11.9***	−0.7611	−3.6***
Owns radio	−0.2998	−5.1***	−0.1169	−0.8
Red River Delta	−0.1269	−0.7	0.5038	1.8*
North Central Coast	−0.1736	−0.8	0.5167	2.0**
South Central Coast	−0.5567	−2.8***	−0.0825	−0.3
Central Highlands	−0.8070	−2.9***	[b]	
South-east	−1.6979	−7.9***	−0.6654	−1.7*
Mekong River Delta	−0.9502	−4.3***	−0.1820	−0.6
Constant	−0.2816	−1.1	−1.8916	−3.6***
N	4,269		1,730	
Correct prediction	77.2%		80.2%	

Notes: Dependent variable is 1 if the household is poor and 0 if not. Regression analysis uses the "svyprobt" command in Stata, taking into account sample design effects. The standard errors are the Huber/White/sandwich estimators.
[a] Variable omitted because it perfectly predicts not being poor.
[b] Variable omitted because there are no urban Central Highland households in the VLSS sample.
* Indicates significance at the 10% level, ** at the 5% level and *** at the 1% level.
Source: Probit regression analysis of 1998 Vietnam Living Standards Survey.

Figure 2.1 shows the district-level poverty rates obtained from applying the semi-log model to the household-level census data. The map indicates that poverty rates are over 80 per cent in the districts bordering China to the north and Laos to the north-west. These areas are mountainous and have low population densities, poor transport infrastructure and a high proportion of ethnic minorities. Many of the districts in the North Central Coast and the Central Highlands also have poverty rates between 40 per cent and 80 per cent. The Mekong Delta (at the southern tip) and the Red River Delta (on the north-eastern coast) have poverty rates of 20–60 per cent. These areas are favoured by intensive irrigation of rice, fruits and vegetables, good transportation networks, and proximity to the largest cities (Ho Chi Minh City and Hanoi). The districts with the lowest poverty rates (below 20 per cent) are near Hanoi and in the South-east region. The South-east region includes Ho Chi Minh City, the largest and most commercially oriented city in Viet Nam. The rural areas around Ho Chi Minh City have become an important centre for commercial agriculture and agro-industry. These patterns conform closely to the results from earlier studies (see World Bank 1995; Poverty Working Group 1999; and Minot 2000).

As mentioned above, with household-level census data it is possible to calculate standard errors and construct confidence intervals around the poverty estimates. The confidence intervals for the district-level poverty estimates in Figure 2.1 range from ± 1.3 to ± 22.0 percentage points, with a mean value of ± 5.8 percentage points (see Minot et al. 2004 for more details).

3.2. Determinants of the errors of aggregation

Suppose that we can obtain only district-level means of the household characteristics from the census and we wish to calculate district-level poverty rates. The sign and magnitude of the error associated with using aggregate census data instead of household-level census data can be estimated using a second-order Taylor expansion as follows:[8]

$$\frac{1}{N}\sum_i \Phi\left[\frac{\ln(z) - X_i^{\mathrm{C}}\beta}{\sigma}\right] \cong \Phi\left[\frac{\ln(z) - \bar{X}^{\mathrm{C}}\beta}{\sigma}\right] + \frac{1}{2}\,\mathrm{var}\left(\frac{\ln(z) - X_i^{\mathrm{C}}\beta}{\sigma}\right) \times \Phi''\left[\frac{\ln(z) - \bar{X}^{\mathrm{C}}\beta}{\sigma}\right], \tag{2.4}$$

where the index i refers to households in the district, N is the number of households in the district, and $\bar{X}^{\mathrm{C}}$ is the vector of district-level means of

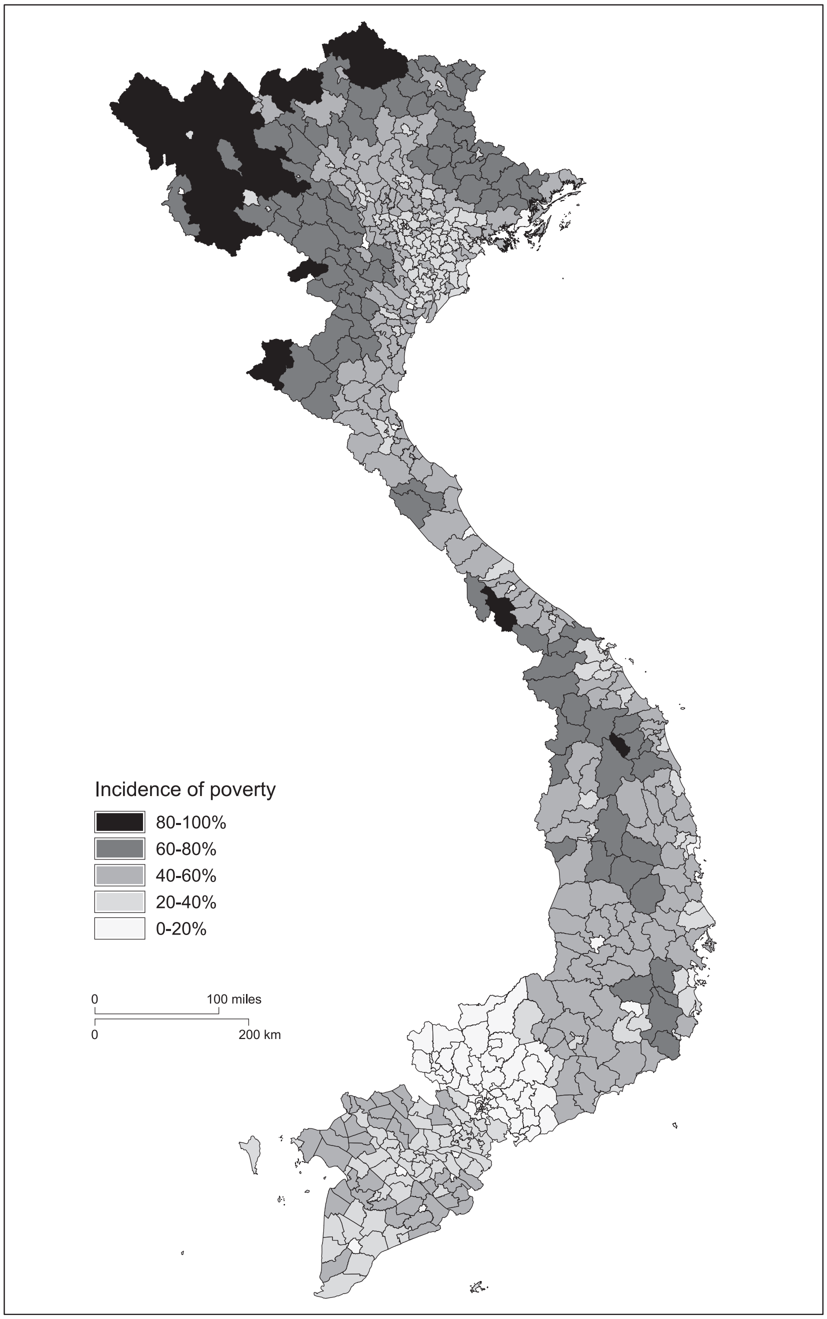

Figure 2.1 District-level estimates of poverty (P_0).
Source: Authors' configuration.

the household characteristics. The left-hand side of this equation represents the incidence of poverty as estimated from household-level census data (X_i^C), as described in section 2.2. The first term on the right-hand side is the (less accurate) estimate of the incidence of poverty rate obtained from the aggregated census data ($\bar{X}^C$). The second term on the right-hand side is the approximate error associated with using aggregate census data rather than household-level census data.[9] This error is a function of the variance of estimated log per capita expenditure within the aggregation region and the second derivative (or "curvature") of the cumulative standard normal function at the means of the aggregation region.[10]

This equation has three implications for the error associated with using aggregate census data in poverty mapping. First, the variance is always positive and, since the second derivative of the cumulative standard normal function is positive (negative) when the value of the function is below (above) 0.5, poverty estimates based on aggregated data will underestimate poverty in regions with poverty rates below 50 per cent and overestimate poverty in regions with poverty rates above 50 per cent. In other words, if a country has regions with poverty rates below 50 per cent and others with rates above 50 per cent, using aggregate data to produce a poverty map will exaggerate the differences in poverty between the two sets of regions. Second, since the curvature of the cumulative standard normal function is zero in the centre of the curve and approaches zero at the two tails of the function, the error term approaches zero when the incidence of poverty is close to 0 per cent, 50 per cent and 100 per cent. Third, the magnitude of the error is proportional to the variance of the estimated log per capita expenditure within the geographical unit of aggregation. In the extreme, if there were no variation across households, there would be no error associated with using aggregate data. If we assume, as is plausible, that the variance in household characteristics is greater in larger geographical units, then aggregation over small units (such as a district) would produce smaller errors than would aggregation over larger units (such as a province).

Although these results provide us with some information about the factors that determine the direction and relative magnitude of the errors associated with using aggregated census data in poverty mapping, they do not give us a sense of the absolute size of the errors. For example, errors of less than 1 percentage point would be considered negligible for most purposes, whereas errors of more than 10 percentage points would be considered unacceptable to most users. In the next section, we use data from Viet Nam to measure the error associated with using aggregated census data to produce estimates of the incidence of poverty.

3.3. Empirical comparison of alternative methods

As shown in Table 2.1, we can estimate the incidence of poverty at different levels of aggregation using census data aggregated to different levels. For example, we can calculate the incidence of national and regional poverty using the original household-level census data on the household characteristics, and compare these results with those produced from household characteristics averaged at different levels: enumeration area (EA), commune, district, province and region. Furthermore, we can use either the probit model or the semi-log model in the first stage. This yields 12 sets of estimates for national and regional poverty, as shown in Table 2.4.

The national poverty rate, estimated using household-level census data and the semi-log model, is 36.7 per cent. Using aggregate census data, the estimates are 2.0 to 2.5 percentage points lower, ranging from 34.1 to 34.7 per cent. Looking at the regional poverty estimates, when aggregated census data are used, the poverty rate is overestimated in the poorest region (rural Northern Uplands) and underestimated in the least poor regions (the two urban strata, the two deltas and Rural South-east). These results are consistent with equation (2.4), which predicts that aggregate data will underestimate (overestimate) poverty when the rate is below (above) 50 per cent. On the other hand, using the semi-log model combined with the EA-, commune-, district- or provincial-level means, the ranking of regions by poverty rate is very similar to that with the household-level data. All 12 methods agree that the rural Northern Uplands region is the poorest and that Hanoi/Ho Chi Minh City is the least poor.

Table 2.5 compares the results from the semi-log model with household census data (column 1 in Table 2.4) and those of other methods (columns 2 to 12 in Table 2.4). The use of aggregate data appears to bias downward the regional poverty rates by between 2 and 3 percentage points on average, for the reasons mentioned above. As expected, the mean absolute error rises with the degree of aggregation in the census data. For example, the mean absolute error associated with the semi-log model rises from 2.1 percentage points for the EA-level aggregation to 3.0 percentage points for district means and 3.9 for regional means. The error associated with the probit models is around 1.6 percentage points higher than that associated with the semi-log models at the same level of aggregation. Rows 5–7 of Table 2.5 show the percentage distribution of the regions according to the size of the error. When poverty is estimated using EA-level means and the semi-log model, the errors for all nine regions are less than 5 percentage points. Even when regional poverty rates are inferred from *regional* means in the household characteristics, the

Table 2.4 Regional poverty estimates using different methods

	Household-level data		EA-level means		Commune means		District means		Provincial means		Regional means	
	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit
Hanoi and Ho Chi Minh City	0.047	0.048	0.018	0.014	0.012	0.009	0.010	0.007	0.009	0.006	0.009	0.005
Other urban areas	0.155	0.135	0.114	0.080	0.099	0.065	0.094	0.060	0.084	0.049	0.073	0.039
Rural Northern Uplands	0.606	0.633	0.614	0.644	0.619	0.651	0.627	0.661	0.637	0.673	0.664	0.710
Rural Red River Delta	0.380	0.387	0.355	0.359	0.350	0.355	0.347	0.353	0.346	0.351	0.345	0.350
Rural North Central Coast	0.506	0.523	0.501	0.519	0.502	0.520	0.503	0.522	0.510	0.532	0.510	0.532
Rural South Central Coast	0.479	0.452	0.468	0.437	0.467	0.435	0.468	0.436	0.472	0.438	0.471	0.438
Rural Central Highlands	0.536	0.486	0.538	0.482	0.541	0.479	0.546	0.480	0.550	0.482	0.552	0.482
Rural South-east	0.126	0.132	0.081	0.082	0.068	0.069	0.063	0.063	0.058	0.059	0.054	0.055
Rural Mekong Delta	0.396	0.405	0.370	0.381	0.363	0.375	0.361	0.373	0.359	0.372	0.356	0.369
Viet Nam	0.367	0.369	0.347	0.346	0.342	0.341	0.342	0.341	0.342	0.341	0.343	0.344

Source: Estimated from 1998 VLSS and 33 per cent sample of 1999 Population and Housing Census.

Table 2.5 Errors in regional poverty estimates using different methods

	Household-level data	EA-level means		Commune means		District means		Provincial means		Regional means	
	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit
Bias	−0.003	−0.019	−0.026	−0.023	−0.030	−0.023	−0.030	−0.023	−0.030	−0.022	−0.028
Mean absolute error	0.018	0.021	0.037	0.027	0.043	0.030	0.046	0.034	0.050	0.039	0.057
Median absolute error	0.017	0.025	0.038	0.030	0.043	0.032	0.043	0.034	0.041	0.039	0.042
Mean squared error	0.001	0.001	0.002	0.001	0.002	0.001	0.003	0.002	0.003	0.002	0.004
Distribution of errors											
0–5 percentage points, %	100	100	78	78	67	78	56	78	56	67	56
5–10 percentage points, %	0	0	22	22	33	22	44	22	33	33	22
Over 10 percentage points, %	0	0	0	0	0	0	0	0	11	0	22
Correlation coefficient	.993	.999	.992	.999	.990	.998	.989	.997	.987	.995	.982
Rank correlation coefficient	0.983	1.000	0.967	1.000	0.967	1.000	0.967	1.000	0.967	1.000	0.967

Notes: Errors are calculated relative to the poverty rates obtained using semi-log regression and household-level census data. Statistics are calculated giving equal weights to each region, so the bias is not equal to the difference in national poverty rates.
Source: Estimated from 1998 VLSS and 33 per cent sample of 1999 Population and Housing Census.

errors are less than 5 percentage points for six of the nine regions. The last two rows of Table 2.5 reveal a high degree of correlation across poverty estimates and high correlations of the regional rankings they generate.

The ability of aggregated census data to estimate regional poverty rates is interesting but perhaps less relevant than their ability to estimate provincial and district-level poverty rates. The real advantage of combining survey and census data is to be able to map poverty at these more disaggregated levels. Table 2.6 presents a summary of the errors in estimating the incidence of provincial poverty. Once again, the aggregated data introduce a small downward bias in the headcount incidence of poverty. The bias remains relatively constant, between −1 and −2 percentage points, regardless of the degree of aggregation of the census data. On the other hand, the mean absolute error is 2.2 percentage points for the semi-log model with EA-level means rising gradually to 3.6 percentage points for the semi-log model with provincial means. The percentage of provinces with absolute errors of less than 5 percentage points falls from 100 per cent with the semi-log model and EA-level means to 77 per cent with the semi-log model and provincial means. The probit models have mean absolute errors about 1 percentage point greater than the semi-log models using the same level of aggregation.

The four diagrams within Figure 2.2 plot the provincial poverty estimates based on household-level census data (on the horizontal axis) against estimates based on different levels of aggregation for the census data (on the vertical axis), using the semi-log model for both. The errors appear as deviations from the diagonal line. Panel (a) shows the close correspondence between provincial poverty estimates derived from household-level census data and those derived from EA-level means of the census data. Panels (b), (c) and (d) illustrate the progressively larger errors as the level of aggregation moves up from commune-level to district-level to provincial means. The elongated S-shaped pattern confirms the pattern predicted from equation (2.4) and discussed above, in which aggregated data result in an underestimate of poverty for less poor regions and an overestimate of poverty for the poorest regions. The goodness-of-fit multiple correlation coefficient (R^2) exceeds .99 for all four pairs of variables. This implies that over 99 per cent of the variation in the provincial poverty rates can be "explained" by the means of the household characteristics in the census data. Similarly, if the poverty estimates are ranked and their ranks compared, the (Spearman) rank correlation coefficient exceeds 0.995 for all pairs.

Table 2.7 and Figure 2.3 compare the district-level poverty estimates obtained from household-level census data and those obtained from aggregated census data. As would be expected, given the smaller sample size, the bias, mean and median errors are somewhat larger than the

Table 2.6 Errors in provincial poverty estimates using different methods

	Household-level data	EA-level means		Commune means		District means		Provincial means	
	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit
Bias	0.001	−0.016	−0.018	−0.020	−0.021	−0.019	−0.020	−0.018	−0.018
Mean absolute error	0.015	0.022	0.031	0.028	0.037	0.032	0.041	0.036	0.046
Median absolute error	0.011	0.021	0.028	0.027	0.037	0.030	0.042	0.035	0.045
Mean squared error	0.000	0.001	0.001	0.001	0.002	0.001	0.002	0.002	0.003
Distribution of errors									
0–5 percentage points, %	93	100	84	90	74	87	64	77	56
5–10 percentage points, %	7	0	16	10	25	13	34	23	43
Over 10 percentage points, %	0	0	0	0	2	0	2	0	2
Correlation coefficient	.991	.999	.990	.999	.989	.998	.988	.997	.987
Rank correlation coefficient	0.981	0.999	0.983	0.999	0.982	0.998	0.981	0.999	0.982

Notes: Errors are calculated relative to the poverty rates obtained using semi-log regression and household-level census data. Statistics are calculated giving equal weights to each province, so the bias is not equal to the difference in national poverty rates.
Source: Estimated from 1998 VLSS and 33 per cent sample of 1999 Population and Housing Census.

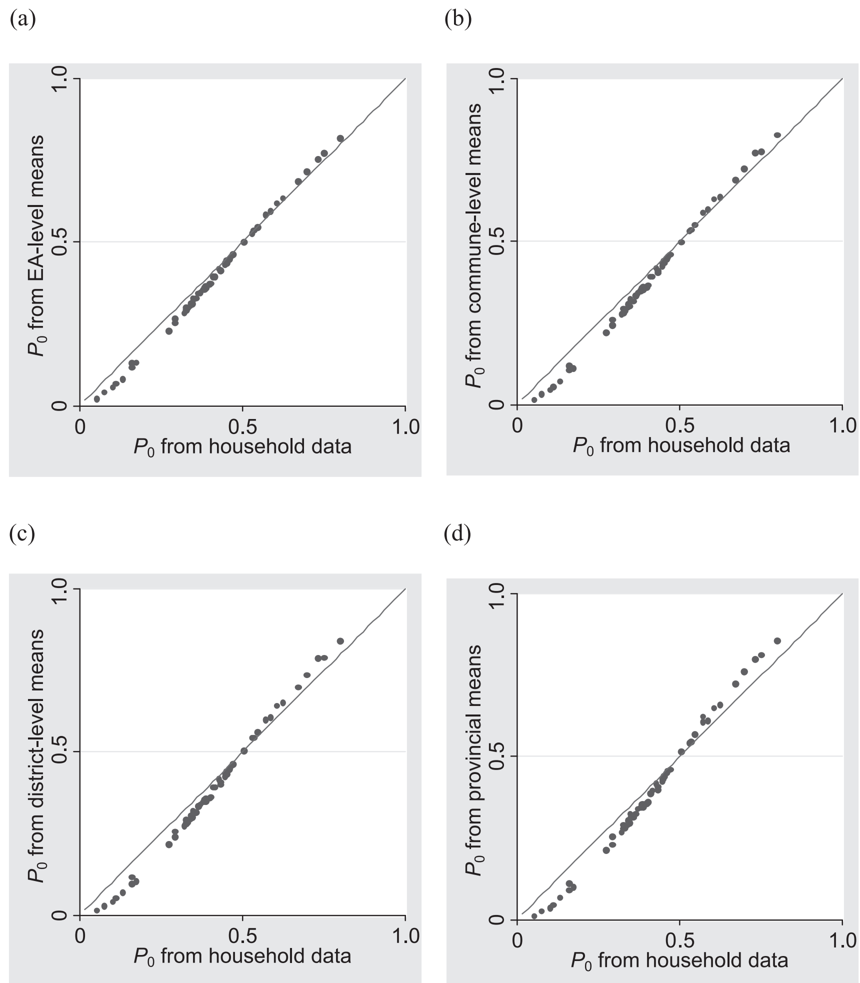

Figure 2.2 Provincial poverty estimates from aggregated census data compared with estimates from household-level census data.

errors in provincial poverty estimates reported in Table 2.6. The bias never exceeds 2 percentage points, and the mean absolute error ranges from 2.0 to 4.8 percentage points, depending on the level of aggregation and the model. However, Figure 2.3 reveals the same pattern of errors as Figure 2.2, in which the incidence of poverty is exaggerated for the poorest districts and understated for the least poor districts. As explained

Table 2.7 Errors in district poverty estimates using different methods

	Household-level data	EA-level means		Commune means		District means	
	Probit	Semi-log	Probit	Semi-log	Probit	Semi-log	Probit
Bias	0.000	−0.014	−0.017	−0.017	−0.020	−0.015	−0.018
Mean absolute error	0.020	0.025	0.036	0.032	0.043	0.038	0.048
Median absolute error	0.014	0.024	0.032	0.031	0.040	0.035	0.044
Mean squared error	0.001	0.001	0.002	0.001	0.003	0.002	0.003
Distribution of errors							
0–5 percentage points, %	91	96	73	83	62	74	56
5–10 percentage points, %	9	4	25	16	35	26	38
Over 10 percentage points, %	1	0	3	0	3	0	6
Correlation coefficient	.991	.999	.990	.998	.989	.997	.988
Rank correlation coefficient	0.987	1.000	0.988	0.999	0.987	0.999	0.987

Notes: Errors are calculated relative to the poverty rates obtained using semi-log regression and household-level census data. Statistics are calculated giving equal weights to each district, so the bias is not equal to the difference in national poverty rates.
Source: Estimated from 1998 VLSS and 33 per cent sample of 1999 Population and Housing Census.

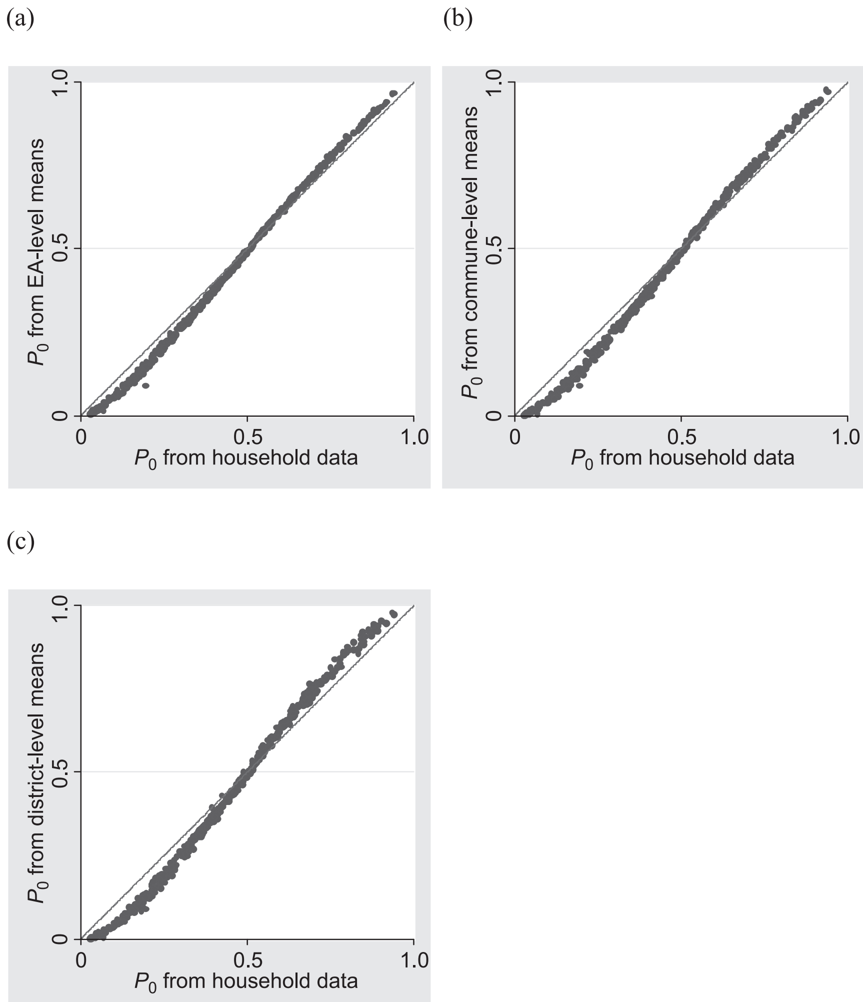

Figure 2.3 District-level poverty estimates from aggregated census data compared with estimates from household-level census data.

above, this is due to the change in sign of the curvature of the cumulative standard normal function when the incidence of poverty rises above 50 per cent. Again, the elongated S-shape is more pronounced when the level of aggregation is higher, in panel (c), which measures the accuracy of district poverty estimates derived from district-level means of the census data on household characteristics.

3.4. Improving poverty estimates derived from aggregate census data

In the previous section, we showed that empirical estimates of the errors associated with using aggregate census data were consistent with our expectations based on equation (2.4). In this section, we show that equation (2.4) can be used to improve poverty estimates derived from aggregate census data. As discussed above, the second term on the right-hand side of equation (2.4) approximates the gap between the poverty estimate obtained from household-level census data and the poverty estimate obtained from aggregate census data. This term includes the variance of the normalized predicted log per capita expenditure, $\mathrm{var}[(\ln(z) - X_i^C\beta)/\sigma]$, and the curvature of the cumulative standard normal curve $\Phi''[(\ln(z) - \bar{X}^C\beta)/\sigma)]$. The curvature component is simply the slope of the standard normal density curve and is easily calculated using numerical methods and the aggregated census data. The variance component, however, requires information at the household level.

One approach is to use the household survey data to calculate the variance component.[11] We can adjust the regional poverty estimates obtained from census data aggregated to the regional level by using regional variances calculated from the VLSS. For example, the estimate of poverty in the rural Northern Uplands using regional means is 0.664, almost 6 percentage points above the estimate of 0.606 based on household-level data. But the variance component is 0.622 and the curvature is -0.154, so the adjusted poverty rate is $0.664 + (0.5)(0.622)(-0.154) = 0.616$, which is just 1 percentage point above the poverty estimate based on the household survey data.

As shown in Table 2.8, the mean absolute error across the nine regions falls from 3.9 percentage points to 1.0 percentage point or 75 per cent. Unfortunately, the variance cannot be reliably estimated at the provincial or district level because of the limited sample size of the VLSS, a problem likely to occur with any household survey. If we try to apply the regional variance to correct provincial and district-level poverty estimates within that region, the results are much less impressive: the adjustment reduces the mean absolute error by just 18–20 per cent (see Table 2.8). Thus, the use of household survey data to estimate the variance component does not seem to be very promising.

An alternative approach is to ask the census authorities to calculate the variance component at some (preferably low) level of aggregation. Even if the census authorities are reluctant to release household-level data for reasons of confidentiality, they may still be willing to calculate this variance at the level of, for example, the enumeration area (EA). In most circumstances, it is sufficient to obtain the variance of $X_i^C\beta$ in order to make these adjustments.[12]

Table 2.8 Effect of adjusting poverty estimates for errors of aggregation

Type of adjustment[a]	Level of poverty estimate	Level of aggregation of census data	Mean absolute error of poverty estimate[b]: Without adjustment	Mean absolute error of poverty estimate[b]: With adjustment	Reduction in mean absolute error due to adjustment, %
Variance[c] at the regional level from household survey data	Region	Region	0.039	0.010	75
	Province	Province	0.036	0.029	18
	District	District	0.038	0.030	20
Variance[c] at the level of the enumeration area from census data	Region	Enumeration area	0.021	0.005	77
	Province	Enumeration area	0.022	0.005	78
	District	Enumeration area	0.025	0.006	74

Notes:
[a] "Adjustment" refers to the method of correcting for errors of aggregation using equation (2.4).
[b] "Mean absolute error" refers to the average absolute value of the difference between the poverty estimates obtained from household-level census data and those obtained from aggregated census data.
[c] "Variance" refers to $\text{var}[(\ln(z) - X_i^C\beta)/\sigma]$ from equation (2.4).
Source: Estimated from 1998 VLSS and 33 per cent sample of 1999 Population and Housing Census.

The lower half of Table 2.8 shows that adjusting poverty estimates using EA-level variances from the census data can dramatically improve the precision of the poverty estimates derived from aggregate census data. In this case, EA-level poverty estimates are calculated using the EA-level means of the household characteristics and the EA-level variance of $X_i^C\beta$. The results are then aggregated to the district, provincial and regional levels and compared with the estimates obtained from household-level census data. These corrections reduce the mean absolute error for regional, provincial and district-level poverty estimates from 2.1–2.5 percentage points to 0.5–0.6 percentage points. Thus, when household-level census data are not available, information about the variance of $X_i^C\beta$ is valuable in sharply reducing the errors associated with using aggregate census data.

4. Summary and conclusions

This chapter explores the errors associated with using aggregated census data instead of household-level census data in carrying out poverty mapping analysis. The issue arises because national statistics agencies in many developing countries (in particular, China and India) are reluctant to release household-level census data. Our analytical results suggest that the use of aggregated data will underestimate the incidence of poverty when the rate is below 50 per cent and overestimate it when the rate is above 50 per cent. The magnitude of the error varies with the estimated incidence of poverty, being smallest when the poverty rate is close to zero, 50 per cent and 100 per cent. Furthermore, the error is proportional to the variance in estimated log per capita expenditure within the aggregated geographical units.

Empirical results using data from Viet Nam indicate that, if census data are aggregated to the level of the enumeration area (each of which has about 85 households), the errors in estimating the incidence of poverty are relatively small, averaging between 2.1 and 2.5 percentage points for national, regional and provincial estimates of poverty. Furthermore, when the poverty rate is estimated using EA-level means of the census data, all 61 provinces and 96 per cent of the 614 districts have errors of fewer than 5 percentage points. Not surprisingly, errors are larger when the level of aggregation is greater. Using census data aggregated to the level of communes or districts produces mean absolute errors of 2.8 to 3.8 percentage points. The study also compared the use of the semi-log regression model with that of the probit regression model. The incidence of poverty estimated from the probit model differed from that obtained from the semi-log model by about 1.0 percentage point for district-level and provincial poverty estimates.

Finally, we propose a method of adjusting the poverty estimates derived from aggregated census data. In particular, we show that information on the variance of $X_i^C\beta$ in the census data can be used to adjust the poverty estimates from aggregate data. This method cuts the mean absolute error associated with using aggregate census data by approximately three-quarters.

What are the implications of these results for other studies that combine household survey data and census data to produce high-resolution poverty maps? Clearly, the best option is to carry out the analysis with household-level census data. Not only does this generate more accurate estimates of the incidence of poverty, but it allows the estimation of various other measures of poverty and inequality (as well as estimates of standard errors of these measures) all of which are difficult to estimate with aggregated census or grouped household survey data (see Chen et al. 1991; Elbers et al. 2003).

At the same time, the results presented in this chapter suggest that if household-level census data are not available, as is often the case, it is possible to generate reasonably accurate estimates of the incidence of poverty (P_0) using aggregated census data. The errors associated with aggregation are more likely to be acceptable if the level of aggregation of the census data is relatively low, such as at the district or enumeration area. Even highly aggregated census data can be used to rank provinces by poverty rate relatively accurately. The results in this chapter provide information to help researchers anticipate the likely size and direction of the errors associated with using aggregate census data. In addition, researchers forced to work with aggregated census data can substantially reduce the aggregation errors if they can obtain from census authorities information on the variance in the estimated log per capita expenditure and apply the adjustment equation described in this chapter.

Overall, these results suggest that, in some cases, high-resolution maps of the spatial patterns in poverty can be generated even in countries for which only aggregated census data are available. Such maps can contribute to efforts in these countries to alleviate poverty through geographically targeted policies and programmes.

Appendix: Derivation of error associated with using aggregate census data

This appendix derives an expression that describes the error associated with using aggregate census data instead of household-level census data in the second step of a poverty mapping analysis. We start with the second-order Taylor expansion:

$$f(x_1) \cong f(x_0) + (x_1 - x_0) f'(x_0) + \frac{1}{2}(x_1 - x_0)^2 f''(x_0).$$

If we duplicate this expression for N values of x, labelled $x_1 \ldots x_N$, and take the sum of the N equations, we get the following:

$$\sum_i f(x_i) \cong \sum_i f(x_0) + \sum_i (x_i - x_0) f'(x_0) + \frac{1}{2} \sum_i (x_i - x_0)^2 f''(x_0).$$

Dividing by N and setting the reference point (x_0) equal to the mean value of x $(\bar{x})$, the result is:

$$\frac{1}{N} \sum_i f(x_i) \cong f(\bar{x}) + \frac{1}{N} \sum_i (x_i - \bar{x}) f'(\bar{x}) + \frac{1}{2N} \sum_i (x_i - \bar{x})^2 f''(\bar{x}).$$

But, since the sum of deviations from the mean is zero, the second term on the right-hand side drops out. Furthermore, the third term on the right-hand side can be expressed in terms of the variance of x:

$$\frac{1}{N} \sum_i f(x_i) \cong f(\bar{x}) + \frac{1}{2} \operatorname{var}(x_i) f''(\bar{x}).$$

Next, we replace $f(.)$ with $\Phi(.)$, the cumulative standard normal distribution, and we replace x_i with $[\ln(z) - X_i^C \beta]/\sigma$, the difference between the log of the poverty line (z) and the estimated log per capita expenditure for household i $(X_i^C \beta)$ divided by the standard error of the regression (σ). The result is:

$$\frac{1}{N} \sum_i \Phi\left[\frac{\ln(z) - X_i^C \beta}{\sigma}\right] \cong \Phi\left[\frac{1}{N} \sum_i \frac{\ln(z) - X_i^C \beta}{\sigma}\right] + \frac{1}{2} \operatorname{var}\left(\frac{\ln(z) - X_i^C \beta}{\sigma}\right) \times \Phi''\left[\frac{1}{N} \sum_i \frac{\ln(z) - X_i^C \beta}{\sigma}\right].$$

If we assume that the poverty line (z) and the regression parameters (β and σ) are constant across the unit of aggregation of the census data, which will normally be the case,[13] then the first term on the right-hand side can be rewritten as follows:

$$\frac{1}{N} \sum_i \Phi\left[\frac{\ln(z) - X_i^C \beta}{\sigma}\right] \cong \Phi\left[\frac{\ln(z) - \bar{X}^C \beta}{\sigma}\right] + \frac{1}{2} \operatorname{var}\left(\frac{\ln(z) - X_i^C \beta}{\sigma}\right) \Phi''\left[\frac{\ln(z) - \bar{X}^C \beta}{\sigma}\right].$$

This equation describes the error associated with using aggregated census data instead of household-level data in estimating the proportion of *households* that are below the poverty line. If we wish to describe the errors in estimating the proportion of *people* below the poverty line, the averages in this equation must be re-

written as weighted averages, where the weights are the household size. This equation is further interpreted in section 3.2.

Acknowledgements

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Notes

1. In this chapter, we use ''poverty rate'', denoted by P_0, to refer to the percentage of people living in households whose per capita expenditure falls below the poverty line.
2. According to calculations based on the World Development Indicators and using the US$1-a-day poverty line, China and India account for 55 per cent of the world's poor (World Bank 2003).
3. This approach has been used in Viet Nam and in Gaza and the West Bank (see Minot 1998, 2000; Astrup and Dessus 2001).
4. Note that some ''household'' characteristics (e.g. education or occupation of the household head) are based on the characteristics of individual members of the household. Some studies (for example, Bigman et al. 2000) also use community-level characteristics in estimating per capita expenditures.
5. Elbers et al. (2003) discuss a number of econometric issues related to this step, including the problems of heteroscedasticity and spatial autocorrelation. In the presence of these problems, our estimated coefficients would not be efficient, but the Huber/White/sandwich estimates of the standard errors used in this study are consistent under heteroscedasticity and take into account the effect of clustering and stratification on sampling error.
6. In Minot and Baulch (2002), we compare the poverty estimates obtained from rural/urban regression models with those obtained from eight stratum-level models. The urban/rural models gave a somewhat better fit (in terms of the value of R^2) and had more statistically significant coefficients. In any case, the difference in poverty estimates between the two approaches was quite modest, with provincial poverty rates (P_0) differing by an average of just 2.2 percentage points.
7. At the time of the 1999 census, Viet Nam had 61 provinces, 614 districts, 10,714 communes and 166,481 enumeration areas (EAs).
8. The derivation of equation (2.4) can be found in the appendix to this chapter.
9. This is the *approximate* error because we started with the Taylor series expanded only to the second order. A more precise estimate of the error would take into account the third- and higher-order terms in the series.

10. Note that the poverty line (z) and the standard error of the regression (σ) are generally constant across the relatively small geographical units for which the incidence of poverty is estimated.
11. We are grateful to an anonymous reviewer for suggesting this approach.
12. Within a single regression domain (in which β and σ are constant) and within a single poverty-line domain (in which z is constant), it is necessary to ask census authorities to calculate only $\mathrm{var}(X_i^C\beta)$ because $(1/\sigma^2)\,\mathrm{var}(X_i^C\beta) = \mathrm{var}[(\ln(z) - X_i^C\beta)/\sigma]$.
13. Typically, the regression analysis is carried out for urban and rural sectors or for each stratum of the household expenditure survey, so there are between 2 and 20 areas over which the regression parameters are constant. Similarly, the number of estimated poverty lines is usually relatively small (fewer than 20). By contrast, aggregated census data are often at the level of the district or enumeration area, of which there are generally more than 100. Thus, within a unit of aggregation, the poverty line and the regression parameters will, in most cases, be constant.

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3

A decomposition analysis of regional poverty in Russia

Stanislav Kolenikov and Anthony Shorrocks

1. Introduction

Along with many other former Soviet bloc countries, the population of Russia has experienced major changes in living standards during the transition era. Economic liberalization caused prices to explode in the early 1990s, with inflation peaking at more than 30 per cent per month in 1992, and then spurting again after the financial crisis of August 1998. At the same time, real GDP fell during much of the early period of reform, so that by the turn of the century it was less than half the level prevailing a decade earlier.

These economic upheavals are reflected in the figures for the number of Russians living in poverty. Official estimates suggest that the proportion of the population below subsistence level grew dramatically from less than 10 per cent in the late 1980s to over 30 per cent during 1992 and 1993. After dropping back to around 20 per cent, the poverty rate then climbed above 40 per cent following the August 1998 crisis. Although these fluctuations in poverty have a clear and expected link to changes in average real incomes, Shorrocks and Kolenikov (2001) show that this was not the only factor at work; increasing inequality was also a major source of rising poverty during the 1990s, and revisions to the subsistence standard caused a spurious decline in reported poverty rates.[1]

Spatial variation is a second, relatively neglected, dimension of inequality and poverty analysis. Given the size of Russia, and the fact that it covers many climatic and time zones with very different living condi-

tions, it is not surprising to find large regional differences. These are indeed huge. Across the 78 main subregions, prices and poverty rates vary by a factor of more than 4, and nominal incomes by a factor of more than 10. In the poorest regions, mean per capita income has been below subsistence level in recent times, and well over half of the population lives in poverty, even by the most generous estimates. This degree of regional disparity is probably not matched in any other country in the world. Nor was it probably matched in Russia in Soviet times, when price controls and fiscal redistribution were used to mitigate the "natural" disparity in regional living standards that have now emerged.[2]

An understanding of the sources of regional differences is therefore crucial to understanding the level and trend of poverty and inequality in the Russian Federation. Yemtsov (2005) assesses the contribution of increasing regional disparity to the rise in inequality in Russia during the period 1994–2000. This chapter focuses instead on the regional dimensions of poverty. Specifically, we investigate some of the proximate explanations for variations in poverty across regions by characterizing regions in terms of per capita income, income inequality and prices, and by showing how the deviations of regional poverty levels from the all-Russia average can be exactly attributed to these three sources.[3] In order to do so, we make use of a new and powerful decomposition framework based on the Shapley value in cooperative game theory.

The chapter is organized as follows. Section 2 provides some essential background to the study of poverty in Russia and its regions. The basic framework and the Shapley decomposition procedure are described in section 3, followed by a discussion of the lognormal model used to generate counterfactual poverty estimates. The results are reported and discussed in section 5, and section 6 concludes.

2. Aspects of regional poverty in Russia

Russia has relatively little experience of research on poverty. The concept of poverty was never used in the Soviet Union, but was instead referred to as "lack of material security". Although a method for calculating the cost of the "minimal consumption basket" was developed in the mid-1960s, most of the Soviet population was never able to attain this consumption level (Mozhina 1993).

In late Soviet times, the per capita cost of the "minimal consumption basket" was set at 75 roubles per month, between one-third and one-half of the average income at that time.[4] Some social payments were linked to this level, so it became recognized as a type of de facto poverty line, albeit one that was relatively high by international standards. Fol-

lowing the relaxation of price controls in 1992, real incomes fell rapidly and substantially, prompting an urgent search for a new way of measuring and monitoring poverty. With assistance from the World Bank, a revised methodology based on nutritional requirements was developed in 1992, one that took account of regional variation in dietary patterns and food prices. The new subsistence figures also distinguished three main population subgroups: adults (the reference category), children (with an equivalence scale factor of about 0.9) and the elderly (with an equivalence scale factor equal to 0.6). Food expenditure was fixed at 68 per cent of total subsistence needs, with the composition of non-food items left unspecified.[5] Although initially regarded as a temporary poverty standard, the new subsistence levels were legally recognized in 2000 following a number of modifications, including the provision of considerable autonomy to regions to choose their own poverty line within certain (fairly relaxed) constraints.

As is common practice in other countries, the proportion of the population in poverty – the so-called "poverty rate" or "headcount ratio" – is computed by comparing the monetary value of available resources (which we call "nominal income") with the poverty line. Official poverty figures are calculated by the Russian State Committee on Statistics (commonly known by its Russian acronym, Goskomstat) and are based on a two-parameter lognormal model fitted to data drawn from the household budget survey and other sources. In essence, the variance of the lognormal is derived from the budget survey, while the mean is obtained from aggregate macroeconomic data.[6]

Many criticisms have been levelled against Goskomstat in the past, with respect to both the data acquisition and the procedures employed in the statistical analysis. The lognormal methodology is described in Goskomstat (1998a) and is discussed below in section 4 and in the appendix. As regards the core household data, Goskomstat surveys about 48,000 households (containing over 140,000 individuals) in 800 administrative units (similar to provinces) of Russia. In the early post-reform period the survey results were of dubious quality. One major deficiency was continued use of the Soviet-style sampling frame, based on interviewing workers at large enterprises (Rimashevskaya 1997). This and other biases associated with poor sample design and survey non-response led many analysts to believe that the sample underrepresented the lower tail of the income distribution and omitted the rich altogether (see Aivazian and Kolenikov 2001). In collaboration with the World Bank, Goskomstat undertook a programme of sample redesign and rotation from 1994 to 1998 in order to improve the representativeness of the sample (which is now based on the 2 per cent microcensus conducted in 1994). However, the household microdata remain unavailable to almost

all researchers, and the methodology described in Goskomstat (1998a) omits many important details.

The measurement of household resources and the concept of household welfare have also changed over time. The crude measure of nominal money income used in the early 1990s was later supplemented by figures on home production. Goskomstat abandoned direct questions on income in 1995, using expenditure data instead to construct several measures of welfare (monetary expenditure, consumption expenditure, final consumption, disposable resources, disposable income). Wage and benefit arrears have been a major problem in some years, and provide another potential source of distortion in the data. If individuals report wages and benefits that should have been received but were not, then the figures for disposable monthly income are biased upward. On the other hand, if accumulated arrears are occasionally paid off, then wages and benefits accrued over several months may be attributed to a single month.[7] Volatility of recorded income is also caused by seasonal fluctuations in agriculture and construction, by the bonuses traditionally paid by Russian enterprises in December, and by the common practice of not fully compensating employees during the summer vacation period.[8]

Published regional data on poverty refer to the 78 primary regions of Russia (‘‘subjects of the Federation’’), which are subdivided into ‘‘republics’’ (21), ‘‘krays’’ (6) and ‘‘oblasts’’ (49), plus the two largest cities, Moscow and St Petersburg.[9] From 1992 to 1998, poverty lines were recalculated each month, and from 1999 onwards each quarter, using the local prices in each region.[10] Poverty rates are also reported for all regions on a monthly or quarterly basis (although the monthly data appear to be rather volatile, suggesting a spurious degree of precision).[11] In addition, Goskomstat reports the ratio of the mean income to the poverty line in each region, a figure that typically lies between 2.0 and 2.5.

Although figures for poverty are relatively abundant in Goskomstat publications, data on inequality are sparse. Quintile shares (i.e. the income share of the poorest 20 per cent of the population, the next 20 per cent, etc.) are reported by region only for 1995.[12] Given our interest in documenting the contribution of inequality to poverty, we focus on the data for 1995, with the expectation that our broad conclusions should also apply to other years.[13]

The regional pattern of poverty in 1995 is portrayed in Figure 3.1. One striking feature is the extent of the variation in poverty rates across the country, with some regions experiencing poverty rates three or four times the level recorded in some other places. The extreme examples are Tuva republic in mid-Siberia with a poverty rate exceeding 70 per cent, and Kemerovo, Tula and Ulyanovsk oblasts with poverty rates around 16 per cent.[14] A second obvious feature is the tendency for the poorer

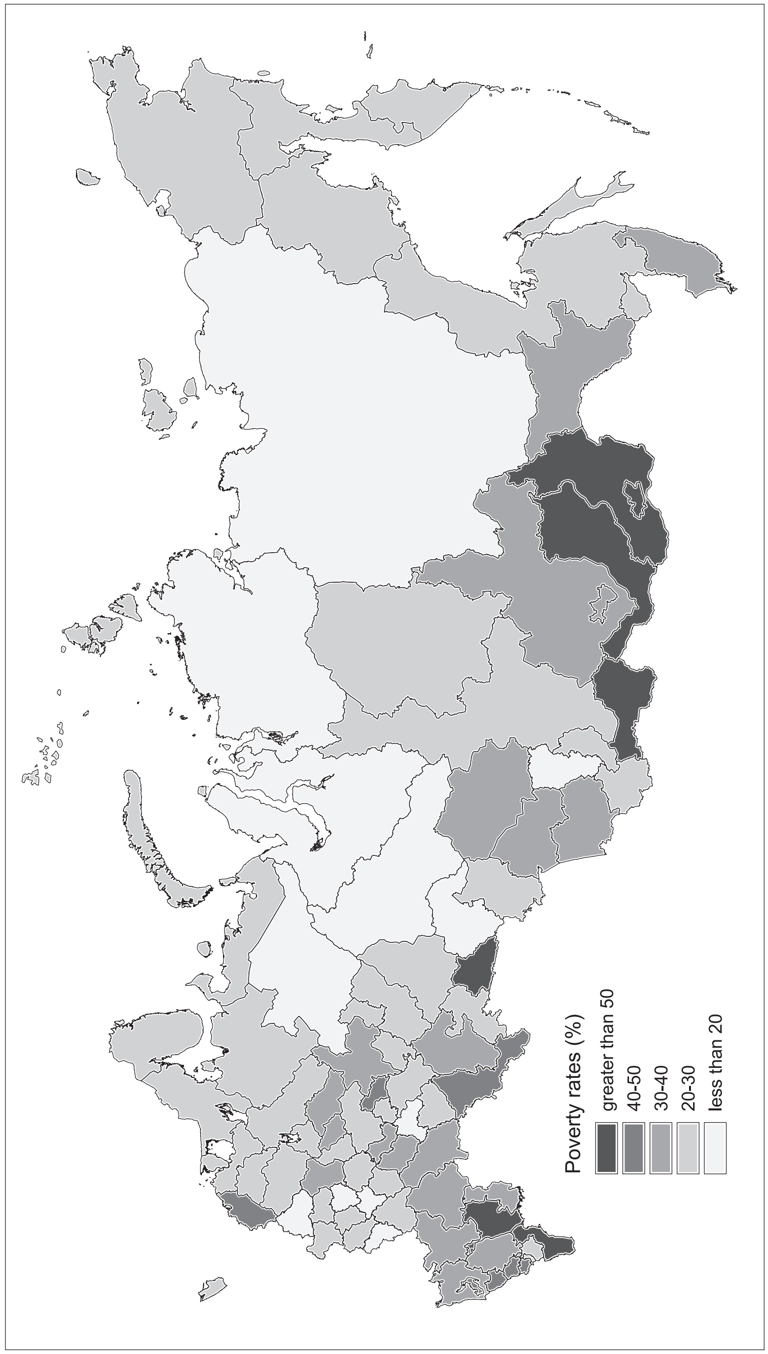

Figure 3.1 Headcount poverty rates in Russian regions.

provinces to be found in the south and east, and the less poor provinces to cluster in the north, despite their locational and climatic disadvantages. Clearly, geography is not the only factor at work here. Natural resources are evidently influential, and other economic and political factors may also play a part. In fact, the diversity of poverty experience and the range of economic and political environments across regions make Russia a particularly rich and interesting laboratory in which to study the factors that determine poverty.[15]

To illustrate the degree and scale of diversity in Russia, Table 3.1 reports summary data on a number of regions.[16] These regions cannot be considered "representative" in any reasonable sense, but they do serve to indicate the extremes of economic development within Russia. Chelyabinsk is a large industrial centre in the Urals. Magadan is a typical northern region of Russia facing the Pacific Ocean. Moscow is the capital of Russia, and Moscow oblast is the region surrounding Moscow (essentially, the suburbs of Moscow). North Osetia is a national republic in the Caucasus. Pskov is a region between Moscow and St Petersburg believed to have had the best climate for foreign direct investment in the country in the late 1990s. Tatarstan is the strongest national republic of Russia, rich with oil; it also has the second-largest automobile enterprise, KamAZ. Tuva is the poorest mid-Siberian region, and Tyumen is the main oil and gas extracting region.[17] Finally, Ulyanovsk is a typical "red belt" region under communist rule.

The data in Table 3.1 reflect the expected relationship between regional poverty rates and per capita incomes. As already mentioned, poverty rates in Russia are calculated by comparing the monetary value of the resources of every household with the corresponding poverty line. More generally, each of the commonly used indices of poverty can be expressed in the form $P = \pi(F, z)$ where F is the distribution function for adult equivalent household incomes across individuals and z is the poverty standard for a single adult. Since the distribution F is fully characterized by its mean, μ, and Lorenz curve, L, the poverty indicator can also be expressed in the form:

$$P = P(L, \mu, z) \tag{3.1}$$

for some suitable function $P(.)$. This indicates that regional poverty levels are completely determined by three factors: income inequality, as captured by the Lorenz curve; nominal income per capita; and the subsistence level for a single adult, which reflects regional price variations. It is therefore worth exploring the importance of each of these proximate sources of poverty if only to confirm, or counter, the common presumption that average income is the dominant influence on poverty.

Table 3.1 Characteristics of selected regions

	Region	Poverty rate (%)	Nominal income (roubles)	Gini (%)	Average subsistence level (roubles)	Population ('000)	Share of urban population (%)	Population density (per km^2)	Mean July temperature (°C)	Mean January temperature (°C)
CH	Chelyabinsk	27.9	415	33.2	254	3,700	81.3	41.8	15.8	–17.4
MA	Magadan	24.6	961	37.4	570	279	87.1	0.5	11.5	–26.9
MW	Moscow city	19.1	1,804	56.2	328	8,717	100.0	320.3	20.4	–6.3
MO	Moscow oblast	31.2	395	27.2	259	6,626	79.7	138.7	18.4	–8.3
NO	North Osetia	42.8	319	30.1	233	659	69.5	82.7	20.6	–3.2
PS	Pskov	42.7	340	30.2	273	835	65.1	14.8	18.5	–5.4
TA	Tatarstan	22.1	394	33.8	192	3,755	73.4	55.6	17.7	–15.9
TU	Tuva	73.2	314	43.3	359	308	48.1	1.8	15.8	–25.2
TY	Tyumen	19.2	1,085	44.3	394	3,157	76.1	2.2	11.3	–26.3
UL	Ulyanovsk	16.3	312	30.2	154	1,492	72.6	39.6	19.1	–13.8
RF	Russian Federation	24.7	515	40.7	264	148,306	73.0	8.6	17.1	–13.2

Source: Goskomstat (1998b), except for Gini values calculated by the authors.

For many purposes it is convenient to go one step further, by combining the mean income and poverty line into a single variable representing average real income. If, as is typically assumed, the poverty level remains the same when the poverty line and all incomes are subject to the same proportional adjustment, equation (3.1) may be rewritten as

$$P = \bar{P}(L, \mu/z). \tag{3.2}$$

Note that equations (3.1) and (3.2) apply not only to the headcount poverty rate but to any standard poverty index. Later we report results for two indices, FGT1 and FGT2, drawn from the Foster–Greer–Thorbecke (Foster et al. 1984) class:

$$\text{FGT}_\alpha = \int_{-\infty}^{z} \left(\frac{z-x}{z}\right)^\alpha dF(x), \qquad \alpha \geq 0, \tag{3.3}$$

with parameters corresponding to $\alpha = 1$ and $\alpha = 2$.

One advantage of confining the analysis to the two factors indicated in equation (3.2) is that it permits a graphical representation of the link between inequality and poverty in Russian regions as shown in Figure 3.2. The horizontal axis indicates the mean income to poverty line ratio as reported by Goskomstat, and the vertical axis gives the value of the Gini index of inequality.[18] Also drawn are the lines connecting the inequality–mean income combinations that yield a certain fixed poverty rate in the context of a two-parameter lognormal model. The reference provided by these ‘‘iso-poverty’’ contours makes it easy to understand the proximate causes of variations in poverty rates across regions.

Disregarding Moscow city, which is clearly an outlier with regard to both mean income and inequality, it is interesting to note the economic and geographical clustering of Russian regions on the graph. In the top right corner, close to the point labelled TY, are found the resource-rich Siberian regions including Tyumen oblast, Krasnoyarsk kray, known for aluminium production and nickel exports, and Kemerovo oblast, producing coal. St Petersburg, the second-largest Russian city, is also located within this group. The other end of the income spectrum on the far left side of the graph is occupied by the poorest regions of Siberia and the far east, with real incomes little above that of Tuva and, as a consequence, poverty rates exceeding 50 per cent. The group of regions with a Gini value of about 0.3 separates into two principal clusters. The first, represented by the points TA and UL on the graph, covers Tatastan and the relatively rich ‘‘red belt’’ regions: Ulyanovsk, Lipetsk, Tula, Smolensk and Kursk oblasts. A second group, below and to the left of the point labelled PS, contains the poorer regions along the Volga river and

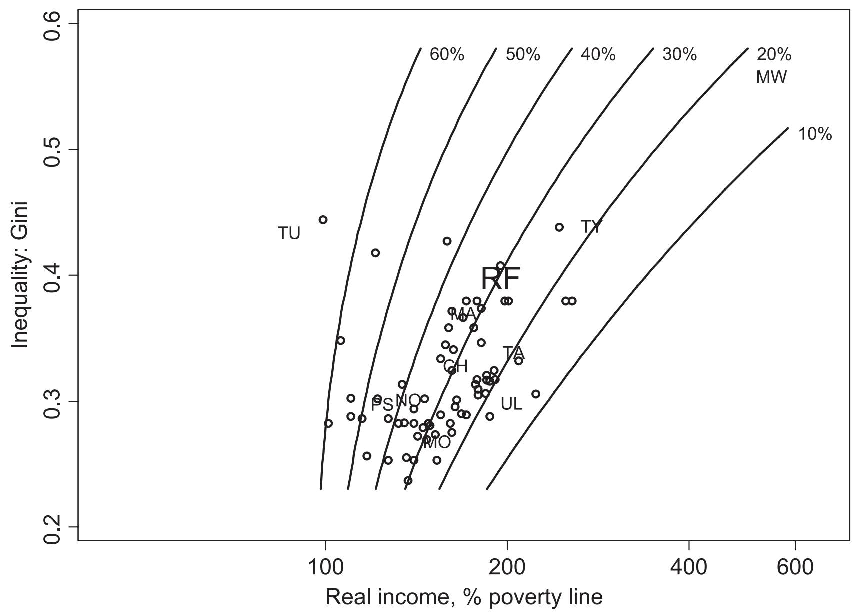

Figure 3.2 Poverty contour map for Russian regions.

in the south, such as the republics of Mari El, Mordovia, Kalmykia and Karachaevo-Cherkessia.

The following sections explore in more detail the way in which inequality interacts with nominal incomes and prices to generate the observed poverty levels. In particular, we seek to establish the quantitative contributions of these three factors to poverty in each region.

3. The decomposition framework

The framework of analysis used in this study has its origins in the decomposition of changes in poverty into growth and redistribution components proposed by Datt and Ravallion (1992) and others. Figure 3.3 illustrates the basic principles in the context of the headcount poverty rate. Given a poverty line z, the initial income distribution represented by the distribution function F_0 generates the poverty rate p_0, which falls to p_1 when the distribution changes to F_1. The move from F_0 to F_1 can be regarded as the combination of two effects: a pure proportionate growth effect captured by the rightward shift of the distribution function from F_0 to F (since the horizontal axis has a logarithmic scale); and a pure redistribu-

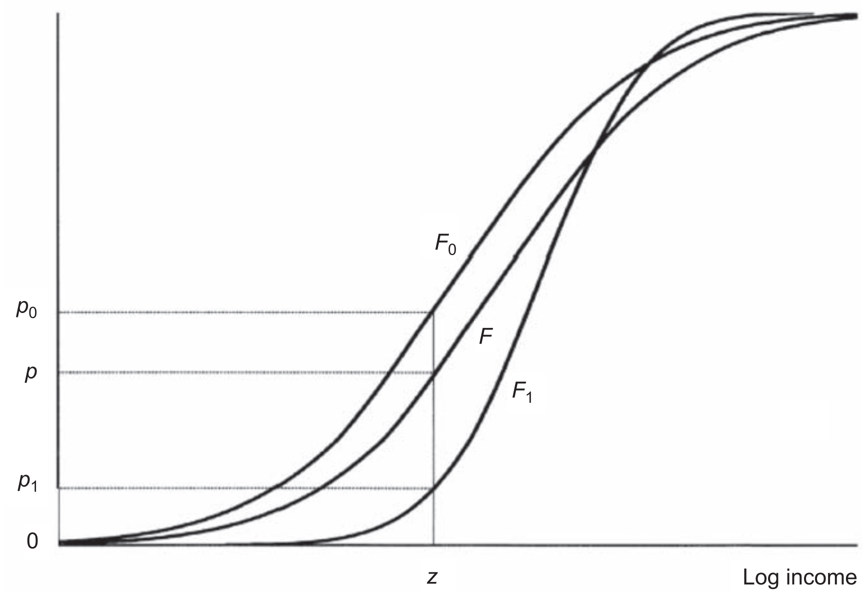

Figure 3.3 Growth–redistribution decomposition of the poverty rate.

tion effect (holding mean income constant) corresponding to the twist from F to F_1. This allows the total change in poverty, $p_1 - p_0$, to be decomposed in a similar fashion, with $p - p_0$ representing the contribution of income growth and $p_1 - p$ indicating the redistribution component. In the situation portrayed in Figure 3.3, the two effects reinforce each other to produce a significant reduction in the headcount poverty rate; but the same analysis can also be applied in less favourable circumstances.

Expressed in the notation of equation (3.1), this procedure allows the change in poverty:

$$\Delta P = p_1 - p_0 = F_1(z) - F_0(z) = P(\mu_1, L_1, z) - P(\mu_0, L_0, z)$$

to be decomposed into the income growth and redistribution effects given respectively by:

$$p - p_0 = P(\mu_1, L_0, z) - P(\mu_0, L_0, z); \tag{3.5a}$$

$$p_1 - p = P(\mu_1, L_1, z) - P(\mu_1, L_0, z). \tag{3.5b}$$

The problem with this specification is that (3.5a) indicates the marginal effect of the change in mean income with the distribution held constant

at the *initial* configuration, whereas (3.5b) computes the marginal impact of redistribution holding mean income constant at the *final* level. One can equally well generate a decomposition with the *ceteris paribus* conditions interchanged and, since there is no logical reason for preferring one configuration over the other, symmetry arguments suggest that the two effects should be averaged to yield the income effect:

$$\tfrac{1}{2}[P(\mu_1, L_0, z) - P(\mu_0, L_0, z)] + \tfrac{1}{2}[P(\mu_1, L_1, z) - P(\mu_0, L_1, z)] \tag{3.6a}$$

and the redistribution component

$$\tfrac{1}{2}[P(\mu_0, L_1, z) - P(\mu_0, L_0, z)] + \tfrac{1}{2}[P(\mu_1, L_1, z) - P(\mu_1, L_0, z)]. \tag{3.6b}$$

Expressions (3.6a) and (3.6b) turn out to be the contributions associated with the level and distribution of income in a two-way Shapley decomposition of the change in poverty. The Shapley decomposition is inspired by the classic cooperative game theory problem of dividing a pie fairly, to which the Shapley solution assigns each player her marginal contribution averaged over all possible coalitions of agents.[19] The reinterpretation described in Shorrocks (1999) considers the various factors (*n* in total, say) that together determine an indicator such as the overall level of poverty, and assigns to each factor the average marginal contribution taken over all the *n*! possible ways in which the factors may be ‘‘removed’’ in sequence. The particular attractions of this technique are that the decomposition is always exact and that the factors are treated symmetrically. Figure 3.4 illustrates how the Shapley procedure can be applied to the decomposition of the change in poverty into three components corresponding to the change in mean income, inequality and the poverty line. The six possible downward routes correspond to the six possible ways in which, starting from the final position, each of the factors can be reset in sequence at their original values.

Shorrocks and Kolenikov (2001) apply the three-way Shapley decomposition to poverty changes over time since 1985. The application here to spatial, rather than temporal, differences in poverty requires a reinterpretation of the analysis. The base-level distribution indicated earlier by the subscript 0 now refers to a suitable reference distribution, which we choose to correspond to the whole of Russia, although it could equally well be a specific region such as Moscow city. With all-Russia as the base, the Shapley decomposition contributions indicate the contributions to poverty associated with deviations of mean income etc. from the Russian level. This is done later for the three-factor decomposition into nominal income, inequality and poverty line (or regional price) effects.[20] To facilitate graphical representation, we also report results for the two-way

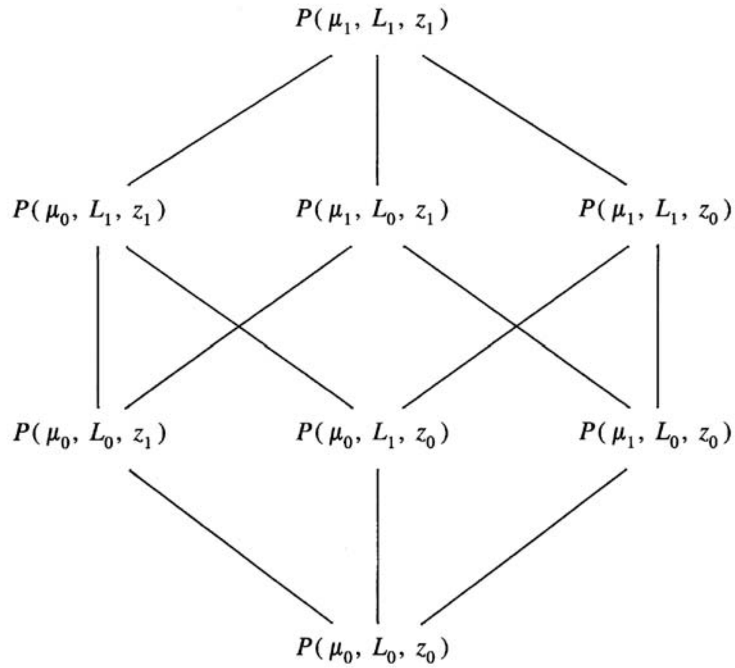

Figure 3.4 Three-way Shapley decomposition.

Shapley decomposition into real income and inequality components, the formula for which corresponds to equation (3.6) with the poverty line suppressed (or absorbed into μ).

4. The lognormal model

To apply the Shapley decomposition framework requires answers to counterfactual questions such as "what level of poverty would Moscow exhibit if Moscow had the same average income as Volgograd" (or the same income as Russia as a whole). Answers to these questions could be calculated directly from a representative household data set for Russia, but this is not currently available. However, income quintile data are occasionally published by Goskomstat for Russian regions, and the basic methodology for constructing these data is reported (Goskomstat 1998a). So we can try to reconstruct the Lorenz curve for each region that, when combined with information on mean incomes, enables the Shapley approach to be applied.

The distributional data reported by Goskomstat, including quintile

shares, Gini values and poverty rates, are obtained by fitting a two-parameter lognormal model (denoted here by LN(μ, σ^2)) to the raw data. In essence, household budget survey data are used to estimate the variance of logarithms parameter σ^2, and the mean income values are set with regard to aggregate balance sheet information.[21] Then all inequality measures are calculated as functions of the variance of logarithms, and the poverty rate is given by the percentile of the lognormal distribution corresponding to the poverty line.[22]

Although there is little support for the lognormal model as a parametric representation of income distribution in Russia or elsewhere,[23] it becomes more justified once the procedures employed by Goskomstat are recognized. Making use of the basic properties of the lognormal outlined in the appendix, the variance of log incomes was derived from the quintile shares reported by Goskomstat, by averaging over the four estimates obtained by applying equation (3A.11) to the income shares recorded for the bottom 20 per cent, 40 per cent, 60 per cent and 80 per cent of the population.[24]

Combining these figures for the variance of log incomes with data on per capita income and on the average value of the poverty line produces estimates of the headcount poverty rate in each region that can be compared with the rates published by Goskomstat.[25] Some support for this approach is provided by Table 3.2, which reports the results of regressing the published headcount poverty rates on our estimated values. The poverty rate itself should not be used as the dependent variable, because it is bounded between zero and one. So we use the probit transformation of the published headcount ratio, $\Phi^{-1}(H)$, on the LHS and the probit transformation of our estimate, $\Phi^{-1}(\hat{H})$, on the RHS.[26]

Table 3.2 reports the results obtained with the single regressor and a second regression with a large set of covariates including economic, demographic and geographical variables taken from the regional database. A number of alternative specifications were tried, with the Akaike information criterion selecting the simplest bivariate regression. The R^2 value of .88 indicates that the basic lognormal model is reasonably accurate, and the absence of significant additional variables in the second regression means that we cannot improve substantially on the simple specification. The results also imply that our estimate of the poverty rate based on the income to poverty line ratio and the variance of logarithms tends to fall below the published Goskomstat figure by several percentage points. Moscow, for instance, would have a poverty rate of 15.8 per cent according to the model, compared with the published figure of 19.1 per cent.

This systematic bias may be owing in part to the neglect of population heterogeneity. The growth–redistribution framework described in section

Table 3.2 Regression results for regional poverty rates

Dependent variable: probit transformation of published poverty rate	Basic regression Coefficient	Basic regression Standard error	Extended regression Coefficient	Extended regression Standard error
Probit transformation of poverty rate from lognormal model	0.873**	0.038	0.8**	0.061
ln population density			0.017	0.018
Mean temperature in January			−0.005	0.003
Mean temperature in July			0.003	0.008
Gross regional product per capita ('000)			−0.003	0.005
Life expectancy at birth			−0.001	0.007
Share of population younger than working age			0.017	0.009
Share of population older than working age			0.011	0.007
Share of social and cultural expenditures in the regional budget			−0.002	0.003
ILO unemployment rate			0.005	0.004
Constant	−0.100**	0.023	−0.754	0.475
Number of observations	76		73	
R^2	.88		.90	

Note: ** indicates significance at 1% level.
Source: CEFIR regional data set based on Goskomstat (1998b); data for 1995 except for temperatures.

3 presupposes a homogeneous population and a single poverty line. When the per capita poverty line depends on household composition – as is the case with the minimum subsistence level in Russia – incomes should be adjusted to take account of composition differences, either by expressing household income as a multiple of the corresponding subsistence level (in which case the poverty line z becomes equal to 1), or by converting all household incomes into, say, the equivalent incomes for a single adult (in which case the poverty line z is the single adult standard for that region). In the absence of more disaggregated data, we are unable to undertake either of these corrections and are obliged instead to treat the data for each region as if they were a homogeneous sample. However, this or any other source of systematic bias should not have a major impact on our empirical results because the contributions in the Shapley decomposition are obtained by averaging over *differences*, and these differences are unaffected by a systematic bias unless it is substantially non-linear.

Table 3.3 Poverty rates for Moscow under alternative scenarios (per cent)

	Real income per capita			
Income inequality	Moscow level	Russian average	Difference	Mean difference
Moscow level	15.8	47.6	−31.8	−29.7
Russian average	3.1	30.7	−27.6	
Difference	12.6	16.9		
Mean difference		14.8		

Source: Authors' calculations.

5. Results

To illustrate how the methods outlined in previous sections can be applied to the Russian regional data, consider the poverty rate for Moscow city, which we estimate to be 15.8 per cent. A natural baseline is provided by the comparable figure of 30.7 per cent for Russia as a whole, again derived from the lognormal model. The higher real income per capita helps explain why Moscow has a lower poverty rate, but this is offset by the greater inequality evident in Table 3.1. As the poverty rate for Moscow is below that for the whole country, the income effect clearly dominates. But what are the relative magnitudes of the two opposing influences?

Table 3.3 summarizes the results of estimating the poverty rate that Moscow would have experienced (in 1995) under a number of alternative hypothetical scenarios. The top line shows that, if inequality in Moscow remained the same but real income per capita fell to the average level for Russia, then the poverty rate would be expected (on the basis of the lognormal model) to treble from 15.8 per cent to 47.6 per cent, a rise of 31.8 points. Keeping average income at the new (lower) value, and allowing inequality in Moscow to fall to the Russian level, causes poverty in Moscow to fall to the baseline figure of 30.7 per cent, a second-round drop of 16.9 points. In this sequence, therefore, the 14.9 point difference between the poverty rates in Russia and Moscow can be attributed to a combination of −31.8 points owing to higher incomes in Moscow and 16.9 points owing to higher inequality. However, reversing the order in which the two Moscow values are changed to the all-Russia levels alters these figures a little. As seen in the first column and second row of Table 3.3, the corresponding contributions would be 12.6 points owing to inequality and −27.6 points to per capita income. The Shapley procedure takes the average of these two scores, so that the impact of the factors is calculated as:

Table 3.4 Shapley decomposition of the poverty rate, selected regions

	Poverty rate		Shapley contributions	
Region	Reported	Estimated	Real income	Inequality
Chelyabinsk	27.9	30.4	8.8	−9.1
Magadan	24.6	33.8	7.1	−4.0
Moscow city	19.1	15.8	−29.7	14.8
Moscow oblast	31.2	26.8	12.7	−16.7
North Osetia	42.8	38.1	19.4	−12.0
Pskov	42.7	45.3	25.5	−11.0
Tatarstan	22.1	19.8	−2.3	−8.7
Tuva	73.2	71.8	39.3	1.8
Tyumen	19.2	21.0	−13.9	4.2
Ulyanovsk	16.3	15.5	−1.8	−13.4
Russian Federation	24.7	30.7	0.0	0.0

Source: Authors' calculations.

$$S_{\text{real income}} = \tfrac{1}{2}(15.8 - 47.6) + \tfrac{1}{2}(3.1 - 30.7) = -29.7\%$$

$$S_{\text{inequality}} = \tfrac{1}{2}(15.8 - 3.1) + \tfrac{1}{2}(47.6 - 30.7) = 14.8\%$$

The net conclusion is that the poverty rate in Moscow city is 29.7 points lower than in Russia because of the high average level of incomes, but 14.8 points higher as a result of greater income inequality – figures that seem to be plausible estimates of the quantitative significance of the two contributory factors.[27]

Similar numbers were calculated for each of the regions. For the sample of regions reported in Table 3.4, the contributions of the two factors tend to operate in opposite directions, indicating that high-income regions usually have high inequality and vice versa, although this may reflect the choice of regions in the sample. The contributions for Tyumen are qualitatively similar to those of Moscow city, but dampened in magnitude. In contrast, Pskov is almost the mirror image of Moscow, with a large enhancement of the poverty rate owing to low average income (25.5 points) mitigated significantly by low inequality (−11.0 points). Tatarstan and Ulyanovsk benefit from both higher-than-average incomes and lower-than-average inequality; but the reverse is true for Tuva, one of only four regions where below-average real income and above-average inequality both contribute towards the high poverty rate.[28]

Although the level of real income is the dominant influence in most of the above examples, there are many regions for which this is not the case. Indeed, inspection of the results for the full set of 75 regions illustrated in

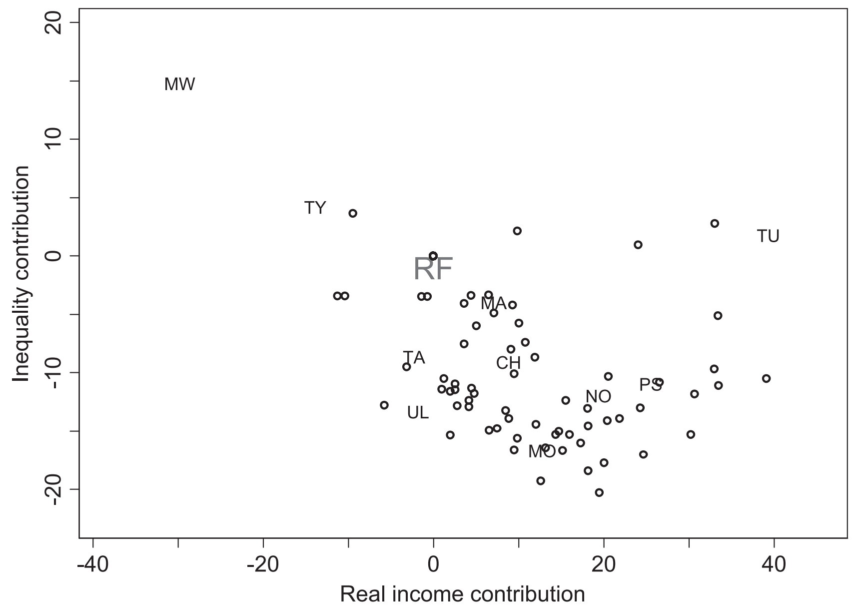

Figure 3.5 Shapley decomposition of the poverty rate.

Figure 3.5 reveals that the magnitude of the inequality contribution is greater than the real income effect in half of the cases (37 out of 75).[29] This finding runs counter to much received wisdom. In Russia, as elsewhere, discussion of policies for poverty alleviation tend to focus almost exclusively on income growth, neglecting the potential role of redistribution or, at the very least, the need to ensure that growth is not accompanied by adverse distributional movements.[30]

The Shapley decomposition procedure can be applied to any poverty index. In order to test whether the magnitudes of the poverty contributions are robust to the choice of indicator, a similar exercise was undertaken with the FGT1 and FGT2 poverty indices. The results reported in Table 3.5 show that, broadly speaking, the Shapley contributions are scaled-down versions of the corresponding numbers in Table 3.4. This is confirmed for the full sample of 75 observations, which yield a correlation coefficient exceeding 95 per cent for the headcount and FGT1 indices (for both the real income and inequality contributions) and a figure of about 90 per cent for the correlation between the headcount and FGT2 indices.

The relationship between the results for these alternative indices is not very surprising for two reasons. First, the index formulas ensure that the value of the FGT2 index is always less than the corresponding FGT1

Table 3.5 Shapley decomposition of FGT1 and FGT2 poverty indices, selected regions

	FGT1		FGT2	
Region	Real income	Inequality	Real income	Inequality
Chelyabinsk	3.6	−5.2	1.8	−3.2
Magadan	3.1	−2.4	1.6	−1.5
Moscow city	−13.7	9.1	−8.1	6.3
Moscow oblast	4.7	−8.8	2.3	−5.1
North Osetia	7.9	−7.4	4.1	−4.6
Pskov	10.9	−7.4	5.8	−4.8
Tatarstan	−0.9	−4.4	−0.4	−2.5
Tuva	24.0	1.9	16.0	1.6
Tyumen	−5.8	2.3	−3.2	1.4
Ulyanovsk	−0.6	−6.3	−0.3	−3.4
Russian Federation	0.0	0.0	0.0	0.0

Source: Authors' calculations.

value, which in turn is less than the headcount index. For this reason, the values of the contributions reported in Table 3.5 are expected to be smaller than those in Table 3.4. Second, application of our lognormal model implies that the sign of each of the contributions depends only on the deviations of the lognormal parameters from their values for Russia, and will therefore be the same for all poverty indices.[31]

Less expected, perhaps, is the fact that the shift from the poverty rate to FGT1 and on to FGT2 attenuates the real income contribution more than the inequality component, so that the magnitude of the inequality effect becomes relatively larger. In fact, for the FGT1 index the magnitude of the Shapley contribution for inequality is greater than the magnitude of the real income term for more than 60 per cent of the regions (48 out of 75); for the FGT2 index the inequality contribution dominates in over 70 per cent of the cases (54 out of 75).[32] This progressive shift in relative importance of the inequality contribution reflects the greater emphasis on extreme poverty in the FGT1 and FGT2 indices, and is therefore likely to appeal to those who understand and appreciate the defects of the headcount index as a measure of poverty. It also adds considerable weight to the above comments regarding the importance of redistribution instruments in poverty alleviation.

As explained in sections 2 and 3, there are good reasons for separating out the impacts of nominal income per capita and prices on regional poverty, rather than combining them in a single factor representing real income per capita. There are two possible ways in which the individual contributions can be identified. The first treats nominal income, prices

Table 3.6 Three-factor decomposition of the poverty rate, selected regions

Region	Reported poverty rate	Estimated poverty rate	Shapley contributions		
			Nominal income	Inequality	Poverty line
Chelyabinsk	27.9	30.4	10.8	−9.1	−2.1
Magadan	24.6	33.8	−27.6	−3.3	33.9
Moscow city	19.1	15.8	−35.4	13.8	6.6
Moscow oblast	31.2	26.8	13.8	−16.6	−1.1
North Osetia	42.8	38.1	25.8	−11.5	−6.9
Pskov	42.7	45.3	23.7	−11.1	1.9
Tatarstan	22.1	19.8	11.9	−8.3	−14.6
Tuva	73.2	71.8	24.5	1.8	14.8
Tyumen	19.2	21.0	−28.7	3.8	15.2
Ulyanovsk	16.3	15.5	21.0	−11.6	−24.7
Russian Federation	24.7	30.7	0.0	0.0	0.0

Source: Authors' calculations.

and inequality as three separate factors and applies the three-way Shapley decomposition illustrated in Figure 3.3. It should be noted, however, that the Shapley contributions of the "unaffected" factors are not typically preserved when one factor is subdivided into subsidiary factors. In the current context this means that the inequality contribution in the three-way decomposition is not expected to remain the same as that reported in Tables 3.4 and 3.5.[33]

Results for the three-way decomposition of the poverty rate are reported in Table 3.6 for the sample of 10 regions. The move from two to three factors has a small and fairly predictable impact on the Shapley contribution of inequality, tending to reduce the magnitude of this component by about 5 per cent. Separating out the price effects also tends to give more prominence to the influence of nominal incomes. For the full set of 75 regions, for instance, nominal income per capita is the single most important contribution in 43 cases, compared with 14 regions for which inequality is the most important influence and 18 regions for which prices (as reflected in the subsistence level) are the dominant factor.[34] Although the overall impact of prices is low – it is the least important of the three factors in half of all the regions – there is a surprisingly large number of regions for which the price level is the principal determinant of the poverty rate, and these contain roughly equal numbers of places where prices are higher than average (such as Magadan) and lower than average (such as Ulyanovsk).

Corresponding results for the three-way decomposition of the FGT1 and FGT2 indicies are reported in Table 3.7. The results confirm the pat-

Table 3.7 Three-factor Shapley decomposition of FGT1 and FGT2 indices, selected regions

	FGT1			FGT2		
Region	Nominal income	Inequality	Poverty line	Nominal income	Inequality	Poverty line
Chelyabinsk	4.4	−5.2	−0.8	2.3	−3.2	−0.4
Magadan	−13.6	−2.2	16.4	−8.0	−1.5	9.6
Moscow city	−16.8	9.0	3.3	−10.2	6.4	2.0
Moscow oblast	5.1	−8.8	−0.4	2.5	−5.1	−0.2
North Osetia	10.7	−7.3	−2.9	5.6	−4.6	−1.6
Pskov	10.1	−7.4	0.8	5.4	−4.8	0.5
Tatarstan	4.7	−4.3	−5.7	2.4	−2.5	−2.8
Tuva	14.8	1.9	9.0	9.8	1.6	6.1
Tyumen	−12.8	2.2	7.0	−7.2	1.5	4.0
Ulyanovsk	8.5	−6.0	−9.5	4.5	−3.5	−4.8
Russian Federation	0.0	0.0	0.0	0.0	0.0	0.0

Source: Authors' calculations.

tern found for the headcount poverty rate. Although deviation of nominal income per capita from the Russian average is the single most important determinant of poverty, all three factors have a significant impact on poverty in most regions.

6. Summary and conclusions

This chapter has sought to understand and explain variations in poverty across the regions of Russia in terms of differences in income per capita, inequality and price levels. The basic approach is similar to that used to decompose changes in poverty over time into ''growth'' and ''redistribution'' components. However, we allow here for three potential sources of poverty variation (rather than two) and apply a powerful new decomposition technique based on the Shapley value in cooperative game theory. In the context of this study, the Shapley procedure considers the marginal impact on poverty of eliminating one source of regional differences (say, price variations) and computes the average of the marginal impacts over all the possible ways in which regional characteristics are replaced in sequence by the average levels for Russia as a whole.

We apply this framework to 1995 aggregate regional data on incomes per capita, income inequality and average subsistence levels (as a proxy for local prices). The lognormal model that Goskomstat uses to estimate

poverty rates and inequality statistics conveniently allows us to plot the real income per capita for each region against the Gini index of inequality as a prelude to a more detailed decomposition analysis. The lognormal model also provides the vehicle for estimating the hypothetical marginal factor contributions required in the Shapley decomposition.

The two-way decomposition yields estimates of the contributions of real income per capita and income inequality to poverty in each region. The results turn out to be somewhat surprising. Contrary to received wisdom, and despite the very large differences in per capita income, inequality has a greater impact on the poverty rate than real income per capita in about half of the regions. Other commonly used poverty indices give even more prominence to inequality variations vis-à-vis real income differences. However, when real income per capita is separated into nominal income and price components, nominal income differences are seen to be more important than either inequality or price effects for the majority of regions. Thus, it would appear that price variations partially offset the impact of nominal income levels on regional poverty levels.

This study confines attention to three proximate sources of poverty differences: income per capita, inequality and local prices. However, the basic decomposition framework can be extended to address the geographical, economic and political factors that help account for poverty variations across regions. We intend to explore the contribution of these more fundamental sources in future research.

Appendix: Properties of the lognormal distribution

A random variable x is said to follow a *lognormal* distribution (written $x \sim \mathrm{LN}(\mu, \sigma^2)$) if $\ln x$ is normally distributed. This appendix outlines some useful properties of the lognormal distribution. For further details see Aitchison and Brown (1957).

The density of a lognormal distribution with the mean of logs parameter μ and the variance of logs parameter σ^2 is given by:

$$f_{\mathrm{LN}(\mu,\sigma^2)}(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right], \tag{3A.1}$$

where $x > 0$ is interpreted as income in our context. The cumulative distribution function of a lognormally distributed variable is:

$$\mathrm{CDF}_{\mathrm{LN}(\mu,\sigma^2)}(z) = \int_0^z \frac{1}{x\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] dx = \Phi\left(\frac{\ln z - \mu}{\sigma}\right) \tag{3A.2}$$

and can again be obtained from the standard results for Gaussian variables.

The expected value of a lognormally distributed variable is:

$$\mu_1 = \int_0^\infty \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right] dx = e^{\mu+\sigma^2/2} \tag{3A.3}$$

and depends on both the location parameter μ and the scale parameter σ. The variance of the lognormal variable is:

$$\int_0^\infty (x - e^{\mu+\sigma^2/2})^2 f_{\mathrm{LN}(\mu,\sigma^2)}(x)\, dx = e^{2\mu+\sigma^2}(e^{\sigma^2} - 1) = \mu_1^2(e^{\sigma^2} - 1), \tag{3A.4}$$

with higher-order moments following the pattern

$$\mu_k = \int_0^\infty x^k f_{\mathrm{LN}(\mu,\sigma^2)}(x)\, dx = \exp\left[k\mu + \frac{k^2}{2}\sigma^2\right]. \tag{3A.5}$$

Given the poverty line z, the poverty rate (or headcount ratio) is obtained immediately as

$$H = \mathrm{CDF}_{\mathrm{LN}(\mu,\sigma^2)}(z) = \Phi\left(\frac{\ln z - \mu}{\sigma}\right), \tag{3A.6}$$

which can be linked via (3A.3) to information on mean income, so that

$$H = \Phi\left(\frac{\ln z - \mu}{\sigma}\right) = \Phi\left(-\frac{\ln \dfrac{\mathit{mean\ income}}{\mathit{poverty\ line}}}{\sigma} + \frac{1}{2}\sigma\right). \tag{3A.7}$$

One advantage of this explicit formula for the poverty rate is that it helps us to appreciate the complex (and highly non-linear) way in which the mean income, inequality and poverty line factors interact to determine the level of poverty.

To construct Lorenz curves and other indices of poverty for lognormally distributed incomes, it is necessary to calculate incomplete moments corresponding to the integrals in (3A.3)–(3A.5) with a finite upper bound. Aitchison and Brown (1957, Theorem 2.6) provide a result that can be restated as:

$$\int_0^z x^k f_{\mathrm{LN}(\mu,\sigma^2)}(x)\, dx = \mu_k \mathrm{CDF}(z \mid \mu + k\sigma^2, \sigma^2) = \mu_k \Phi\left(\frac{\ln z - \mu - k\sigma^2}{\sigma}\right). \tag{3A.8}$$

Using this result, the Lorenz ordinate associated with the population proportion $q \in [0, 1]$ and the corresponding income-level z can be written as

$$L(q) = \frac{1}{\mu_1}\int_0^z x f_{\mathrm{LN}(\mu,\sigma^2)}(x)\, dx = \Phi\left(\frac{\ln z - \mu - \sigma^2}{\sigma}\right), \tag{3A.9}$$

where $q = \Phi\left(\frac{\ln z - \mu}{\sigma}\right)$ via (3A.2). Eliminating z yields

$$L(q) = \Phi\left(\frac{\ln z - \mu - \sigma^2}{\sigma}\right) = \Phi(\Phi^{-1}(q) - \sigma), \tag{3A.10}$$

or, equivalently,

$$\sigma = \Phi^{-1}(q) - \Phi^{-1}(L(q)), \tag{3A.11}$$

the relationship used in this chapter to estimate σ from published data on quintile shares. Common measures of inequality can be computed immediately, because they depend only on the scale parameter σ. For example, the Gini index for a log-normal distribution is given by:

$$Gini = 2\Phi(\sigma/\sqrt{2}) - 1, \tag{3A.12}$$

the rule used to generate the Gini values reported in Table 3.1 and elsewhere.

The Foster et al. (1984) class of indices specified in equation (3.3) contains the headcount index H given in (3A.7), which corresponds to $\alpha = 0$. Using (3A.8), the indices corresponding to $\alpha = 1$ and $\alpha = 2$ may be computed as:

$$\begin{aligned} FGT1 &= \int_{-\infty}^{z} \frac{z - x}{z} f_{\mathrm{LN}(\mu,\sigma^2)}(x)\,dx = H - \frac{1}{z}\int_{-\infty}^{z} x f_{\mathrm{LN}(\mu,\sigma^2)}(x)\,dx \\ &= H - \frac{\mu_1}{z}\Phi\left(\frac{\ln z - \mu - \sigma^2}{\sigma}\right) \end{aligned} \tag{3A.13}$$

$$\begin{aligned} FGT2 &= \int_{-\infty}^{z} \left(\frac{z - x}{z}\right)^2 f_{\mathrm{LN}(\mu,\sigma^2)}(x)\,dx \\ &= H - \frac{2\mu_1}{z}\Phi\left(\frac{\ln z - \mu - \sigma^2}{\sigma}\right) + \frac{\mu_2}{z^2}\Phi\left(\frac{\ln z - \mu - 2\sigma^2}{\sigma}\right). \end{aligned} \tag{3A.14}$$

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Notes

1. See also Braithwaite (1997), Commander et al. (1999), Klugman and Braithwaite (1998) and McAuley and Ovcharova (2005) for a review of inequality and poverty trends during the 1990s. Milanovic (1998) and Galbraith et al. (2004) compare the experience in Russia with other transition countries.
2. Berkowitz and DeJong (2002) discuss some of the potential negative consequences of substantial regional variations in living standards and weakly integrated markets.
3. Dhongde (Chapter 12 of this volume) undertakes a similar analysis of regional poverty in India using a two-factor decomposition.
4. The dollar equivalent is difficult to establish because there was no market exchange rate. The official exchange rate for US$1 was 0.6 roubles, but the black market price was about 3 roubles.
5. For further details, see Klugman and Braithwaite (1998), McAuley (1997), Mozhina (1998) and Ovcharova et al. (1998). Some have argued that the poverty line for Russia remains generous compared with WHO recommendations, since it exceeds the expenditure needed to satisfy minimal nutritional requirements by 45 per cent. Others, including Klugman and Braithwaite (1998: 41), claim that the standard is relatively austere. Rimashevskaya (1997) notes that food may account for up to 80 per cent of expenditures at the subsistence level. Also significant is the fact that the fall in living standards during the 1990s has shifted the nutritional intake of the population towards carbohydrates (roughly speaking, from meat and milk towards bread and potatoes).
6. Goskomstat undertakes a special Balance of Incomes and Expenditures of Population, initially designed to estimate the demand for money, but used more broadly to try to reconcile data on income and expenditure data drawn from different sources. See Kim et al. (2005) for more details.
7. See Lehmann et al. (2001) for an analysis of the distributional implication of wage arrears.
8. Indeed, irregularities in income receipts may have been one of the causes of the extreme volatility of the official poverty rates observed in the early 1990s.
9. Republics are typically defined in terms of the ethnicity of the traditional population and tend to have greater autonomy. Some krays also contain smaller ethnically based subregions called "okrugs" which are often treated as separate units of analysis, along with the krays in which they are nested: for example, poverty data have been reported for 11 okrugs since 1999. An okrug is roughly comparable to, say, the Basque region when viewed as part of Spain.
10. Our analysis below is based on the official regional subsistence levels. Subjective poverty lines are also available for broad regional groupings, and tend to show less spatial variation than the official poverty lines (see Milanovic and Jovanovic 1998).
11. The conflict zone republics of Dagestan, Ingush and Chechnya have been excluded from our analysis owing to lack of data on income inequality. But they are among the poorest regions. Dagestan, for example, recorded a poverty rate of 71.2 per cent in 1995. Note that the Goskomstat procedures are applied separately to each region and to the Russian Federation as a whole, resulting in a poverty rate for all-Russia that is not a weighted sum of the regional values. This inconsistency does not affect our results since we use the all-Russia figures simply as a reference point from which to measure deviations.
12. Regional inequality data for 2001 have become available since this study was completed.
13. This is not to deny that the situation in Russia has changed considerably since 1995, with respect both to the macroeconomic climate (the 1998 financial crisis and the subsequent

recovery) and to the construction of social indicators. As regards the latter, 1995 was the last year that Goskomstat asked direct questions on income in its household budget survey, and the published poverty data for 1995 are based on money incomes alone. This contrasts with more recent years for which money incomes are estimated as the sum of cash expenditures and cash savings, and total income includes in-kind components. These changes have undoubtedly affected the pattern of regional inequality and poverty across Russia as a whole, but may have had less impact on the relative importance of average income variations vis-à-vis inequality.

14. Poverty rates for all-Russia and for the 75 regions (i.e. excluding Dagestan, Ingush and Chechnya) are reported in Appendix Table 1 of Kolenikov and Shorrocks (2003).
15. See also the discussion of regional poverty variations in Braithwaite (1997) and the analysis of regional differences by Mikheeva (1999).
16. The data used here and elsewhere in this chapter are drawn from the CEFIR regional data set, which contains several hundred regional indicators from 1970 onwards. The CEFIR data set is itself based primarily on the annual publications of Goskomstat for Russian regions (see, for example, Goskomstat 1998b).
17. Actually, oil is extracted in Khanty and Mansy autonomous okrug, and gas is extracted in Yamal and Nenets autonomous okrug within Tyumen oblast.
18. See section 4 and the appendix for details of the Gini calculations. Note that, under the lognormality assumption, all inequality measures are increasing functions of the variance of logarithms, and hence monotonic transformations of the Gini coefficient. The iso-poverty contours are derived using the relation between mean income and inequality given in appendix equation (3A.7).
19. See, for example, Moulin (1988: ch. 5) for a discussion of the Shapley value, originally developed by Shapley (1953).
20. Yemtsov (2005) notes that using regional subsistence levels as the price deflator gives quite different results from using the regional consumer price index (CPI) series because the CPI is based on a different basket of goods. For our purposes, the cost of a basket of goods consumed by the poor is a better reflection of the relevant price variations across regions. In his study of China, Hussain also makes use of regionally constructed poverty lines, but reports that most of the regional variation is due to non-price factors (Hussain 2003: 7).
21. It should be borne in mind that the estimates of per capita income obtained from the balance sheets greatly exceed the figures derived from the household budget data (Yershov 1998).
22. In fact the procedure is slightly more complicated. Goskomstat applies separate models to the rural and urban areas, then combines the information into a single regional distribution. In addition, for certain regions, Goskomstat uses a mixture of two weighted lognormal distributions corresponding to "rich" and "poor" subpopulations. The published data are therefore not completely consistent with a pure lognormal distribution. However, since the urban and rural subdistributions are not so different within regions, the assumption that they are identical is not a serious distortion.
23. Kloek and van Dijk (1978) found that at least four parameters are typically required to characterize income distribution adequately. See also Ryu and Slottje (1999) for a recent review. Using a semiparametric model of income distribution, Aivazian and Kolenikov (2001) conclude that the lognormal model does not adequately describe Russian data, and suggest that income distribution in the reform era has tended to flatten out the mode of the distribution and to produce fatter tails.
24. These estimates were in almost perfect correspondence with each other, differing only in the third decimal point for most regions, i.e. within the accuracy of the published quintile data, which are given to two decimal points.

25. Although the two sets of figures are broadly similar, there are some significant discrepancies; see Table 3.4 below and the more detailed regional breakdown in Appendix Table 1 of Kolenikov and Shorrocks (2003). The reasons for the discrepancies are not immediately evident, although it is possible that different adjustments have been applied to the figures for regional income per capita compared with those used to compute regional poverty rates.
26. See, for example, Fox (1997). Note that, in the lognormal framework, the RHS of the regression equation is linked directly to mean income and inequality via appendix equation (3A.7).
27. We have developed a STATA software package to handle certain types of Shapley decompositions. This can be downloaded from the STATA applications website: 〈http://ideas.repec.org/〉.
28. The very high poverty rate in Tuva is mainly caused by the low average level of real income. Although this is partly due to low nominal incomes, income per capita is not exceptionally low (see Table 3.1). What distinguishes Tuva is that low nominal incomes are compounded by high prices, and hence a high poverty line. See Table 3.6 for details of the separate nominal income and poverty line effects.
29. See Appendix Table 1 of Kolenikov and Shorrocks (2003) for the detailed figures. The absence of a clear pattern in Figure 3.5 would be more evident if Moscow is excluded as an outlier. Note that the preponderance of points in the bottom right quadrant reflects the fact that per capita income and income inequality in most regions are both below the level for the Russian Federation, the latter owing in part to the fact that income inequality in Russia as a whole combines intraregional income variations with interregional inequality.
30. For recent contributions to this debate, see van der Hoeven and Shorrocks (2003) and Shorrocks and van der Hoeven (2004).
31. Excluding perverse situations arising, for instance, when the poverty line exceeds mean income. Then an increase in inequality can cause the headcount poverty rate to fall.
32. The figures for North Osetia in Tables 3.4 and 3.5 well illustrate this trend, switching from a substantially higher real income contribution for the headcount poverty rate to a marginally higher real income contribution for the FGT1 index, and then an inclination towards inequality for the FGT2 measure.
33. An alternative procedure involves a sequential Shapley decomposition in which contributions are first assigned to real income and inequality (as was done above), and then the real income contribution is reallocated between nominal income and price effects. This latter "hierarchical" decomposition introduces an extra level of complexity in programming, and has not been undertaken in this chapter.
34. Individual results are reported in Appendix Table 3 of Kolenikov and Shorrocks (2003). The regions with higher prices and the most important price contributions are in the far east, whereas the low-price regions are agricultural areas in the red belt south of Moscow. The places with the highest inequality contributions tend to be the industrial regions in the European part of Russia and the Urals, although the pattern is not particularly strong.

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4

Trade liberalization and spatial inequality: A methodological innovation in Vietnamese perspective

Henning Tarp Jensen and Finn Tarp

1. Introduction

Viet Nam has come a long way since the *doi moi* reforms were initiated in 1986. Wide-ranging institutional changes have been initiated and Viet Nam has, in parallel with domestic reforms, started a process of opening up its economy to regional and global economic forces. Openness to trade as measured by the share of imports and exports in gross domestic product (GDP) grew considerably during the 1990s. Nevertheless, average tariff rates increased from 10.7 per cent in 1992 to 16.2 per cent in 2000,[1] and this is not consistent with Viet Nam's commitment to continuing and deepening the process of trade liberalization. Viet Nam is a major world market actor in several important agricultural sectors, including coffee, pepper and rice, but is not yet a member of the World Trade Organization (WTO). Membership has, however, become a priority since China joined the WTO as its 143rd member in 2001, and Viet Nam will no doubt face stern demands for trade liberalization before it can join the WTO. Yet it is also becoming clear that Viet Nam is willing to pay the price in terms of policy choices. Proactive integration in the international economy emerged as an overriding goal at the Ninth Party Congress, as pointed out by the Central Institute of Economic Management (2003). Thus, there is in Viet Nam increasing need to understand how impending trade liberalization, including reduced trade taxes, may affect the well-being of poor people throughout the country. This need is further alluded

to by Rama et al. (2003), who provide an encyclopaedic picture of poverty in Viet Nam.

Measuring the poverty impact of macro policy interventions within a computable general equilibrium (CGE) model framework has recently been studied by Decaluwé et al. (1999) and Azis et al. (2001). Decaluwé et al. use a specific statistical distribution function as an approximation to the distribution of income within aggregate household categories. They argue, in particular, that the beta distribution represents a sufficiently flexible functional form so as to provide a more appropriate functional specification for within-household income distribution than the log-normal and Pareto distributions, which have previously been studied by Adelman and Robinson (1979: 256–289) and de Janvry et al. (1991). Azis et al. also rely on a top-down modelling approach, but in contrast they use actual (non-parametric) income and expenditure distributions based on household survey data.

In this chapter we aim at moving the existing methodology one step forward by solving a disaggregate CGE model for the entire distribution of income and consumption among a representative set of 5,999 micro households. By modelling micro household behaviour individually we capture potentially important feedback effects from changes in the micro-level distribution of income and expenditures to macro-level variables. In addition, we allow for detailed assessments of the poverty impact of macro policies without having to rely on distributional approximations regarding intra-household income and assumptions to shift these distributions in relation to changes in macro variables. To assess the importance of these feedback effects, we compare our results with poverty estimates derived from a top-down approach involving an aggregate CGE model with 16 household categories along the lines pursued by Decaluwé et al. and Azis et al.

2. Data and model framework

The data underlying the current analyses are the 1998 Vietnam Living Standards Survey (VLSS98) and the 2000 Vietnam Social Accounting Matrix (VSAM) established by Tarp et al. (2002). The VSAM includes accounts for 97 activities and commodities, 14 factors, 16 household categories and 3 enterprises, as well as accounts for the current government budget, capital accumulation, inventories and the balance of payments. The factors include capital and land in addition to 12 different kinds of labour categorized according to gender (male/female), location (rural/urban) and educational level (low/medium/high). Similarly, households

are categorized according to location (rural/urban), gender of the household head (male/female) and employment status of the household head (farmer/self-employed/waged worker/unemployed).

The disaggregation of the VSAM household account into 16 separate household categories was based on information from VLSS98. This survey covers 5,999 households making up a countrywide representative sample.[2] The first step was to categorize the micro households into the aggregate categories in VSAM. Based on a mapping, which allocated each micro household to one and only one aggregate category, income and expenditure patterns of the micro households were aggregated to derive prior values for the income and expenditure patterns of the 16 aggregate categories. This information was subsequently used in deriving the consistent VSAM matrix.

The mapping between the aggregate household categories from VSAM and the micro households from VLSS98 was in turn used to establish a consistent economy-wide Vietnamese social accounting matrix (SAM) with 5,999 micro households. Since each aggregate household category was made up of a unique set of micro households, the problem of disaggregating household categories into micro households consisted of 16 subproblems, each representing a standard problem in achieving consistency among SAM data accounts. Consistency was achieved for each of the micro household accounts by applying minimum cross-entropy as proposed by Golan et al. (1994).

To make the above calculations feasible, the dimensions of the production and goods sectors were reduced, so the original 97 activity and commodity accounts were aggregated into 10 accounts. They consist of three agricultural accounts (rice; other agricultural crops; livestock and fish), three industrial accounts (mining and oil; food processing; manufacturing) and four service sectors (water, gas and electricity; construction; trade; other services). Altogether, the fully consistent micro household SAM data set used in this chapter contains 10 activities, 10 commodities, 14 factors, 5,999 households and 3 enterprises, in addition to accounts for the current government budget, capital accumulation, inventories and the balance of payments. From a methodological point of view, the creation of the full SAM data set can be seen as a two-step procedure, whereby a consistent SAM with 16 aggregate household categories is established in the first step, whereas the full disaggregation into 5,999 micro households is left to a second step. The two-step procedure is useful in the current case, since it breaks one large statistical balancing problem into 16 smaller and more manageable tasks. Another important aspect of our procedure is that it allows for reconciling micro household income and expenditure information with available macro totals.

Key features of the Vietnamese economy can be derived from VSAM.

Table 4.1 The structure of the Vietnamese economy (per cent)

	VA	E	M	E/X	M/Q
Rice	9.3	0.7	0.1	2.9	0.3
Other agricultural crops	10.1	8.6	2.7	37.6	12.5
Livestock and fish	7.2	3.5	0.2	16.4	0.9
Mining and oil	8.7	17.5	2.2	77.1	9.4
Food processing	7.3	16.3	5.4	33.4	10.6
Manufacturing	11.1	27.0	76.0	41.4	53.1
Water, gas and electricity	2.8	0.0	0.1	0.0	1.3
Construction	5.7	0.0	0.0	0.0	0.0
Trade	12.8	8.2	0.0	27.5	0.0
Other services	25.0	18.0	13.3	24.6	16.1
Total	100.0	100.0	100.0	28.3	29.3

Notes: VA = value-added, E = exports, M = imports, X = production, Q = demand.
Source: Authors' calculations based on Vietnam Social Accounting Matrix with 5,999 households.

The overall structure of the economy, including the composition of value-added, exports and imports, as well as measures of international trade, is presented in Table 4.1. The composition of value-added confirms the continuing importance of primary agriculture sectors in the Vietnamese economy. The combined value-added of rice, other agricultural crops, and livestock and fishery accounts for more than 26 per cent of total value-added, and food processing accounts for more than 7 per cent. In contrast, the manufacturing sector contributes a mere 11 per cent, so Viet Nam is still at the beginning of its economic transformation to a more developed economy. This is in spite of the impressive growth rates recorded over the past decade in combination with a successful policy to change the demographic structure of the population and reduce the dependency ratios.

The importance of the primary agricultural sector in value-added creation is not directly mirrored in export performance. Primary agricultural goods account for less than 13 per cent of total exports. However, export trade shares of production are very high for the primary extraction industries, and other agricultural crops (excluding rice paddy) also export more than one-third of their production. These relatively high trade shares are a reflection of the focused export strategy that the Vietnamese government has pursued over the past decade. A strong state focus on reallocating resources towards the expansion of key export cash crops such as coffee and pepper, in combination with appropriate economic policy, has made Viet Nam a key player in several world commodity markets. Moreover, food-processing industries account for more than 16 per cent of to-

tal exports, indicating that agricultural goods are increasingly being processed before they are sold in export markets. This is encouraging from a development perspective. It suggests that Viet Nam is on the way towards a more diversified economic structure, although Viet Nam continues of course to be vulnerable to international price shocks.

The vulnerability to international events is highlighted by the fact that imports are completely dominated by manufactured goods, which account for more than 75 per cent of total imports. This indicates that, whereas import shares are relatively low in most sectors, Viet Nam is strongly dependent on imports of capital goods for the development of the food-processing and manufacturing sectors. It is against this background that the steady performance of the macro economy in recent years has strengthened Viet Nam's international creditworthiness. In particular, domestic political stability, combined with improved opportunities for foreign investors, has certainly helped promote foreign direct investment, and other capital inflows are also high. Against this background, exposure to international terms of trade is gradually becoming less of a problem.

The structure of indirect taxes, including trade taxes, which are in focus in the current chapter, is presented in Table 4.2. VSAM includes three sets of indirect taxes: value-added taxes (VAT), export taxes (TE) and import tariffs (TM).[3] VAT rates range from around 3 per cent in the food-processing, manufacturing and construction sectors, to 6–8 per cent in the other seven primary production and service sectors. The structure of production taxes therefore seems to provide a small incentive bias in

Table 4.2 The structure of indirect taxes (per cent)

	VAT/X	TE/E	TM/M
Rice	7.3	22.1	5.5
Other agricultural crops	8.0	4.1	5.0
Livestock and fish	6.0	4.1	6.4
Mining and oil	7.0	1.8	3.0
Food processing	2.6	0.3	13.8
Manufacturing	3.0	3.0	6.6
Water, gas and electricity	6.4	0.0	0.5
Construction	2.9	0.0	0.0
Trade	7.5	0.0	0.0
Other services	6.1	0.0	0.0
Total	5.1	1.8	6.0

Note: VAT = value-added taxes, X = production, E = exports, TE = export taxes, M = imports, TM = import taxes.
Source: Authors' calculations based on Vietnam Social Accounting Matrix with 5,999 households.

favour of food processing and manufacturing. This incentive bias is mirrored in the structure of export taxes, which are consistently higher for primary agricultural exports as compared with food-processing and manufacturing exports. The export tax rate is particularly high on rice paddy, indicating a significant bias against domestic producers of paddy. At the same time, this creates a significant implicit subsidy for domestic producers of processed rice, which promotes exports of processed rice. The strategy of protecting and promoting processed food sectors, including processed rice, is further underlined by the relatively high import tariffs levied on this sector. All this helps explain the export performance referred to above.

The differential economic characteristics across the three geographical regions (north, centre and south) are clearly of interest in interpreting the simulation results in this chapter. Overall, the VSAM data set indicates that 46 per cent of total household income is generated in the south, 33 per cent in the north, and 21 per cent in the central region. This distribution reflects in part the fact that the industrially developed south has higher average wages than do other regions of Viet Nam. At the same time, Table 4.3 shows that household income in the south stems mainly from low-skilled labour sources for both rural and urban people. This confirms that low-skilled labour wages are significantly higher in the south compared with the centre and north. Transfers from the state account for significant proportions of household income in the north and centre, but less so in the south. Urban households in the northern region are particularly dependent on state transfers.

The regional structure of poverty reported in Table 4.4 shows that poverty is mainly a rural phenomenon in Viet Nam.[4] Poverty is clearly most

Table 4.3 The regional structure of household income sources (per cent)

	Northern region		Central region		Southern region	
	Rural	Urban	Rural	Urban	Rural	Urban
Low-skilled labour	59	35	55	47	75	64
Medium-skilled labour	15	22	19	22	10	16
High-skilled labour	3	7	4	5	2	7
Land	4	4	4	12	5	6
Capital	2	2	2	2	2	2
State transfers	18	31	16	12	6	6
Domestic income	64	36	71	29	46	54

Source: Authors' calculations based on Vietnam Social Accounting Matrix with 5,999 households.

Table 4.4 The regional structure of poverty and population

	Northern Region		Central Region		Southern Region	
	Rural	Urban	Rural	Urban	Rural	Urban
Poverty headcount (%)	41	6	46	5	30	2
Poverty gap (VND billion)	5,601	128	4,908	42	2,767	81
Poor (million people)	9.4	0.3	8.3	0.1	6.0	0.2
Population (million people)	22.9	5.4	18.0	3.0	20.1	8.3

Source: Authors' calculations based on Vietnam Social Accounting Matrix with 5,999 households.

severe in central and northern Viet Nam, where 41–46 per cent of rural people are poor, compared with a national headcount index of 31.3 per cent. Rural monetary poverty gaps are also very high in the north and centre, amounting to 4,900–5,600 billion Vietnamese dong (VND) (or US$350–400 million). Turning to the number of poor, there are 8.3 million rural poor in the central region and 9.4 million in the north, compared with 6.0 million rural poor in the south. Finally, in terms of poverty headcounts, the total population is relatively equally distributed from north to south, although the centre is clearly the smallest region. Urbanization is relatively high in southern parts and relatively low in the centre.

Our model framework is similar to the model put forward by Arndt et al. (2000). We use this basis to construct two Vietnamese CGEs, which differ only in the level of disaggregation of the household sector. In all other respects, the two models are similar. We rely on Cobb–Douglas specifications for production of value-added and Leontief specifications for determining intermediate demand. In addition, a linear expenditure system (LES) is relied on for household consumption, including home consumption of goods at the activity level, and marketed consumption of goods at the commodity level. Savings and tax rates are calibrated from VSAM, and most rates are kept fixed throughout the simulations. Finally, constant elasticity of transformation (CET) functions determine the supply of goods for the export market, and Armington (CES) specifications establish the demand for imported goods.

The linear expenditure system was implemented by assuming zero minimum consumption levels. Furthermore, the CET and CES functional relationships were implemented by assuming that transformation and substitution elasticities for the 10 Vietnamese commodities are similar to estimates derived in Arndt et al. (2002).[5] In general, the closures of the two models include full employment of factor resources, savings-driven

investment, as well as a flexible real exchange rate and fixed foreign savings inflows. The assumption of full employment of factors is justified by the fact that we are conducting a short-to-medium-term analysis of trade reforms, and a closure rule with a flexible exchange rate and fixed foreign capital inflows seems reasonable owing to the focus of the Vietnamese government on domestic and external macroeconomic balance. The closure of the government budget varies with the set of experiments. Most experiments use a standard revenue-neutral closure, where uniform variation in household tax rates makes up for lost revenue from reduced trade taxes.[6] The general focus on a revenue-neutral government closure is also consistent with the focus on domestic macroeconomic balance. Moreover, the use of lump-sum income taxes allows for the proper measurement of efficiency losses owing to trade taxation. Finally, the consumer price index for marketed goods is used as the price numeraire.

The current static model set-up assumes a relatively simple specification of the factor market. Labour is perfectly mobile between production sectors but cannot upgrade skills or migrate between rural and urban areas. Thus, different labour skill categories are treated as separate production factors, as is typical in a static short-to-medium-term analysis. Nevertheless, the disaggregation of the labour market makes it possible to capture the importance of heterogeneity in the composition of initial factor endowments among micro households within aggregate household categories. Similarly, we capture the significance of differences in consumption patterns of micro households. The macroeconomic significance of disaggregating household categories in relation to reductions in trade taxes and tariffs therefore arises from: (i) the supply side, where changes in the relative protection/taxation of domestic production sectors feed through to relative factor prices and the distribution of household income; and (ii) the demand side, where changes in relative consumer price indices affect the distribution of consumption among individual micro households.

The model framework was implemented on the basis of the VSAM data set with, respectively, 16 aggregate household categories and 5,999 disaggregate micro households. In applying the aggregate model, a top-down approach was used to study the distributional impact at micro level. The top-down approach covers two ways of calculating poverty indices based on macro prices: (i) the simple application of representative household consumption growth rates to derive consumption and poverty indices for all micro households in the respective categories; and (ii) the application of aggregate factor prices to initial factor endowments for each of the 5,999 micro households to derive the impact on micro household income, and the subsequent application of (new) tax and savings rates to derive micro household consumption and poverty.[7]

Different dimensions of poverty can be analysed using the traditional Foster–Greer–Thorbecke (FGT) measures of poverty. These measures are convenient because they allow for simple additive decompositions among household groupings with different characteristics. In the present analysis, we use the FGT poverty headcount (P_0) to measure the relative number of poor individuals within a specific household grouping (region). We do not, however, rely on the poverty gap measure (P_1), which is a measure of average poverty per individual – poor or non-poor. Instead we use the monetary poverty gap (POVGAP), which relates specifically to poor individuals and which is defined as the total amount of money necessary to raise the income of all poor households to the poverty line. Our poverty indices are calculated on the basis of an updated poverty line for 2000, derived from the cost of basic needs (CBN) methodology. The updated poverty line for 2000, which takes into account basic food and non-food expenditures, amounts to VND1.68 million, or approximately US$120 per year. The poverty line updates the official poverty line for 1998 of VND1.65 million based on official price changes for food and non-food items.[8]

3. Results

Our set of trade policy experiments is outlined in Table 4.5. They include a base run experiment, which replicates the underlying 2000 VSAM data set. Experiment 1 measures the impact of eliminating export taxes, whereas we eliminate all import tariffs in Experiment 2. Finally, Experiment 3 brings out the combined effect of removing all trade taxes. In what follows we first use this set of experiments to address various methodological issues and the impact on (spatial) poverty more narrowly. Subsequently, we discuss the impact of our trade policy experiments in greater detail, including a review of macroeconomic indicators and other dimensions of poverty. This more elaborate analysis of the impact of trade liberalization on the distribution of welfare and poverty in Viet Nam is based on results from the model with 5,999 endogenous micro households, assuming a revenue-neutral government budget closure.

Table 4.5 Trade tax experiments

Base run	Calibrated 2000 SAM values
Experiment 1	Elimination of export taxes
Experiment 2	Elimination of import tariffs
Experiment 3	Experiments 1 & 2

Source: Authors' CGE-model experiments.

3.1. Endogenous micro households and government budget closure

Table 4.6 presents the impact of trade liberalization on monetary poverty gaps when the income distribution of micro households is (i) modelled endogenously using the model with 5,999 micro households, and (ii) derived from top-down procedures without feedback effects using the model with 16 representative households. Two top-down approaches are distinguished: (a) the application of representative household consumption growth rates to micro household consumption; and (b) the application of aggregate factor prices to initial micro household factor endowments and the subsequent derivation of micro household consumption and poverty.

The elimination of export taxes in Experiment 1 has a relatively small impact on regional poverty, regardless of the treatment of micro households. However, poverty declines with endogenous micro households and increases with the aggregate consumption top-down approach, but remains (virtually) unchanged with the disaggregate factor income top-down approach. The fact that the overall impact switches sign when micro households are modelled endogenously is an important methodological observation. Moreover, since the direction of impact is the same across regions for each of the three approaches, it appears that the differential impacts are the result of household characteristics, which are similar across regions.

Poverty is mainly a rural phenomenon, and we know that poor rural households have (i) relatively high agricultural consumption propensities, and (ii) relatively high factor endowments of unskilled rural labour. This

Table 4.6 Monetary poverty gaps and income distribution (percentage changes)

Income distribution	Region	Base run (VND billion)	Exp. 1	Exp. 2	Exp. 3
Endogenous	North	5,729	−0.3	1.1	0.9
	Centre	4,949	−0.1	1.1	1.0
	South	2,848	−0.2	1.9	1.8
	Total	13,526	−0.2	1.3	1.1
Top-down (aggregate consumption)	North	5,729	0.3	1.6	2.0
	Centre	4,949	0.3	1.6	2.0
	South	2,848	0.4	2.2	2.7
	Total	13,526	0.3	1.7	2.2
Top-down (disaggregate factor income)	North	5,729	0.0	1.1	1.3
	Centre	4,949	0.1	1.0	1.2
	South	2,848	0.0	1.6	1.7
	Total	13,526	0.0	1.2	1.3

Source: Authors' CGE-model simulations.

suggests both that increasing agricultural terms of trade should have a relatively direct beneficial impact on poor households in all three regions, and that there may be positive feedback effects on poverty because the poor predominantly consume goods that are produced by themselves. The elimination of export taxes does indeed increase agricultural terms of trade as well as relative unskilled rural (male) wages, as can be seen in Tables 4.8 and 4.11 below. We will return to these tables later, but argue here that the model with endogenous households captures the positive feedback effects of increasing rural incomes, which the other top-down approaches miss.

The "aggregate consumption" top-down approach captures only aggregate consumption growth among the representative households. Increasing household taxes introduced to compensate for lower export tax revenues therefore lead to an increase in poverty. The in-between "disaggregate factor income" top-down approach captures the relative increase in rural unskilled wages. This relative increase in the income of poor rural households is (just) enough to compensate for increasing household tax rates. This approach therefore predicts, as shown in Table 4.6, that poverty remains unchanged. In contrast, the "endogenous household" approach captures both the relative increase in rural unskilled wages (following from the change in the terms of trade) as well as the positive feedback effects, and they more than compensate for increasing household tax rates. In this case, we therefore find that the elimination of export taxes will lower poverty uniformly across all regions of Viet Nam. In sum, the general intuition behind the above result is that agricultural exports are taxed disproportionately, and lower taxation therefore reduces the bias against poor agriculture-dependent households. Moreover, the methodological importance of the above observations on export taxes is that they demonstrate that poverty impacts can change sign depending on whether the income distribution is modelled endogenously or not. Moreover, it is not sufficient to account for the relative factor endowments of micro households. Feedback effects from the endogenous modelling of the income distribution among micro households may be essential when the focus is on capturing both the direction and the full impact on poverty of trade liberalization and other policy interventions.

Turning to Experiment 2, the elimination of import tariffs has a significant adverse impact on poverty, whether or not the income distribution is modelled endogenously. High industrial protection is concentrated in food-processing sectors and, although food processing is an industrial sector, the intensive use of primary agricultural inputs in this sector means that the import tariffs are implicitly protecting agricultural production. It therefore comes as no surprise that elimination of the import tariff

structure lowers the agricultural terms of trade and relative rural unskilled wages. In combination with increasing household taxes, this increases poverty.

We also note that the endogenous modelling of micro household income and expenditure decisions shows a milder poverty impact compared with the aggregate consumption top-down approach. This suggests that taking account of relative micro household factor endowments and feedback effects from the endogenous modelling of income distribution has an important dampening effect on the negative poverty impact. Comparing the endogenous household approach with the disaggregate factor income approach shows that this dampening effect is mostly the result of accounting for differences in micro household factor endowments. Accordingly, the endogenous income distribution method seems to have negative feedback effects on poverty, consistent with the fact that the elimination of import tariffs lowers agricultural terms of trade. In any case, feedback effects from changes in the distribution of income and consumption appear once again as potentially very important in determining the direction and overall impact on poverty of trade liberalization.

This conclusion is reinforced when looking at the combined third experiment, where all trade taxes are eliminated simultaneously. Here, the endogenous household approach implies an increase in the monetary poverty gap of 1.1 per cent compared with 1.3 per cent with the disaggregate factor income top-down approach and 2.2 per cent with the aggregate consumption top-down approach.

The regional ranking in Table 4.6 also seems to depend on the modelling approach. The south sees the largest increase in relative terms, whereas the north experiences the largest increase in absolute terms. The underlying intuition is that the burden of trade taxes is partly borne by enterprises whereas the incidence of household taxes is strictly on households. The lowering of agricultural terms of trade combined with increasing household tax levels therefore increases poverty gaps across regions. The large number of poor households in the north leads to a strong absolute increase in the monetary poverty gap here, whereas the smaller (average) poverty gap in the south leads to a stronger relative increase. Overall monetary poverty gaps increase the least with endogenous micro households, but there are some southern households that are losing out owing to feedback effects from the endogenous income distribution. Accordingly, poverty increases by 1.7 per cent in the south with the disaggregate factor income approach, compared with 1.8 per cent with the endogenous household approach. This demonstrates that the endogenous income distribution approach can affect the poverty of subgroups in opposite directions.

Table 4.7 Monetary poverty gaps and government budget closure (percentage changes)

Government budget closure	Region	Base run (VND billion)	Exp. 1	Exp. 2	Exp. 3
Fixed revenues	North	5,729	–0.3	1.1	0.9
	Centre	4,949	–0.1	1.1	1.0
	South	2,848	–0.2	1.9	1.8
	Total	13,526	–0.2	1.3	1.1
Flexible revenues	North	5,729	–2.3	–6.1	–8.3
	Centre	4,949	–2.2	–6.0	–8.1
	South	2,848	–3.1	–8.4	–11.4
	Total	13,526	–2.4	–6.5	–8.9

Source: Authors' CGE-model simulations.

Table 4.7 summarizes simulation results from the model with endogenous micro households, using two different choices of government budget closure: (i) a non-revenue-neutral closure where household tax rates are kept fixed (flexible revenues); and (ii) a revenue-neutral closure where household tax rates are allowed to vary uniformly (fixed revenues). The latter set of results mirror the results presented in Table 4.6, but Table 4.7 demonstrates that the government fiscal response is very important in determining the impact on poverty of full trade liberalization in the short to medium term (Experiment 3). When the government neutralizes the revenue impact of declining trade tax revenues by resorting to (lump-sum) household taxation, regional monetary poverty gaps generally tend to increase. In contrast, if tax rates remain the same and the Vietnamese government resorts to deficit financing, the overall monetary poverty gap decreases by almost 9 per cent.

The regional ranking of poverty is also affected by the government closure. Poverty *increases* relatively strongly in the more developed south when household taxes are raised in response to declining revenue. In contrast, when no taxes are raised, poverty *declines* relatively strongly in the south. Nevertheless, when no taxes are raised the largest absolute decrease in poverty occurs in the north, indicating that trade liberalization will, as a stand-alone measure, reduce poverty the most in the north. The regional impact patterns of the two scenarios with and without flexible tax rates are consistent with the fact that households in the south have higher average income and that poor southern households are generally located closer to the poverty line.

As already indicated, agricultural terms of trade tend to decline as a result of full trade liberalization (Experiment 3). Declining poverty in the scenario with fixed tax rates therefore follows mainly from increased overall efficiency in resource allocation and reduced indirect taxation of

Table 4.8 Macroeconomic indicators

	Base run	Exp. 1	Exp. 2	Exp. 3
Real GDP (VND billion)	444.7	0.0	0.1	0.1
Absorption (VND billion)	455.1	–0.1	0.0	–0.1
Value-added price index	100	1.0	3.6	4.7
Export producer price index	100	0.9	3.2	4.1
Import purchaser price index	100	–0.9	–2.6	–3.5
Cost of living index (rural)	100	–0.2	–0.8	–1.0
Cost of living index (urban)	100	–0.4	–0.8	–1.3
Real exchange rate index	100	0.2	0.4	0.5
Agricultural terms of trade: producer	100	0.4	0.6	0.9
Agricultural terms of trade: value-added	100	0.2	–0.5	–0.3
Agricultural terms of trade: export	100	3.6	0.0	3.6
Agricultural terms of trade: import	100	0.0	0.9	0.9

Note: Base run price values are index values unless otherwise indicated.
Source: Authors' CGE-model simulations.

rural households, rather than from improved relative price incentives for rural agricultural production. On the other hand, the results also show that replenishment of government income through direct household taxation will put large burdens on households and thereby lead to uniformly increasing poverty among households in all regions of Viet Nam.

3.2. The economic impact of trade liberalization

Having analysed the importance of modelling methodology, we now turn to an in-depth analysis of how trade liberalization would affect the Vietnamese economy.[9] Tables 4.8–4.11 summarize the macroeconomic effects of trade liberalization in Viet Nam. The indicators in Table 4.8 show that the elimination of trade taxes in a comparative static framework with full employment will have little macroeconomic impact. Real GDP expands marginally owing to improved efficiency in the allocation of otherwise fixed factor stocks, while nominal GDP declines marginally owing to changes in relative (factor) prices. Moreover, nominal absorption declines marginally, suggesting that the overall welfare level of the Vietnamese people will decrease slightly from trade liberalization in the short to medium term.

Table 4.8 also shows how the elimination of export taxes leads to higher export prices as perceived by domestic producers, while the elimination of import tariffs leads to lower import prices as perceived by domestic consumers. Higher export prices and lower prices on (imported) intermediate inputs drive domestic producer and value-added prices up, while declining import prices drive domestic demand prices down. The

intuition behind the increase in value-added prices is that trade liberalization with compensatory direct taxation leads to a change in the composition of GDP at market prices. Thus, lower indirect tax revenues lead to an expansion of GDP at factor cost through higher factor prices.

The real exchange rate tends to depreciate slightly in all experiments. Nevertheless, the real depreciation is the result of different underlying effects. In Experiment 1, the real exchange rate depreciates slightly as increasing export prices owing to lower export taxes are partially offset by a nominal exchange rate appreciation of 0.8 per cent. In Experiment 2, the real exchange rate depreciation reflects that declining import prices due to lower tariffs are more than offset by a nominal exchange rate depreciation of 3.2 per cent. Both the former nominal appreciation and the latter nominal depreciation tend to offset the pressures for movements of the current account balance. The (real and nominal) exchange rate impact in Experiment 3 is basically the sum of the impacts in Experiments 1 and 2.

Cost-of-living indices for rural and urban households, including the impact of changes in the value of home consumption, show little variation across households.[10] Trade liberalization affects urban costs of living by less than 0.1 per cent, but has slightly larger numerical effects on rural costs of living. The lower costs of living for rural households reflect the fact that reduced export taxes lead to a decline in costs of home consumption. In contrast, the elimination of import tariffs raises both agricultural producer prices and the implicit cost of home consumption, and therefore leads to increases in costs of living for rural households. This is due to a strong nominal exchange rate depreciation, which outweighs the reduction in agricultural-related protection afforded by the import tariffs. Finally, Experiment 3 shows that full trade liberalization increases rural costs of living by an amount that equals the net effect of reducing export taxes and import tariffs separately.

Agricultural price indices are presented in Table 4.8 to assess the transmission of relative price changes through the economy. The elimination of export taxes and import tariffs leads to increases in relative agricultural export and import prices. Relative agricultural export prices increase in Experiment 1, since agricultural exports are more heavily taxed than other exports. Similarly, relative agricultural import prices increase in Experiment 2, since direct agricultural trade protection is lower than for other non-agricultural sectors. The former increase in export prices leads to increasing relative value-added prices for agricultural output, while the latter increase in relative import prices leads to declining relative value-added prices. Accordingly, high export taxes are biasing price incentives against agricultural production, whereas high tariff protection of food-processing industries is implicitly subsidizing agricultural produc-

Table 4.9 Equivalent variation for households (percentage changes)

Household	Base run	Exp. 1	Exp. 2	Exp. 3
Rural male farm	0.0	–0.1	–1.0	–1.1
Rural male self-employed	0.0	0.0	–0.6	–0.7
Rural male wage	0.0	–0.1	–0.8	–0.9
Rural male non-employed	0.0	–1.3	–2.1	–3.4
Rural female farm	0.0	–0.2	–1.1	–1.4
Rural female self-employed	0.0	–0.6	–0.9	–1.5
Rural female wage	0.0	–0.3	–0.9	–1.2
Rural female non-employed	0.0	–1.5	–1.0	–2.6
Urban male farm	0.0	–0.4	–1.5	–1.9
Urban male self-employed	0.0	–0.3	–0.9	–1.3
Urban male wage	0.0	–0.4	–0.8	–1.2
Urban male non-employed	0.0	–1.3	–2.5	–3.8
Urban female farm	0.0	–0.3	–1.6	–1.9
Urban female self-employed	0.0	–0.5	–0.8	–1.4
Urban female wage	0.0	–0.5	–0.7	–1.2
Urban female non-employed	0.0	–1.7	–1.2	–2.9

Source: Authors' CGE-model simulations.

tion. The net impact can be judged from Experiment 3, and it shows that value-added prices decline by 0.3 per cent. This indicates that the overall Vietnamese trade tax structure is biasing price incentives slightly in favour of agricultural production and against non-agricultural production.

Table 4.9 presents measures of equivalent variation for each of the 16 aggregate household categories.[11] It appears that no households gain from the combined elimination of trade taxes in Experiment 3, and the small number of households with non-employed heads experience particularly strong losses. Accordingly, this group of households does not share in the income expansion following from increasing factor prices. All other households lose welfare in the range of 0.7–1.9 per cent. Urban (farm) households are the main losers since the relative factor price of their main factor endowment, which is urban unskilled labour, is declining. This can be seen from Table 4.11. In contrast, the welfare loss of rural (farm) households is relatively mild since rural (male) labour wages are increasing in relative terms.

Table 4.10 shows how the composition of real GDP changes with trade liberalization. The two consumption items, including home and marketed consumption, decline, whereas investment and trade aggregates expand. The simultaneous reductions in consumption and increases in investment come about as household tax income replaces the tax revenue of the government lost owing to trade liberalization. The burden of trade taxes is partly borne by enterprises through reduced returns to capital. The sole reliance on household taxes to make up for lost revenue therefore re-

Table 4.10 Components of real GDP (percentage changes)

	Base run (VND billion)	Exp. 1	Exp. 2	Exp. 3
Home consumption	23,400	0.0	−2.0	−2.0
Marketed consumption	272,500	−0.3	−0.8	−1.1
Recurrent government	28,200	0.0	0.0	0.0
Investment and stocks	130,900	0.7	2.3	3.0
Exports	241,400	0.6	1.6	2.2
Imports	−251,700	0.5	1.6	2.1
Real GDP	444,700	0.0	0.1	0.1

Source: Authors' CGE-model simulations.

Table 4.11 Factor prices (percentage changes)

Factor	Base run	Exp. 1	Exp. 2	Exp. 3
Rural male low education	100.0	1.3	3.5	4.8
Rural male medium education	100.0	1.3	3.8	5.0
Rural male high education	100.0	1.2	4.1	5.3
Rural female low education	100.0	0.9	3.5	4.3
Rural female medium education	100.0	0.8	3.5	4.3
Rural female high education	100.0	0.9	3.4	4.3
Urban male low education	100.0	1.1	3.2	4.2
Urban male medium education	100.0	0.9	3.9	4.8
Urban male high education	100.0	0.7	4.2	5.0
Urban female low education	100.0	0.6	3.6	4.3
Urban female medium education	100.0	0.5	3.8	4.3
Urban female high education	100.0	0.5	3.8	4.3
Capital	100.0	1.0	4.2	5.2
Land	100.0	1.6	2.0	3.5

Source: Authors' CGE-model simulations.

leases funds for enterprises – funds that are partly used to increase savings and accordingly investment. In contrast, household consumption has to be reduced along with household disposable income since the increased tax burden more than outweighs increased factor income. Trade aggregates expand in parallel owing to trade tax-induced changes in relative export and import prices and the need to maintain a fixed balance of payments.

Table 4.11 shows that factor prices generally change in parallel, but also that some variation occurs owing to differences in relative factor intensities among production activities. Agricultural production activities and construction have relatively high male factor intensities, whereas food processing, manufacturing, trade and other services have relatively high female factor intensities. Capital intensities are relatively low in

agricultural production activities and relatively high in oil production/mining and in the supply of water and gas, while land is used exclusively in agricultural production. The elimination of relatively high agricultural export tax rates leads to increasing agricultural terms of trade. This spills over into relative increases in wages for rural and urban males with low education and in returns to land, which are all used relatively intensively in agricultural production. The expansion of real investment owing to increased enterprise savings also benefits male wages, whereas (urban) female wage increases are below average, since the female factor intensity is particularly low in construction.

Experiment 2 shows that the elimination of import tariffs has a similar differentiated impact on relative factor prices. Male wages again tend to increase relative to female wages. Import tariff collection is concentrated in food processing and manufacturing. The elimination of these tariffs has a negative effect on relative female wages, since it leads to reduced protection in these sectors. This effect is reinforced by the expansion of real investment, which leads to increasing demand for male factors and increasing relative male wages. Returns to highly educated male labour increase particularly strongly since construction has high factor intensity for this labour category. The factor price movements in the combined Experiment 3 reflect the sum of the factor price movements in the two separate Experiments 1 and 2. Male wages increase relative to female wages, and highly educated male wages increase the most. Returns to capital increase above average and returns to land increase below average, since the elimination of import tariffs raises relative non-agricultural value-added prices.

We now turn to the issue of assessing how trade policy affects the poor in our comparative static framework. Table 4.12 presents the impact on poverty headcount indices and monetary poverty gaps at the regional

Table 4.12 Regional households, poverty indices and monetary poverty gaps (percentage changes)

Measure	Region	Base run	Exp. 1	Exp. 2	Exp. 3
P_0 (rate)	North	0.343	0.4	2.4	2.0
	Centre	0.404	0.2	0.8	1.1
	South	0.217	−0.2	0.4	0.4
	Total	0.314	0.2	1.3	1.3
POVGAP (VND billion)	North	5,729	−0.3	1.1	0.9
	Centre	4,949	−0.1	1.1	1.0
	South	2,848	−0.2	1.9	1.8
	Total	13,526	−0.2	1.3	1.1

Source: Authors' CGE-model simulations.

Table 4.13 Rural households, poverty indices and monetary poverty gaps (percentage changes)

Measure	Region	Base run	Exp. 1	Exp. 2	Exp. 3
P_0 (rate)	North	0.411	0.4	2.4	2.0
	Centre	0.462	0.2	0.8	1.1
	South	0.298	–0.2	0.4	0.4
	Total	0.389	0.2	1.3	1.3
POVGAP (VND billion)	North	5,601	–0.3	1.1	0.9
	Centre	4,908	–0.1	1.0	1.0
	South	2,767	–0.2	1.9	1.8
	Total	13,275	–0.2	1.2	1.1

Source: Authors' CGE-model simulations.

level. The experiments indicate that the elimination of export taxes and import tariffs per se will do little to raise people out of poverty if the government responds with increased taxation at the household level. The elimination of export taxes will, by itself, lower monetary poverty gaps and raise a small number of individuals above the poverty line in the south. Nevertheless, the main impact will be to increase the number of poor people in the central region and, in particular, the north. Moreover, the elimination of import tariffs will increase the poverty headcount by 1.3 per cent and move an additional 320,000 people into poverty. The overall number of poor individuals does not change when export taxes are eliminated on top of import tariffs. Nevertheless, the overall decline in agricultural terms of trade will lead to strongly increasing poverty headcounts in the north, and a relative expansion of monetary poverty gaps in the south. The economy-wide impact shows a relatively strong 1.1 per cent increase in the overall monetary poverty gap, equivalent to an increase of VND153 billion (US$11 million).

Tables 4.13–4.14 present the FGT headcount and monetary poverty gap measures for micro households defined by rural and urban location. As outlined in section 2, poverty is concentrated among households located in rural areas. Comparing rural headcount measures (P_0) with regional headcount totals in Table 4.12, rural poverty headcount measures are uniformly above average across all regions. The data indicate that the share of poverty-stricken individuals in rural areas amounts to 41.1 per cent in the north, 46.2 per cent in the centre and 29.8 per cent in the south, whereas comparable figures for urban areas amount to, respectively, 5.6 per cent, 4.9 per cent and 2.3 per cent. Similarly, rural poverty gaps add up to VND13,275 billion (US$950 million) whereas urban poverty gaps amount to a mere VND251 billion (US$20 million).

The results on rural poverty presented in Table 4.13 are therefore very similar to the economy-wide poverty indicators presented in Table 4.12.

Table 4.14 Urban households, poverty indices and monetary poverty gaps (percentage changes)

Measure	Region	Base run	Exp. 1	Exp. 2	Exp. 3
P_0 (rate)	North	0.056	0.0	1.9	1.9
	Centre	0.049	0.0	0.0	0.0
	South	0.023	0.0	0.0	0.0
	Total	0.038	0.0	0.9	0.9
POVGAP (VND billion)	North	128	−0.0	3.7	3.8
	Centre	42	1.2	2.4	3.7
	South	81	0.9	1.9	2.9
	Total	251	0.5	2.9	3.5

Source: Authors' CGE-model simulations.

Whereas elimination of export taxes has relatively minor effects on rural poverty, elimination of import tariffs increases rural poverty more visibly. The combined third experiment shows that trade liberalization leads to increasing numbers of poverty-stricken rural inhabitants and increasing levels of rural monetary poverty, although the economy-wide average poverty gap among poor people is relatively unaffected. The impact on urban poverty presented in Table 4.14 is different from the impact on rural poverty in the sense that the economy-wide poverty headcount increases modestly, whereas the monetary poverty gap increases strongly. The associated increase in the average poverty gap among the poor is particularly strong for urban areas in central provinces.

Comparing the poverty impact of trade liberalization between rural and urban areas, it appears that the number of poor expands more rapidly in rural areas compared with urban areas. Trade liberalization will therefore tend to worsen the rural poverty headcount bias in Viet Nam in the short to medium term. On the other hand, the depth of poverty measured by average monetary poverty gaps will become more equally distributed among rural and urban areas after trade liberalization. This conclusion is supported by the relatively strong 3.5 per cent increase in the urban monetary poverty gap compared with the more modest 1.1 per cent increase in the rural monetary poverty gap. Looking at absolute numbers, it is, however, clear that the increase in rural poverty of VND146 billion (US$10 million) completely dominates the VND9 billion (US$0.6 million) increase in urban poverty.

4. Conclusion

This chapter has applied a novel methodology for analysing the impact on poverty of macro policies within a CGE model framework, which

does not rely on assumptions regarding intra-household distributions of income. Income distribution is modelled endogenously by disaggregating the household sector into 5,999 micro households. Each of the micro households is characterized by a different composition of factor endowments, implying rich adjustments in response to changes in relative factor prices. Our results show that feedback effects from the micro-level distribution of income and expenditures to macro-level variables are important in determining the impact on poverty of trade policy interventions in a comparative static framework.

We compared our model approach with 5,999 micro households with a top-down approach based on a model with 16 representative households. The top-down approach measured poverty by (i) applying aggregate consumption growth rates to micro household consumption, and (ii) applying aggregate factor prices to derive micro household factor income and consumption. This approach may be interpreted as a decomposition where the top-down approach is considered to be an intermediate step between the crude application of aggregate consumption growth rates and the more sophisticated modelling of micro household income and expenditure decisions. Our results show that endogenous modelling of the household income distribution is important for properly assessing the size and direction of the impact on poverty. In particular, our results show that a top-down approach, which relies on micro household factor endowments, is not sufficient to mirror the results from the endogenous modelling of the income distribution.

Relying on headcount and monetary poverty gap measures, we also find that the impact on poverty of eliminating trade taxes depends critically on the fiscal response of the government. In particular, the short-to-medium-term impact on poverty levels among the poor is inversely related to changes in investment expenditures. Accordingly, our results indicate that poverty may increase within a static setting, where overall welfare as measured by total absorption remains unchanged. This suggests that the government can, and should, choose a combination of measures to make up for lost revenue from reduced trade taxes. At one extreme, we find that poverty headcounts and monetary poverty will increase if the government decides to make up for lost revenues by relying solely on increased household taxation. At the other extreme, we find that a policy of pure deficit financing of the ensuing budgetary gap will lower the economy-wide monetary poverty gap by almost 9 per cent.

All in all, we do not suggest that the government should allow trade liberalization to be accompanied by an unbalancing of the budget and crowding-out of private investment. Nevertheless, our analysis of the distributional implications of reductions in trade taxes and associated changes in tax incidence does suggest that great care should be exercised

in formulating the fiscal response to trade liberalization so as to avoid increasing poverty in the short to medium term. On a methodological note, our results demonstrate the value of including disaggregated micro households within analyses of poverty and income distribution. In particular, this kind of disaggregation allows for a functional impact of changes to the income distribution – a crucial element that is not captured in a simple top-down approach.

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Notes

1. As discussed by Niimi et al. (2003).
2. VLSS98 surveyed 6,002 households, but three were dropped from our analysis owing to missing observations.
3. Value-added taxes are actually taxes on production value, so they are levied on total production value in the model underlying the results presented in section 3.
4. This is subject to the caveat that a single poverty line is used for both rural and urban areas. Owing to higher urban prices and variations in the consumption basket, reported estimates are likely to underestimate urban poverty.
5. Although the Arndt et al. (2002) study was concerned with Mozambique, the elasticity estimates are typical across developing-country CGE models. The only major exception is the relatively high import substitution elasticity for food crops. This reflects the particular history of Mozambique over the estimation period used in the Arndt et al. study. It was therefore decided to impose the more moderate import substitution elasticity estimate for cash crops on both the rice and other agricultural crops sectors in the current study.
6. In the following, it is specifically noted when the government closure is not revenue neutral.
7. In Table 4.6 in the results section, the label "Top-down (aggregate consumption)" refers to the top-down approach where representative household consumption growth rates are applied, whereas "Top-down (disaggregate factor income)" refers to the top-down approach where factor prices are applied to micro household factor endowments. The label "Endogenous" refers to the model (with 5,999 individual households), which captures feedback effects from changes in the distribution of income and consumption.
8. These poverty lines are measured in local currency terms and are not corrected to take account for possible systematic divergence from purchasing power parity. This might ex-

plain the very low level of the poverty lines. Moreover, it is noted that the estimates of the number of poor will differ slightly from official estimates. This is not owing to the updating of the poverty line but follows from the statistical adjustments made here to attain consistency with macro accounts of VSAM.

9. See Jensen and Tarp (2003) for more elaborate analyses of poverty implications.
10. Cost-of-living indices vary little by construction because the consumer price index for marketed goods is used as the price numeraire.
11. The equivalent variation measures are calculated from trade tax experiments with aggregate households, i.e. without endogenous micro household behaviour.

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Part II

Inequality in Asia

5

Fifty years of regional inequality in China: A journey through central planning, reform and openness

Ravi Kanbur and Xiaobo Zhang

1. Introduction

The second half of the twentieth century saw a tumultuous history unfold in China – the early years of communist rule in the 1950s culminating in the Great Famine, the Cultural Revolution and its aftermath in the late 1960s and the 1970s, the reform of agriculture in the late 1970s and the 1980s, and an explosion of trade and foreign direct investment (FDI) in the late 1980s and the 1990s. All these events have affected the course of economic growth and income distribution. However, although a large literature has studied growth through these different phases of Chinese history (McMillan et al. 1989; Lin 1992; Fan et al. 2003), few studies have matched the evolution of inequality over the long run with these different periods in communist Chinese history over its entire course.

This chapter presents and analyses the evolution of Chinese regional inequality since the Communist Revolution right up to the present. Most studies on China's inequality (e.g. Hussain et al. 1994; Khan and Riskin 2001; Chen and Ravallion 1996; Aaberge and Li 1997; Tsui 1998) have focused on relatively short periods, mostly during the post-reform years, making use of the new household surveys that became available during this period. Of the studies that come closest to the spirit of our interest in Chinese inequality over the long run, Tsui (1991) stops in 1985 and Lyons (1991) stops in 1987, just as the increase in trade and FDI was beginning; Yang and Cai (2000) go up to 1996, but focus only on the rural–urban gap at the national level; and Kanbur and Zhang (1999)

disaggregate down to the rural–urban level within provinces to calculate a regional inequality index, and present a decomposition of regional inequality by its rural–urban and inland–coastal components, but their study is only for the post-reform years of 1983–1995.

Using a data set of provincial and national data covering the second half of the twentieth century, we are able to construct a comprehensive time series of regional inequality in China, including its decompositions into rural–urban and inland–coastal components, from 1952 to 2000. We find that changes in regional inequality match the phases of Chinese history remarkably well, as do its rural–urban and inland–coastal components. The peaks of inequality in China have been associated with the Great Famine, the Cultural Revolution and the current phase of openness and decentralization. We further use econometric analysis to establish that regional inequality is explained to different degrees in different phases by three key policy variables: the share of heavy industry in gross output value; the degree of decentralization; and the degree of openness.

2. Constructing a long-run time series for regional inequality in China

Ideally, for an analysis of the evolution of inequality over communist Chinese history we would have available representative national household surveys for the entire period. Unfortunately, although such surveys have been conducted throughout the past 50 years, they are available to researchers only for the post-reform period and, in any case sporadically, for restricted years with varying but limited coverage. Thus, for example, Chen and Ravallion (1996) had access to official household survey data but only for four provinces between 1986 and 1990. Aaberge and Li (1997) analyse urban household surveys for Liaoning and Sichuan provinces for the same period, and Tsui (1998) analyses rural surveys for 1985, 1988 and 1990, but only for Guangdong and Sichuan. Yang (1999) analyses both rural and urban parts of the household survey for four years between 1986 and 1994, and for Guangdong and Sichuan. This different coverage across studies reflects the differential access to official data. Researchers have also conducted and analysed independent surveys; for example, Hussain et al. (1994) did one for 1986 and Rozelle (1994) for Township and Village Enterprises between 1984 to 1989 in Jiangsu province. The Chinese Academy of Social Sciences conducted a household survey for 1988 and 1995 (Khan and Riskin 2001).

The inequality analysis that has been done on household surveys for the late 1980s and 1990s has been extremely valuable in illuminating specific aspects of the distributional dimensions of Chinese development in

the late 1980s and early 1990s. In general these analyses decompose inequality by income sources, but few have aligned the patterns of inequality with national development policies. The bottom line is that researchers simply do not have comprehensive access to household surveys that are national and that cover the entire, or even a substantial part of, the half-century sweep of Chinese history that is of interest to us in this chapter.

In the face of this data restriction, we are forced to look for data availability at higher levels of aggregation than at the household level. As it turns out, certain types of data are indeed available at the province level, disaggregated by rural and urban areas, stretching back to 1952. This chapter constructs a time series of inequality by building up information on real per capita consumption in the rural and urban areas of 28 of China's 30 provinces (unfortunately, data availability is not complete for Tibet and Hainan provinces).[1]

With these sub-provincial rural and urban per capita consumption figures, together with population weights for these areas, a national distribution of real per capita consumption can be constructed and its inequality calculated for each year between 1952 and 2000, thus covering the vast bulk of the period from 1949 to the present day. Of course, what this means is that overall household-level inequality is being understated, since inequality within the rural and urban areas of each province is being suppressed. Moreover, we cannot say anything about the evolution of household-level inequality *within* these areas. Our measures do provide a lower bound on inequality over this entire period, but the fact remains that our study of inequality is essentially a study of regional inequality.

A detailed discussion of our basic data is provided in the appendix to this chapter. A number of studies have used province-level data to study regional inequality in the past. Many of them used Soviet-type statistics, largely because long-term data series existed for these (Lyons 1991; Tsui 1991), and they did not in general disaggregate by rural and urban areas within provinces. With the availability of rural–urban disaggregations on per capita consumption stretching back to the 1950s, these studies can be substantially improved and extended in terms of time and space coverage. In the recent literature, Yang and Cai (2000) use the same data sources as we have used, but they focus solely on the average rural–urban gap at the national level and do not go into inequalities across provinces.

Using the information available, we calculate the Gini coefficient of inequality using the standard formula. However, the bulk of our analysis is done with a second inequality index, a member of the decomposable generalized entropy (GE) class of inequality measures as developed by Shorrocks (1980, 1984):

$$I(y) = \begin{cases} \sum_{i=1}^{n} f(y_i)\left\{\left(\frac{y_i}{\mu}\right)^c - 1\right\} & c \neq 0, 1 \\ \sum_{i=1}^{n} f(y_i)\left(\frac{y_i}{\mu}\right)\log\left(\frac{y_i}{\mu}\right) & c = 1 \\ \sum_{i=1}^{n} f(y_i)\log\left(\frac{\mu}{y_i}\right) & c = 0 \end{cases} \tag{5.1}$$

In the above equation, y_i is the ith income measured in Chinese yuan, μ is the total sample mean, $f(y_i)$ is the population share of y_i in the total population and n is total population. For $c < 2$, the measure is transfer sensitive, in the sense that it is more sensitive to transfers at the bottom end of the distribution than to those at the top. The key feature of the GE measure is that it is additively decomposable. For K exogenously given, mutually exclusive and exhaustive, groups indexed by g:

$$I(y) = \sum_{g}^{K} w_g I_g + I(\mu_1 e_1, \ldots, \mu_K e_K), \tag{5.2}$$

$$\text{where } w_g = \begin{cases} f_g\left(\frac{\mu_g}{\mu}\right)^c & c \neq 0, 1 \\ f_g\left(\frac{\mu_g}{\mu}\right) & c = 1 \\ f_g & c = 0 \end{cases}$$

In equation 5.2, I_g is inequality in the gth group, μ_g is the mean of the gth group and e_g is a vector of 1's of length n_g, where n_g is the population of the gth group. If n is the total population of all groups, then $f_g = n_g/n$ represents the share of the gth group's population in the total population. The first term on the right-hand side of (5.2) represents the within-group inequality. The second term is the between-group component of total inequality. For simplicity, we present results in this chapter only for $c = 0$.[2] The within-group inequality part in (5.2) represents the spread of the distributions in the subgroups; the between-group inequality indicates the distance between the group means. With our time series of inequality in China over the long term, we are now in a position to investigate dimensions of inequality in the different phases of Chinese development over the past half-century.

3. Inequality change through the phases of Chinese history: A narrative

Following standard discussions, communist Chinese history can be divided into several phases: 1949–1956 (revolution and land reform), 1957–1961 (the Great Leap Forward and the Great Famine), 1962–1965 (post-famine recovery), 1966–1978 (the Cultural Revolution and transition to reform), 1979–1984 (rural reform) and 1985 to the present day (post-rural reform, decentralization and opening up to trade and FDI).

Table 5.1 presents economic indicators for China from 1952 to 2000. It includes three key indicators of economic policy: the share of heavy industry in the gross value of total output (a measure of the bias against agriculture and China's comparative advantage); the ratio of trade volume to total gross domestic product (GDP) (a measure of the degree of openness); and the ratio of local government expenditure to total government expenditure (a measure of decentralization).[3] Figure 5.1 shows the evolution of real per capita GDP through the different phases identified above. Table 5.2 presents long-run inequality series, and Figure 5.2 graphs the evolution of China's regional inequality, as measured by the Gini and the GE indices, through the six phases of development identified above. The two indices move in close relation to each other, and match the different phases of Chinese development remarkably well.

Inequality was relatively low and steady in the early first years of communist rule when land reform was introduced. However, it rose precipitously during the Great Leap Forward and the Great Famine, reaching a peak in 1960. It fell during the recovery from the famine, reaching a trough in 1967. But the effects of the Cultural Revolution, which began in late 1966, started an increase in inequality that peaked in 1976. The transition from the Cultural Revolution to the period of rural reform saw a decline in inequality, which gathered pace in the early 1980s and reached a trough in 1984. In the post-reform period after 1984, when China decentralized, opened up and experienced an explosion of trade and FDI, inequality rose steadily and sharply right through to the end of our data series, in 2000.

Thus, over the past 50 years inequality has peaked three times – during the Great Famine, at the end of the Cultural Revolution and in the current period of global integration. In fact, the Gini coefficient of regional inequality in China in 2000 exceeds the peaks of inequality reached at the end of the Cultural Revolution in 1976 and during the Great Famine in 1960. Using the Gini coefficient, inequality in 2000 is about 16 per cent higher than that in 1960. Similarly, there are three major troughs in the overall evolution of inequality: in 1952, right at the beginning of the

Table 5.1 China: Economic indicators, 1952–2000

Year	GDP (billion yuan)	Imports (billion yuan)	Total expenditure (billion yuan)	GAIOV[a] (billion yuan)	Tariff rate (%)	Trade ratio[b] (%)	Decentralization[c] (%)	Industrialization[d] (%)
1952	67.9	3.8	17.2	81.0	12.8	9.5	25.9	15.3
1953	82.4	4.6	21.9	96.0	11.0	9.8	26.1	17.5
1954	85.9	4.5	24.4	105.0	9.2	9.9	24.7	18.9
1955	91.0	6.1	26.3	110.9	7.6	12.1	23.5	19.7
1956	102.8	5.3	29.9	125.2	10.2	10.6	29.6	21.7
1957	106.8	5.0	29.6	124.1	9.6	9.8	29.0	25.5
1958	130.7	6.2	40.0	164.9	10.4	9.8	55.7	35.2
1959	143.9	7.1	54.3	198.0	9.9	10.4	54.1	43.8
1960	145.7	6.5	64.4	209.4	9.2	8.8	56.7	52.1
1961	122.0	4.3	35.6	162.1	14.5	7.4	55.0	37.7
1962	114.9	3.4	29.5	150.4	14.3	7.0	38.4	32.3
1963	123.3	3.6	33.2	163.5	11.6	6.9	42.1	33.5
1964	145.4	4.2	39.4	188.4	10.4	6.7	42.9	34.4
1965	171.6	5.5	46.0	223.5	10.3	6.9	38.2	30.4
1966	186.8	6.1	53.8	253.4	10.6	6.8	36.9	32.7
1967	177.4	5.3	44.0	230.6	7.3	6.3	38.7	28.1
1968	172.3	5.1	35.8	221.3	12.4	6.3	38.7	26.9
1969	193.8	4.7	52.6	261.3	13.5	5.5	39.3	31.7
1970	225.3	5.6	64.9	313.8	12.5	5.0	41.1	36.4
1971	242.6	5.2	73.2	348.2	9.5	5.0	40.5	39.5
1972	251.8	6.4	76.6	364.0	7.8	5.8	43.7	40.2
1973	272.1	10.4	80.9	396.7	8.7	8.1	44.4	39.9
1974	279.0	15.3	79.0	400.7	9.2	10.5	49.7	38.7
1975	299.7	14.7	82.1	446.7	10.2	9.7	50.1	40.2
1976	274.4	12.9	80.6	453.6	11.6	9.6	53.2	40.3
1977	320.2	13.3	84.4	497.8	19.8	8.5	53.3	41.9
1978	362.4	18.7	112.2	563.4	15.3	9.8	52.6	42.8

1979	403.8	24.3	128.2	637.9	10.7	11.3	48.9	41.3
1980	451.8	29.9	122.9	707.7	11.2	12.6	45.7	38.5
1981	486.0	36.8	113.8	758.1	14.7	15.1	45.0	34.5
1982	530.2	35.8	123.0	829.4	13.3	14.5	47.0	34.9
1983	595.7	42.2	141.0	921.1	12.8	14.4	46.1	36.1
1984	720.7	62.1	170.1	1,083.1	16.6	16.7	47.5	37.0
1985	898.9	125.8	200.4	1,333.5	16.3	23.0	60.3	38.6
1986	1,020.1	149.8	220.5	1,520.7	10.1	25.3	62.1	38.6
1987	1,195.5	161.4	226.2	1,848.9	8.8	25.8	62.6	38.7
1988	1,492.2	205.5	249.1	2,408.9	7.5	25.6	66.1	38.4
1989	1,691.8	220.0	282.4	2,855.2	8.3	24.6	68.5	39.4
1990	1,859.8	257.4	308.4	3,158.6	6.2	29.9	67.4	38.3
1991	2,166.3	339.9	338.7	3,478.2	5.5	33.4	67.8	41.5
1992	2,665.2	444.3	374.2	4,368.4	4.8	34.2	68.7	44.8
1993	3,456.1	598.6	464.2	5,939.8	4.3	32.6	71.7	49.7
1994	4,667.0	996.0	579.3	8,592.7	2.7	43.7	69.7	35.5
1995	5,749.5	1,104.8	682.4	11,223.5	2.6	40.9	70.8	33.1
1996	6,685.1	1,155.7	793.8	12,195.3	2.6	36.1	72.9	30.0
1997	7,314.3	1,180.7	923.4	13,749.7	2.7	36.9	72.6	29.2
1998	7,801.8	1,162.2	1,079.8	14,320.5	2.7	34.4	71.1	27.0
1999	8,206.8	1,373.7	1,318.8	15,063.0	4.1	36.4	68.5	23.6
2000	8,940.4	1,863.9	1,588.7	n.a.	4.0	43.9	65.3	n.a.

Notes:
[a] Gross agricultural and industrial output value.
[b] The ratio of trade volume to total gross domestic product.
[c] The ratio of local government expenditure to total government expenditure.
[d] The share of heavy industry in the gross value of total output.
Source: See the appendix for data sources and definition of variables.

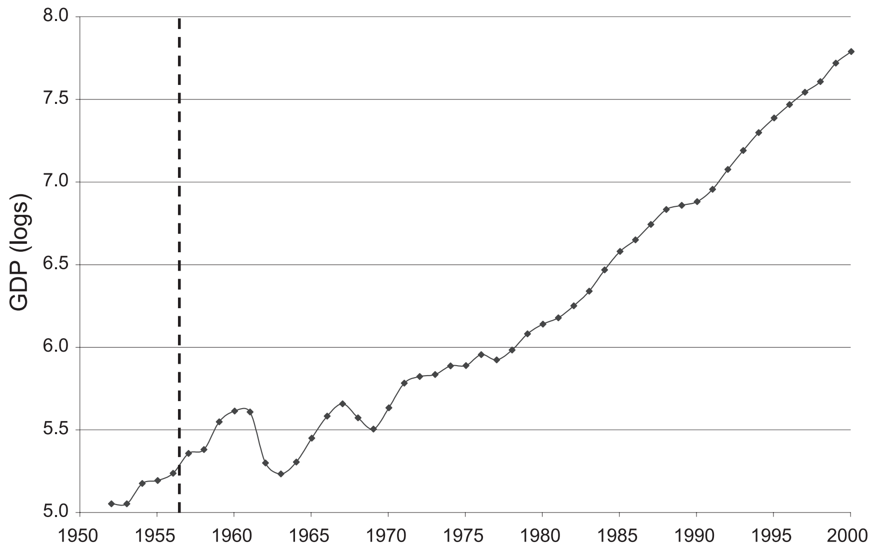

Figure 5.1 Per capita GDP in constant 1980 prices, 1952–2000.

data series; in 1967, at the end of the recovery from the Great Famine and before the effects of the Cultural Revolution set in; and in 1984, at the end of the rural reform period and the start of the expansion based on global integration. Overall, inequality seems to have been low when policy supported agriculture and the rural sector generally, and high when this sector was relatively neglected. These effects can be further investigated by decomposing overall inequality into subcomponents and examining the evolution of these components.

As discussed in the previous section, the GE index is subgrouped additively decomposable, allowing us to look deeper into the make-up of inequality. The 56 data points in each year from which the overall distribution is constructed (a rural and an urban observation for each of 28 provinces) can be divided into rural and urban observations across the provinces and, using equation (5.2), the GE can be decomposed into a ''within rural–urban'' and a ''between rural–urban'' component (hereafter, the rural–urban inequality). The overall GE and the rural–urban inequality are shown in Table 5.2. The within rural–urban component is the difference between these two components.

A key dimension of inequality in China, especially in the post-reform period, is that between inland and coastal provinces (Tsui 1993; Chen and Fleisher 1996; Yao 1997; and Zhang and Kanbur 2001). We follow the practice of classifying the provinces of Beijing, Liaoning, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejang, Fujian, Guangdong and

Table 5.2 Inequalities and decompositions, 1952–2000 (per cent)

Year	Gini	GE	Inequality	
			Rural–urban	Inland–coastal
1952	22.4	9.0	6.9	0.6
1953	24.7	10.7	8.6	0.7
1954	23.2	9.4	7.9	0.6
1955	22.0	8.6	7.3	0.3
1956	22.9	9.4	8.2	0.2
1957	23.8	9.8	8.5	0.1
1958	24.4	10.2	8.8	0.2
1959	29.7	14.3	11.6	0.2
1960	32.2	16.6	13.5	0.3
1961	30.3	14.5	11.2	0.2
1962	28.5	13.1	10.7	0.2
1963	27.6	12.4	9.6	0.2
1964	28.2	12.8	9.5	0.2
1965	26.7	11.8	8.7	0.2
1966	26.6	11.7	9.1	0.2
1967	25.5	10.8	8.5	0.2
1968	26.3	11.3	8.7	0.3
1969	27.1	12.2	9.9	0.3
1970	27.0	12.1	9.8	0.3
1971	26.9	12.1	9.8	0.3
1972	28.1	12.8	9.8	0.3
1973	27.9	12.7	9.9	0.3
1974	28.8	13.5	10.3	0.3
1975	29.5	14.2	11.2	0.5
1976	30.9	15.5	12.1	0.5
1977	30.8	15.4	12.1	0.5
1978	29.3	14.0	11.0	0.4
1979	28.6	13.3	10.1	0.4
1980	28.2	13.1	9.9	0.5
1981	27.0	12.0	9.1	0.6
1982	25.6	10.6	7.2	0.5
1983	25.9	11.1	6.8	0.4
1984	25.6	10.9	6.3	0.4
1985	25.8	11.1	6.6	0.5
1986	26.8	11.9	6.9	0.5
1987	27.0	12.0	6.8	0.6
1988	28.2	13.1	7.7	0.8
1989	29.7	14.4	9.3	1.0
1990	30.1	14.9	9.5	1.0
1991	30.3	14.9	9.9	1.2
1992	31.4	16.0	10.2	1.5
1993	32.2	16.8	10.9	1.7
1994	32.6	17.2	10.8	2.0
1995	33.0	17.7	11.5	2.3
1996	33.4	18.2	11.7	2.6

Table 5.2 (cont.)

			Inequality	
Year	Gini	GE	Rural–urban	Inland–coastal
1997	33.9	18.9	11.7	2.7
1998	34.4	19.6	12.2	2.9
1999	36.3	23.4	12.8	3.2
2000	37.2	24.8	13.9	3.8

Note: GE refers to the generalized entropy index with $c = 0$. GE with $c = 1$ was also calculated but the results are similar and not reported here.
Source: Authors' calculations.

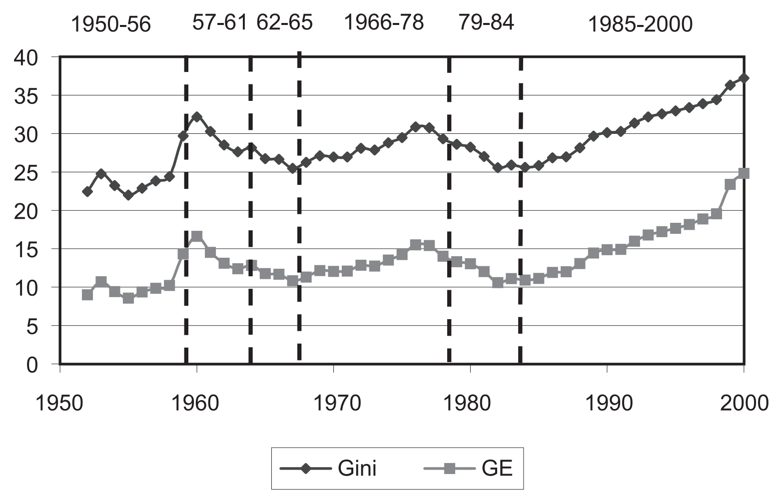

Figure 5.2 The trends of regional inequality, 1952–2000.
Source: From Table 5.2.

Guangxi as coastal and the other provinces as inland. We therefore divide our 56 observations into 22 coastal and 34 inland observations and decompose the GE measure accordingly. The ''between inland–coastal'' component (hereafter, the inland–coastal inequality) is reported in Table 5.2.

Figures 5.3–5.5 go a long way in translating the above narrative into impacts on overall inequality and the rural–urban and inland–coastal inequalities, and provide some initial hypotheses for econometric testing in the next section. Under the central planning system, the central government had large powers to allocate and utilize financial revenues to achieve the goal of equity even if at the expense of efficiency. With eco-

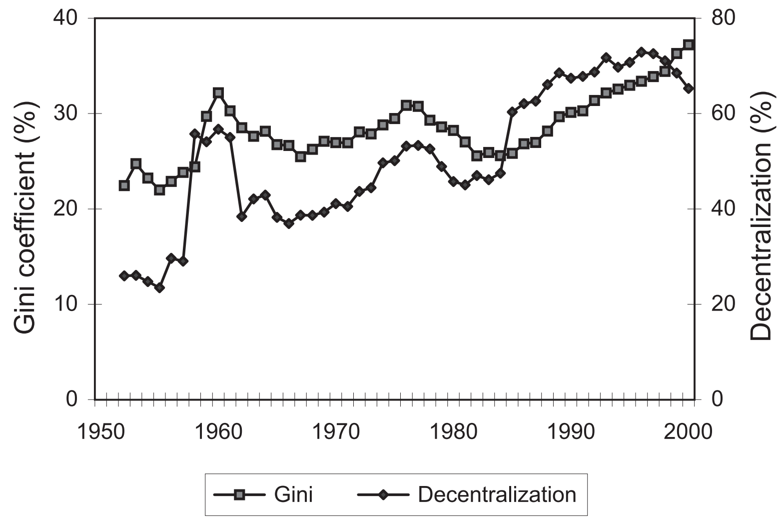

Figure 5.3 Decentralization and overall inequality (Gini coefficient), 1952–2000.

nomic reforms, the central government has granted local governments more autonomy in allocating their resources and bearing more responsibilities (Ma 1997; Lin et al. 1997; Qian and Roland 1998). Figure 5.3 shows that, in general, the share of local government expenditure has increased in the reform period, although there are some blips as the government reassessed its priorities periodically. With the new fiscal structure, local governments have more incentive to promote economic growth. However, because of differences in historical development level and geographical locations, the rate of growth may differ across regions. Under fiscal decentralization, regions with agriculture as the major means of production must rely more on the extraction of levies and compulsory apportionment, which hinder local economic growth. Regions with a more diverse economic structure and a larger revenue base have a greater degree of freedom to finance their economic development (Zhang et al. 2004). Not surprisingly, as shown in Figure 5.3, inequality moved closely in tandem with decentralization.

Although Lin et al. (1997) and Zhang and Zou (1998) have in particular analysed the relationship between fiscal decentralization and economic growth for China, few studies except Tsui (1991) have investigated the effect of decentralization on regional inequality. Using a graph analysis based on data series up to 1985, Tsui (1991) detected a positive relationship between decentralization and worsening regional inequality. Based on lessons drawn from other countries, Prud'homme (1995) has

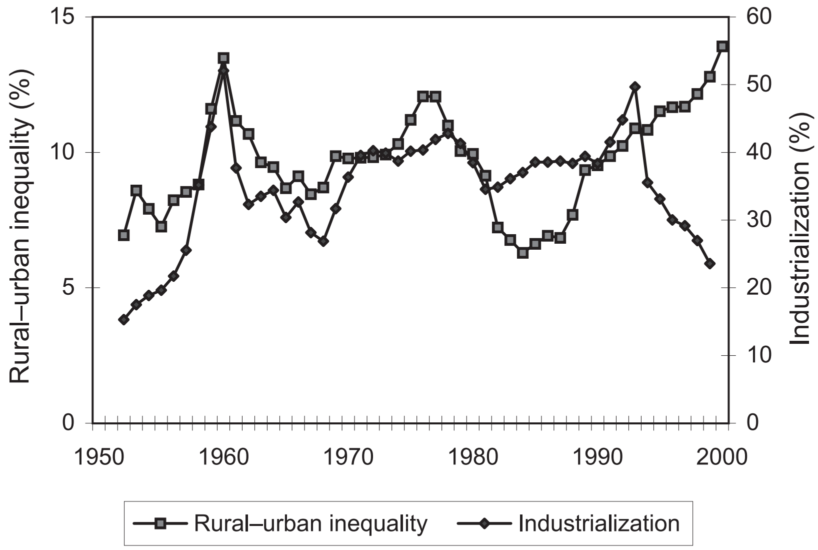

Figure 5.4 Heavy industry development strategy and rural–urban divides, 1952–2000.

cautioned about the possible detrimental effects of decentralization on inequality. This leads to the following hypothesis.

In order to accelerate the pace of industrialization after the initial period of land reform, the state extracted massive resources from agriculture, mainly through the lowering of agricultural prices and restrictions on labour mobility (Lin et al. 1996). Almost all the scarce investment funds were allocated to heavy industry in neglect of light industry and agriculture. As shown in Figure 5.4, the share of heavy industry in gross output value rose from 22 per cent in 1956 to 52 per cent in 1960. Because this policy greatly reduced China's comparative advantage, it could not be implemented without imposing administrative distortions. The main enforcement mechanisms were a trinity of institutions: the household registration system; the unified procurement and sale of agricultural commodities; and the people's communes.

In particular, the government established the ''Hukou'' system of household registration in this period, confining people to the village or city of their birth in order to ensure there was enough agricultural labour to produce sufficient grain for urban workers (Solinger 1993). Although, to some extent, the urban wage was also depressed, employment was guaranteed and urban residents enjoyed many exclusive subsidies, such as free housing and numerous in-kind transfers from the government. Consequently, the large rural–urban divide became a major feature of

China's inequality (Yang 1999; Yang and Cai 2000), and the policies eventually led to the Great Famine. During the Famine, however, most urban residents were protected from starvation, at a cost of about 30 million deaths in the rural areas (Lin and Yang 2000). These developments are reflected in the sharp increases, up to 1960, in the rural–urban inequality (see Table 5.2 and Figure 5.4).

In reaction to the Great Famine, agriculture was once again given priority. The slogan ''Yi liang wei gang, gang ju mu zhang'' (grain must be taken to be the core; once it is grasped everything falls into place) reflects the spirit of this policy. In the years between 1961 and 1964, 20 million state workers and 17 million urban high school students were sent to the countryside for ''re-education'' by participating in agricultural production (Selden 1992). Meanwhile, central planning was loosened a little, boosting agricultural productivity (Fan and Zhang 2002). Not surprisingly, the share of heavy industry fell and the rural–urban divide narrowed. This is reflected in the declining rural–urban inequality during this period, which pulled overall inequality down to its next trough, just before the start of the Cultural Revolution.

With the outbreak of the Cultural Revolution in 1966, pro-Mao leftists came into the ascendancy. The combination of a lack of incentives in the agricultural sector and investment in military and heavy industry during the Cold War atmosphere of the time – as reflected in the rise in the share of heavy industry in Figure 5.4 – led to the rural–urban divide increasing to another peak at the end of the Cultural Revolution, on the eve of the 1979 reforms.

With the end of the Cultural Revolution, the Chinese economy was on the verge of collapse. In response to the agricultural crisis, the government started to give greater incentives to household producers. The ''household responsibility'' system spread from its origins in Anhui province to cover 98 per cent of all villages in China by 1983 (Lin 1992). These and other market-oriented strategies led to a remarkable growth in agricultural output, and the share of heavy industry dropped. The first five years of the post-1979 reforms saw a sharp decline in the rural–urban divide. Overall inequality fell as well (as shown in Figure 5.3).

In general, the heavy industry development strategy in the pre-reform period reduced China's comparative advantage at a time when capital was scarce and labour was abundant. To ensure low food costs for urban workers and to extract funds from the agricultural sector, agricultural product prices had to be lowered as well and the mobility of rural residents was greatly restricted. This leads to the second hypothesis.

The latest phase in China's history begins in the mid-1980s. As is well known, this was a period of accelerating integration into the global economy through greater openness in trade and especially in FDI. As seen in

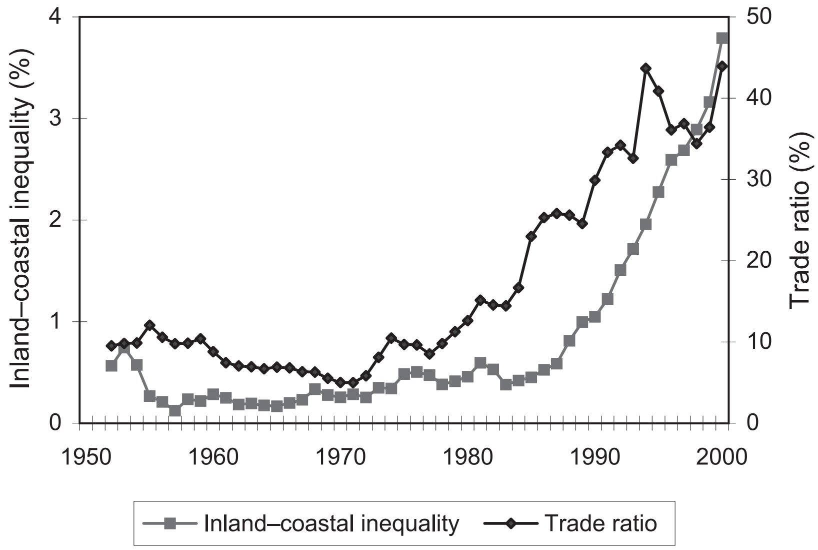

Figure 5.5 Openness and inland–coastal inequality, 1952–2000.

Figure 5.5, the trade ratio, after showing no change for 35 years, began a steady increase in the mid-1980s both because of reductions in nominal tariffs and because of increases in import volumes. Between 1984 and 2000, the value of exports grew 11 per cent per year. Changes in FDI flows were even more impressive. We do not of course have long-run time series for these but, from an almost isolated economy in the late 1970s, China has become the largest recipient of FDI among developing countries. In order to speed up its integration with world markets, China has implemented a coastal-biased policy, including establishing special economic zones in coastal cities and providing favourable tax breaks to coastal provinces. Obviously, the policy is biased against inland regions and may have enlarged the inland–coastal inequality. In other words, the opening process has been intertwined with a regionally biased development policy.

As is by now well appreciated, and as is shown in Figure 5.1, there has been spectacular growth in the past two decades, largely thanks to the reforms and open-door policy. But the gains have not been evenly distributed across regions. Coastal provinces have attracted far more FDI and generated more trade volume than inland provinces during the liberalization process. In 2000, in terms of attracting FDI, three coastal provinces – Guangdong, Jiangsu and Shanghai – were the top three, whereas three inland provinces – Guizhou, Inner Mongolia and Jilin – were the bottom three. The above three coastal provinces alone contributed to more than

60 per cent of total foreign trade in 2000. The difference in the growth rates between coastal and inland regions has been as high as three percentage points during the past two decades (Zhang and Zhang 2003).

We can use Guangdong and Sichuan provinces to illustrate how internal geography affects the response to openness. In 1978, the coastal Guangdong province ranked fourteenth in labour productivity, which was almost the same as the fifteenth rank of inland Sichuan province. In a closed economy, Guangdong did not enjoy any obviously better resource endowments than inland provinces. Since China opened its door to the world, however, Guangdong has become one of the most favoured places for FDI and international trade, largely owing to its proximity to Hong Kong. Meanwhile, labour productivity in Sichuan declined from fifteenth rank in 1978 to twenty-third in 2000. Clearly, the relative comparative advantages of the two provinces have changed significantly and are associated with the opening up to the outside and the decentralization that facilitated this response.

The story of Guangdong and Sichuan is reflected nationwide in the behaviour of the inland–coastal component of inequality. The major change in the behaviour of these components over the whole 50-year period came in the mid-1980s. After relative stability up to this point, inland–coastal inequality began to increase sharply. Although still quite small as a contributor to overall inequality, its contributions to *changes* in inequality increased dramatically. As shown in Figure 5.5, inland–coastal inequality has closely followed the path of the trade ratio.

When an economy opens up to world markets, theory suggests that there could well be effects on regional inequality, as argued by Fujita et al. (1999). External trade liberalization can change internal comparative advantage and hence location patterns. Coupled with decentralization, opening up to world markets provides local governments with an opportunity to exploit comparative advantage more. Trade liberalization could also lead to specialization and industry clustering. Empirical evidence for the impact of globalization on income distribution in developing countries has been limited, and the findings of existing studies are at best mixed. The existing work for developing countries has been limited to the effects of trade liberalization on wage inequality (for example, Wood 1997; Hanson and Harrison 1999), which sheds little light on the effect on regional inequality. Jian et al. (1996) have argued that China's regional inequality is associated with internal geography. China's rapid change from a closed economy to an open one provides a good testing ground for our third hypothesis.

Our narrative of the phases of Chinese development, and of the evolution of inequality and its components, is suggestive of the forces behind the changes in inequality over this half-century.

We now turn to an econometric analysis of the correlates of inequality, to see if these hypotheses can be confirmed statistically.

4. The correlates of regional inequality: An econometric analysis

Our task is to test the association between inequality and its components on the one hand, and heavy industrialization, decentralization and openness, on the other. Following several analyses of Chinese data (e.g. Lin 1992), we use one-period lagged values of the independent variables as regressors to reduce potential endogeneity problems.[4] In the regressions, all the variables are in logarithms. We have compared regressions in levels and log levels, and the latter give a better fit based on R^2 and the RESET misspecification test. In addition, the heteroscedasticity problem is greatly reduced after taking logarithms. A central issue in this long-run time series is structural breaks. It is common in the econometric literature on China (e.g. Lin 1992; Li 2000) to locate the break at the start of the reforms in the late 1970s. As shown in regression R1 in Tables 5.3 and 5.4 on overall inequality and rural–urban inequality, the Chow tests indicate a significant break in 1979. The Chow test p-value is .105 in the regression on inland–coastal inequality (R1 in Table 5.5), indicating a marginally significant structural break.

There are two ways to handle structural break. One way is to estimate the equations separately for the pre-reform period (1952–1978) and the post-reform period (1979–1999). However, in so doing, some degrees of freedom will be lost. Here, we adopt a second way by estimating the equations for the whole period but allowing coefficients to vary across the two periods. Regressions R2 in Tables 5.3–5.5 provide the estimation results under this specification. The Chow test p-values indicate that structural break has been correctly captured in the new specification.

Because the three inequality series are not stationary, it is important to check whether regressing one variable on other policy variables produces stationary residuals, which means there is co-integration among variables. If the residuals are not stationary, the regressions with non-stationary data may give spurious results. Here we adopt two co-integration tests. The first one is the Phillips–Ouliaris test (PO test), which is designed to detect the presence of a unit root in the residuals of regressions among the levels of time series. The null hypothesis is that the residuals have unit roots (there is no co-integration). The critical values for the PO test can be found in the appendix of Phillips and Ouliaris (1990). In addition to the Phillips–Ouliaris test, we also perform the KPSS test (Kwiatkowski, Phillips, Schmidt and Shin 1992) to check the

Table 5.3 Regression results: Total inequality

Variables	R1 Whole period (1952–2000)	R2 Before reform (1952–1978)	After reform (1979–2000)
Decentralization	0.279**	0.011	0.267**
	(0.072)	(0.068)	(0.056)
Trade ratio	0.295**	0.151**	0.455**
	(0.060)	(0.071)	(0.056)
Heavy industry ratio	0.003	0.488**	−0.161
	(0.111)	(0.113)	(0.128)
Chow test p-value	.000		.997
F-test for coefficients (p-value)			.001
Phillips–Ouliaris test	−3.350		**−5.012**
KPSS statistic	**0.116**		**0.054**
Adjusted R^2	.675		.817

Notes: All the variables are in logarithmic forms and independent variables have a one-year lag. Figures in parentheses are robust standard errors. * and ** indicate statistical significance at the 10% and 5% levels, respectively. The null hypothesis of the Chow test is that there is no structural break in 1979. The F-test is for testing whether the coefficients are the same across the two periods. The Phillips–Ouliaris Z_t test is for testing the null hypothesis of no co-integration. Phillips and Ouliaris (1990) report the critical values for regressions with up to only five independent variables. The critical values to reject this null hypothesis with three and five independent variables at the 10% significant level are −3.833 and −4.431, respectively. The KPSS statistic is for testing the null hypothesis of co-integration. If the statistic is larger than 0.347, the null will be rejected at the 10% significance level. The bold figures indicate that the tests are significant at the 10% level.
Source: Authors' calculations.

co-integrated relationship. In contrast to the PO test, the KPSS test is to test the null hypothesis that the regression residuals are stationary (the variables are co-integrated).

Consider Table 5.3 first and start with the results for overall inequality. Regression R2 has better specification than R1 because it does not have structural breaks and passes both co-integration tests. The F-test indicates that the coefficients in the two periods are statistically different. In the pre-reform period, the heavy industry coefficient is significant and has the highest value (0.488), suggesting that the heavy industry development strategy implemented in the central planning era was a dominant force behind overall inequality. Turning to the post-reform period, the coefficients for decentralization and the trade ratio are significantly positive. In particular, the trade ratio has the largest impact on overall inequality in this period. The coefficient for decentralization has changed from in-

Table 5.4 Regression results: Rural–urban inequality

	R1	R2	
Variables	Whole period (1952–2000)	Before reform (1952–1978)	After reform (1979–2000)
Decentralization	0.256**	–0.018	0.369**
	(0.078)	(0.060)	(0.079)
Trade ratio	0.128**	0.208**	0.406**
	(0.036)	(0.087)	(0.067)
Heavy industry ratio	–0.080	0.458**	0.121
	(0.108)	(0.102)	(0.159)
Chow test *p*-value	.000		.993
F-test for coefficients (*p*-value)			.001
Phillips–Ouliaris test	–2.596		**–4.529**
KPSS statistic	**0.153**		**0.036**
Adjusted R^2	.302		.669

Notes: See Table 5.3.
Source: Authors' calculations.

significant to significant, confirming the observation in Figure 5.3 that decentralization has a closer relationship with overall inequality in the reform period. Despite the importance of the heavy industry ratio in the pre-reform period, it faded into insignificance in the reform period as China changed its development strategies.

As in Table 5.3, regression R2 with varying coefficients in Table 5.4 has a better specification than regression R1 with constant coefficients. The *F*-test shows that there exists systematic difference in coefficients across the two periods. The results are similar to those in Table 5.3. In the pre-reform period, a greater favouring of heavy industry increases the rural–urban spread. The impact of openness on the rural–urban divide has almost doubled as China transforms to a more open economy. In the reform period, greater decentralization has widened the rural–urban disparity.

In Table 5.5 the two specifications on inland–coastal inequality produce similar results. The PO test and KPSS test indicate that the first regression, R1, is co-integrated in levels. The coefficients for all three policy variables are significant, with signs consistent with our hypotheses. In particular, the trade ratio has the largest impact on inland–coastal inequality, reflecting the dramatic changes in regional comparative advantage as a result of coastal-biased policy as well as the opening up to world markets. The negative coefficient for the heavy industry ratio tells the same story. In the centrally planned era, most heavy industries were established in the interior regions, thereby reducing the inland–coastal

Table 5.5 Regression results: Inland–coastal inequality

Variables	R1 Whole period (1952–2000)	R2 Before reform (1952–1978)	R2 After reform (1979–2000)
Decentralization	0.564**	0.341*	0.440**
	(0.119)	(0.203)	(0.163)
Trade ratio	1.409**	1.070**	1.412**
	(0.072)	(0.280)	(0.133)
Heavy industry ratio	–0.611**	–0.260	–1.100**
	(0.293)	(0.421)	(0.363)
Chow test *p*-value	.105		.242
F-test for coefficients (*p*-value)			.566
Phillips–Ouliaris test	**–3.908**		–3.895
KPSS statistic	**0.152**		**0.137**
R^2	.828		.825

Notes: See Table 5.3.
Source: Authors' calculations.

disparity. When China started to open up, the coastal regions found a pronounced comparative advantage in labour-intensive exporting sectors (usually light industries) in world markets. The faster growth in the coastal regions has widened the inland–coastal gap. In the second regression, R2, the coefficient for decentralization increased by nearly 30 per cent from the pre-reform period to the post-reform period, indicating that greater decentralization has had a larger detrimental effect on inland–coastal inequality.

Overall, these results represent broad support for the hypotheses advanced earlier on heavy industry, decentralization and openness. Heavy industry increases inequality, especially its rural–urban component, and particularly in the pre-1979 period. Decentralization, when it is significant, increases overall inequality, rural–urban inequality and inland–coastal inequality. The trade ratio is associated with greater overall inequality and, in particular, inland–coastal disparity in the reform period.

5. Conclusions

The tremendous growth in per capita GDP since the reform period, and its impact on poverty in China, has been much discussed and celebrated (Piazza and Liang 1998; Fan et al. 2002). But this has not prevented concern about growing inequality, for at least two reasons. First, as is well known, the poverty-reducing effects of a given growth rate are lower at

higher levels of inequality (e.g. Ravallion 2001). Secondly, rising inequality may itself lead to tensions within a country and impede the prospects for future growth through a variety of social, political and economic mechanisms (Kanbur 2000; Kanbur and Lustig 2000). In the case of China, such concerns have been expressed widely (Wang et al. 2002).

This study has tried to comprehend the driving forces behind the changes in China's regional inequality over half a century. We find that the evolution of inequality matches different political-economic periods in Chinese history. In particular, we find that the heavy industry development strategy played a key role in forming the enormous rural–urban gap in the pre-reform period, whereas openness and decentralization contributed to the rapid increase in inland–coastal disparity in the reform period of the 1980s and the 1990s.

The empirical findings also have relevance to the ongoing debate on how globalization affects regional inequality in developing countries. Convergence or divergence of a nation's economy is dependent not only on its domestic policies but also on its openness. With China joining the World Trade Organization, the economy will become more liberalized and open, which is likely to result in more dramatic shifts in regional comparative advantages. If the government continues to favour the coastal region in its investment strategy, then regional disparities may widen even more. Further liberalizing and investing in the economies of inland regions is thus an important development strategy for the government both to promote economic growth and to reduce regional inequality.

Appendix: Data

GDP

Nominal GDP is from State Statistical Bureau (SSB), *China Statistical Yearbook* (2001: 49). The constant GDP (1980 prices) used in Figure 5.1 is calculated based on the nominal GDP value in 1980 as well as the annual real growth rate of GDP in *China Statistical Yearbook* (2001).

Per capita consumption

Following Kanbur and Zhang (1999) and Yang and Zhou (1999), this study uses rural and urban per capita consumption data at the provincial level, but covering a longer period – 1952–2000. Prior to 1990, the data are from *Regional Historical Statistical Materials Compilation (1949–1989)* (SSB 1990). Alongside nominal per capita consumption, the accumulative growth rates of real per capita consumption for rural and urban residents at a provincial level, with 1952 as a basis, are also published. By assuming the prices were the same across provinces in 1952, we can derive real per capita consumption by province with a rural–urban divide

since 1952. For the period 1990–2000, the annual real growth rates are available from various issues of the *China Statistical Yearbook*. Using the calculated per capita consumption in 1989 and the annual real growth rates since 1989, we can obtain the real capita consumption for this period. However, the published real growth rates are identical to nominal growth rates for the years 1999 and 2000.[5] So, for these two years, we further adjust the real growth rates with rural and urban consumer price indices by province.

There do exist differences between this data set and another data set (per capita living expenditure) in the section on people's livelihoods in various issues of the *China Statistical Yearbook*. Yang and Zhou (1999) discuss the differences between the two sets of measures. The consumption data set may be more consistently compiled over time for three reasons. First, the data set includes information on real growth rates whereas the other data set lacks this information. Second, per capita expenditure data were estimated from survey data, which carry different imputations at different times. Third, the consumption data include consumption in-kind, such as the value of housing and food subsidies from the government to urban households, according to the explanatory notes in the *Yearbook*. As a result, the consumption estimate is significantly higher than the living expenditure estimate.

We should be aware that there exists some non-comparability between rural and urban residents' consumption. For instance, urban residents enjoy some housing and medical care subsidies whereas rural residents do not. In addition, the calculation of the price index may not have reflected the improvement in quality of consumer goods, which is more evident in cities. The relatively higher increase in urban prices may be partly owing to quality improvements. In addition, price support in cities has been gradually phased out over recent decades and the procurement price for major grains in rural areas has long been very low, which may also lead to differences in price levels between rural areas and cities. In spite of these shortcomings in the consumption measure, it is the only summary measure at a provincial level that is readily available, is consistently compiled and covers both rural and urban populations in all the provinces for nearly half a century.

Population

When calculating inequality measures we need to use population by province as weights. There are two sets of population data. One is for the agricultural and non-agricultural population, and the other is for the rural and urban population. In general, these two sets are quite close except for a few provinces, such as Heilongjiang and Xinjiang, where state farming is a large sector. In this chapter, we use rural and urban population data, consistent with per capita consumption data that have a rural and urban divide as well.

The population data prior to 1978 are from *Regional Historical Statistical Materials Compilation (1949–1989)* (SSB 1990). For several provinces without data on the rural and urban population, we use the agricultural and non-agricultural population data instead. The total population data for 1978–2000 are from *Comprehensive Statistical Data and Materials on 50 Years of New China* (SSB 1999), and

the rural population data for the same period are available from *Comprehensive Agricultural Statistical Data and Materials on 50 Years of New China* (SSB 2000). The total population and rural population data for 1999 and 2000 are from *China Statistical Yearbook* (2000, 2001) and *China Rural Statistical Yearbook* (2000, 2001). The difference between the total population and the rural population gives the urban population.

Urban and rural residence refers to the status recorded in the household register system. Principally speaking, rural and urban residents are presumed to specialize in farm work and non-farm work in their respective registration areas. The strict household register system used to a large extent to prevent people from moving freely. However, with the success of rural reform, many workers are freed from agriculture activities and are moving to urban areas, especially to the big cities, to seek opportunities even without the entitlement to subsidies that urban residents enjoy. These floating migrants are not covered in the SSB sample, which includes only registered resident households. Hence, possible biases result from using the official registered numbers of rural and urban population. However, more than 80 per cent of these floating migrants are labourers who work outside during the off-harvest season (SSB, *China Development Report 1998*). These migrants usually send remittances back home (Tsui 1998), to some extent reducing the bias resulting from migration that is not captured by the official population statistics.

Decentralization

We use the share of local government expenditure in total government expenditure as a proxy for fiscal decentralization. In the literature, some other measures are also used as a proxy for decentralization, but they do not cover a long enough period for our time series analysis. For example, Lin et al. (1997) create a fiscal decentralization index based on the revenue-sharing formula, but their index dates back to only 1985. The total, central and local government expenditure data for 1953–2000 are available from SSB, *China Statistical Yearbook* (2001: 258). The data for 1952 are obtained from *Comprehensive Statistical Data and Materials on 50 Years of New China* (SSB 1999: 19).

Openness

There are two ways to measure openness. One is the effective tariff rate, which is defined as the ratio of tariff revenue to total imports. The other commonly used measure is the trade ratio – the share of trade (imports plus exports) in total GDP. The data on imports and exports prior to 1999 are from *Comprehensive Statistical Data and Materials on 50 Years of New China* (SSB 1999: 60). The information on 1999 and 2000 is from *China Statistical Yearbook* (2001: 586). The tariff data are from *China Statistical Yearbook* (2001: 248).

Heavy industry ratio

The heavy industry ratio is defined as the ratio of the gross heavy industrial output value relative to the gross agricultural and industrial output value (GAIOV).

For 1949–1998, the gross agricultural output value, the gross industrial output value and the gross heavy industrial output value are available from *Comprehensive Statistical Data and Materials on 50 Years of New China* (SSB 1999: 30, 38). For 1999, the gross agricultural output value and the gross industrial output value are from SSB, *China Statistical Yearbook* (2000: 374, 409). The gross output value of heavy industry is from the same source (2000: 412). For 2000, the *China Statistical Yearbook* publishes gross output values only for enterprises with revenue of over 5 million Chinese yuan. Therefore the data are incompatible with previous years. Because we take a one-year lag for this variable and other policy variables in the regressions, the omission of data in 2000 does not affect the results.

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Notes

1. Data for Hainan province since 1988 are incorporated into those for Guangdong province, and data for Chongqing province since 1997 are included in those for Sichuan province.
2. Results for $c = 1$ are similar and not reported here.
3. We note here criticisms by Rodrik (2000) of various standard measures of "openness". Since our measure is based partly on trade volume, it does not fully isolate the pure effects of a policy of openness.
4. Given data restrictions, it is impossible to find suitable alternative instruments covering the entire 50-year period under consideration.
5. Thanks to Professor D. Gale Johnson for pointing this out. As a matter of fact, the inflation (deflation) rates in the two years were rather low.

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6

Income inequality in rural China: Regression-based decomposition using household data

Guanghua Wan and Zhangyue Zhou

1. Introduction

Many studies have appeared, in both English and Chinese, focusing on income distribution in rural China.[1] They point to a worsening trend since the late 1970s when China initiated economic reforms. Such a trend has serious implications for China's ability to maintain sustainable growth and, if unabated, will undermine social and political stability. The issue of income distribution ranks as one of the top priorities in the government's policy agenda. Two very important national conferences held in March 2003 – the National People's Congress and the Chinese People's Political Consultative Conference – expressed unprecedented concerns about rural income and income inequality.

Although a consensus has been reached about the increasing trend in income inequality in rural and urban China, this is not the case regarding the causes of such increases. Generally speaking, variables affecting income generation will also determine income inequality. Thus, economic theory and common knowledge can be used to identify these variables. In other words, one could easily compile a list of factors that may explain income gaps, such as different resource endowments and policy biases. However, for the purpose of setting policy priorities, it is necessary to rank the variables in terms of their relative contributions to total inequality. This usually requires inequality decomposition.

Conventional approaches to inequality decomposition typically follow Shorrocks (1980, 1982, 1984) and Bourguignon (1979). Under these

frameworks, one can carry out decomposition either by population subgroups or by factor components. The former produces the so-called "within" and "between" components. It has been used to examine issues such as urban–rural income gaps, male–female wage differentials, and so on (for a recent reference, see Shorrocks and Wan 2004a). For example, Kanbur and Zhang (1999) find that 70–78 per cent of regional income inequality in China is made up of the "between" (urban and rural) component, and the rest is the "within" component. This kind of decomposition is silent on the fundamental determinants of the two components. Also, the decomposition is likely to produce spurious results. For example, decomposition of wage inequality by gender might give rise to a sizeable between-gender component. However, this may have little to do with sex discrimination in the workplace if females are less educated before they enter the labour market, a not uncommon phenomenon in many developing countries. Similarly, a large between-race component may have little to do with skin colour unless other personal attributes such as education, age or occupation can be assumed to be identical. Clearly, one must be able to control for other factors in order to identify and measure the contribution of a particular variable. This is not possible with the conventional approaches.

Decomposition by factor components requires complete information on all income sources. It also requires an identity that expresses total income as a sum of factor incomes. Apart from a data unavailability problem, this approach cannot be used to quantify the contributions of fundamental determinants to income inequality either. For example, it is known that income is determined by education, experience and other personal or household characteristics. These fundamental determinants affect all sources of income, including wages, investment returns and transfer income. It would be interesting and useful to decompose total inequality into components associated with each of the fundamental determinants. However, decomposition by factor components allows one to attribute total inequality only to the income sources, not to the fundamental determinants.

This chapter contributes to the literature on income inequality in rural China in a number of ways. It represents an early attempt to analytically identify the fundamental determinants of income inequality in rural China. The use of regression-based decomposition is novel in that it allows ranking of these determinants according to any inequality measure. Moreover, household-level data are used in this chapter, complementing the existing literature, which is mostly based on aggregate data.

In the next section, we present a brief discussion on income disparity in rural China and on the data source. Section 3 describes the regression-based decomposition technique and the income generation function. This

is followed by interpretation of the decomposition results and policy implications in section 4. Section 5 concludes.

2. Income disparity in rural China and the data source

Income disparity can be examined at different levels of aggregation. At the national level, provinces or regions (in some cases, representative counties) are usually taken as the unit of analysis. This is the basis of most publications on rural income inequality in China.[2] In this context, income gaps are found to be large. For example, in 2002 per capita annual net income in rural Shanghai was 6,224 yuan, whereas that in rural Guizhou was only 1,490 yuan. As shown in Table 6.1, rural incomes are generally higher in the relatively developed east. Most provinces located in central China have per capita rural incomes around the national average. All those with a per capita income below 2,000 yuan are located in the west.

Over the years, the interregional income gaps have risen. In 1985, the highest per capita rural net income was 3.2 times that of the lowest. This ratio increased to 4.3 in 2002 (SSB 2003: 368). When provinces are ranked in terms of per capita income level, the rankings change little from year to year. This is particularly true regarding the top and bottom positions. This suggests that convergence has not taken place in China despite continuous economic growth at the national and regional levels.

Based on data from three provinces with different development levels, Figure 6.1 indicates that the income gaps were relatively small in the mid-1980s but expanded rapidly in the mid-1990s.[3] This expansion implies that factors other than geography must have played a more and more important role. Figure 6.1 also shows that income growth in rural China has slowed significantly since the mid-1990s. Given China's consistent growth performance, the slowdown implies a worsening urban–rural gap. The slower growth, coupled with rising inequality, naturally hinders progress in eradicating poverty.

Not only is there a wide income disparity between provinces, significant income inequality also exists between villages within a province and between households within a village. Table 6.2 reports the frequency distribution of household income for nine villages. The last row of the table reveals that, in Yunnan province, village 1 possesses a level of per capita income that is 12 times that of village 2 in the same province. Within Hubei, 65 per cent of households in village 3 have per capita incomes below 2,000 yuan, whereas this percentage is only 17 in village 2. Income difference is also evident across villages in Guangdong. As explored later, the inter-village income differences account for some 40 per cent of total in-

Table 6.1 Per capita income in rural China, by province, 2002

Province	Per capita income (yuan)
Shanghai	6,224
Beijing	5,398
Zhejiang	4,940
Tianjin	4,279
Jiangsu	3,980
Guangdong	3,912
Fujian	3,539
Shandong	2,948
Liaoning	2,751
Hebei	2,685
Hubei	2,444
Hainan	2,423
Heilongjiang	2,405
Hunan	2,398
Jiangxi	2,306
Jilin	2,301
Henan	2,216
Shanxi	2,150
Anhui	2,118
Sichuan	2,108
Chongqing	2,098
Inner Mongolia	2,086
Guangxi	2,013
Ningxia	1,917
Xinjiang	1,863
Qinghai	1,669
Yunnan	1,609
Shaanxi	1,596
Gansu	1,590
Guizhou	1,490
Tibet	1,462
National average	2,476

Source: SSB (2003: 368).

equality. At the household level, the gap is even larger. In Yunnan, 55 per cent of households in village 2 have a per capita income below 500 yuan, whereas, in Guangdong, nearly 90 per cent of households in village 1 have per capita income over 10,000 yuan. Such large inter-household income gaps imply an alarming level of inequality in rural China.

The high and rapidly rising inequality in China has attracted considerable attention.[4] In what follows, we will use household-level survey data to compute various inequality indices and conduct the inequality decomposition. The data are collected by the Research Centre for Rural Economy (RCRE) of the Ministry of Agriculture of China. The RCRE survey

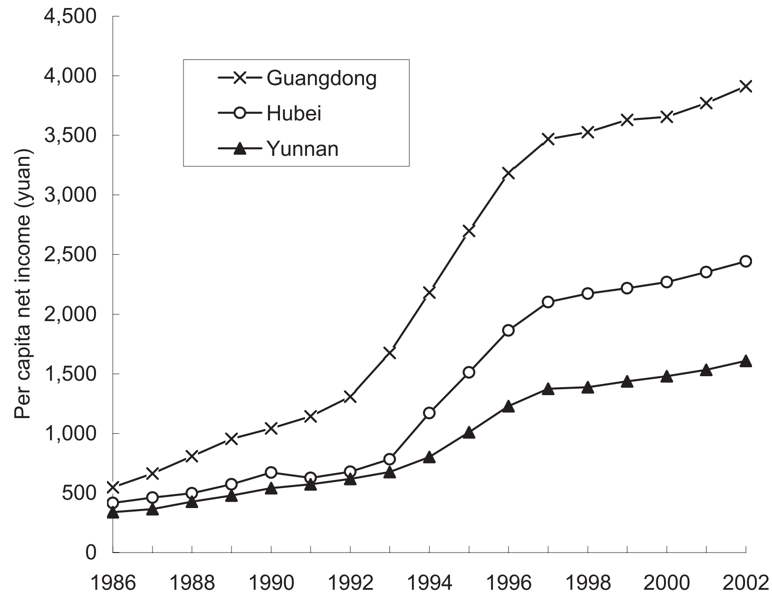

Figure 6.1 Per capita rural income in selected provinces in China, 1986–2002.
Source: State Statistical Bureau, *China Statistical Yearbook* (various issues).

began in 1986, and has since been conducted every year except for 1992 and 1994. All households covered by the survey are asked to keep records of incomes and expenses and of other information. These are collected, checked, processed and reported on by the survey team. The survey instruments have evolved over the years. Those used for 1986–1991 were the same (with 312 variables). They were expanded for the 1993 survey (with 394 variables) and further expanded in 1995 (with 439 variables). Data between 1995 and 2002 are used in this study to ensure the consistency of variables over time.

It is not possible to access the complete data set. For this study, we used data from three provinces – Guangdong, Hubei and Yunnan. Guangdong, located in south-east China, is among the richest provinces. Hubei, a province in central China, is of medium development status. Western China is represented by Yunnan, well known as a poor province. From each province, three villages were chosen, representing differing development status within the county (see Table 6.2). Although not claiming to be representative of China, the data do cover a variety of geo-economic conditions and are more representative than studies relying on data from a single province or single county. Notwithstanding the novelties discussed earlier, this chapter can be viewed as an extension to Morduch

Table 6.2 Frequency distribution of rural household income in selected provinces in China, 2002

Per capita income (yuan)	Hubei			Guangdong			Yunnan			All villages
	Village 1	Village 2	Village 3	Village 1	Village 2	Village 3	Village 1	Village 2	Village 3	
<500	–	–	10	–	1	–	–	55	–	8
500–1000	7	–	20	–	10	9	–	33	12	10
1,000–2,000	20	17	35	–	32	36	1	11	45	22
2,000–3,000	28	47	22	1	27	33	8	1	27	20
3,000–4,000	8	22	2	3	14	16	12	–	9	9
4,000–6,000	23	13	10	1	7	6	34	–	6	11
6,000–8,000	3	–	2	4	4	–	22	–	1	4
8,000–10,000	5	2	–	4	2	–	5	–	–	2
>10,000	5	–	–	87	2	–	17	–	–	14
Number of households	60	60	60	100	97	100	99	100	100	776
Village-level per capita income (yuan)	4,124	2,875	1,880	22,519	2,801	2,255	7,076	578	2,101	5,477

Source: Authors' calculations based on RCRE household-level survey data.

and Sicular (2002), who use survey data on 259 rural households in Zouping county of Shandong province, covering the period 1990–1993.

3. Regression-based decomposition and the income generation function

The regression-based decomposition methodology was proposed in the early 1970s (Blinder 1973; Oaxaca 1973) but had not gained much attention until recently (see Juhn et al. 1993; Bourguignon et al. 2001). Wan (2002) provides a detailed account of the development of this technique. For recent empirical applications, see Fields and Yoo (2000), Adams (2002), Morduch and Sicular (2002), Heltberg (2003), Zhang and Zhang (2003) and Wan (2004).

As the first step of the regression-based decomposition, an income generation function must be obtained. In specifying such a function for rural China, consideration must be given to both human capital theory and production theory. This is because farmers, unlike wage earners, must use land and physical capital in addition to labour in deriving their income. Thus, standard production inputs of land, labour and capital should be included. The human capital theory calls for the inclusion of skill variables such as education, training and experience (often represented by age). As an accepted practice in the development literature, the education level and age of the household head will be used.

It is also necessary to consider factors that could alter income even if production inputs and human capital are the same. One such factor is the type of business activity that a household engages in; the RCRE classifies households into 10 different categories: cropping, forestry, animal husbandry, fishery, industry, construction, transportation, retailing, food and other services, and, finally, no business activity. These indicate the main sector from which a household derives most of its income. Clearly, a set of dummy variables is needed to capture differences in income levels arising from different business activities. These dummy variables, taken together, will be referred to as a sector indicator. On the other hand, it is known that grain-cropping in China is often enforced administratively owing to low or negative returns (Wan 2004). Consequently, two identical households may receive different incomes simply because one grows grain and the other grows vegetables or other cash crops. Thus, the cropping pattern is crucial, and is defined as the ratio of area sown to grain crops in the total sown area.

Finally, consider two rural households with the same amount of resources but one has wage earners and the other does not. Wage earners are those working for the government or for industries not run by the

household. The number of wage earners reflects the level of urbanization, thus inclusion of this variable in the model enables one to make inferences about the impact of urbanization on income inequality in rural China. Ideally, urbanization should be defined at the town or county level. However, this is not possible given that only household-level data are available.

Geography is important in income determination because it is closely related to non-removable resources as well as to market access, infrastructure and local culture. Lack of data prevents direct inclusion of geographical variables. However, given the control for physical and human capital inputs and other factors, village dummies can be used to capture the effects of geography or location. It is noted that inclusion of these village dummies does not necessarily entail a fixed-effects model because household-level observations are to be used to estimate the income generation function. Finally, year dummies are included in the estimation to take into account the impact of technical changes and reform. The variables included in the income function are given below.[5]

Dependent variable:

Income: per capita annual net income

Independent variables (dummy variables not listed):

Capital: per capita capital stock

Land: per capita arable land area

Labour: number of labourers divided by household size

Wage earner: proportion of wage earners in household labour force

Education: number of schooling years of household head

Education squared

Training: proportion of household members who received vocational training

Age: age of household head

Age squared

Grain: ratio of grain sown area to total sown area

The choice of the parametric functional form is dictated by the standard Mincer model, augmented with production inputs and other variables. In other words, the income generation function takes the form of:

$$\text{Ln(Income)} = f(\text{Land, Labour, Capital}, \ldots, \text{dummy variables}),$$

where f stands for the standard linear function. The use of the semi-log specification is also prompted by the finding that the income variable can be approximated well by a lognormal distribution (Shorrocks and Wan 2004b). The panel data model can be estimated by various techniques. However, the iterative generalized least squares method outlined in Kmenta (1986) is found to work well with Chinese data (Wan and Cheng

Table 6.3 Estimated income generation function (dummy variables not included)

Variable	Coefficient estimate	*T*-ratio	Level of significance
Capital	0.0958	15.59	.000
Land	0.0192	2.59	.009
Labour	0.5999	17.18	.000
Wage earner	0.0224	3.43	.001
Education	0.1365	3.72	.000
Education squared	−0.0107	−1.51	.130
Training	0.1318	2.74	.006
Age	0.1450	4.88	.000
Age squared	−0.0255	−5.33	.000
Grain	−0.3164	−11.72	.000
Constant	7.0841	84.61	.000

Note: Log likelihood value = −4648.32. Sample size = 6,121.
Source: Authors' calculations.

2001). This method allows for both heteroscedasticity across households and autocorrelation over time. The model estimation results are tabulated in Table 6.3.

Leaving the dummy variables aside, all coefficient estimates are of the expected signs and most of them are statistically significant at the 1 per cent or 5 per cent level of significance. In particular, the negative estimates for the quadratic age and quadratic education variables are consistent with standard human capital theory. As expected, the cropping pattern variable, denoted by "Grain" in Table 6.3, has a negative and significant coefficient estimate.

For a given income generation function, alternative approaches can be used to decompose total income inequality (Wan 2002). Note, however, that the semi-log specification implies a non-linear income generation function in terms of the original income variable. Thus, the Shapley value framework of Shorrocks (1999) must be adopted in a regression-based decomposition context. The constant term becomes a scalar once the estimated semi-log function is solved for the original income. It can be ignored in inequality measurement or decomposition as long as relative inequality measures are used. The same can be said of the yearly dummy variables, which differentiate income generation functions for different years only by differences in the constant term.

The Shapley value decomposition involves rather extensive computing. Suppose $Y = f(X_1, \ldots, X_K)$ is a general income generation function. Usually Xs are different for different individuals. Replacing X_k by its sample mean would eliminate any differences in X_k among individuals.

It is easy to re-compute Y after this replacement. The resulting income, denoted by Y_k, differs from individual to individual because Xs other than X_k differ for different individuals. However, the differences cannot be attributed to X_k any more. In other words, inequality in Y_k, denoted by $I(Y_k)$, is due to differences in Xs excluding X_k. According to the most natural rule of Shorrocks (1999), the contribution of X_k to total inequality, C_k, can be obtained as $I(Y) - I(Y_k)$ for $k = 1, \ldots, K$. Shorrocks (1999) terms these contributions the first-round effect, which is obtained when only one independent variable, X_k, is replaced by its sample mean. One can obtain a second-round C_k by replacing two variables X_k and X_j with their sample means in computing Y_{kj}. The second-round contribution can be written as $C_k = I(Y_j) - I(Y_{jk})$ for $k, j = 1, \ldots, K$ $(k \neq j)$. By the same token, the third-round contribution can be obtained as $C_k = I(Y_{ij}) - I(Y_{ijk})$ for $k, j, i = 1, \ldots, K$ $(k \neq j \neq i)$. This process continues until all Xs are replaced by their sample means. At each round, it is possible to have multiple C_k, which are averaged first and then averaged across all rounds – see Shorrocks (1999) for details.

What about the residual term? Admittedly, one may not be able to analyse the residual contribution. However, it can show how much the estimated model explains total inequality. If the model explains only 30–40 per cent of total inequality, leaving the rest to the residual term, policy makers may well be advised not to rely on the decomposition results. In this study, the residual term is dealt with according to the procedure proposed in Wan (2002, 2004). With the semi-log income generation function, the contribution of the residual term can easily be computed as the difference between total inequality and the sum of contributions of all explanatory variables.

4. Decomposition results and discussions

Table 6.4 tabulates total inequality by various measures. It is clear that the squared coefficient of variation (CV^2) indicates a small dip in 1999 and a substantial reduction in 2001. Other measures indicate two slight dips in 1998 and 2001. Nevertheless, they all point to a trend of increasing inequality. Since these inequality values are obtained using household-level data, they must be larger than those based on aggregate data. Use of provincial or county-level data permits measurement only of the between-province or between-county component, whereas the results presented in Table 6.4 contain all ''within'' components (within province, within county and within village).

Table 6.5 presents the decomposition results for selected years, where inequality is measured by two different indicators.[6] Both absolute and

Table 6.4 Total income inequality, 1995–2002

	Gini	Atkinson	Theil-L	Theil-T	CV^2
1995	0.467	0.322	0.388	0.403	1.282
1996	0.505	0.370	0.462	0.482	1.667
1997	0.509	0.371	0.464	0.548	3.006
1998	0.500	0.358	0.443	0.541	3.259
1999	0.520	0.399	0.509	0.567	3.122
2000	0.553	0.433	0.567	0.684	4.547
2001	0.537	0.419	0.543	0.592	2.664
2002	0.638	0.539	0.774	0.907	5.761

Source: Authors' calculations.

percentage contributions are shown in the table. Not unexpectedly, different measures give rise to different decomposition results. This is because different measures are underlined by different social welfare functions and are sensitive to different segments of the Lorenz curve. Nevertheless, some broadly consistent findings can be drawn from Table 6.5. In reality, one has to choose a particular inequality measure when inconsistent results are obtained. Owing to the popularity of the Gini coefficient, the Gini values will be used for discussions hereafter.

Referring to Table 6.5, geography as represented by village dummies contributes a fairly constant amount to total inequality. This finding reflects the fact that the spatial distribution of geographical factors cannot be easily altered in the short or medium run. Since total inequality has been increasing over time, the percentage contribution of geography displays a decreasing trend. Despite this, geography still explains almost 40 per cent of total inequality in 2002, 15 per cent lower than in 1995. Apart from its role in determining market access, geography is closely associated with natural resource endowments such as water and weather conditions. Natural resources are particularly crucial for farm production activities and they are neither tradable nor removable. Infrastructure provision may improve market access for the poor areas, but it could also benefit the rich regions. Thus, the overall impact of infrastructure development on total inequality could be small. Needless to say, geography will continue to play an important role in rural income inequality. This finding can be used to justify regional development policies such as the western development campaign. In passing, it is noted that redistributive policies implemented in the past did not produce equalizing effects because the role of transfer income is found to increase inequality (Wan et al. 2003).

In contrast to the declining share of geography, capital input contributes more and more to total inequality. Its contribution was negligible in

Table 6.5 Decomposition results, selected years

	Gini	%	Thiel-L	%
1996				
Capital	0.0113	2.23	0.0085	1.84
Land	−0.0018	−0.36	−0.0053	−1.15
Labour	0.0259	5.13	0.0086	1.87
Wage earner	0.0102	2.02	0.0076	1.64
Education	0.0170	3.36	0.0110	2.37
Training	0.0039	0.77	0.0022	0.48
Age	0.0051	1.01	0.0017	0.38
Grain	0.0407	8.06	0.0287	6.22
Sector dummies	0.0384	7.61	0.0227	4.91
Village dummies	0.2545	50.43	0.2105	45.55
All *X*s	0.4052	80.27	0.2963	64.11
Total	*0.5048*	*100.00*	*0.4621*	*100.00*
1998				
Capital	0.0182	3.64	0.0150	3.39
Land	−0.0021	−0.42	−0.0055	−1.25
Labour	0.0233	4.66	0.0059	1.34
Wage earner	0.0107	2.15	0.0082	1.85
Education	0.0173	3.45	0.0116	2.61
Training	0.0036	0.71	0.0021	0.48
Age	0.0051	1.03	0.0019	0.42
Grain	0.0452	9.03	0.0336	7.59
Sector dummies	0.0348	6.96	0.0216	4.88
Village dummies	0.2600	51.98	0.2161	48.82
All *X*s	0.4162	83.19	0.3104	70.13
Total	*0.5003*	*100.00*	*0.4427*	*100.00*
2000				
Capital	0.0885	16.00	0.1112	19.61
Land	−0.0022	−0.41	−0.0060	−1.06
Labour	0.0271	4.91	0.0105	1.84
Wage earner	0.0106	1.92	0.0089	1.56
Education	0.0154	2.78	0.0096	1.69
Training	0.0024	0.43	0.0013	0.22
Age	0.0045	0.82	0.0012	0.21
Grain	0.0486	8.79	0.0419	7.39
Sector dummies	0.0451	8.15	0.0402	7.08
Village dummies	0.2591	46.85	0.2366	41.71
All *X*s	0.4990	90.23	0.4552	80.26
Total	*0.5531*	*100.00*	*0.5672*	*100.00*
2002				
Capital	0.1517	23.76	0.2106	27.20
Land	−0.0026	−0.40	−0.0066	−0.85
Labour	0.0239	3.75	0.0086	1.11
Wage earner	0.0100	1.56	0.0085	1.10
Education	0.0132	2.07	0.0071	0.92

Table 6.5 (cont.)

	Gini	%	Thiel-L	%
Training	0.0057	0.90	0.0084	1.08
Age	0.0045	0.70	0.0010	0.13
Grain	0.0494	7.73	0.0476	6.14
Sector dummies	0.0551	8.63	0.0589	7.60
Village dummies	0.2544	39.84	0.2547	32.89
All *X*s	0.5653	88.54	0.5988	77.32
Total	*0.6384*	*100.00*	*0.7744*	*100.00*

Source: Authors' calculations.

the 1990s, typically around 2–4 per cent. It increased to 16–24 per cent in the new millennium.[7] In fact, the increase in total inequality in recent years can be largely accounted for by the increased contribution of the capital variable. This is in line with the modernization of the rural economy in China. As the rural sector becomes more capital intensive and as capital becomes more unevenly distributed, its increasing share in total inequality is inevitable. Based on this finding, it is suggested that the government should give prime attention to credit services in rural areas, paying especial attention to the poor. The provision of such services is important in terms of both income growth and inequality reduction. Interestingly, taking urban and rural China as a whole, capital input is also found to play a dominant and increasing role in determining total inequality (Zhang and Zhang 2003).

Cropping pattern, represented by the variable ''Grain'', is found to be a positive and important contributor to income inequality. Throughout the 1990s and up to 2002, this factor contributed almost 10 per cent to total inequality. The percentage is larger than the contributions of labour input, human capital input or urbanization (as denoted by the variable ''Wage earner'' in Tables 6.3 and 6.5). This finding implies that a pro-grain policy would help narrow income gaps. Policy initiatives to assist grain producers are likely to reverse the sign of this variable in the income generation function. As a result, grain may become an equalizing factor rather than an inequality-increasing factor. The reversal of the sign could mean a significant reduction in the overall inequality. For example, if the sign of the contribution is reversed while the magnitude is maintained, the Gini value would fall by 0.1, which is rather substantial.

The next noticeable contributor is labour input. Its contribution is positive because per capita labour input implicitly captures the effects of the dependency variable. It is not difficult to infer that poor households have

a higher dependency ratio (or lower per capita labour input) and thus a lower income level. Inequality induced by this variable is likely to be transitory since an examination of rural population data indicates a trend towards convergence in household size and the dependency ratio. Thus, the positive contribution of labour input is expected to decline in the future.

Land is the only equalizing factor in inequality. This is understandable because land is known to be more abundant in less developed areas, and those who are poorer are largely associated with farming. Unfortunately, the equalizing impact is negligible. To enhance this impact, policy initiatives are needed to increase returns to land and encourage land transfer to poor farmers. For a long time, economists have been arguing for the formation of a market in land in China, which could promote land transfers. The very fact that land is collective owned and cannot be traded constitutes a major obstacle to the establishment of a proper land market in China. Many households are reluctant to give up land because it acts as security in the event of economic or political crisis. Therefore, in the near future, increasing returns to land would be more effective than enhancing land transfers as far as reducing inequality is concerned.

Substantial income gaps exist between households engaged in different business activities. The sector dummies are associated with a considerable share of total income inequality, signalling barriers to entry and constraints on resource movement between sectors of the rural economy. These may include institutional barriers (e.g. lack of a transparent legal framework for granting business licences) and economic barriers (e.g. accumulation of funds needed to set up companies). Adding education, age and training together, human capital contributes about 4–5 per cent to total inequality. This small contribution implies either that human capital has a small effect on income generation or that the distribution of human capital across rural households in China is less uneven than expected. Nevertheless, the contribution is positive and human capital will play an increasingly prominent role in rural economic growth as technology advances. On the other hand, economic reforms have eroded the state-funded education system and education gaps are widening between the rich and the poor at all levels in China. Therefore, the Chinese government must act quickly to address the problem of access to education. Otherwise, this could become one of the major driving forces of income inequality in the not-too-distant future.

Referring to the second last row of each panel in Table 6.5, it is clear that our empirical model explains over 80 per cent of total inequality as measured by the Gini index. The figure is smaller, but still over 60 per cent, for other inequality indicators.

5. Conclusion

To analyse income inequality in rural China, this chapter has combined the Shapley value framework developed by Shorrocks (1999) and the regression-based decomposition technique. Our use of household-level data is complementary to most existing studies and the availability of time series data has allowed us to examine changes in total income inequality and its components over time. We found that geography is the most significant contributor and will remain so in the future. Capital input has become a very important factor in income inequality in rural China. The only equalizing variable is land input, but its impact is minimal. The cropping pattern is more crucial than inputs of labour and human capital in constituting total income inequality. We have suggested that China should endeavour to improve rural credit services and raise the returns to grain-cropping in order to reduce inequality. The impact of education on inequality is small but is expected to grow. The current labour force enjoyed fairly equal educational access prior to the reforms. As gaps in education have expanded and as the rural economy demands more skills, the contribution of education to income growth and inequality is expected to rise.

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Notes

1. See Wan (2001) and references therein.
2. For a comprehensive discussion on inequality in China (not just rural China), see Kanbur and Zhang (2005).
3. Guangdong represents an economically developed region, Hubei a medium developed region, and Yunnan an economically less developed region.
4. See, for example, Griffin and Zhao (1993), Rozelle (1996), Hu et al. (1997), Yao (1997), Ravallion and Chen (1999) and Wu (2000: 261–281). Apart from Kanbur and Zhang (1999, 2005), most of the published works provide only a snapshot, without a time profile. Many of them use proxy variables such as agricultural output (Howes and Hussain 1994), regional national income (Tsui 1991), collective income (Griffin and Saith 1982) or even grain output (Lyons 1991), rather than personal income. These proxies may not adequately represent living standards in China (Wei et al. 1997). These deficiencies are recognized by Tsui (1991), Knight and Song (1993) and Chen and Fleisher (1996). Chen and

Fleisher (1996) explicitly appeal for the use of per capita income data to address the inequality issue in China.

5. Morduch and Sicular (2002) also consider political variables in their model, represented by membership of the Communist Party and the presence of government officials in households. However, they find that these variables contribute little to income generation or inequality. Surprisingly, Morduch and Sicular (2002) do not include the capital variable, which is a very important contributor to income generation and inequality in China (Zhang and Zhang 2003).
6. CV_2 is known to be inferior to other inequality measures because it violates the transfer axiom. Further, results under Theil-T and CV^2 are similar. The Atkinson index is a monotonic transformation of the Theil-L. Thus, we prefer to use the Gini and the Theil-L.
7. The jump in the contribution of the capital variable in 2000 might be partly caused by the launch of capital-intensive projects in some villages. Although the magnitude of the jump is unexpected, this problem generated by the data does not seem to affect our major findings.

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7

Divergent means and convergent inequality of incomes among the provinces and cities of urban China

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1. Introduction

In the mid-1980s, economic reform began in earnest in urban China. This involved the gradual dismantling of central planning, the decentralization of decision-taking to enterprises and the emergence of markets. Reform of the labour market was tardy but both the decentralization and the introduction of market forces were likely to affect wages and, more generally, incomes. The changes occurred at different rates across provinces and cities. A spatial analysis of urban wages and income per capita may therefore reveal interesting patterns. Indeed, we show that this is the case, using two national household surveys with data available at the microeconomic level. Between the survey years 1988 and 1995, province mean wages and incomes per capita grew rapidly but diverged across provinces. Yet, over the same period, intra-province wage and income inequality grew rapidly but converged across provinces. We will analyse the extent of, and reasons for, the convergence of inequality. We will also examine the divergence of means and its causes. Our approach to understanding these processes is by means of various forms of decomposition analysis.

The first of our questions – what happens to the spatial inequality of income inequality? – has been posed rarely if at all; but the second – what happens to the spatial inequality of mean incomes? – is now common. There is a lively and growing literature on economic convergence

across countries (for instance, Barro and Sala-i-Martin 1995: Chapter 12). The same authors (1995: Chapter 11) also reported a number of regional studies of convergence. They used measures of β-convergence (the relation between changes in the logarithm of income per capita and its initial value) and of σ-convergence (changes in the standard deviation of the logarithm of income per capita). They found evidence of β-convergence among US states, Japanese prefectures and European regions, both absolute and conditional convergence (standardizing for other variables). They also generally found σ-convergence. A likely explanation for these results, along with technological diffusion, is that equilibrating flows of labour and capital tend to equalize incomes. Convergence should accordingly be weaker when the equation is standardized for net migration. However, the authors found, if anything, the opposite result, which they attributed to the endogeneity of migration. As with cross-country convergence, cross-region convergence of mean incomes is a common phenomenon that is not yet well understood.

Research on spatial income inequality in China has generally been conducted at the province level. A good deal of such research is now being done on China, but the results so far do not add up to a clear pattern – varying as they do according to time period, unit of analysis, data set, dependent variable and conditioning variables. One of the obvious complications is that some areas that had a distinct locational and policy advantage, such as Guangdong and Fujian, and therefore have grown very rapidly, started off poor but in recent years have been rich. For instance, Jian et al. (1996) examined inequality among provinces over the period 1978–1993, using data on provincial mean income per capita, based on the official national household survey. Their equations implied convergence during the period up to 1985, but the evidence for the period after 1985 was weak. In neither case was there evidence of conditional convergence or divergence; i.e. the effect of initial income on its growth became insignificant when other explanatory variables were introduced into the equation.

Another reason for the inconsistency of results is that there may be divergence at one level of aggregation and convergence at another. Kanbur and Zhang (1999), using province-level data on household consumption per capita, found that there was a sharp rise in the contribution of the coast–inland difference to overall inequality over the period 1983–1995, and a fall in the contribution of intra-coastal and intra-inland inequality. They attributed their contrasting results to the relative lack of long-distance mobility. Similar findings of province convergence within diverging regional "clubs" (east, central and west China) were obtained by Zhang et al. (2001) and Yao and Zhang (2001), both using province gross

domestic product (GDP) per capita data over the reform period 1978–1997.

The reasons for the recent absolute divergence among provinces have been the subject of debate, the main distinction being between geography and policy. Cai et al. (2002) found evidence of conditional convergence in province GDP per capita over the period 1978–1998. However, some of their conditioning variables, such as the degree of marketization, were potentially influenced by initial GDP per capita. Bao et al. (2002) similarly found that the coefficient on initial GDP per capita was always negative in their test for conditional convergence among provinces over the period 1978–1997. Because their conditioning variables were locational – e.g. length of coastline, distance to coast – they argued that the absolute divergence among provinces was owing to the locational disadvantage rather than the poverty of some provinces. Nevertheless, locational effects may have been strengthened by endogenous government policies. At one extreme, the Special Economic Zones were established along the coast in the 1980s; at the other, many cities in the interior were opened up to the world only in 1994 (Yang 2002).

Much of the literature does not distinguish between urban and rural areas, yet the administrative and economic divide between urban and rural China makes it important to analyse the two sectors separately. There are several studies of trends in inequality within rural China but few studies for urban China. However, Jones et al. (2003), using city-level data for the largest 200 cities, found great differences in growth rates of GDP per capita over the period 1989–1999. There was conditional convergence among cities after standardization for such factors as Special Economic Zone status and foreign direct investment; the authors thus attributed the absolute divergence largely to differential policies of openness. Another study of urban China, by Xu and Zou (2000), used published percentile income distribution data from the official urban household surveys over the years 1985–1995 to create estimates of urban income inequality within provinces. They found this inequality to rise with the non-state share of employment and with the growth rate of GDP, both measured at the province level.

Because household-level data from the official national household surveys are not available to researchers, we make use of two other national household surveys, for 1988 and 1995, in order to analyse the change in inequality within as well as between provinces. The two surveys were designed by a team comprising researchers at the Institute of Economics, Chinese Academy of Social Sciences, and foreign scholars, and including ourselves. The surveys were conducted by the National Bureau of Statistics, drawing subsamples from the samples used in the annual national

household surveys. The rural and urban samples were drawn separately, reflecting their administrative and economic differences. In 1988, there were 9,009 households in the urban survey and 10,258 households in the rural survey; in 1995 the corresponding figures were 6,931 and 7,998. Not all provinces could be surveyed; there were 10 common provinces in the urban surveys and 19 in the rural surveys. The questionnaires were designed not only to describe income distribution in China but also to explain it. The main results from the two projects were published in Griffin and Zhao (1993) and Riskin et al. (2001). Some of the results of this chapter are drawn from our earlier work (Knight et al. 2001).

2. Convergence in inequality

Why study income inequality at the province rather than the national level? Inequality is a matter of policy concern because it is perceived to create injustice, in an objective sense, but also, in a subjective sense, to generate the dissatisfaction and unhappiness associated with feelings of relative deprivation. People are more aware of the inequality they observe than of the inequality they cannot observe; hence the likelihood that people are more sensitive to income inequality within their province than across the nation. This is particularly true of China, whose provinces are as large as countries in other parts of the world and whose provincial governments have powers to redress inequality. This reasoning provides a case for enquiring whether inequality has risen over time in the various provinces.

Why study the inequality of intra-province inequality? Is it helpful to know whether intra-province inequality has converged or diverged among provinces? Our objective here is instrumental rather than ultimate. Patterns of convergence or divergence can be used to understand the reasons for the rise in intra-province inequality, and whether it will continue to rise in the future. Our ultimate concern is with household income per capita and not earnings per worker. However, in 1988 wage income represented 80 per cent of urban household income, and even in 1995, after a decade of urban economic reform, it was as high as 77 per cent. In order to understand the inequality of income, therefore, it is necessary to investigate the inequality of labour earnings.

This section is divided into three parts. First, we test for divergence or convergence in intra-province inequality across provinces over the period 1988–1995. Second, we examine the same relationship among cities. Third, we attempt to explain the convergence that we observe. Our method is to attempt various decompositions of the growth in inequality that occurred generally, but to varying degrees, over the seven years.

Table 7.1 The level and change in the Gini coefficients of earnings per worker and income per capita in urban China, by province, 1988–1995

	Earnings				Income			
Province	1988	1995	Change in Gini coefficient	% change	1988	1995	Change in Gini coefficient	% change
Beijing	20.4	26.1	5.7	27.9	17.0	21.5	4.5	26.5
Shanxi	24.9	29.7	4.8	19.3	23.0	26.6	3.6	15.7
Liaoning	17.4	28.8	11.4	65.5	15.7	23.4	7.7	49.1
Jiangsu	18.3	28.8	10.5	57.4	17.4	23.2	5.8	33.3
Anhui	24.3	27.8	3.5	14.4	21.5	22.1	0.6	2.8
Henan	22.4	30.1	7.7	34.4	21.6	28.4	6.8	31.5
Hubei	18.5	27.7	9.2	49.7	18.1	22.5	4.4	24.3
Guangdong	27.7	33.1	5.4	19.5	24.9	28.6	3.7	14.9
Yunnan	19.7	23.1	3.4	17.3	19.8	21.5	1.7	8.6
Gansu	27.6	27.1	−0.5	−1.8	26.8	22.5	−4.3	−16.0
Coastal	23.8	32.9	9.1	38.2	21.3	27.7	6.4	30.1
Interior	23.3	28.1	4.8	20.6	22.0	24.3	2.3	10.5
Total	24.1	31.9	7.8	32.4	23.2	28.3	5.1	22.0
SD	3.84	2.64	−1.20	−31.3	3.63	2.77	0.86	−23.7

Note: The coastal region comprises Beijing, Liaoning, Jiangsu and Guangdong; the interior region comprises Shanxi, Anhui, Henan, Hubei, Yunnan and Gansu.
Source: The data for this table, and for all subsequent tables except Table 7.9, are drawn exclusively from the urban samples of the 1988 and 1995 national household surveys of the Institute of Economics, Chinese Academy of Social Sciences (CASS).

2.1. *Convergence in intra-province inequality among provinces*

Table 7.1 shows the Gini coefficient of earnings per worker and household income per capita in 1988 and 1995, and the change in the Gini coefficient, both the percentage change and the change in percentage points. In all provinces except Gansu there was a rise in inequality over the seven years. The increase in the Gini coefficient for the group of 10 provinces common to the urban samples was by 7.8 percentage points in the case of earnings and 5.1 percentage points in the case of income. In each case the increase was greater for the four coastal provinces than for the six inland provinces (9.1 versus 4.8 percentage points for earnings, and 6.4 versus 2.3 percentage points for income). There was a good deal of variation among the provinces.

In order to discern patterns we estimated the following relationship:

$$G_1 - G_0 = a + bG_0, \tag{7.1}$$

Table 7.2 The inter-province relationship between the initial Gini coefficients of earnings and income and their growth, urban China, 1988–1995

	Change in Gini coefficient (percentage points)			
	Earnings		Income	
Equation	1	2	3	4
Intercept	21.993***	19.190***	17.147	13.426*
Initial Gini coefficient	−0.715**	−0.669**	−0.666**	−0.582*
Proportionate growth in earnings/income		0.041		0.040
Adj. R^2	.512	.542	.422	.410
F-value	10.449**	6.332**	7.556**	4.123*
Mean value of dependent variable	6.110	6.110	3.450	3.450
Number of observations	10	10	10	10

*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
Source: See Table 7.1.

where G = the Gini coefficient and the subscripts 0, 1 = year 1988 and 1995, respectively. The coefficient b is a test of convergence ($b < 0$) or divergence ($b > 0$). The coefficient indicates whether the initial level of inequality hinders or assists its growth.

Table 7.2 tests across provinces for convergence or divergence in the intra-province Gini coefficient (columns 1 and 3). We see that the coefficient on initial inequality is significantly negative. For both earnings per worker and income per capita, a reduction in the initial Gini coefficient by 10 percentage points raises its subsequent growth over seven years by 7 percentage points. When the proportionate growth in earnings or income is added as an explanatory variable, its coefficient is positive but small and not statistically significant (columns 2 and 4). When initial mean earnings or income are included, the coefficient is positive but not at all significant (equations not shown).

2.2. Convergence in intra-city inequality among cities

Because there are only 10 provinces in the urban sample, our results might be owing to the particular or idiosyncratic behaviour of one or two provinces. The same analysis cannot be conducted on all 30 provinces because official intra-province inequality measures are not available. However, information is available to estimate equation (7.1) for the 60 cities common to our two surveys.

Table 7.3 The growth of the Gini coefficients of income per capita and earnings per worker as a function of their initial values, by city, urban China, 1988–1995

	Change in Gini coefficient	
	Income	Earnings
Intercept	0.197***	0.202***
Initial value (G_0)	−0.922***	−0.793***
Adj. R^2	.589	.489
F-value	84.158***	56.443***
Mean of dependent variable ($G_1 - G_0$)	0.015	0.031
Number of observations	60	60

*** indicates statistical significance at the 1% level.
Source: See Table 7.1.

Table 7.3 shows powerful and statistically significant evidence of convergence in inequality among cities. The coefficient b on G_0 is no less than -0.92 in the case of income and -0.79 in the case of earnings, i.e. a 10 per cent lower initial value of the Gini coefficient raises its increment by 8 percentage points or more. A pattern is therefore established: the convergence of inequality is a general phenomenon, applying not only among provinces but also, even more powerfully, among cities.

2.3. Explaining convergence

In all but one province, urban inequality rose between 1988 and 1995, but it rose more rapidly in those provinces that started with low inequality in 1988. The provinces were becoming more similar in their degree of urban inequality. How is this trend to be explained? One possibility is that the observed convergence is merely a statistical illusion: the regression of the change in a variable on its initial value is subject to errors-in-variables bias. Assume that measurement errors in the initial year and the final year are uncorrelated. If the initial value is underreported, the change is equivalently overreported. This reduces the estimated coefficient on the initial value, biasing it towards -1 and thus towards convergence. The extent of the bias increases with the proportion of the variance in the initial value that is attributable to measurement error. A common method of attempting to correct for such bias – instrumenting the initial value by means of the value of a contiguous year – is not open to us. Nor do we possess good proxies for the initial value (such as a coastal dummy) that are not correlated with the error term of the dependent variable. However, there are two pieces of evidence against the bias explanation.

First, we conducted a simple experiment to answer the question: what proportion of the variation in the initial value would have to be the

result of measurement error for convergence to disappear? Accordingly, we set each initial province value 20 per cent, and then 50 per cent, closer to the initial mean value. The coefficient on the initial Gini remained significantly negative in the former case, and had a negative value exceeding -0.3, albeit not significant, in the latter. Secondly, β-convergence is a necessary but not a sufficient condition for σ-convergence (Barro and Sala-i-Martin 1995: 385). The former tends to generate the latter, although this process can be offset by new disturbances that increase dispersion. We find that, between 1988 and 1995, σ-convergence occurred in every case: the standard deviation of the Gini coefficient fell sharply among provinces (Table 7.1) and also among cities; and the coefficient of variation even more. This is a further indication that the β-convergence observed is not an illusion.

Our second approach is to conduct a decomposition analysis of the Gini coefficient in each province in 1988 and 1995 by component of income, and then to decompose the rise in the Gini coefficient between 1988 and 1995 into the contributions made by the different components. We make use of the following property:

$$G = \Sigma \pi_i = \Sigma u_i C_i, \tag{7.2}$$

where
$G =$ the Gini coefficient of income inequality
$u_i =$ the ratio of the ith component of income to total income, i.e. its share of the total
$C_i =$ the concentration ratio of the ith component of income
$\pi_i =$ the contribution of the ith component to the Gini coefficient.
The concentration curve $C_i(x)$ represents the share of component i received by the lowest x proportion of recipients of *total* income. The concentration ratio C_i is then derived from the concentration curve in exactly the same way as the Gini coefficient is derived from the Lorenz curve. The contribution made by each component of income to the Gini coefficient is given by $B_i = u_i - C_i$.

We decompose the rise in the Gini coefficient of income per capita in each province between 1988 and 1995 (Table 7.4). The contribution of each component is given by $\pi_{i1} - \pi_{i0}$, and the proportion due to each component by $(\pi_{i1} - \pi_{i0})/(G_1 - G_0)$. There is a sharp coastal–interior contrast in the contribution of different income components to the change in income inequality between 1988 and 1995. In the coastal region, wage income was the main reason for increased inequality, whereas it made no contribution at all in the interior region; there, inequality rose on account of pensions, self-employment income and property income.

Table 7.4 The contribution of income components to the change in income inequality, urban China, 1988–1995 (per cent)

Province	Income components					Total
	Y_1	Y_2	Y_3	Y_4	Y_5	
Beijing	130.5	4.1	8.6	13.3	–56.5	100.0
Shanxi	–89.3	157.5	26.3	33.0	–27.4	100.0
Liaoning	58.9	32.4	7.7	19.2	–18.1	100.0
Jiangsu	64.6	28.2	1.4	29.1	–23.3	100.0
Anhui	–879.8	798.0	176.6	258.0	–252.8	100.0
Henan	–6.2	117.2	13.7	9.8	–34.5	100.0
Hubei	87.8	9.1	9.3	28.1	–34.3	100.0
Guangdong	93.5	33.1	26.6	39.9	–93.1	100.0
Yunnan	–189.9	183.3	28.1	128.5	–50.0	100.0
Gansu	77.8	–45.4	15.1	–35.8	88.3	100.0
Coastal	93.7	22.0	6.7	21.0	–43.4	100.0
Interior	–18.9	119.3	26.7	58.2	–85.3	100.0
Total	76.2	37.5	10.1	25.8	–49.6	100.0

Notes: Y_1 = wage income of workers; Y_2 = pension and income of retired people; Y_3 = earnings of private owners and self-employed; Y_4 = household property income; Y_5 = other income. The coastal region comprises Beijing, Liaoning, Jiangsu and Guangdong; the interior region comprises Shanxi, Anhui, Henan, Hubei, Yunnan and Gansu.
Source: See Table 7.1.

We are now in a position to examine the proximate causes of the inter-province convergence of intra-province inequality. We estimate variants of equation (7.1):

$$\pi_{i1} - \pi_{i0} = a + bG_0 \tag{7.3}$$

$$\pi_{i1} - \pi_{i0} = c + d\pi_{i0}. \tag{7.4}$$

Equation (7.3) indicates whether, and to what extent, a particular component of income contributed to convergence in the Gini coefficient. Equation (7.4) indicates whether, and to what extent, the contribution of a particular component was itself subject to convergence. We see from Table 7.5 that wage income made much the largest contribution to the inter-province convergence in the Gini coefficient. The contribution of each component, except pensions, was itself strongly convergent. There is thus no single component responsible for the convergence that we seek to explain. The only component that we can rule out is pensions, which appeared to have a divergent effect.

Table 7.5 The inter-province relation between the contribution of a component to the change in income inequality and the initial contribution of the component or the initial Gini coefficient

	Coefficient on the initial value of:	
	G_0	π_{i0}
Wage income	−0.681*	−0.917**
Pension	0.187	0.427
Income from self-employment	−0.011	−0.857**
Property income	0.015	−1.117
Other income	−0.169*	−1.108***

*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level.
Source: See Table 7.1.

Table 7.6 The inter-province relation between the contribution of a component to the change in earnings inequality and the initial contribution of the component or the initial Gini coefficient

	Coefficient on the initial value of:	
	G_0	π_{i0}
Basic wage	−0.302	−0.008
Bonus	−0.101	0.101
Cash subsidy	−0.105	−1.233**
Income from self-employment	−0.074	−1.020**
Other earnings	−0.147	−1.028***

*** indicates statistical significance at the 1% level and ** at the 5% level.
Source: See Table 7.1.

Because of the importance of wages in producing the convergence of income inequality, Table 7.6 re-estimates equations (7.3) and (7.4) for the components of earnings. The basic wage made the greatest contribution to the convergence of the Gini coefficient. However, each component was itself subject to convergence except the bonus, which was weakly, and not significantly, divergent.

How then can we explain convergence, if it depended mainly on wage income and, within wage income, on the basic wage? It is possible that convergence was owing to the uneven timing of reforms. Those provinces and cities that reformed early – during the period 1985–1988 – had higher inequality by 1988. In these cases, inequality did not rise much more between 1988 and 1995. Those provinces and cities that commenced reforms later had lower inequality in 1988 but higher increases in the ensuing seven years. To test this hypothesis we need to measure the progress

Table 7.7 The inter-province and inter-city relation between the Gini coefficients of earnings and income and the proxy for the extent of reform, urban China, 1988

	Earnings		Income	
	Provinces	Cities	Provinces	Cities
Intercept	26.704	27.663***	20.190	25.784***
Basic wage as proportion of earnings	−0.084	−0.115*	0.007	−0.110*
Adj. R^2	−.106	.029	−.125	.031
F-value	0.135	2.701*	0.001	2.898*
Mean of dependent variable	22.120	21.431	20.586	19.828
Number of observations	10	60	10	60

*** indicates statistical significance at the 1% level and * at the 10% level.
Source: See Table 7.1.

in reform that had been achieved by 1988. To a considerable extent, the proportion of earnings other than basic wages represents the degree of decentralized freedom to determine earnings that employers then possessed. In 1988 this proportion was 46 per cent in the sample as a whole, but it varied from 36 to 58 per cent among the 10 provinces. We use this as our proxy for the extent of labour market reform in a province in 1988. Accordingly, Table 7.7 shows inter-province and inter-city estimates of the equation:

$$G_0 = a + bW_0, \tag{7.5}$$

where $W =$ basic wages as a percentage of earnings. The hypothesis is that $b < 0$. Indeed, we find that b is negative in three of the four cases but significantly so only in the equations for cities. Our evidence that the reforming provinces had higher initial inequality is weak but it remains our favoured explanation for convergence.

3. Divergence in means

Why study whether mean incomes are converging or diverging across provinces? Divergence in provincial mean incomes can make an important contribution to income inequality at the national level. The issue is particularly important in China, for two reasons. First, both central government, through its fiscal relationships with the provinces, and provincial governments, through their development policies, have the power to equalize or disequalize the pattern of provincial economic growth rates.

Secondly, the remarkably low mobility of labour in China, both between provinces and from rural to urban areas, may prevent or restrict the equilibrating flows of labour that might otherwise counteract divergence in the urban mean incomes of the provinces.

We approach the analysis of the growth in intra-province mean earnings and incomes in the same way as for intra-province inequality. First, we test for convergence or divergence in the means across provinces. Second, we extend the analysis to the sample of cities. Third, we explore the underlying reasons for the powerful divergence evident in our equations.

3.1. Divergence in mean income and earnings among provinces

Table 7.8 provides the basic data on mean real earnings from employment and mean household real income per capita for each of the 10 provinces common to our urban samples of 1988 and 1995, and the corresponding percentage increases. It is notable that provinces diverged

Table 7.8 The mean values of earnings per worker and income per capita, 1988 and 1995, at constant (1988) prices, urban China, by province, and their rates of growth

	Earnings			Income		
Province	1988	1995	% change	1988	1995	% change
Beijing	2,022	3,722	84.1	1,612	2,933	81.9
Shanxi	1,632	2,088	27.9	1,093	1,538	40.7
Liaoning	1,835	2,449	33.5	1,402	1,872	33.5
Jiangsu	1,895	2,950	55.7	1,459	2,403	64.7
Anhui	1,725	2,160	25.2	1,249	1,764	41.2
Henan	1,531	2,044	33.5	1,144	1,604	40.2
Hubei	1,749	2,590	48.1	1,307	1,994	52.6
Guangdong	2,723	4,876	79.1	2,053	3,673	78.9
Yunnan	1,988	2,514	26.5	1,321	1,926	45.8
Gansu	1,898	1,972	3.9	1,327	1,467	10.6
Coastal	2,144	3,300	53.9	1,584	2,502	58.0
Interior	1,739	2,205	26.8	1,177	1,632	38.7
Total	1,900	2,646	39.3	1,336	1,995	49.3

Notes: The coastal region comprises Beijing, Liaoning, Jiangsu and Guangdong; the interior region comprises Shanxi, Anhui, Henan, Hubei, Yunnan and Gansu. The income concept used throughout excludes the housing subsidy and the imputed rent of privately owned housing. Because these are based on market rents, which tend to be high in prosperous provinces irrespective of the quality of the housing, their inclusion would raise income misleadingly in those provinces.
Source: See Table 7.1.

sharply over the seven years. For instance, earnings per worker rose by 84 per cent in Beijing and 79 per cent in Guangdong but by only 3 per cent in Gansu and 27 per cent in Yunnan. The percentage growth in earnings in the coastal provinces is double that of the interior provinces. Very similar results are obtained for income per capita.

Again, we test for convergence or divergence using the equation:

$$y_1 - y_0 = a + by_0, \tag{7.6}$$

where $y =$ the natural logarithm of mean earnings or income. Table 7.9 (columns 1 and 5) shows equations for the growth of earnings and income, respectively, over the seven-year period. In both cases the coefficient on the base year value is significantly positive. In the case of earnings it implies that a 10 per cent higher initial income involves growth that is faster by 6 percentage points; in the case of income the growth is 5 percentage points faster. This constitutes strong evidence of inter-province divergence in earnings and income levels. Note the corresponding result in Table 7.7; comparing the coastal and interior groups of provinces, we see that the coastal region had both higher initial mean values and faster growth in earnings per worker and income per capita than the interior region.

Table 7.9 also shows the equivalent equations using official data for all 29 provinces (columns 2 and 6). Evidence of divergence is again found, although it is not quite so powerful, nor is it statistically significant in the case of earnings. We are observing a general phenomenon that is not just the result of outliers in our 10-province sample. The same equation estimated for the previous decade (1978–1988), using official data for the 29 provinces, is reported in columns 4 and 7 of Table 7.9. The results are quite different for this period; they indicate strong and statistically significant convergence of both earnings per worker and income per capita. Something happened to set different forces in motion during the later period. One likely explanation is the urban economic reforms – involving the decentralization of control and the dismantling of planning – which commenced in the mid-1980s.

A further pointer to this explanation is provided by the addition of two proxies for labour market reform in the 29-province equation for 1988–1995 (column 3): the bonus as a percentage of total earnings, and employment other than by the state or urban collectives as a percentage of total employment. Both reflect the extent of managerial autonomy; both coefficients are positive and significant. Moreover, the initial earnings coefficient becomes slightly negative and not at all significant. It appears that the differential growth of bonus payments and of the private sector was responsible for the divergence of earnings among provinces.

Table 7.9 The inter-province relationship between initial mean earnings and income per capita and their growth, urban China

	Proportionate growth in						
	Earnings per worker				Income per capita		
	CASS	SSB			CASS	SSB	
	1988–1995	1988–1995	1988–1995	1978–1988	1988–1995	1988–1995	1978–1988
Equation	1	2	3	4	5	6	7
Intercept	−4.184	−1.715	0.501	3.768***	−3.302*	−2.144***	2.843**
Initial income	0.600*	0.269	−0.059	−0.479**	0.511**	0.366***	−0.351*
Percentage bonus			0.011**				
Percentage private employment			0.012*				
Adj. R^2	.20	.040	.685	.178	.314	.357	.062
F-value	3.265*	2.175	18.803**	7.050**	5.125**	16.534***	2.858*
Mean of dependent variable	0.335	0.292	0.292	0.382	0.389	0.446	0.553
Number of observations	10	29	29	29	10	29	29

Notes: The 1995 data on earnings and incomes are deflated to 1988 figures using the urban consumer price index (which rose by 128 per cent). Inflation was very similar across the 10 provinces, the mean annual rate being 13.0 per cent and the standard deviation 1.0 per cent. Use of the province price indices had a negligible effect on the divergence coefficient, raising it from 0.600* to 0.610* in equation 1 and lowering it from 0.511** to 0.475* in equation 5.

*** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level.

Sources: CASS 1988 and 1995 household surveys, urban samples; SSB, official data on household incomes and earnings from employment.

Table 7.10 The growth of income per capita and earnings per worker as a function of their initial values, by city, urban China, 1988–1995

	Proportionate growth in	
	Income	Earnings
Intercept	0.845	1.167
Initial value (y_0)	0.068	−0.112
Adj. R^2	−.014	−.010
F-value	0.198	0.446
Mean of dependent variable $(y_1 - y_0)$	0.362	0.324
Number of observations	60	60

Note: None of the coefficients is significantly different from zero even at the 10% level.
Source: See Table 7.1.

3.2. Divergence in mean income and earnings among cities

The equation was re-estimated using the sample of 60 cities. In contrast to Table 7.9, Table 7.10 shows no sign of divergence in mean earnings or mean income among cities. The coefficients are not significantly different from zero. How is the difference in the results for cities and for provinces to be explained? One possibility is that labour is more mobile among the cities of a province than among cities of different provinces. Such mobility would tend to equalize incomes, so producing convergence among the cities of a province.

We test this hypothesis by estimating intra-province income equations for the seven provinces that contain at least six cities (Table 7.11). Given such small samples, it is hardly surprising that only two of the income coefficients are significantly different from zero. These are in the two provinces – Jiangsu and Guangdong – that have grown fastest and moved furthest towards a market economy. However, all seven coefficients are negative and four of them exceed –0.5. In these cases, a 10 per cent lower initial income raises the growth rate by over 5 percentage points. Very similar results are obtained for the earnings equations (not shown). Again, inter-city convergence is most powerful within Jiangsu and Guangdong.

3.3. Explaining divergence

We investigate the reasons for the divergence in province mean earnings and incomes in two ways. One is to decompose the mean increases into their component parts, in order to discover which components of earnings or incomes contribute to the divergence. Second, we decompose the

Table 7.11 The growth of income per capita as a function of its initial values, by cities within provinces, urban China, 1988–1995

	Shanxi	Jiangsu	Anhui	Henan	Hubei	Guangdong	Yunnan
Intercept	1.252	15.181**	4.165	1.999	4.040	7.984*	1.594
Initial income	−0.146	−2.037**	−0.543	−0.248	−0.511	−0.992*	−0.173
Adj. R^2	−.239	.480	.235	.140	.105	.278	−.076
F-value	0.034	8.387**	2.540	0.140	1.702	3.698	0.508
Mean of dependent variable	0.250	0.443	0.326	0.286	0.421	0.520	0.359
No. of observations	6	9	6	8	7	8	8

** indicates statistical significance at the 5% level and * at the 10% level.
Source: See Table 7.1.

Table 7.12 The growth of income components, urban China, by province, 1988–1995 (per cent)

Province	Income components Y_1	Y_2	Y_3	Y_4	Y_5	Income
Beijing	91.5	113.1	627.8	1,537.5	–82.2	82.0
Shanxi	21.6	35.4	261.8	1,588.6	–49.4	40.7
Liaoning	29.4	154.4	767.9	834.7	–86.1	33.5
Jiangsu	48.1	161.1	119.6	1,162.7	–64.7	64.7
Anhui	20.1	266.5	97.7	8,091.5	–81.2	41.2
Henan	16.0	229.7	460.8	460.8	–74.5	40.2
Hubei	46.4	141.0	891.7	681.9	–65.2	52.6
Guangdong	82.6	183.1	222.0	810.8	–85.3	78.9
Yunnan	37.3	145.8	159.2	1,309.4	–69.7	45.8
Gansu	–0.7	192.7	10.6	800.2	–81.6	10.6
Coastal	58.6	127.0	180.8	768.8	–81.8	58.0
Interior	29.9	145.8	197.1	893.7	–70.9	38.7
Total	44.5	141.4	198.7	817.3	–75.4	49.3

Notes: Y_1 = wage income of workers; Y_2 = pension and income of retired people; Y_3 = earnings of private owners and self-employed; Y_4 = household property income; Y_5 = other income. The coastal region comprises Beijing, Liaoning, Jiangsu and Guangdong; the interior region comprises Shanxi, Anhui, Henan, Hubei, Yunnan and Gansu.
Source: See Table 7.1.

mean differences between four samples (coast, interior; 1988, 1995) in order to throw light on the reasons for these differences.

The components of growth in income per capita are reported in Table 7.12. Apart from "other income" (Y_5), wage income (Y_1) tended to grow least rapidly. Income involving capital (from self-employment, Y_3, and from property, Y_4) grew most rapidly, both on the coast and in the interior. Table 7.13 shows that divergence of income per capita across provinces is overwhelmingly owing to the behaviour of wage income. Indeed, the other sources of income all have significantly negative coefficients in the second column, indicating that these components actually converged across provinces. It is therefore necessary to investigate the reasons for the divergence in earnings.

Table 7.14 shows the percentage growth in the components of earnings in each province between 1988 and 1995. The growth in basic wages (E_1) generally exceeded that in total earnings, as did the growth in the cash value of subsidies (E_3), whereas bonuses (E_2) grew less rapidly, and they actually fell in the interior region. The decline in the share of wages paid in the form of bonuses may be misleading. Bonuses were unimportant prior to the urban economic reforms that commenced in 1984. The pro-

Table 7.13 The contribution of income components to the divergence of income across provinces, urban China, 1988–1995

	Coefficient on the explanatory variable	
Explanatory variable	Initial income (y_0)	Initial component income (y_{i0})
Wage income	0.861***	0.878**
Pension	−0.451	−0.260*
Income from self-employment	0.115	−0.730***
Property income	−0.552	−0.844***
Other income	−1.412*	−0.830**

Notes: *** indicates statistical significance at the 1% level, ** at the 5% level and * at the 10% level. The analysis relates to the 10 provinces for which common urban samples are available in 1988 and 1995. The dependent variable is the proportionate growth in the income component ($y_{i1} - y_{i0}$).
Source: See Table 7.1.

Table 7.14 The growth of earnings components, urban China, by province, 1988–1995 (per cent)

	Earnings components					
Province	E_1	E_2	E_3	E_4	E_5	Earnings
Beijing	85.5	95.9	68.6	−38.6	85.6	84.1
Shanxi	46.4	−7.0	71.1	−26.9	−15.3	28.0
Liaoning	58.0	−24.5	33.5	300.4	−2.0	33.5
Jiangsu	79.4	33.2	71.0	−61.1	−18.5	55.7
Anhui	65.8	−40.5	−11.4	79.1	6.3	25.2
Henan	32.9	−6.9	82.6	540.8	5.3	33.5
Hubei	63.9	5.7	47.2	107.3	27.2	48.1
Guangdong	86.8	65.7	98.3	60.2	65.6	79.1
Yunnan	42.7	−31.3	90.1	39.1	−44.1	26.5
Gansu	24.3	27.5	−5.4	−86.2	−46.3	3.9
Coastal	64.0	29.8	61.7	11.9	24.8	53.9
Interior	43.3	−18.5	40.8	26.8	−15.0	26.8
Total	53.8	9.8	50.9	11.4	5.5	39.3

Notes: E_1 = basic wage of workers; E_2 = bonus of workers; E_3 = cash subsidy of workers; E_4 = earnings of private owners and self-employed; E_5 = other income.
Source: See Table 7.1.

portion rose from 13 per cent in 1983 to 19 per cent in 1988; this trend was not confined to the state sector. The proportion rose further, to 22 per cent, in 1993. However, in 1994 a dramatic increase in the basic wage occurred in the government sector, and this was generally followed in the enterprise sector. Employers responded to the wage reform by

Table 7.15 The contribution of earnings components to the divergence of earnings across provinces, urban China, 1988–1995

	Coefficient on the explanatory variable	
Explanatory variable	Initial earnings (y_0)	Initial component earnings (y_{i0})
Basic wage	0.481*	0.018
Bonus	1.296	0.466
Cash value of subsidy	0.747	0.218
Earnings from self-employment	–0.715	–0.788
Other earnings	0.825	0.215

Notes: The analysis relates to the 10 provinces for which common urban samples are available in 1988 and 1995. The dependent variable is the proportionate growth of the earnings component ($y_{i1} - y_{i0}$).
* indicates statistical significance at the 10% level.
Source: See Table 7.1.

paying the basic increase partly from bonus funds. In 1994 the average wage rose by 8 per cent in real terms, but this comprised a rise in ''non-bonus income'' (mainly the basic wage) by 18 per cent and a fall in the bonus by 13 per cent of total pay. The consolidation was not reversed in 1995: the share of the bonus was down to 16 per cent. It is plausible, therefore, that the bonus, being the payment most subject to managerial and least subject to government control, was the dynamic element primarily responsible for the growth of earnings, and its spatial divergence, over much of our seven-year period.

We estimate the inter-province equations:

$$y_{i1} - y_{i0} = a + by_0 \tag{7.7}$$

$$y_{i1} - y_{i0} = c + dy_{i0}, \tag{7.8}$$

where y_{ij} = log of earnings component i per worker in year j

y_j = log of total earnings per worker in year j.

Equation (7.7) indicates whether each component contributes to the divergence of earnings ($b > 0$), and equation (7.8) whether each component itself diverges over the period ($d > 0$).

Table 7.15 shows the contribution made by each component of earnings to the divergence in the growth of earnings across provinces. Only self-employment earnings have the wrong sign, and the contributions of bonuses and subsidies are important. For instance, a 10 per cent higher

initial level of earnings raises the growth of bonuses by 13 per cent and that of subsidies by 7 per cent. However, the importance of the basic wage in total earnings means that it contributes more in absolute terms to the divergence. We see from the second column that bonuses and subsidies, rather than basic wages, are themselves subject to the strongest divergence.

We decided to pursue the distinction between the coastal and the interior provinces. In 1988 the ratio of coastal to interior mean earnings was 123 per cent, and in 1995 it was 150 per cent. The ratio of 1995 to 1988 mean earnings was 154 per cent in the coastal provinces and 127 per cent in the interior provinces. To what extent was the growing divergence between the two regions owing to growing regional differences in the mean income-earning characteristics of workers and to what extent was it owing to growing regional differences in the income generation process itself? We attempt to answer this question by conducting standard decomposition analyses of the difference in mean earnings both between the two regions and between the two years:

$$\begin{aligned}\overline{y_i} - \overline{y_j} &= f_i(\overline{\boldsymbol{x_i}}) - f_j(\overline{\boldsymbol{x_j}}) \\ &= f_i(\overline{\boldsymbol{x_i}}) - f_i(\overline{\boldsymbol{x_j}}) + f_i(\overline{\boldsymbol{x_j}}) - f_j(\overline{\boldsymbol{x_j}}) \\ &= f_i(\overline{\boldsymbol{x_i}} - \overline{\boldsymbol{x_j}}) + f_i(\overline{\boldsymbol{x_j}}) - f_j(\overline{\boldsymbol{x_j}}), \qquad (7.9)\end{aligned}$$

where $i, j = 1995, 1988$ or coast, interior, a bar over a variable indicates its mean value, and $\boldsymbol{x}$ is a vector of explanatory variables. The first term measures the component attributable to the difference in mean characteristics and the second term the component attributable to differences in earnings functions. The alternative decomposition is:

$$\overline{y_i} - \overline{y_j} = f_j(\overline{\boldsymbol{x_i}} - \overline{\boldsymbol{x_j}}) + f_i(\overline{\boldsymbol{x_i}}) - f_j(\overline{\boldsymbol{x_i}}). \qquad (7.10)$$

The competitive market prediction is that the income generation mechanism should be the same everywhere. However, endowments of workers' characteristics could differ spatially, and it is this that would produce spatial differences in means (and in inequality) in a fully competitive economy. China does not have such an economy: we see in Table 7.16 that the earnings difference between the coast and the interior in both years was owing entirely to differences in coefficients and not at all (the effect was negative) to differences in characteristics. Similarly, we see that changes in coefficients were overwhelmingly important to the increase in mean real earnings between 1988 and 1995 in both regions.

It is worth exploring further which explanatory variables contributed

Table 7.16 Decomposition analysis of the difference in mean earnings in urban China, coast–interior, 1988–1995

	Percentage of the difference in mean earnings owing to	
	Coefficients	Mean values
Coastal provinces		
Equation (7.9)	68.8	31.2
Equation (7.10)	90.0	10.0
Interior provinces		
Equation (7.9)	67.1	32.9
Equation (7.10)	81.1	17.9
Coast–interior		
1988		
Equation (7.9)	110.4	–10.4
Equation (7.10)	109.6	–9.6
1995		
Equation (7.9)	101.0	–1.0
Equation (7.10)	106.4	–6.4

Source: See Table 7.1.

Table 7.17 The contribution of each worker characteristic to the regional difference in mean earnings attributable to coefficients, urban China, 1988 and 1995

	1988		1995	
Equation used	(7.9)	(7.10)	(7.9)	(7.10)
Intercept	94.1	94.9	57.7	54.7
Sex	–0.9	–1.0	–1.2	–1.1
Age	13.8	13.1	–12.8	–13.3
Education	–13.9	–14.5	53.0	49.0
Party membership	–4.5	–4.0	4.3	3.8
Minority status	–1.9	–1.1	–3.0	–1.6
Ownership category	–19.9	–22.9	17.1	20.5
Occupation	5.1	4.6	–2.9	–2.9
Employment status	11.4	12.0	–17.2	–15.0
Sector	16.7	18.9	5.0	5.9
Total	100.0	100.0	100.0	100.0

Source: See Table 7.1.

most to the part of the mean earnings gap that was attributable to the difference in coefficients (Table 7.17). In comparing the coastal and interior regions, we see that the intercept term was crucial in 1988, accounting for some 95 per cent of the total. This represented the characteristics omitted from the earnings function analysis (male, aged 25–29, 0–3 years of edu-

cation, Han, not a Party member, production worker, in state sector manufacturing, self-employed), i.e. what might be regarded as urban basic unskilled labour.

The mean real earnings difference between the regions attributable to coefficients rose from 450 to 1,140 yuan per annum over the seven years. In 1995 education accounted for no less than half of this difference, having had a slight negative effect in 1988. The intercept term accounted for the other half. In addition, ownership had a positive effect and age a negative effect. Age, the key determinant of earnings under central planning, was better rewarded in the interior than at the coast. Of crucial importance were the differential returns to education. The premium on higher education relative to 0–3 years of primary school was 92 per cent at the coast and 49 per cent in the interior. This helped to raise the relative mean earnings of coastal workers. It appears that pressure of demand for educated workers in the coastal provinces raised their pay and contributed to the divergence of earnings among provinces.

4. Conclusions

Using the urban samples of the CASS national household surveys of 1988 and 1995, we established two interesting results that deserve attention and explanation. First, there was a tendency for intra-province inequality in both earnings per worker and household income per capita not only to rise in each province but also to converge across provinces. The same tendencies were to be found at the regional (coastal–interior) and city levels. Secondly, there was a tendency for both province mean earnings per worker and mean household incomes per capita not only to rise in each province but also to diverge across provinces. This chapter was concerned to establish these patterns and then to explain them. We did better in achieving our first objective than in achieving our second. We explored various avenues but could not produce conclusive explanations.

Our analysis to decompose inequality by source indicated that the basic wage was the most important reason for the general increase in earnings inequality. Moreover, the basic wage made the greatest contribution to the convergence of earnings inequality across provinces, although other sources were themselves more powerfully convergent. The one exception was bonuses, which were divergent. With regard to inequality of income, wage income was the main reason for the increased inequality in the coastal region, but it made no contribution in the interior region, where pensions were crucial. Wage incomes made the greatest contribution to the convergence of inequality across provinces, but all components of income other than pensions were convergent.

The fact that convergence of earnings inequality appeared to be stronger for "staff" than for "workers", and for non-state than for state employees, suggests that market forces played a role in producing convergence. It is likely that the uneven timing of reforms also played a role: those provinces and cities that reformed early had greater inequality in 1988 but a smaller increase in inequality thereafter. Our proxy measure of the extent of labour market reform in 1988 did indeed have a positive effect on inequality in that year.

Our analysis of the inequality of inequality appears to break new ground. Given competitive markets all round, the spatial convergence of income or earnings inequality would require that economies become more alike in their distribution of productive characteristics among households or workers. However, markets in China have by no means been competitive throughout. They became more competitive between 1988 and 1995, although the process was spatially uneven. We explained convergence in terms of the process and timing of market reforms in different provinces and cities.

The most dynamic component of income growth was income from capital but wage income made the greatest contribution and pensions were also important in the interior. The divergence of income per capita across provinces is owing to the behaviour of wage income, because all other components actually converged. The decomposition of the growth in mean earnings showed basic wages to be the main, and the most dynamic, component. Basic wages also made the largest contribution to divergence, although bonuses and subsidies were themselves subject to stronger divergence.

A decomposition analysis of the difference in mean earnings in coastal and interior provinces showed that it was owing entirely to the difference in their income generation processes. The widening of the difference over the seven years was the result partly of the relative improvement in the pay of unskilled labour and partly of the sharper rise in the premium on education in the coastal provinces. This last finding suggests that market pressures for scarce labour were a driving force. Another indication that market forces were at work is the finding that mean earnings converged among the cities of a province but diverged among provinces, i.e. mobility of labour limits divergence and assists convergence.

Bonuses are the component of wages over which enterprises probably have greatest autonomy. Their part in our story therefore deserves scrutiny. Being dependent on the profitability and negotiating power (over soft budgets) of enterprises, bonuses tend to segment the labour market by enterprise. Walder (1987) argued that bonuses are fairly equally distributed within the enterprise, reflecting worker pressures and preferences. However, there may be as many work units as households in our

urban sample. We found bonuses to be the most disequalizing component of earnings. Bonuses were more unequally distributed among workers and also among provinces in 1995 than in 1988, probably because of greater segmentation among enterprises. For instance, Knight and Li (2005) found powerful wage segmentation among firms according to profitability in 1995, the result of profit-sharing and lack of labour mobility. Bonuses do not help to explain the inter-province convergence of earnings inequality that we observed; indeed, their effect is divergent. Bonuses are also an important source of the inter-province divergence of mean earnings. The share of bonuses in earnings fell over the seven years. They may nevertheless have been the driving force behind the growth of earnings, a role that could have been concealed by the consolidating wage reform of 1994.

The policy of permitting state-owned enterprises to pay bonuses was intended to improve incentives for efficiency, at least at the level of the enterprise. However, the continuing weakness of both product market and labour market forces made possible large differences in enterprise profitability and thus in enterprise pay. Bonuses weakened the convergence in the inequality of wages and incomes and strengthened the divergence of mean wages and incomes. Convergence of mean incomes among economies is consistent with models of technological diffusion and with neo-classical growth models of closed economies. It is also consistent with increased factor mobility across economies. There is much evidence of conditional economic convergence around the world. However, we found economic divergence among the regions of urban China. The most plausible explanation is the relative lack of factor mobility and the weakness of market forces. The former permitted very different income generation functions to exist, and the latter permitted wages in general, and bonuses in particular, to be influenced by rent-sharing behaviour as well as by local supply and demand conditions.

If our interpretations of the results are correct, two policy conclusions follow. First, economic reform may have a once-for-all and finite effect on inequality. At the least, there is a once-for-all component. The growth of inequality is limited by the processes that produced cross-province convergence in inequality. Secondly, although divergence in mean earnings, and thus in incomes, may continue across provinces, further reform of the labour market – assisting labour mobility, removing the policy restrictions on migration across provinces, between rural and urban areas and among cities, and giving more rein to market forces in the slower-reforming provinces – can slow it down and may eventually reverse it. Nevertheless, forces of cumulative causation appear to be at work in the Chinese economy, which may keep divergence going for some years yet.

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8

Industrial location and spatial inequality: Theory and evidence from India

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1. Introduction

Spatial inequality refers to a condition in which different spatial or geographical units are at different levels on some variable of interest, usually (average) income. Why should different geographical units within a nation be at different income levels? This question is not answered simply. There are several overlapping reasons for the existence of intra-national spatial inequality; history, natural resources, human capital, local political economy and culture have all been identified as contributory factors. Here, we seek to understand spatial inequality in terms of industrialization and industrial location. We argue that modern economic growth is driven by productivity increases, which, in turn, are driven by industrialization in the developing world. Therefore spatial units that have industrialized are more productive and have higher incomes than spatial units that have not industrialized or have industrialized less (we are not considering post-industrial, service sector-led growth, a condition that is characteristic of developed nations but quite marginal in developing nations). In other words, geographical variation in industrialization is a primary cause of geographical variation in average income in developing nations.

This is the first part of our argument, which we view as self-evident and therefore will not seek to prove. Our interest is in understanding the process of spatial industrial variation, that is, in identifying the factors that determine industrial location decisions, and to show how recent policy

changes have led to increasing spatial industrial inequality and, therefore, spatial income inequality. We argue, following the tradition of the cumulative causation theorists, that industrialization follows the classic ''virtuous cycle'' principles. New industries locate where other industries already exist. This is done to make use of productivity advantages in existing industrial regions. However, not all industries seek such profit-maximizing locations. State-owned industry location decisions include consideration of regional balance, national security and political gains. However, the role of the state as industrial owner and industrial location regulator has been substantially curtailed under the regime of liberalization and structural reforms. Therefore, with the increasing dominance of private sector industrialization, we expect that industries will be more spatially concentrated in leading industrial regions, which will lead to higher levels of spatial inequality.

We test this theoretical framework with Indian data from the 1990s. First we test the hypothesis that economic geography factors influence productivity by examining the cost structure of eight manufacturing industry sectors.[1] In a significant departure from existing models of industry clustering, we show that only a single economic geography factor has cost-reducing effects – this is industrial diversity (which is high in metropolitan and other mixed industrial regions). Next, we show that location decisions of state-owned industry and private sector industry are, indeed, influenced by different factors, with private industrial units favouring locations in existing industrial areas. We also show that the private sector is the primary source of new industrial investments. We conclude that liberalization and structural reforms have led to higher levels of spatial inequality in industrialization in India.

The material in this chapter brings together two interconnected research programmes. We draw on two somewhat distinct literatures, use two clearly distinct methodologies, and analyse similar but distinct data sets. Therefore, we present the arguments, the literature, the methodology and the findings in two separate sections. Section 2 is on the cost effects of manufacturing industry location, and section 3 looks at the location patterns of private and state capital. We reconcile the findings of the two sections in a single concluding section.

Before we proceed further, however, it is necessary to explain the meaning of spatial inequality as used in this chapter. What is the appropriate scale for measuring income differences? Spatial inequalities exist at all scales – from the neighbourhood, the municipality and the district or county, through the province or state, to the nation. Which of these inequalities are most meaningful? For the purpose of this chapter, we suggest that inequalities between spatial units that are also discrete policy units and for which income data are available are meaningful units. That

is, there may indeed exist significant inequalities between neighbourhoods, but if neighbourhoods cannot create policies that affect income, or if income cannot be measured at the neighbourhood level, they are not considered to be relevant spatial units. To the extent that municipalities can create policies that influence income generation and such income can be measured, they should be considered relevant units; however, rural areas will have to be left out of such calculations. Inequality between nations is a large subject with its own literature. We are left with district and provincial inequality. The latter, also termed regional inequality, has typically been the unit of interest in inequality studies, largely because it is the smallest spatial unit for which income data are available.[2] Our ultimate interest is also in the provincial scale, which, in India, is represented by linguistically defined states. However, since location analysis is best carried out at scales smaller than Indian states (some of which are large enough to be large countries), the analysis here is undertaken at the district scale.[3]

2. The cost effects of industry location

Our empirical strategy in this section is to estimate a cost function to see how costs (thereby profits) are affected by the economic geography of the region in which the firm is located. If specific factors related to the local economic geography have cost-reducing impacts, then firms are likely to choose regions with disproportionately higher levels of these factors. The analytic framework to examine the location of manufacturing industry primarily draws on recent findings from the ''new economic geography'' (NEG) literature. Here, Krugman (1991) and Fujita et al. (1999) analytically model increasing returns, which stem from technological and pecuniary externalities. In models of technological externalities, inter-firm information spillovers provide the incentives for agglomeration. Assuming that each firm produces different information, the benefits of interaction increase with the number of firms. This provides incentives for the entrepreneur to locate the firm in close proximity to other firms, leading to agglomeration.

In addition, there are pecuniary benefits from sharing specialized input factors, utilizing scale economies in the production of shared inputs, collaboration to share information, and the presence of interrelated industries. Transport costs are also important. According to Krugman (1991), agglomeration occurs at intermediate transport costs when the spatial mobility of labour is low (Fujita and Thisse 1996). Transport costs can be reduced by locating in areas with good access to input and output markets that also have high-quality infrastructure linking firms to urban

market centres. In summary, insights from NEG and regional science models suggest that own and interrelated industry concentrations, availability of reliable infrastructure to reduce transport costs and enhance market access, regional amenities and economic diversity are important for reducing costs, thereby influencing location and the agglomeration of industry.

To provide visual evidence of the degree to which industry locations are clustered over the national space, we include district-level maps of location quotients (LQ) for four industry sectors in Figure 8.1. The LQ is a simple measure of regional concentration used in regional science. It calculates the ratio of the share of a given variable to the share of population. Here, $LQ = 1$ indicates that the region's share of a particular sector is equal to its share of all industry. If $LQ = 3$, it indicates that the region's share of that sector is three times its share of all industry. Our goal is to analyse the cost implications of these location decisions.

Before moving on to describe the economic geography variables and specifying the econometric specification, it is useful to think why these sources of externalities may matter in the estimation of costs over and beyond the benefits that are capitalized in the price of input factors. After all, if a region has relatively better endowments, the benefits should be reflected in lower prices of intermediate inputs, and may also bid up the prices of labour and capital as more people and firms migrate to that region. If the extent of agglomeration economies is purely market based, it is possible that net benefits are capitalized. However, non-pecuniary externalities of information- and knowledge-sharing do not lend themselves to direct capitalization. Further, market failures, including coordination failure, reduce the extent to which the economic geography variables are capitalized in input prices. Finally, the extent to which these costs and benefits are capitalized into input prices is an empirical question, and one that we will examine in the following sections.

2.1. Economic geography variables

We now identify and define the specific economic geography variables that are expected to influence industry location by generating competitive cost effects.

Market access

In principle, improved access to consumer markets (including inter-industry buyers and suppliers) will increase the demand for a firm's products, thereby providing the incentive to increase scale and invest in cost-reducing technologies. Access to markets is determined by the firm's distance from market centres and by the size and density of market

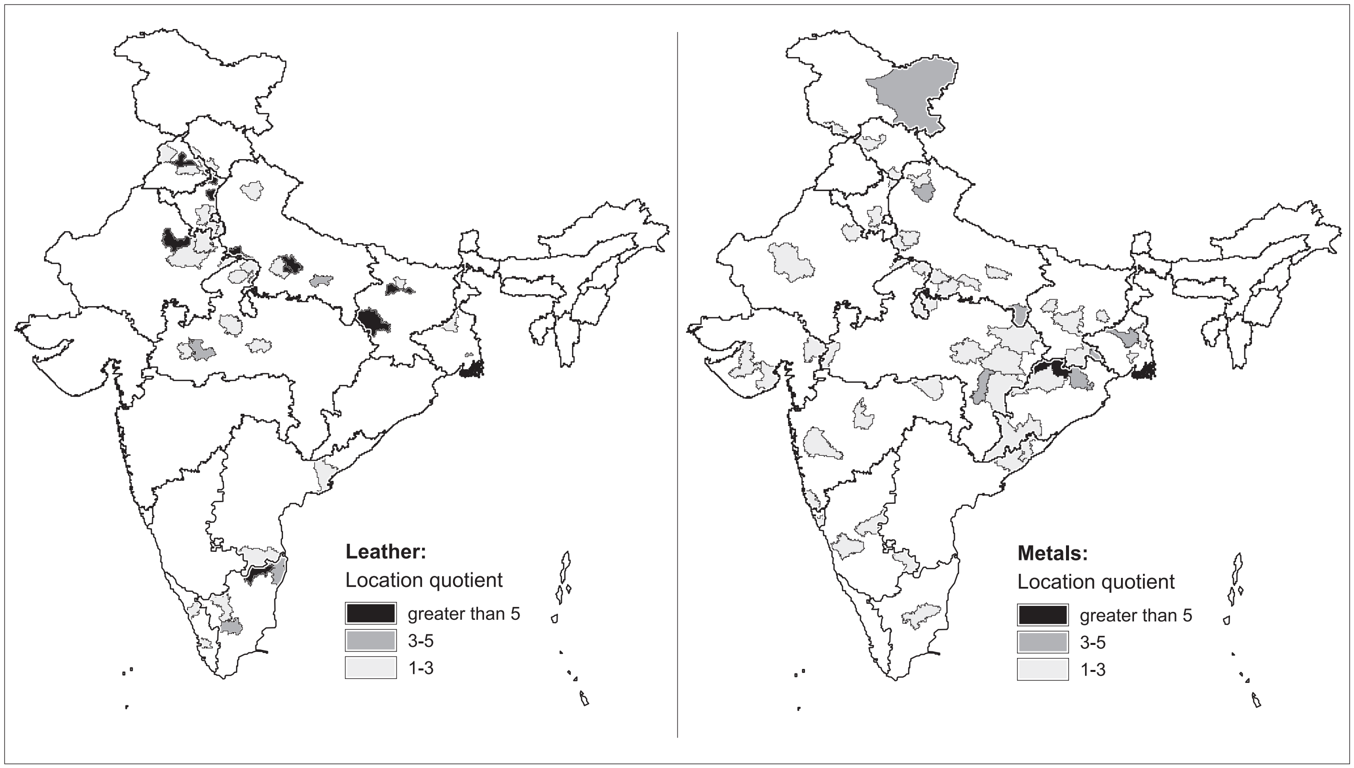

Figure 8.1 The spatial distribution of employment in India.
Source: Data from CSO, *Annual Survey of Industries*, 1998–1999.

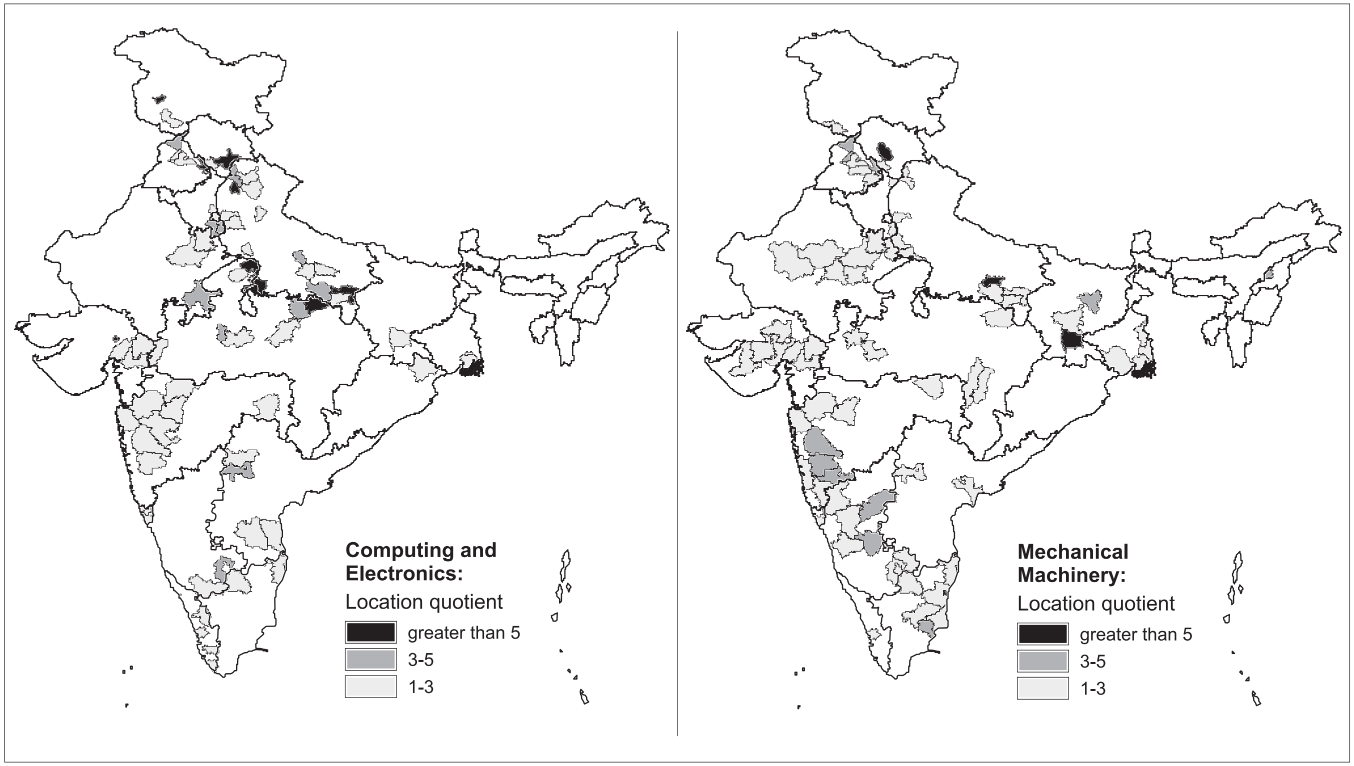

Figure 8.1 (cont.)

centres in its vicinity. There is no prior reason why the extent of the market should be limited to a firm's spatial vicinity (i.e. its own district), as long as there are adequate transport networks to connect its products to a greater market area, which could be the province, the nation or the rest of the world. To model this type of potential interaction through a transport network, we draw on the classic gravity model, which is commonly used in the analysis of trade between regions and countries (Evenett and Keller 2002). Following Hansen (1959), we calculate access from the following definition:

$$I_i^{\mathrm{ne}} = \sum_j S_j \cdot e^{(-d_{ij}^b/2a^2)},$$

where I_i^{ne} is the potential accessibility indicator for location i based on the negative exponential distance decay function, S_j is a size indicator at destination j (for example, population, purchasing power or employment), d_{ij} is a measure of distance (or, more generally, *friction*) between origin i and destination j, and b describes how increasing distance reduces the expected level of interaction, and the parameter a is the distance to the point of inflection of the negative exponential function. We use the market access (MA) indicator developed by Lall et al. (2004a), who use population as the measure of size in S_j and network distance as the basis of the inverse weighting parameter. Their accessibility index describes market access using information on the Indian road network system and the location and population of urban centres.[4]

In addition to market access, we develop indicators of local spatial externalities, which include own and inter-industry linkages. The main distinction in modelling these externalities and the treatment of market access is that we limit the spatial extent of the potential externality to the firm's own district. We follow this approach because much of the literature on technological and pecuniary externalities suggests that localization economies are limited to firms that are located in close proximity (close being defined as census tracts in literature on the United States). Thus, given the already large size of Indian districts, we do not consider the impact of firms located in neighbouring districts. Our aggregation scheme does introduce a problem: we tend to underestimate parameters for localization economies because the "true" interaction often occurs at spatial scales below the district (for example, neighbourhoods).[5] We develop the following indicators of local spatial externalities.

Own-industry concentration

The co-location of firms in the same industry (localization economies) generates externalities that enhance the productivity of all firms in that

industry (Henderson 1988, 2000; Ciccone and Hall 1996). Of the several ways of measuring localization economies, we use own-industry employment in the district to measure localization economies. Own-industry employment is calculated from employment statistics provided in the 1998–1999 sampling frame of the *Annual Survey of Industries* (ASI), conducted by the Central Statistical Office of the Government of India (CSO), which provides employment data on the universe of industrial establishments in India.

Inter-industry linkages

In addition to *intra*-industry externality effects, we also include a measure to evaluate the importance of *inter*-industry linkages in explaining firm-level profitability, and thereby location decisions. In particular, we are interested in finding out if proximity to suppliers reduces the cost of inputs, in addition to providing non-pecuniary benefits of information/technology-sharing.[6] Several approaches can be used to define and measure supplier access – input–output linkage based, labour skill based, and technology flow based. The most common approach is to use the national-level input–output account as a template for identifying strengths and weaknesses in regional buyer–supplier linkages (Feser and Bergman 2000). Commonly, backward linkages are measured as technical coefficients from a national industry-by-industry transactions table. Technical coefficients are defined as column industry purchases from the row industry divided by the sum of all column industry sales and relate to the dollar value of intermediate purchases from the upstream sector required to produce a dollar of the column industry's output. Thus, the technical coefficient measures the degree of the column industry's dependence on other industries for inputs to production. Following the methodology adopted in Lall et al. (2004b), we measure the firm's dependence on backward linkages as the sum of its industry's backward linkages with all other relevant sectors. For each column industry, backward linkages with each row industry are defined as the technical coefficient weighted by the region's location quotient for the row industry. A matrix of regionally weighted backward linkages is defined as:

$$\underset{(r\,x\,j)}{\Lambda} = \underset{(r\,x\,i)}{L}\,\underset{(i\,x\,j)}{\Omega},$$

where L is a region-by-industry matrix of location quotients for selling sectors and Ω is a national direct requirements matrix of technical coefficients,[7] with purchasing industries as columns and supplying sectors as rows. Each column vector of Λ is a composite measure of the jth industry's backward linkages for regions r. Therefore, a firm in region r and industry j has a measure of backward linkages Λ_{rj}.

Economic diversity

In addition to buyer–supplier linkages, there are other sources of inter-industry externalities. Prominent among these is the classic Chinitz–Jacobs' diversity. The diversity measure provides a summary measure of urbanization economies, which accrue across industry sectors and provide benefits to all firms in the agglomeration. Chinitz (1961) and Jacobs (1969) proposed that important knowledge transfers primarily occur across industries and the diversity of local industry mix is important for these externality benefits. Here, we use the well-known Herfindahl measure to examine the degree of economic diversity in each district. The Herfindahl index of a region r (H_r) is the sum of squares of employment shares of all industries in region r:[8]

$$H_r = \sum_i \left(\frac{E_{ir}}{E_r}\right)^2.$$

2.2. *Econometric specification*

In this subsection, we present the econometric specification to test the effects of economic geography factors in explaining the location of economic activity. Our basic premise is that firms will locate in a particular location if profits exceed some critical level demanded by entrepreneurs. We estimate a cost function with a mix of micro-level factory data and economic geography variables that may influence the cost structure of a production unit. A traditional cost function for a firm i is (subscript i is dropped for simplicity):

$$C = f(Y, w), \tag{8.1}$$

where C is the total cost of production for firm i, Y is its total output, w is an n-dimensional vector of input prices. However, the economic geography – or the characteristics of the region in which the firm is located – is also an important factor affecting the firm's cost structure. We modify the basic cost function to include the influence of location-based externalities:

$$C_r = f(Y, w_r, A_r), \tag{8.2}$$

where C_r is the total cost of a firm i in region r, w_r is an input price vector for the firm in district r, and A is an m-dimensional vector of location externalities (i.e. economic geography variables such as access to markets, buyer–supplier networks, own-industry concentration) at location r.

The model has four conventional inputs: capital, labour, energy and materials. Therefore, the total cost is the sum of the costs for all four inputs. With respect to agglomeration economies, it is assumed that there are four sources of agglomeration economies at the district level such that $A = \{A_1, A_2, A_3, A_4\}$, where A_1 is the market access measure, A_2 is the concentration of own-industry employment, A_3 is the strength of buyer–supplier linkages, and A_4 is the relative diversity in the region.

Shephard's Lemma produces the optimal cost-minimizing factor demand function for input j corresponding to input prices as follows:

$$X_{j,r} = \frac{\partial C_r}{\partial w_{j,r}}(Y, w_r, A_r), \qquad j = 1, 2, 3, 4, \ldots, n, \tag{8.3}$$

where $X_{j,r}$ is the factor demand for the jth input of a firm in district r. It is clear that the firm's factor demand is determined by its output, factor prices and location externalities. Therefore, production equilibrium is defined by a series of equations derived from equations (8.2) and (8.3). The empirical implementation of the above model is based on a translog functional form, which is a second-order approximation of any general cost function. Since there are four conventional inputs and four location externalities (agglomeration) variables, a translog cost function can be written as:

$$\begin{aligned}\ln C = {} & \alpha_0 + \alpha_y \ln Y + \sum_j \alpha_j \ln w_j + \sum_l \alpha_l \ln A_l + 1/2\beta_{yy}(\ln Y)^2 \\ & + 1/2 \sum_j \sum_k \beta_{jk} \ln w_j \ln w_k + \sum_j \beta_{jy} \ln Y \ln w_j \\ & + 1/2 \sum_l \sum_q \gamma_{lq} \ln A_l A_q + \sum \sum \gamma_{jl} \ln w_j A_l + \sum_l \gamma_{ly} \ln Y \ln A_l \\ & (j \neq k; 1 \neq q; j, k = 1, 2, 3, 4; l, q = 1, 2, 3, 4). \end{aligned} \tag{8.4}$$

The final model estimated includes two additional dummy variables that identify locational characteristics that may not be captured by agglomeration variables. Locations are categorized as rural, non-metro urban (D_1) and metro urban (D_2), and rural location is used as a reference category. In addition, we use a dummy variable to test if there are differences between public and private sector firms, and age to examine if profitability varies by firm age.

The impact of the economic geography factors on the cost structure (or profitability) of the firm can be evaluated by deriving the elasticity of costs with respect to the economic geography variables. From equation (8.4) the cost elasticities are:

$$\frac{\partial C}{\partial A_l} = \alpha_l + \sum_j \gamma_{jl} \ln w_j + \sum_q \gamma_{lq} \ln A_q + \gamma_{ly} \ln Y, \tag{8.5}$$

and the elasticity of input demands with respect to agglomeration factors A_l is:

$$\frac{\partial \ln v_j}{\partial \ln A_l} = \frac{\partial C}{\partial A_l} + \frac{\gamma_{jl}}{A_l}. \tag{8.6}$$

2.3. *Data sources*

We use plant-level data for 1998–1999 from the Annual Survey of Industries (ASI) conducted by the Central Statistical Office of the Government of India. The ‘‘factory’’ or plant is the unit of observation in the survey and data are based on returns provided by factories. Data on various firm-level production parameters such as output, sales, value-added, labour cost, employees, capital, materials and energy are used in the analysis (see Table 8.1 for details). In summary, factory-level output is defined as the ex-factory value of products manufactured during the accounting year for sale. Capital is defined as the gross value of plant and machinery. It includes not only the book value of installed plant and machinery but also the approximate value of rented-in plant and machinery. Labour is defined as the total number of employee person days worked and paid for by the factory during the accounting year.

The factory- or plant-level data from the Indian ASI allow us to compute input costs. With respect to input costs and input prices, the capital cost is defined as the sum of rent paid for land, building, plant and machinery, repair and maintenance costs for fixed capital, and interest on capital. The labour cost is calculated as the total wage paid for employees. The energy cost is the sum of the electricity (both generated and purchased), petrol, diesel, oil and coal consumed. The value of self-generated electricity is calculated from the average price that a firm pays to purchase electricity. The material cost is the total aggregate purchase value of domestic and foreign intermediate inputs. We define the price of capital as the ratio of total rent to net fixed capital. The price of labour is calculated by dividing the total wage by the number of employees. Energy and material prices are defined as weighted expenditure per unit output. Output value is weighted by factor cost shares.

Table 8.1 Characteristics of firms in the study sectors

Location	Industry	No. of firms	Employment (No. '000)	Wages/employee (Rs '000)	Output/ employee (Rs '000)	Value added/ employee (Rs '000)
Nationwide	All industries	23,201	4,605	60	277	127
	Food processing	4,168	671	47	253	147
	Textiles	3,409	1,111	44	140	76
	Leather	468	79	41	211	135
	Paper products & printing	1,043	129	70	314	204
	Chemicals	2,811	474	83	376	79
	Metals	2,331	410	77	261	114
	Mechanical machinery	1,300	237	78	189	95
	Electrical/electronics	1,267	251	101	344	65
	Other industries	6,404	1,243	54	385	195
Non-urban		8,343	1,494	50	301	126
Non-metro urban		9,446	1,972	58	235	125
Metropolitan areas		5,412	1,139	74	320	133

Source: CSO, *Annual Survey of Industries*, 1998–1999.

Table 8.2 Number of establishments

Industry	Small (0–49)	Medium (50–99)	Large (100+)	Total
Food and beverages	1,808	708	1,484	4,000
Textiles	1,289	406	1,613	3,308
Leather	227	73	144	444
Printing and publishing	657	151	212	1,020
Chemicals	1,544	350	870	2,764
Metals	1,372	296	615	2,283
Mechanical machinery	799	160	316	1,275
Electrical/electronics	709	168	375	1,252
Total	8,405	2,312	5,629	16,346

Source: See text.

2.4. Analysis results

Summary results for the estimated cost functions of the economic geography variables, as defined in equation (8.5), are reported in Table 8.3. To make allowances for the heterogeneity in firm size, and to test if in fact there are differences in production costs and the impact of economic geography across firms of different sizes, we classify firms into three categories: small, medium and large. Small firms are defined as those with fewer than 50 employees, medium-sized firms have 50–99 employees and large firms have 100 or more employees. The number of firms by size category is reported in Table 8.2.[9]

There are four sets of location/economic geography variables in the analysis: (a) access to markets (Access); (b) own-industry concentration (Emp); (c) buyer–supplier or input–output linkages (IO link); (d) local economic diversity (Diversity). The results for each industry sector are provided in four parts. The first column has industry-wide cost elasticities. These are followed by estimates for small, medium and large firms, respectively. As we can see, sorting by firm size shows that there is significant variation in the extent to which firms of different sizes benefit from location-based characteristics. In general, there is considerable heterogeneity in the impact of location characteristics on costs incurred at the firm level. This heterogeneity applies to the overall effects across industries, and includes differences across firms of different sizes and by sources of agglomeration economies.

Let us begin by looking at the impact of access to markets. Market access measures effective demand for a firm's products and inputs and the ease with which the firm can reach buyers and suppliers. Therefore, good market access is likely to reduce the cost of intermediate inputs as well as increase demand for the firm's products. The entrepreneur will have

Table 8.3 Cost elasticities of economic geography variables

Industry	Access				Emp				IO link				Diversity			
	Overall	Small (0–49)	Medium (50–99)	Large (100+)	Overall	Small (0–49)	Medium (50–99)	Large (100+)	Overall	Small (0–49)	Medium (50–99)	Large (100+)	Overall	Small (0–49)	Medium (50–99)	Large (100+)
Food and beverages	–0.002	–0.001	–0.001	0.000	**0.016**	0.000	0.002	0.011	0.006	–0.001	–0.002	**0.024**	**–0.075**	0.000	–0.012	**–0.067**
Textiles	0.004	**0.023**	0.008	–0.022	0.016	0.004	–0.033	–0.001	–0.002	–0.005	**0.037**	0.011	**–0.102**	–0.121	–0.210	–0.005
Leather	**0.072**	–0.017			**0.025**	0.005			–0.014	0.010			–0.023	–0.172		
Printing and publishing	0.022	0.005		0.032	0.000	0.012		0.034	–0.009	–0.005		–0.092	–0.062	**–0.248**		0.0516
Chemicals	–0.016	–0.024	–0.056	–0.044	**0.021**	0.021	0.059	**0.049**	0.000	0.003	–0.041	–0.012	–0.076	**–0.457**	0.042	0.250
Metals	–0.017	–0.008	**0.163**	–0.012	0.003	0.004	0.137	–0.036	–0.012	0.000	**–0.177**	0.033	0.003	**–0.163**	0.603	0.039
Mechanical machinery	**–0.047**	–0.016		**0.091**	0.000	0.006		–0.018	–0.001	0.000		–0.026	–0.007	–0.042		0.167
Electrical/ electronics	0.008	–0.009		0.035	**0.019**	0.038		0.035	–0.004	0.004		**0.378**	–0.162	**–0.835**		**–2.355**

Note: Coefficients in bold are significant at 1%, coefficients underlined are significant at 5%.
Source: See text.

incentives to increase the scale of production and invest in cost-reducing technologies (Lall et al. 2004a). At the industry-wide level, the results show that market access does not have a significant net cost-reducing impact in most industry sectors. The estimated cost elasticities are negative and statistically significant for two industry sectors – metals and mechanical machinery; the elasticity values are insignificant for other sectors. For example, in mechanical machinery, the coefficient of −0.047 means that a 10 per cent improvement in market access will be associated with an approximately 0.5 per cent reduction in overall costs at the firm level. There is a counterintuitive result for the leather industry, where the cost elasticity is positive and significant. For small firms, the estimated elasticities are generally negative, indicating benefits from improved market access. However, the estimates are statistically significant at the 5 per cent level for only two industry sectors – chemicals and metals. We also find a positive and significant estimate for the textiles industry, suggesting that there are costs associated with higher market access. Most of the estimates for medium and large industries are not statistically significant.

Next we look at results for own-industry concentration, which is measured as the sum of employment in the particular industry in the region. The industry-wide estimates suggest that there are no net benefits of being located in own-industry concentrations. All the estimated elasticities are positive, which suggests that costs increase if firms locate in regions with high concentrations of the same industry. These coefficients are statistically significant at the 1 per cent level for four sectors and significant at 5 per cent for one industry sector. We find that, even when disaggregated by firm size, own-industry concentration systematically provides no net benefits; on the contrary, in some instances, own-industry concentration increases costs at the firm level.

The elasticities for input–output linkages (IO link) show that, for most industry sectors, proximity to buyers and suppliers potentially reduces costs at the firm level. Although the estimated elasticities are negative for six sectors, it is statistically significant at the 5 per cent level only for the metals industry. The coefficient of −0.01 means that a 10 per cent increase in the strength of buyer–supplier linkages is associated with firm-level cost reductions of 0.1 per cent. That is, doubling the strength of buyer–supplier linkages is associated with a 1 per cent reduction in firm-level production costs. When we look at the elasticities for small firms, we find that the estimates are insignificant for most cases. For medium-sized firms, the elasticity is negative and significant for the metals sector. The coefficient of −0.17 means that a doubling of IO linkages is associated with a 17 per cent reduction in firm-level costs. This effect is considerably stronger than the other estimates, where the cost elasticities rarely exceed 5 per cent. For large firms, we find that costs increase for food and

beverages and for electrical/electronics when firms are located in regions with relatively higher buyer–supplier linkages. In fact, the coefficient of 0.38 for electrical/electronics means that doubling of IO links increases costs by 38 per cent.

The estimates for local economic diversity indicate that there are considerable cost-reducing benefits from being located in a diverse region. The industry-wide estimates are negative for all sectors, and significant at the 1 per cent level for the food and beverages and textiles sectors. The coefficient of −0.10 for textiles means that doubling the region's economic diversity will reduce firm-level costs by 10 per cent. The results are even stronger for small firms. The estimated elasticities are negative for all industry sectors, and statistically significant for five sectors. The magnitude of these effects is really striking. For example, the estimated cost elasticity for electrical/electronics is 83 per cent and for chemicals it is 46 per cent. These estimates clearly indicate that there are very significant benefits of being located in a diverse economic region. For medium and larger firms, however, the results do not show similar benefits of location in diverse economic regions. The cost-reducing effects of being located in a diverse region are greater for small firms because they can rely on location-based externalities to a larger extent than can medium and big firms. The benefits come from better opportunities for subcontracting, access to a general pool of skilled labour, and access to business services such as banking, advertising and legal services. In addition to these pecuniary externalities, there are potential technological externalities from knowledge transfer across industries. Larger firms, being more vertically integrated and with higher fixed costs, are not likely to benefit from these externalities.[10]

In general, we find that regional economic geography has a reasonable degree of impact on the cost structure of firms. The sources and the magnitudes of these impacts vary considerably across industry sectors. The only major source of benefits that are likely to influence location choice at the margin is the location's economic diversity. This is especially likely to be the case for small firms. The magnitude of the other effects is so small (elasticity values of less than 5 per cent) that they are unlikely to influence firms' location choices.

3. Location patterns of private and state capital

This section contains an empirical test of the hypothesis that the location logic of state capital is different from that of private capital. Much of this material is summarized from Chakravorty (2003). Private capital seeks profit-maximizing or efficient locations. As shown above, these are the

already leading, diverse industrial regions that have the necessary infrastructure and economies of agglomeration (which, we show, are not necessarily cost reducing). The location decisions of state capital, on the other hand, are not as oriented towards the leading industrial regions because, besides efficiency, these decisions are based on equity and security considerations.

We will not revisit the literature on industrial location theory that is summarized well in Fujita et al. (1999). The basic assumption in this literature is that all capital is private capital and all location decisions are made by profit-maximizing private firms. The fact that the state is a significant owner of firms and industries is not considered. This is an omission of some consequence for three major reasons. First, state decisions on industry location are not necessarily or usually profit maximizing.[11] Second, in all developing nations industrialization has been state led, so that the state, to some degree, still owns the ''commanding heights'' of the industrial sector. Third, state industrial location decisions have considerable influence on the location decisions of private firms (mainly through the provision of shared infrastructure and localization economies).

Let us, like others before us, presume that market considerations are the only ones that need to be factored into the industrial location decision. There are two broad approaches to identifying the factors that influence firm location. One is survey based – it asks decision makers what location factors are important to them. The second is a modelling approach used to identify revealed preferences based on site/region characteristics. A large number of factors, with some overlap, have been identified using these two approaches. In general, the most important firm location criteria are: market access, infrastructure availability, agglomeration economies, state regulations (such as environmental and pollution standards, incentives in lagging regions or for emerging technologies) and the general level of political support (see Hanushek and Song 1978; Webber 1984; McCann 1998). The survey-based approaches reveal that there is a substantial random element in the choice of location: personal reasons, chance and opportunity are given as explanations almost half the time (see Mueller and Morgan 1962; Calzonetti and Walker 1991).

This analysis follows the revealed preference modelling approach. We consider the following categories of factors:

1. Capital, which refers to the quantity and productivity of the existing capital investments, and the availability of industrial capital from lenders.
2. Labour, which refers to the size of the industrial and total labour pool in the region, and the productivity of industrial labour. The size of the industrial labour pool is a measure of urbanization economies.

3. Infrastructure, which includes elements of physical and social infrastructure. Physical infrastructure elements such as roads and transportation hubs (ports, airports) are widely considered to be key determinants of plant location. Indicators of social infrastructure such as health and education standards provide an understanding of quality-of-life conditions, and may be considered to be worker amenities, which may be critical for some industries.
4. Regulation, which broadly refers to the system of incentives (such as tax breaks) and disincentives (such as environmental standards) that have to be factored into the location decision. This kind of highly localized or disaggregated information is difficult to get at the national level. This is especially true of India, where the key to decision-making may not be the localized incentive system but a sense of political support for industrialization in the region led by the private sector. Regimes that are ideologically opposed to liberalization are unlikely to provide the conditions that welcome new private investments, or may be perceived to be unfriendly to capital.
5. Geography, which includes spatial characteristics such as coastal or metropolitan location. Coastal locations provide access to the external world and physical amenities desired by high-level managers. Metropolitan locations provide large local markets, urbanization economies and, often, localization economies.

3.1. Data and summary conditions

Earlier we have shown why it is necessary to conduct location analysis using small spatial units. We have also discussed the ASI database. Here the ASI for 1993–1994 provides data for the pre-reform or initial conditions.[12] The second or post-reform database was created from the published records of the private sector firms, the Center for Monitoring the Indian Economy (CMIE). It is widely acknowledged that the best economic data in India are being generated by the CMIE (especially since there is no state agency tracking post-reform projects). The database used here is a collation of new project information published quarterly by the CMIE for the period 1992–1998. The 1991 data were ignored because they were unlikely to be an accurate list of "new" investments; after all, the reforms were only announced in July 1991. This database, which has about 4,650 records or projects (covering the entire period) and contains only those projects that have been completed or are under implementation and those that are not being funded solely by local government, forms the basis of all the post-reform calculations.

The new or post-reform investments, as identified from the CMIE data, total just over Rs 7 trillion (not including the direct investments

Table 8.4 Distribution of industrial investment by type of ownership (per cent)

	Fixed capital				
Ownership	1973–74	1985–86	1989–90	1994–95	1992–98
Public	60.1	61.6	55.0	43.3	30.7
Joint	5.6	10.2	7.5	9.5	12.0
Private	34.3	28.2	37.5	47.2	57.3

Source: CSO, *Annual Survey of Industries*, various years, and Center for Monitoring the Indian Economy for 1998 (authors' calculations).

made by state/local governments, which have been ignored throughout this analysis).[13] Exactly 50 per cent of this investment is by the domestic private sector, 7.3 per cent is foreign direct investment (FDI), 30.7 per cent is by the central government, and 12.0 per cent is in the joint sector (or private–public partnerships). For the purposes of the analysis here, the domestic private sector and FDI are added together to comprise the private sector. The joint sector data, which belong in neither of our exclusive categories, have also been omitted from the analysis.

Table 8.4 shows the extent to which the relative shares of the public and private sectors have evolved since the early 1970s. The decline of the public sector since the beginning of the Rajiv Gandhi reforms in 1985–1986 is evident. The new investment data (1992–1998) suggest that this decline has accelerated. This is a fundamental condition of liberalization and structural reform, and underlines our assertion that the state's role in industry ownership and location is now much diminished. Table 8.5 provides some indications of the spatial distribution of the post-reform investments. The data show that private sector investments have a wider spatial coverage and a much stronger coastal bias (almost half the total private investments are in coastal districts). The metropolitan data are unclear; certainly the intensity of investments in these districts is far higher than the non-metropolitan averages for both private and state sectors, but there appears to be some dispersal away from metropolitan districts.

3.2. *The model and methodological notes*

Following the earlier discussions, a general model of new investment location determination can be written formally as:

$$I_{\text{new}} = f\{K, L, I, R, S\}, \tag{8.7}$$

Table 8.5 Summary investment statistics by location

	Private sector	Central government
Number of districts with investment	294	164
Average investment in receiving districts (Rs billion)	13.55	11.40
All India per-district investment (Rs billion)	9.84	4.61
Metropolitan districts		
Number of districts with investment	17	14
Average investment per receiving district (Rs billion)	40.14	25.14
Share of total sectoral investment (%)	17.13	18.82
Non-metropolitan districts		
Number of districts with investment	277	150
Average investment per receiving district (Rs billion)	11.92	10.12
Share of total sectoral investment (%)	82.87	81.18
Coastal districts		
Number of districts with investment	48	32
Average investment per receiving district (Rs billion)	40.82	22.00
Share of total sectoral investment (%)	49.18	37.65
Inland districts		
Number of districts with investment	246	132
Average investment per receiving district (Rs billion)	8.23	8.84
Share of total sectoral investment (%)	50.82	62.35

Note: In June 2003, US$1 = Rs 48.
Source: Data sources are discussed in the text.

where K, L, I, R and S represent sets of explanatory capital, labour, infrastructure, regulation and spatial/geographical variables, respectively. I_{new} is the log transformation of the raw investment amount where the investment amount depends on the sector being modelled. That is, I_{new} is I_{newP} when only private sector investments are considered and is I_{newG} when only central government investments are considered. The *capital* set K has three variables:[14]

1. ASI-LOG is the log of total pre-reform investment (fixed capital).
2. IND_CREDIT is per capita lending to local industry by financial institutions.
3. CAPITAL_PROD is a measure of the productivity of capital at the district level, and is calculated as the value-added per unit of fixed capital for existing industry (calculated from the ASI data).

There are three *labour* variables:

1. LOGPOP is the log of district population.
2. LABOR_MANUF is the percentage of workers employed in non-household manufacturing industry.
3. LABOR_PROD is a measure of the productivity of labour and is calculated as the value-added per unit of factory labour (calculated from the ASI data).

There are three *infrastructure* variables:

1. INFRA is a measure of physical infrastructure, and is calculated as a function of proximity to national highways, airports and ports. The values of INFRA range from 0 to 3, where 3 represents a situation where the given district has at least one national highway passing through it (weight 1), has at least one airport within 100 kilometres (weight 1), and has at least one port within 100 kilometres (weight 1). INFRA is expected to be positively related to I_{new}, especially I_{newP}.
2. LITERACY is the percentage of the adult population that is literate.
3. INFNT_MORT is the mortality rate at age 5 years per 1,000 live births.

The only *regulation* variable is:

1. SOCIALIST, which is a dummy variable that takes a value of 1 for every district in West Bengal and Kerala, the two consistently communist-ruled states in the country. Districts in Tripura (another socialist state) were not used in the analysis, and we chose not to assign districts in Bihar as socialist. Bihar has what may be called a populist caste-based government, and giving it the distinction of socialism, for better or worse, may be inappropriate. The other problem with including Bihar in this category is that every other state that had left-of-centre governments in the early 1990s (such as Karnataka and Orissa) would have to be similarly characterized. Insofar as this variable is meant to represent political will – which may be resistance to liberalization or its counterpart, enthusiasm for reforms – Bihar should be so categorized. But, understanding the lack of investment in Bihar is an important goal, and we preferred not to cloud the issue by introducing the socialist element.

The *spatial* set S has three elements:

1. COASTAL, a dummy variable that takes a value of 1 for all coastal districts (57 districts were classified as coastal, i.e. situated on either the Bay of Bengal or the Gulf of Arabia).
2. METROPOLITAN, a dummy variable that takes a value of 1 for all metropolitan districts, i.e. the core city district and the surrounding suburban districts (26 districts were classified as metropolitan).
3. SPATIAL_LAG, which is a term that corrects for spatial autocorrelation and also has geographical meaning.[15] It is a measure of spatial

clustering, and the parameter estimates for this term will indicate the degree to which new investments cluster together; i.e. the extent to which I_{newP} is likely to locate in the proximity of other I_{newP}.

A major problem in undertaking ordinary least squares (OLS) regressions with these data is that the assumption of normality of the dependent variable is seriously violated. There are large numbers of districts with no investment (the private sector has 294 districts with investment, 113 without investment; the central government sector has 164 districts with investment, 241 without investment). These are not missing data but are a real measured absence of industrial investment. Hence, we cannot use OLS models on the full data set. But using only the non-zero data would not allow analysis of the absence of investment. Therefore we use two sets of models: a linear model set for the non-zero cases; and a logistic model set where the dependent variable is binary – i.e. it takes a value of 1 when there is some non-zero investment (call this situation "success") and 0 when there is no investment (call this situation "failure").

3.3. Model findings

The private sector logistic model (see Table 8.6) has far greater explanatory power than the model for the central government. The chi-square value is higher, as is the percentage of correctly predicted non-zero new investment districts. The two most important determinants of success or failure for private investment, that is, whether or not a district receives any new private sector investment, are the quantity of investment in the pre-reform era (ASI-LOG) and the quantity of new private investment in the neighbouring districts in the post-reform era (SPATIAL_LAG). On the other hand, the SPATIAL_LAG term is not significant for central government investment, implying that there are no clustering effects in this case. Similarly, the ASI-LOG variable has the expected but less significant effect in the central government model.

The set of labour variables (population size, size of manufacturing labour force and labour productivity) are all significant for the private sector model, indicating that labour considerations play a significant role in the private sector location decision. In the central government model, labour is a less important consideration – the district population size is significant, as is, to a lesser extent, the size of the manufacturing labour force, but labour productivity is of no consequence. The role of infrastructure is as expected. The literacy and infant mortality levels have little bearing on whether a district receives private sector or central government investment. The availability of physical infrastructure, on the other hand, plays a weak positive role in attracting private sector investment, but has no bearing on locating central government investment. Fi-

Table 8.6 Determinants of probability of receiving investment

Variable	Private sector	Central government
ASI-LOG	0.170***	0.177*
	(11.01)	(6.22)
IND_CREDIT	$4 * 10^{-4}$	$4 * 10^{-4}$
	(0.46)	(1.91)
CAPITAL_PROD	−0.405	0.224
	(1.89)	(0.65)
LOGPOP	0.663***	0.947***
	(7.70)	(14.47)
LABOR_MANUF	0.093*	0.059*
	(2.77)	(3.04)
LABOR_PROD	0.003**	$9 * 10^{-4}$
	(5.86)	(2.21)
INFRA	0.353**	0.093
	(4.52)	(0.50)
LITERACY	−0.003	−0.007
	(0.06)	(0.38)
INFNT_MORT	−0.002	$-3 * 10^{-4}$
	(0.16)	(0.01)
SOCIALIST	−1.189*	0.181
	(3.67)	(0.12)
COASTAL	−0.733	−0.366
	(1.57)	(0.845)
METROPOLITAN	4.109	−0.215
	(0.11)	(0.07)
SPATIAL_LAG	0.429***	0.076
	(22.98)	(0.55)
Constant	−7.957***	−11.225***
	(13.68)	(29.89)
Chi-square	172.32	117.40
Correctly predicted non-zero districts	91.50%	59.15%

Notes: Total number of districts = 405. Number of districts with non-zero private sector investment = 292. Number of districts with non-zero central government investment = 164. Figures in parentheses are Wald statistics.
*** indicates significance at 1% level, ** at 5% level, * at 10% level.
Source: Authors' calculations.

nally, private investment tends to avoid socialist states, but central government investments appear to be indifferent to local political orientation.

The OLS regression model (see Table 8.7) for the private sector is strong and robust; for the central government it is weak, with little explanatory power. The two most revealing trends of the logistic models are further confirmed here. First, the two most significant predictors of the quantity of new private investment are ASI-LOG and SPATIAL_LAG, whereas in the central government model ASI-LOG is not signifi-

Table 8.7 Determinants of quantity of investment

Variable	Private sector ($n = 292$)	Central government ($n = 164$)
ASI-LOG	0.161***	0.077
	(3.33)	(0.89)
IND_CREDIT	$2 * 10^{-6}$	$3 * 10^{-4}$*
	(0.02)	(1.91)
CAPITAL_PROD	0.059	0.109
	(0.19)	(0.32)
LOGPOP	1.453	−0.335
	(0.81)	(1.11)
LABOR_MANUF	0.063***	0.001*
	(2.63)	(1.70)
LABOR_PROD	0.001**	−0.042
	(2.35)	(1.21)
LITERACY	−0.0005	−0.113
	(0.06)	(0.67)
INFNT_MORT	0.006**	−0.007
	(2.35)	(0.45)
INFRA	0.162	$9 * 10^{-5}$
	(1.52)	(0.02)
SOCIALIST	−0.826*	−0.583
	(1.93)	(1.04)
COASTAL	0.965***	0.540
	(3.18)	(1.21)
METROPOLITAN	0.609	0.532
	(1.23)	(0.77)
SPATIAL_LAG	0.225***	0.337***
	(3.51)	(2.63)
Constant	−0.276	6.408**
	(0.19)	(2.48)
F (significance)	11.13 (.00)	2.30 (.00)
R^2 (adjusted)	.310	.094

Notes: This is an OLS regression model. The dependent variable is LOG of (private sector or central government) investment.
*** indicates significance at 1% level (two-tailed), ** at 5% level (two-tailed), * at 10% level (two-tailed).
Source: Authors' calculations.

cant; however, the SPATIAL_LAG variable is significant (unlike in the logistic model), suggesting that, though the odds of getting new central government investment are no better in clusters, when such investments do take place the quantity of investment is spatially correlated. In other words, the quantity of existing investment in a given district *i* or the quantity of new private investment in the neighbours of district *i* are the most important predictors of the quantity of new private sector invest-

ment in that district. Second, labour characteristics are significant in predicting the quantity of new private sector investments but not central government investments. In fact, population size and manufacturing labour force size have the counterintuitive sign (though not statistically significant) in the central government model.

The infrastructure variables generally have the least explanatory power in both OLS models. In the central government model, none of the infrastructure variables is significant. Unexpectedly, infant mortality is seen to be weakly but positively related to new private sector investment. It is possible that this is an artefact of the coexistence of high infant mortality levels and the richness of natural resource availability. Finally, the coastal variable is strongly significant in the private sector model. This is expected from the data reported in Table 8.5.

3.4. Discussion

This analysis was based on the argument that private sector investment location decisions are based on profit-maximizing or efficiency-related factors, whereas the central government investment location decisions would be less influenced by them. We also argued that, in seeking efficient locations, private sector investments would tend to favour existing industrial clusters and metropolitan centres with access to the coast and avoid regions with inhospitable local governments. The results provide definite support for both propositions. The location decisions of the private sector are indeed guided by efficiency-related factors to a far greater extent than are such decisions by the central government. In addition, private sector investments are seen to favour existing industrial clusters (providing support for the idea that the already leading industrial regions would benefit most) and coastal districts, and are seen to be averse to communist or socialist states. There is less support for the argument that such investments also favour metropolitan regions. On the other hand, central government investments appear not to be guided by any clear geographical consideration. These findings are consistent in both modelling frameworks: success/failure and the quantity of new investment – in other words, in determining whether or not a district gets new investment, and in determining the quantity of new investment.

It is clear that, for the private sector, the most significant factors are the size of investment from the pre-reform period in the same district and the size of new post-reform investment in the neighbouring districts. The first factor suggests continuity, or evidence of a historical process of investment location. The second factor suggests that new investments are clustered. In the central government models there is very weak evidence of some continuity (none as far as the quantity of new investment is con-

cerned), and somewhat stronger evidence of clustering (though not nearly as strong as for the private sector).[16]

4. Conclusion

Our main finding from the first part of the analysis is that industrial diversity (that is, the local presence of a mix of industries) provides significant cost savings for individual firms. Empirical evidence from Indian firms shows that this cost saving is the most significant factor for firms of all sizes and in all sectors of manufacturing industry. Other spatial factors that, in theory, have some productivity-enhancing effects (such as market access, own-industry clustering) are found to have little or no influence on profitability. At the national level, this raises questions about the validity of developing ''specialized clusters'' in remote areas, as instruments to promote regional development in lagging or backward regions. Such approaches have been implemented with limited success historically, but have seen a resurgence with the ''Porter-style'' competitive advantage analysis. On the other hand, policies that encourage the creation and growth of mixed industrial districts are likely to be more successful than single-industry concentrations.

The second part of the analysis confirms our expectations that private industry seeks profit-maximizing locations whereas state industry is far less oriented toward such locations. The emerging spatial pattern of industrialization is led by investments by the private sector, which is demonstrably averse to lagging and inland regions, just as the central government is becoming a weaker player. If the state will not or cannot be any more involved (for the foreseeable future the state can be only less involved in industrial ownership), and the private sector cannot be induced to lagging regions until some local political-economic problems are resolved (and these local problems may not be resolved without investment and growth), how can industrial development reach the lagging regions? And, without spatially balanced industrial growth, how can spatial income inequalities be mitigated?

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Notes

1. Throughout this chapter the term "industry" specifically refers to manufacturing industry, and does not include financial or business services.
2. There is a large literature on intra-national regional inequality, starting with the general approaches of Myrdal (1957), Hirschman (1958), Borts (1960), Williamson (1965), and Friedman (1973: 41–64). More recently, Barro and Sala-i-Martin's (1992) work on regional convergence has received attention, especially in developed nations. State-level regional inequality studies of India have been done by Chakravorty (2000) and Ghosh et al. (1998).
3. The district is the second tier of subnational administration in India, similar to counties in the United States and *municipios* in Brazil.
4. The urban centres database used in Lall et al. (2004a) includes latitude and longitude coordinates and 1991 population for 3,752 cities with a total population of about 217 million. The digital transport network data set includes an estimated 400,000 km of roads categorized into four classes by quality. The weighting parameter used in the accessibility computation is an estimate of travel time. As the exact geographical location of each firm is not publicly available, the authors summarize the accessibility for each district by averaging the individual values for all points that fall into the district.
5. This, however, is the best available option because we cannot identify firms below the level of the district.
6. In this analysis, we limit the analysis to buyer/supplier access, and do not include explicit measures of forward linkages (i.e. final demand). This is because the market access measure captures much of the forward linkages (sales to other firms and final consumers).
7. For Ω, we use a 1996 matrix of national technical coefficients from the "Input Output Transactions Table 1993–94", Ministry of Statistics and Programme Implementation. Each element of L is a standard location quotient calculated as the sum of employment in region r and industry i.
8. For a more intuitive interpretation of the measure for the diversity index in our model, H_r is subtracted from unity. Therefore, $DV_r = 1 - H_r$. A higher value of DV_r signifies that the regional economy is relatively more diversified.
9. There are some cells in Table 8.3 with no values. We do not report the estimated parameters in these cases because there are too few observations (see Table 8.2) to allow any meaningful interpretation of the results, especially when the model estimates around 50 parameters. As a rule of thumb, we do not report results for estimations with fewer than 200 observations (firms).
10. Although the estimated elasticity for large electrical/electronics firms is 235 per cent, it is likely that this result is a statistical artefact, and driven by some outliers.
11. Other approaches to location analysis recognize the "different locational considerations" of state capital, especially the following: the need to include and provide for the "poor and the geographically peripheral"; the absence of competition in what are often (loss-making) monopolies; the need to seek popular support, and the use of state investment as a method of doing so; the use of industrial location as the principal tool in regional development policy; consideration of the location of security-oriented or defence-related industry, which is obviously not dictated by market factors. See Harrington and Wharf (1995), Markusen et al. (1991), Chapman and Walker (1991).

12. Since the 1993–1994 data cover every unit that was in operation in 1993, whenever built, and since the period 1991–1993 (the first two reform years) is too short for any substantial industrial unit to be approved and go into production, this is the most realistic measure of Indian industry for the pre-reform period.
13. These figures also do not include investments in Jammu and Kashmir or any of the far north-eastern states (Arunachal Pradesh, Manipur, Meghalay, Mizoram, Nagaland or Tripura). The total of these investments comprises less than 0.2 per cent of nationwide investment, is almost entirely by the central and state governments, and is probably of dubious reliability. These data can be ignored without much loss of information or rigour.
14. The data definitions and sources, unless mentioned otherwise, are as follows.
    Literacy: from the 1991 population census, reported in ''Profiles of Districts'' (CMIE 1993), defined as the percentage of the population that is literate.
    Infant mortality: from Rajan and Mohanchandran (1998), defined as the number of deaths per 1,000 live births at age 5, estimated from the 1991 population census.
    Manufacturing labour: from the 1991 population census, reported in ''Profiles of Districts'' (CMIE 1993), defined as the percentage of workers employed in non-household manufacturing industries.
    Industrial credit: reported in ''Profiles of Districts'' (CMIE 1993), defined as the per capita bank credit to industries derived from the information on scheduled commercial bank branches, deposits and credits on the last Friday of March 1993.
15. The existence of spatial autocorrelation or spatial dependence poses serious problems in regression modelling, much like serial autocorrelation does (see Anselin 1995). One of the ways of dealing with this problem is to add a ''spatial lag'' term on the right-hand side, where the lag value for a given parcel is some summary of the dependent variable in proximate parcels. The argument for using the spatial lag correction for a given district is that its investment is not independently caused by the regressors but is dependent on the regional investment situation. Therefore, the spatial lag term corrects for spatial autocorrelation in spatial regression models, and at the same time is a measure of clustering.
16. Note that these models are unable to identify all the factors that influence industrial location decisions. There is a random element in the distribution (remember that personal preference or chance is the most common factor in the location decision). Also there are non-random local factors – such as local- or state-level policy changes (tax incentives, the location of export processing and/or free trade zones, etc.), and some intangibles such as culture, entrepreneurship and initiative – that have not been modelled here.

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9

Spatial horizontal inequality and the Maoist insurgency in Nepal

S. Mansoob Murshed and Scott Gates

1. Introduction

The landlocked Himalayan kingdom of Nepal is in the grips of a Maoist insurgency. Nepal is a low-income developing country, and it ranked 129th out of 162 countries in the composite human development index (HDI) in 2001, making it a low human development nation (see UNDP 2001). Nepal is also a new democracy, having been an absolute monarchy prior to 1991. Nepal is composed of 75 districts across five geographical areas: eastern, central, western, mid-western and far western. Each of these areas is divided into three ecological zones: mountain, hill and plain (tarai).

The Maoist insurgency in Nepal began in 1996.[1] Between February 1996 and July 2001, in the "people's war" or first phase of the present conflict, the total casualties numbered 1,593 (see Gautam 2001). This means that it was a medium-intensity conflict (see Wallensteen and Sollenberg 2000 for the definition of conflict intensity[2]), with engagements taking place mainly between the police and Maoists. After the failure of the first peace talks (July–November 2001), the conflict entered a new and more intense phase involving the Royal Nepalese Army (RNA), and, judging by the number of casualties, it is one of the highest-intensity internal conflicts in the world at present. Between November 2001 and April 2002, there were 2,046 conflict-related deaths. This death toll continued to mount in 2002. The civil war has also led to widespread human rights abuses (see Amnesty International 2002), including the murder,

rape and torture of civilians by the RNA, extortion and the use of civilians as human shields by the Maoists.

It is the contention of this chapter that inter-group inequality and landlessness play a central part in motivating and sustaining the conflict in Nepal. The concept of horizontal or inter-group inequality, which is highly relevant in explaining the Nepalese civil war, has both an ethnic and a caste dimension. Additionally, there is a spatial aspect to the conflict, which is most intense in the mid-western and far western regions of Nepal, economically the most disadvantaged regions in terms of human development indicators and asset (land) holdings. This conclusion is based upon econometric analysis using district-wide data on human development indicators (UNDP 1998) for 1996, the year the conflict commenced, district-wide data on landlessness as well as geographical characteristics, alongside figures for fatalities in all of the districts of Nepal. Using the intensity of the conflict (measured by the number of deaths) as the dependent variable and HDI indicators and landlessness as explanatory variables, we find that the intensity of conflict across the districts of Nepal is significantly explained by inequality indicators.

The rest of the chapter is organized as follows. Section 2 looks at horizontal inequality and other explanations for contemporary civil wars. Section 3 moves on to apply these ideas to the specificities of the Nepalese case. Section 4 outlines the econometric results, and section 5 concludes with policy implications.

2. The causes of civil war

2.1. Greed versus grievance

In recent years, economists have started paying more attention to internal conflict, motivated by the pressing need to understand continued development failure. This literature makes a distinction between *grievance*, based on a sense of injustice owing to the way in which a social group is treated, often with a strong historical dimension; and *greed*, an acquisitive desire similar to crime, often on a much larger scale. According to the proponents of the greed theories of civil war, "greed" is disguised as political grievance – see Berdal and Malone (2000) and Collier and Hoeffler (2001) for examples of these types of arguments. By contrast, the alternative set of explanations emphasizes grievances, particularly discrimination against well-defined groups based on ethnicity or religion. The inequality that arises from this process is described as *horizontal* inequality (Stewart 2000), which should be distinguished from vertical inequality across a relatively homogeneous community. Discussion of greed as a

motive for conflict has mainly arisen in the context of mineral resource endowments, an abundance of which appears to increase the risk of a country falling into serious conflict. Greed might drive civil war, but it is mainly in the context of capturable resource rents, such as oil, diamonds or drugs. Addison et al. (2002) argue that it is not only resource rents that cause conflict; grievances also play their part in fuelling conflict, as does poverty. In practice, greed and grievance are inextricably intertwined.

Most contemporary civil wars in developing countries have an ethnic dimension, in the sense of well-defined and ethnically distinct groups fighting one another. One reason is that ethnicity resolves the collective action problem of mobilizing groups to fight one another. Ethnicity – whether based on religion, language or some other form – is a powerful organizing principle, far superior to social class. It overcomes the collective action problem (Olson 1965), whereby groups are unable to cooperate owing to mutual suspicions. Well-defined grievances, however, are required for ethnically based conflict. That is why horizontal inequality can be so important. Some of the causes of this type of inequality may be historical, others are a product of discrimination and policy failures. Of course, collective action based on ethnicity requires conflict entrepreneurs or warlords to do the organizing (Gates 2001). Some of the salient aspects of horizontal inequality are briefly described below:

1. *Asset inequality*: Land inequality and the dispossession of peasant communities provide fertile ground for insurrection, particularly when the dispossessed belong to separate and distinct groups drawn along caste, ethnic or religious lines.
2. *Unequal access to public employment*: Discrimination in the allocation of public employment is particularly resented in societies where it represents the principal avenue for personal advance.
3. *Unequal access to public services and overtaxation*: The overtaxation of smallholders encourages insurrection, and indigenous peoples often face discrimination in access to schooling, health care and public sector jobs.
4. *Economic mismanagement*: The risk of civil war is greater in low-income developing countries where poverty and poor human development indicators abound in the context of low growth rates. The lack of normal economic occupation amongst young males has been found to contribute significantly to the risk of civil war (Collier and Hoeffler 2001).

2.2. The social contract and institutions of conflict management

The catalogue of reasons outlined above pertains to the *risk* of war. For large-scale violence to break out, other factors must be present. Not all

societies with characteristics contributing to the risk of conflict, even those highly at risk, descend into open warfare. For that to occur there has to be a failure of the institutions of conflict management and a degeneration of the systems of redistribution. This is what Addison and Murshed (2001) and Murshed (2002a) refer to as the social contract. Such a viable social contract can be sufficient to restrain excessive opportunistic behaviour and the violent expression of grievance. Conflict-affected nations typically have histories of weak social contracts or a once strong social contract that has degenerated.

What causes poor institutions to emerge? Several theories abound (see Murshed 2002b for a survey of the endogenous political economy literature). In certain cases an extractive and predatory pattern of production is set up. This prevents superior institutions, especially related to property rights and the rule of law, from taking root. An extractive or predatory form of production is not exclusively related to plantations and mines, but can also be associated with agricultural feudalism and the tax farming associated with it. As the extractive state is expropriatory and predatory, poor institutions emerge and become entrenched over time. Such societies also tend to depress the middle-class share of income in favour of elites. These elites use their power, which is identical with the forces of the state, to coerce and extract rents (Bourguignon and Verdier 2000). The important point made by Easterly (2001) is that small elite-based societies do not have a stake in the long-term development of the land. Unlike in societies dominated by the middle class, there is less publicly financed human capital formation and infrastructure, depressing growth prospects and increasing the risk of conflict.

Are democratic societies less prone to descend into violent conflict? Hegre et al. (2001) have demonstrated a U-shaped relation between democratic institutions and the incidence of civil war over time. The probability of civil conflict is lowest both in established, well-functioning democracies and in perfect autocracies. It is at some intermediate or transitory stage between autocracy and democracy that the risk of internal conflict is greatest. This suggests that state failure is more likely in between autocracy and well-functioning democracy. In this connection it should be pointed out that until recently (1991) Nepal was an autocracy and the transition to democracy is still at an early stage, increasing the risk of conflict. Indeed, Hegre et al. (2001) find that political transition is a primary factor in increasing the risk of civil war. Moreover, Nepal has reverted to being an autocracy, under the personal rule of the monarch (see Gates and Strand 2004, who statistically demonstrate that the risk of new democracies collapsing is greatest in the early years of democracy).

The duration of conflict is clearly related to the financing of the war ef-

fort, especially but not exclusively for the rebels (Addison et al. 2001). The work of Buhaug and Gates (2002) suggests that, in general, civil wars and conflict in the context of a mountainous region or where the conflict zone abuts an international frontier can increase the duration and intensity of the conflict. Generally speaking, the longer a conflict persists, the greater the price of peace in terms of the concessions that need to be made. The work of Walter (2001) across a cross-section of countries demonstrates that it takes several attempts at peace-making, and many failed peace agreements, before lasting peace emerges. This suggests an imperfect commitment to peace at various stages by the belligerent parties to civil war and insurrection. Addison and Murshed (2002) point out that this may be because of an impatience to consume the rents that arise in the context of war and the war economy.

3. Horizontal inequality and institutional failure in Nepal

The cultural context of the Nepalese conflict is analysed in detail in Bista (1991). The overlap between caste and ethnicity in explaining horizontal inequality in Nepal occurs because people from the less privileged castes in Nepal (the non-Bahun–Chetri–Newari peoples)[3] are often also from different ethnic groups from the elite. Because the civil war in Nepal has a Maoist ideological orientation, this adds an element of class struggle and is an extension of political struggles against elite (Bahun–Chetri–Newari) domination of political and economic life. There is little in the sense of capturable natural resources in Nepal to point to ''greed'' as a motivating factor in the onset of Nepal's conflict, unlike in much of Africa. The circumstances here point to grievances as the major catalyst for conflict, at least on the Maoist side, although greed-related motivation could emerge if the war persists.

3.1. Horizontal inequality in Nepal

Data pertaining to the human development index are presented in Tables 9.1 and 9.2 – Table 9.1 refers to the period 1999–2000 (the latest available data) and Table 9.2 reports statistics for 1996, when much more detailed information at the district level was available. District-level indicators are unavailable for 1999–2000.

Nepal made progress in terms of the HDI between 1996 and 2000, with the national HDI rising from 0.325 to 0.466. The HDI is an equal-weighted sum of income per capita, educational attainment and longevity. The improvement in Nepal was mainly a result of a rise in the adult literacy rates. The poverty headcount according to the national standard

Table 9.1 Human development indicators for Nepal, 1999–2000

	PPP GDP per capita		HDI		Life expectancy		Adult literacy	
		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)
Nepal	1,237		0.466		59.5		50.7	
Rural	1,094	88	0.446	96	58.7	99	48.0	95
Urban	2,133	172	0.616	132	71.1	119	69.0	136
Ecological zone								
Mountains	898	73	0.378	81	49.8	84	44.5	88
Hill	1,262	102	0.510	109	65.1	109	55.5	109
Tarai	1,267	102	0.474	102	62.4	105	46.8	92
Development zone								
Eastern	1,073	87	0.484	104	62.0	104	56.6	112
Central	1,713	138	0.493	106	61.3	103	49.8	98
Western	1,022	83	0.479	103	62.8	106	51.7	102
Mid-western	861	70	0.402	86	53.2	89	47.8	94
Far western	899	73	0.385	83	52.1	88	43.0	85

Note:
[a] "Gap" refers to the percentage difference from the corresponding figure for Nepal.
Source: UNDP (2001).

of 4,404 Nepal rupees per annum was about 42 per cent (42 per cent of the population live below the national poverty line). The Gini coefficient measure of inequality for Nepal as a whole is 35 (UNDP 2001).[4]

If we look at the purchasing power parity (PPP) GDP per capita or income per head across the regions, we find that it worsened for the far western and mid-western regions between 1996 and 1999 (Tables 9.1 and 9.2). These regions, which are where the contemporary Maoist armed struggle in Nepal started, have not benefited from the recent growth in the rest of the economy, prima facie evidence of *worsening* horizontal inequality. The picture is even more startling when we examine district-wide data for 1996, the year in which the current "people's war" commenced (sourced from UNDP 1998). The mid-western districts of Rolpa, Jajarkot and Salyan had only 25, 19 and 17 per cent, respectively, of the average income in Kathmandu. In the far western district of Achham, the average income was only 24 per cent of that in Kathmandu in 1996. Accompanying the per capita income differentials are wide gaps in HDI indices. For example, the HDI for Rolpa, Jajarkot and Salyan was only 45, 44 and 35 per cent, respectively, of the Kathmandu level in 1996. In Achham, the HDI for 1996 was only 39 per cent of that in Kathmandu. All of these indicators are evidence of extreme inequality vis-à-vis the capital in

Table 9.2 Human development indicators for Nepal, 1996

	PPP GDP per capita		HDI		Life expectancy		Adult literacy	
		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)
Nepal	1,186		0.325		55.0		36.7	
Eastern	1,148	97	0.339	104	55.4	101	41.9	114
Mountain	1,033	87	0.342	105	58.9	107	38.4	105
Hill	892	75	0.368	113	64.2	117	40.2	109
Tarai	1,326	112	0.378	116	59.8	109	43.2	118
Central	1,442	122	0.339	104	55.7	101	35.1	96
Mountain	1,099	93	0.269	83	53.1	97	22.2	60
Hill	1,871	158	0.441	136	64.7	118	45.0	123
Tarai	1,185	100	0.310	95	56.2	102	29.1	79
Western	1,082	91	0.350	108	59.3	108	39.5	108
Mountain	1,075	91	0.313	96	52.7	96	39.5	108
Hill	1,235	104	0.351	108	57.2	104	41.0	112
Tarai	867	73	0.349	107	62.5	114	37.0	101
Mid-western	933	79	0.276	85	51.2	93	32.2	88
Mountain	770	65	0.241	74	52.7	96	19.6	53
Hill	961	81	0.311	96	56.8	103	33.2	90
Tarai	943	80	0.307	94	55.7	101	33.9	92
Far western	916	77	0.286	88	52.1	95	34.6	94
Mountain	648	55	0.261	80	52.7	96	29.6	81
Hill	909	77	0.260	80	48.9	89	31.5	86
Tarai	1,061	89	0.327	101	55.9	102	39.5	108

Note:
[a] "Gap" refers to the percentage difference from the corresponding figure for Nepal.
Source: UNDP (1998).

areas of Nepal that can be described as the major flashpoints of the Maoist insurgency.

We can attempt to calculate pseudo-Gini coefficients for spatial inequality based on the information in Tables 9.1 and 9.2. Several caveats are in order here. First, the five geographical regions of Nepal do not correspond to income group quintiles, each with an equal share (20 per cent) of the population. Second, and more importantly, the figures are based on highly aggregated data. These conceal a great deal of within-group inequality. The range of variation in income between the richest and poorest region (about double in 1999–2000) is considerably smaller than one would expect in a society where the Gini coefficient is about 35 across income groups based on household expenditure surveys. Nevertheless, pseudo-Gini coefficients do provide some information, bearing in mind that they are considerably smaller than normal Gini coefficients.

Table 9.3 Caste differences in Nepal, 1996

	PPP GDP per capita		HDI		Life expectancy		Adult literacy	
		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)		Gap[a] (%)
Nepal	1,186		0.325		55.0		36.7	
Brahmin (Bahun)	1,533	129	0.441	136	60.8	111	58.0	158
Chetri	1,197	101	0.348	107	56.3	102	42.0	114
Newar	1,848	156	0.457	141	62.2	113	54.8	149
Limbu	1,021	86	0.299	92	53.0	96	35.2	96
Muslim	979	83	0.239	74	48.7	89	22.1	60
Ahir	1,068	90	0.313	96	58.4	106	27.5	75
Occupational castes	764	64	0.239	74	50.3	91	23.8	65
Other	1,130	95	0.295	91	54.4	99	27.6	75

Note:
[a] "Gap" refers to the percentage difference from the corresponding figure for Nepal.
Source: UNDP (1998).

In fact, one would expect lower Gini coefficients associated with horizontal inequality, as long as low- and high-income groups exist in all regions and communities. The spatial Gini coefficient based upon regional per capita income did, however, worsen from 9 in 1996 to 13 in 1999–2000. The Gini coefficient for the overall HDI remained at 5 during this period, as did the Gini coefficient for adult literacy. The life expectancy Gini coefficient rose from 3 to 4 during the same period.

So far we have focused on the spatial dimensions of horizontal inequality in Nepal. We now move on to ethnic or caste aspects. Table 9.3 presents inequality across caste lines, another and perhaps more powerful form of horizontal inequality. The upper castes (Bahun–Chetri–Newar) constitute only 37.1 per cent of the population according to the 1991 census, yet their human development indicators can be about 50 per cent greater than those of the hill ethnic, tarai ethnic and occupational caste groups. Income per capita amongst the disadvantaged hill ethnic groups is about 55 per cent of that of the Newaris.

The caste/ethnic-level pseudo-Gini coefficients are subject to the same caveats as mentioned earlier. We have data pertaining only to 1996, for which the pseudo-Gini based on caste is greater than the spatial pseudo-Gini (14, compared with 9). This suggests that the caste dimension to horizontal inequality exceeds its spatial counterpart. The pseudo-Ginis for HDI (13), life expectancy (5) and adult literacy (20) are also more unequal than the corresponding spatial measures (5, 3 and 5, respectively). It seems educational inequality is the worst of all.

Table 9.4 Central civil service by caste, 1989 and 2000 (per cent)

	Section officer	Assistant secretary	Deputy secretary	Joint secretary	Additional secretary	Secretary
1989						
Brahmin (Bahun)	62.1	54.5	45.6	54.9	46.2	31.3
Chetri	9.5	11.2	13.4	17.1	15.4	31.3
Newar	21.0	26.6	29.9	22.5	34.6	25.0
Hill ethnic	2.0	0.9	2.1	0.0	3.1	–
Tarai ethnic	4.2	5.2	7.9	5.4	–	9.4
Muslim	0.3	0.3	0.0	0.0	–	–
Others	0.8	1.3	0.9	0.0	–	–
2000						
Brahmin and Chetri				73.4		74.3
Newar				22.3		17.9
Others				4.3		7.8

Note: Numbers may not sum to 100 per cent because of rounding and missing data.
Sources: Gurung (1998: 121) for 1989; ESP (2001: 84) for 2000.

Table 9.4 presents the breakdown of the composition of the central civil service by caste. Not surprisingly, the upper castes dominate, and their representation is vastly in excess of their population share. The table shows that, at least in the upper echelons (secretary or joint secretary), Bahun–Chetri–Newar domination was even more entrenched in 2000 (in the post-democracy era) than in 1989, when Nepal was under the direct rule of the monarch. According to Gurung (1998: 121), in 1992 about 87 per cent of all graduates came from the higher castes. The lack of employment opportunities for ethnic peoples at the level of the central civil service, combined with landlessness and the debt trap, greatly reduces their opportunities for peaceful employment, making the alternative – armed rebellion – a less unattractive option (Grossman 1991).

Table 9.5 presents the pattern of landholding in Nepal based on official figures. It shows that, following land reform and land ceiling acts, the percentage of large holdings (greater than 4 hectares) declined, as did the area covered by large holdings. However, the percentage of medium-sized holdings (1–4 hectares) shows an upward trend, at least in terms of the acreage or area covered by such holdings. The table also suggests that there is a great deal of avoidance of land ceiling legislation by parcelling off ownership to relatives. The area covered by small holdings appeared to be on the rise during the 1980s. The 2001 census states that about 1.2

Table 9.5 Landholding in Nepal

	1961		1971		1981		1991	
	Households	Area	Households	Area	Households	Area	Households	Area
Landless (million)	1.43	–	0.80	–	0.37	–	1.17	–
<1 hectare (%)	73.89	24.03	76.77	27.20	66.32	17.33	68.63	30.50
1–4 hectares (%)	19.56	35.68	18.39	39.29	28.05	46.13	27.68	50.80
>4 hectares (%)	5.13	41.42	4.03	33.74	5.35	36.54	2.51	18.70

Note: Numbers may not sum to 100 per cent because of rounding and missing data.
Source: Central Bureau of Statistics (cited in Karki 2001: 27).

million households, around a quarter of all Nepalese households, are landless. It is not landlessness per se that is the problem, but the corrupt practices associated with land redistribution and the even more invidious debt trap nexus that lie at the heart of rural grievance so central to the Maoist uprising. These are considered in the next subsection.

3.2. Institutional failure in Nepal

The bonded labour system

The practice of bonded labour (Kamaiya) is widespread in the tarai and mid-western regions of Nepal, and has its historical antecedents in a system of compulsory unpaid labour services, which all classes except the exempt Bahuns and Chetris had to render. The modern Kamaiya system is related to the debt nexus (*saunki*), which forces the indebted to render labour services in lieu of debt servicing. In principle, there is a voluntary contract, but in practice the renewal of the contract is based on compulsion and occasionally on the falsification of the debt outstanding (Karki 2001). The movement against this system began in the 1950s. But, importantly, this campaign has intensified, especially within the Kamaiya community, with Maoist support since the restoration of democracy in 1991. The failure to deal with this problem is evidenced by the fact that it was only officially abolished on 17 July 2000. Land given to the Kamaiyas under official land redistribution systems has eventually ended up back in the hands of the erstwhile landlords, with the Kamaiyas once again falling into debt, owing to their inability to generate enough income.

Landlessness (sukumbasi)

Along with the Kamaiya system, landlessness and the unfair practices connected with it are at the centre of rural unrest fanning the Maoist insurgency. Central to the Maoist movement is the destruction of (sometimes false) mortgage and debt documents. Various attempts at land reform since the 1960s, motivated by donor (American) pressure to contain the spread of communism in Asia, failed to redistribute land successfully amongst the landless (Karki 2001). Redistributed land ended up in the hands of the non-poor and, as long as the debt nexus was not modified, the burden of debt servicing rendered the recent landless once again landless.

The extractive state

Since the Rana period (1846–1950), the Nepalese state has been extractive in the sense of exacting excess rents from the peasantry and smallholders. The landlord was a tax farmer. The effect is the development of

poor institutions as discussed above. The state is akin to a roving bandit, and not a stationary bandit with an encompassing interest in the land (Olson 1996). It also lacked the far-sightedness (or a sufficient fear of communism) of the leadership in north-eastern Asia (South Korea and Taiwan), whose redistribution of land proved central to their future development. In Nepal, on balance, the state has chosen to suppress rather than placate or remedy grievances, particularly rural demands. Nepal's imperfect democracy since 1991 raised expectations but failed to deliver, and the state is seen to be ineffectual and corrupt. In many ways, corrupt and rent-seeking politicians have replaced the former feudal tax farmer.

4. Empirical results

4.1. Hypotheses

Our central hypothesis is that violent civil conflict, specifically its intensity, is caused by asset (and horizontal) income inequality. Landlessness serves as a proxy for the former, whereas HDI is a proxy for the latter. We further hypothesize that natural resource rents are absent. Moreover, we posit that criminality and loot are not currently an issue in the Nepalese conflict.

4.2. Data

To evaluate civil violence, we examine the number of people killed in each of the 75 districts of Nepal, and analyse these figures with respect to a common set of independent variables. The data for the dependent variable are based on Gautam (2001). Some Maoist fighters may travel to the conflict zones but, nevertheless, areas where the fighting is most intense reflect local conditions and a degree of regional support, because many of the guerrillas reside there. The common independent variables are also based at the district level and include: life expectancy (measured in years); years of schooling; human development index (HDI); landlessness (the proportion in a district that hold no land); road density (a measure of the concentration of paved roads); a natural resource index; the extent of mountainous terrain (the percentage of area sloping by more than 30 degrees); and, as a means of controlling for a curvilinear effect, the mountainous area squared. Because we are particularly interested in the extent of horizontal inequality, several of these variables are transformed with respect to the gap between Kathmandu and each district. We rely on five such variables to test our hypothesis: the life expectancy gap, the schooling gap, the HDI gap, the landlessness gap and the road

Table 9.6 Summary statistics of dependent and independent variables

Variable	Mean	Std. dev.	Min.	Max.
Killed (number)	50.216	94.4729	0.0	521.0
Life expectancy (years)	55.647	6.1491	36.0	66.5
Life expectancy gap	−11.353	6.1491	−31.0	−0.5
Schooling (years)	2.023932	0.7038	0.813	4.385
Schooling gap	−3.330	0.7038	−4.541	−0.969
HDI	0.3170	0.0656	0.147	0.523
HDI gap	0.526	0.1089	0.244	0.867
Road density	0.0567	0.1047	0.0	0.785
Road density gap	0.060	0.1120	0.0	0.837
Landlessness	0.389	0.1410	0.176	0.847
Landlessness gap	0.129	0.1410	−0.083	0.587
Natural resource index	0.38	21.7950	1.0	75.0
Mountainous area	0.515	0.2570	0.0	0.93
Mountainous area squared	0.335	0.2451	0.0	0.859

Note: Number of observations = 74 districts. "Gap" refers to the percentage difference from the corresponding figure for Kathmandu.
Source: Authors' calculations.

density gap. The natural resource index and mountainous area parameters control for geographical factors. The data for all the independent variables come from UNDP (1998) and pertain to 1996, the year the conflict began. The summary statistics for these data are presented in Table 9.6. The count is a cumulative value of the number killed.

4.3. Method and results

To examine the data on specific counts of incidents of civil violence, we utilize a Poisson regression analysis. The Poisson distribution is especially appropriate when dealing with small numbers of events. The Poisson distribution describes the probability that an event occurs λ times, given that each occurrence is independent and has a constant probability.[5] The shape of the Poisson distribution depends on the value of its mean (which is equal to its variance). If the mean is close to zero, then the distribution is skewed; if the mean is larger, the peak moves further from the vertical axis. (If the mean is very large, the Poisson distribution can be approximated with the normal distribution.) Figure 9.1 portrays the distribution of the dependent variable. This distribution is clearly skewed, demonstrating the appropriateness of Poisson regression analysis.

The Poisson distribution for Y_i is a function of λ, the mean probability of an event occurring in a fixed period:[6]

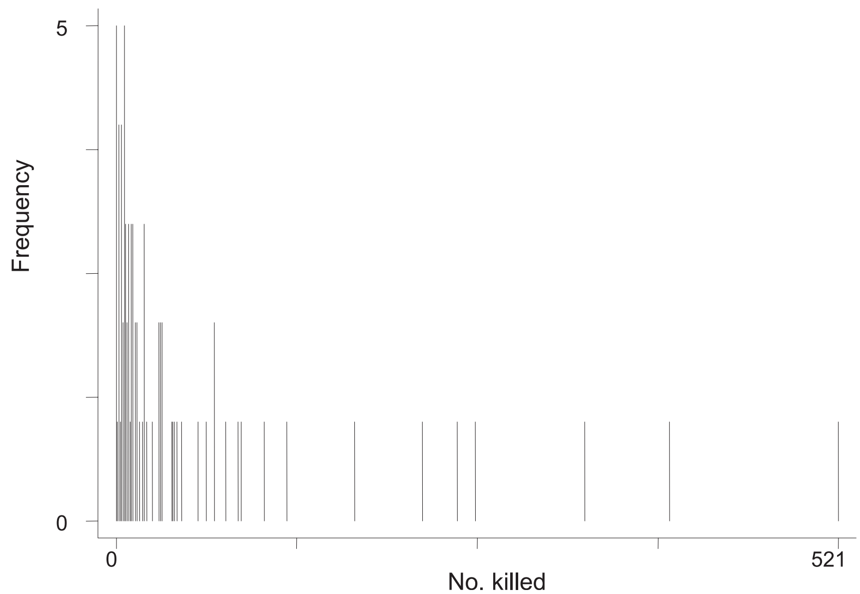

Figure 9.1 The distribution of the dependent variable.

$$\Pr(Y_i = \text{event of violent civil conflict}) = f(y_i) = \frac{\exp(-\lambda_i)\lambda_i^y}{Y_i!}.$$

We reparameterize λ in terms of some set of explanatory variables, x_i, and coefficients b. Because λ must be positive, we choose exponentiation as the link function, i.e. $\lambda = \exp(x_i b)$. These procedures are standard. The results of this analysis are presented in Table 9.7.

Poisson regressions (with a linear link as we use here) are somewhat unique for maximum likelihood estimates in that the coefficient estimates can be interpreted in a way similar to OLS coefficients. We have also reported the marginal effect of the explanatory variables, $\partial\mu/\partial X_i$,[7] that is, the rate of change of the mean value (number killed) with respect to an independent variable.

All independent variables except the mountain resources interactive variable are statistically significant, with p-values well below the standard 0.05 criteria (the p-values were estimated using White robust standard errors.) The gaps between a district and Kathmandu in terms of life expectancy, schooling, road density and the natural resource index are all negatively associated with deaths resulting from armed civil conflict. By increasing life expectancy and education (or, more particularly, by decreasing the gap with Kathmandu), a district would see the number of

Table 9.7 Poisson regression analysis of number killed by civil violence

Dependent variable: Number killed	Coefficient	Robust SE	$P > \|z\|$	Marginal effect
Life expectancy gap	−0.1905	0.08393	.012	−3.6494
Schooling gap	−1.505	0.59489	.005	−28.838
HDI gap	16.6702	7.19407	.010	31.942
Landlessness gap	1.88209	1.01157	.032	3.606
Road density gap	−25.47	6.48825	.000	−48.805
Natural resource index	−0.0215	0.01053	.021	−0.412
Mountainous area	4.4713	3.37231	.092	
Mountainous area squared	−6.5367	3.4469	.029	
Constant	−11.034	6.44902	.044	
Number of observations	74 districts			
Wald chi-squared (8)	81.12			
Probability > chi-squared	0.0000			
Log likelihood	−1929.3594			
Pseudo R^2	.5069			

Note: The dependent variable is a count of the number of people killed by civil violence in each district of Nepal. The *p*-values are for one-tail tests.
Source: Authors' calculations.

deaths drop. Schooling has a strongly negative substantive effect. An increase in the average level of schooling by one year in a district is associated with a corresponding drop in casualties of approximately 29. Similarly, an increase in road density of 10 per cent is associated with a reduction in the number killed by nearly 49. Factors that can improve the life of the citizenry could lead to a marked reduction in the predicted degree of violence in a district.

Other indicators of horizontal inequality (measured in terms of the gap between a district and Kathmandu) play a notably strong role in increasing the propensity for civil conflict. The gaps in the human development index and landlessness both possess strong coefficient values. The effect of increasing the HDI gap is especially strong. We find that the greater the degree of inequality in a district relative to Kathmandu, the greater the intensity of conflict. An increase in the HDI gap of 10 per cent is associated with an increase of 32 killed by political violence on average. These results lend strong support to our central hypothesis. Resource availability is associated with lower levels of civil violence. This result tends to contradict the proposition that resource abundance leads to conflict. Indeed, it appears that resource-rich districts are likely to experience fewer deaths as a result of civil conflict than resource-poor districts, but the substantive effects are modest. We also examined the effect of geography and find a curvilinear pattern, evidenced by the statistical sig-

nificance of the squared term for the portion of mountainous terrain in a district. Our results indicate that the extremely mountainous areas and the valleys are less prone to violence, whereas the areas in between are most vulnerable.

The results from the Poisson regression analysis prove to be quite robust and significant. In addition to numbers killed as a result of acts of civil violence, we also examined the incidence of civil conflict in general (bombings and other forms of property destruction). These results are quite similar to those presented here.

5. Conclusions and policy implications

As presented in sections 3 and 4, horizontal inequalities in Nepal robustly explain the intensity of the Maoist insurgency. Many of these inequalities have worsened in recent years, and group differences based on caste and ethnicity are central to explaining the genesis of the present conflict. The caste dimension to horizontal inequality appears to exceed the spatial dimension. Reducing horizontal inequalities is part and parcel of the strategy of overall poverty reduction. The difference with conflict countries such as Nepal is that there needs to be an equal focus on tackling horizontal inequalities in addition to the general strategy of poverty reduction. The twin strategies of poverty and horizontal inequality reduction are *complementary* and do not compete with one another. It also has to be remembered that poverty, the lack of employment opportunities and other forms of horizontal inequality assist Maoist recruitment and retention, making life in Maoist cadres a relatively attractive option. The key areas of horizontal inequality that need to be addressed are landlessness, the debt burden of the rural poor and greater access for lower castes to state-sector jobs.

Donor support and aid can play a pivotal role in reducing conflict intensity. Despite the fact that aid is fungible and money allocated for social sector expenditure may be diverted to military use, aid could prove useful in reducing the intensity of fighting. This is because military expenditure is very resilient in the presence of civil war. Without aid, social sector expenditure might be even lower than in the presence of aid. The peace party within the state needs to be encouraged, and improvements in matters relating to human rights could be a condition of aid. Development assistance needs to be related to "commitment technologies", actions that promote lesser conflict intensity (see Addison and Murshed 2002).

At a fundamental level there is a trade-off for the state that involves fighting the insurgents or appeasing them. It is, therefore, unfortunate

that some donors encourage military solutions by providing military aid and tolerating Nepal's slide back to autocracy on the basis of an inapplicable excuse – fighting international terrorism. Outright military victory for either side is unlikely. A narrow focus on the prosecution of war also serves to distract all concerned from the root causes of the insurgency: inter-group inequality, poverty and widespread human rights abuses.[8] Military strategies do not assist the process of the removal and redress of human rights abuses, which is so central to eliminating the ordinary Maoist guerrilla's intrinsic motivation to fight.

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Notes

1. See Bray et al. (2003) for further details on the origins and time-line of this conflict.
2. Low-intensity armed conflict: at least 25 battle-related deaths per year and fewer than 1,000 battle-related deaths during the course of the conflict. Medium-intensity armed conflict: at least 25 battle-related deaths per year and an accumulated total of at least 1,000 deaths, but fewer than 1,000 deaths per year. High-intensity armed conflict: at least 1,000 battle-related deaths per year.
3. In traditional Indian Hinduism, there are five castes: Brahmins, Kashtriyas, Vaishyas, Sudras and outcastes (untouchables or Dalits). The first two correspond to the upper strata of society. In Nepal they are known as Bahun and Chetri, respectively, to which the Newari group is added to form the upper-caste group. Ethnic groups in the hills, mountains and the tarai constitute the lower castes. Nepal also has its untouchable or Dalit group, frequently referred to as the "occupational" castes.
4. There is very little variation in the Gini coefficient across the different regions. It is 32.1 for the eastern region, 35.0 for the central region, 32.6 for the west, 29.4 for the mid-west and 36.2 for the far west. This makes the far western region the most unequal and the mid-west region the most equal, and both these regions are the most conflict-prone areas of Nepal. But these figures pertain to within-region inequality and not interregional inequality.
5. To check this assumption of independence, we also estimated these results using a negative binomial regression and a generalized event count model. We found no evidence of overdispersion or underdispersion. Moreover, the results remain robust across estimations.
6. See Gourieroux et al. (1984: 702–703); Lee (1986: 690–691).

7. These values were calculated using the statistical package CLARIFY (Tomz et al. 2003).
8. Some of the fiercest Maoist guerrillas are women who have been raped by the Nepalese army or the security forces. This serves to illustrate that people fight not just for material gain (extrinsic motivation) but also out of a sense of injustice (intrinsic motivation).

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10

Changes in spatial income inequality in the Philippines: An exploratory analysis

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1. Introduction

The Philippines has long been known for its high level of inequality in income and wealth distribution. A widely held view on inequality in the Philippines is that development policy has favoured the island of Luzon and discriminated against the peripheral islands (provinces) of Visayas and (especially) Mindanao. Moreover, the poor performance of the Philippine economy over the past three decades has been attributed partly to the relatively large variations in access to infrastructure and social services between major urban centres and rural areas (e.g. Ranis and Stewart 1993; Balisacan 1993a; Bautista 1997). Spatial variations in certain summary measures of human development are also evident (UNDP 1996).

If spatial income disparities are indeed at the core of the poverty and inequality problems in the Philippines, then policy reforms aimed at reducing these disparities would have to be central elements in the country's poverty reduction programme. This might also promote efficiency goals; important dynamic externalities can arise from targeting by area- or sector-specific characteristics (Bardhan 1996; Ravallion and Jalan 1996). Investments in physical infrastructure (e.g. roads, communications and irrigation) in backward areas, or in the rural sector in general, may improve the productivity of private investments, influence fertility through their effects on labour allocation and educational investment decisions, promote the development of intangible "social capital" (in the

form of social networks, peer group effects, role models, etc.), and mitigate the erosion in the quality of life in urban areas through their effects on rural–urban migration decisions.

However, if the disparity in incomes and human achievements *within* each of the regions or areas of the country is the major problem, then a different approach to poverty reduction will have to be found. It is possible, for example, that systematic differences in the levels of human capital between low- and high-income groups within a geographical area translate into considerable differences in earning opportunities between these groups. In this case, policy prescriptions to reduce overall income inequality and poverty would have to involve expanding the access of low-income groups to basic social services, technology and infrastructure. Important policy priorities thus depend crucially on some of the basic factual information on inequality such as whether or not inequality is increasing and what the main sources of inequality are. The primary purpose of this chapter is to establish some basic facts for the Philippines about spatial income inequality. We focus on income inequality (and, thus, ignore other important dimensions of inequality) in the Philippines and address the following three questions:

- How much of the national-level income inequality in the Philippines is owing to spatial inequality?
- Was spatial income inequality increasing in the Philippines during the period 1988–2000?
- What were the major sources of differential income growth across provinces in the Philippines?

The chapter is organized as follows. Section 2 provides a general overview of income inequality in the Philippines, such as trends in nationwide income inequality and international comparisons. Section 3 focuses on the sources of nationwide income inequality and examines how much of the national-level income inequality is attributable to spatial inequality. Section 4, by examining the patterns of mean income growth across provinces, addresses the question of whether spatial income inequality is increasing over time in the Philippines and examines the sources of the differential mean income growth rates across provinces. The final section concludes the chapter.

2. Growth and inequality in the Philippines: A nationwide overview

An almost regular pattern of boom and bust growth has characterized the Philippine economy during the past three decades. Bust and stagnation soon followed each episode of boom, fuelled largely by massive foreign

borrowing and capital-intensive import-substituting industrialization. The period also saw heavy government regulation of the market economy, as well as political instability, natural disasters and major shocks in global trade and finance. For these reasons, during most of the 1980s and early 1990s, the country acquired an unenviable image as the ‘‘sick man of Asia’’. However, the growth episodes in the 1990s, notwithstanding the interruption in 1998 caused by the combined impact of the Asian economic crisis and the El Niño phenomenon, appear to have had a fundamentally different character from previous ones. The growth took place in an environment of political stability, economic deregulation and institutional reforms. Although policy coordination problems (e.g. in public investments) persisted, the country at the end of the first millennium was closer to a market economy than it ever had been in the past (see also Bautista and Tecson 2003).

Four distinct phases characterize the growth episodes from the mid-1980s.[1] The first was the brief period of economic growth (1986–1989) following the sharp contraction in 1984 and 1985 when per capita GDP shrank by an average of 10 per cent a year (Figure 10.1). Based on household consumption data from the Family Income and Expenditure Survey (FIES), the real mean living standard in 1988 was 10 per cent

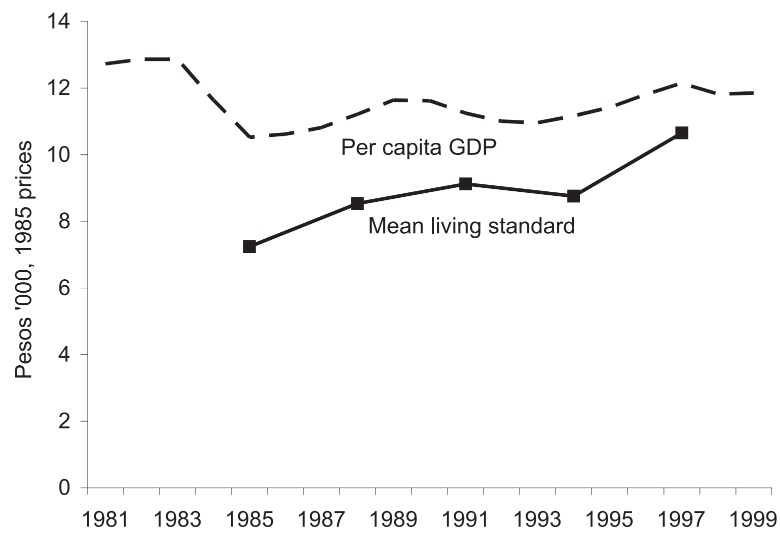


Figure 10.1 Per capita GDP and mean living standards in the Philippines, 1980s and 1990s.
Sources: Per capita GDP – National Income Accounts; mean living standard – Family Income and Expenditure Survey.

higher than that in 1985, although still much lower than the level prevailing at the beginning of the 1980s.

Political instability, natural disasters and macroeconomic mismanagement caused overall economic growth to falter in the succeeding four years (1990–1993). Nonetheless, the mean living standard in 1991 managed to rise by approximately 6 per cent compared with 1988. Very modest per capita GDP growth resumed in 1994, but the combined impact of the contraction in the previous two years could have offset the effect of this growth on mean living standards. Indeed, by 1994, the average living standard dipped 2 per cent below that in 1991. Following restoration of political stability and deepening of policy and institutional reforms, GDP growth accelerated in the next three years (1995–1997). The mean living standard in 1997 was approximately 21 per cent higher than that in 1994, the highest three-year growth achieved since the mid-1980s. However, owing to the combined impact of the Asian economic crisis and of the El Niño phenomenon in 1998, as well as of the slow recovery in the following year, the mean per capita expenditures (and possibly mean living standard) at the turn of the new millennium were just at the level reached at the beginning of the 1980s.

Table 10.1 also provides the summary measures of inequality in per capita consumption expenditures in the 1980s and 1990s. Despite the large fluctuations in macroeconomic performances as discussed above, the level of expenditure inequality, as measured by these summary indexes, remained remarkably stable. The level of inequality measured by the expenditure Gini ratio in the mid-1980s was 41.2 per cent. After falling slightly to 40.0 per cent in 1988, it rose to 42.8 per cent in 1991 but fell back again to the 1988 level in 1994. It then rose to 42.7 per cent in 1997. The level of inequality in 2000 (Gini ratio of 42.9 per cent) was roughly the same as it had been in 1997. Essentially the same pattern emerges for

Table 10.1 Living standards and inequality in the Philippines, 1985–2000

	1985	1988	1991	1994	1997	2000
Mean living standard at 1997 prices (Philippine pesos)	17,197	18,926	20,049	19,600	23,694	22,865
Inequality						
Gini	0.412	0.400	0.428	0.397	0.427	0.429
Theil-T	0.330	0.298	0.363	0.302	0.376	0.368

Note: Living standards are defined as household consumption expenditures adjusted for family size and provincial cost-of-living differences (see Balisacan 1999 for details).
Source: Authors' estimates, based on Family Income and Expenditure Survey data.

Theil-T, which is more sensitive than the Gini index to changes in the tails of the distribution. Given the relatively small changes in the summary measures of inequality over the 12-year period, it is indeed difficult to draw definitive conclusions about the direction of the changes in expenditure inequality in the Philippines. For example, Balisacan (1999) shows that the observed intertemporal changes in the summary measures of inequality (especially the Gini coefficient and the mean logarithmic deviation) are quite sensitive to the assumption about the existence of scale economies in household consumption, which can even reverse the direction of the changes in the time trend in inequality.[2]

Many observers of the Philippine economy have long pointed out its high level of inequality in income and asset distribution. Based on the income distribution data compiled by Deininger and Squire (1996), Balisacan (1999) observes that the Gini ratios of income inequality in the Philippines were indeed higher than those of other Asian countries, except for Malaysia during the 1970s and the early 1980s and Thailand after the mid-1980s. However, he also notes that, while inequality was rising in Thailand, China and Hong Kong in the 1980s and 1990s, inequality in the Philippines tended either to remain constant or to fall slightly. On the other hand, the oft-heard remark in reference to economic inequality, that the Philippines is a Latin American country misplanted in East Asia, appears to be a bit of an exaggeration. A comparison of the Gini ratios of per capita income indicates that the level of income inequality in the Philippines was lower than that of most of the Latin American countries and roughly equal to that of the Latin American economies with the lowest inequality levels. Admittedly, however, the same comparison also shows that the inequality levels of most of the other Asian countries (except for Malaysia and Thailand, as mentioned above) were much *lower* than that of *any* Latin American country (Balisacan 1999: Figures 8–11).

3. Spatial and sectoral sources of income inequality in the Philippines

3.1. Sources of inequality levels

In this section we examine the sources of national-level income inequality. More specifically, we address the issue of how much of nationwide inequality can be accounted for by spatial inequality. To start with, one useful disaggregation of inequality data is the urban–rural divide. Poverty in the Philippines is often described as a largely rural phenomenon (Balisacan 1993a). Progress in reducing rural poverty would thus go a long way in advancing the overall poverty reduction goal.[3] Table 10.2

Table 10.2 Living standards and inequality by locality, 1985–2000

	1985	1988	1991	1994	1997	2000
Urban						
Mean living standard at 1997 prices (P)	24,099	26,283	26,213	25,093	31,657	30,219
Inequality						
Gini	0.410	0.390	0.421	0.392	0.425	0.423
Theil-T	0.327	0.286	0.355	0.295	0.379	0.359
Rural						
Mean living standard at 1997 prices (P)	12,838	14,414	13,864	14,154	16,475	15,794
Inequality						
Gini	0.352	0.350	0.359	0.336	0.352	0.360
Theil-T	0.226	0.217	0.238	0.205	0.230	0.242

Notes: Inequality estimates are based on per capita consumption expenditures adjusted for provincial cost-of-living differences.
Source: Authors' estimates, based on Family Income and Expenditure Survey data.

shows the mean living standards for the urban and rural sectors. The high mean consumption disparity between urban and rural areas is apparent. The mean consumption level in urban areas is nearly twice that in rural areas. The mean living standard rose significantly during the high-growth periods of 1985–1988 and 1994–1997 for both sectors. The direction of inequality for both sectors also generally followed the overall pattern reported in Table 10.1.

Table 10.3 and Figure 10.2 show the population shares and the mean living standards, respectively, for selected characteristics (i.e. locality, region, and employment sector of household head). Clearly, the average living standards vary substantially between urban and rural areas, as well as across regions. Metro Manila, which accounts for about 14 per cent of the population, has the highest mean living standard. In 2000, its mean living standard was roughly 1.7 times the national average and about 3 times the mean living standard for Western Mindanao, the poorest region of the country. Except for Bicol and Cagayan, the mean living standards for the Luzon regions are higher than for most of the regions in Visayas and Mindanao. Note, however, that the ranking of most regions changed between 1985 and 2000. Eastern Visayas, for example, was the second-poorest region in 1985 but it ranked the fourth-poorest in 2000, whereas Western Mindanao, the fifth-poorest in 1985, became the poorest region in 2000. Only Metro Manila maintained its relative positions during the period. An even greater disparity in living standards exists among employment sectors. As expected, agriculture, which employed 37 per cent

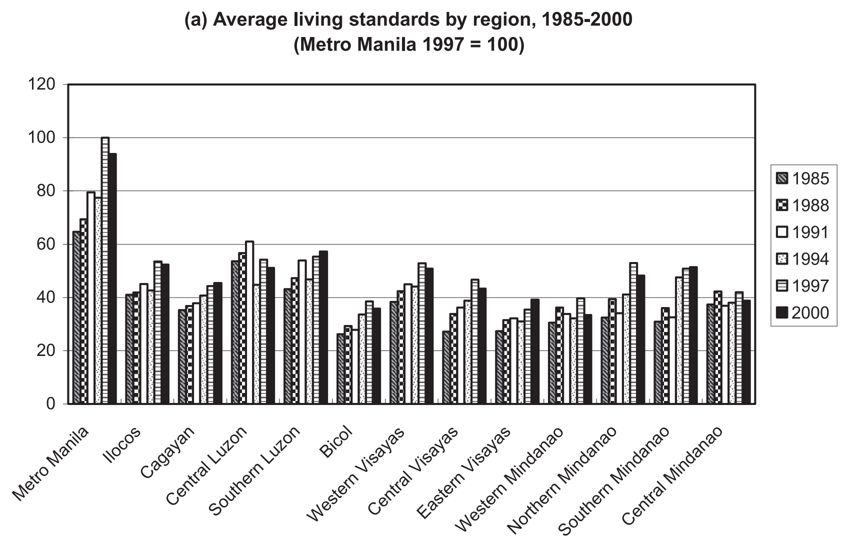
Table 10.3 Population shares by locality, region and sector, 1985 and 2000

	Population share (%)	
	1985	2000
Philippines	100.0	100.0
Locality		
Urban	38.7	49.0
Rural	61.3	51.0
Region		
Metro Manila	14.0	14.2
Ilocos	7.2	6.5
Cagayan	4.6	4.0
Central Luzon	9.9	9.9
Southern Luzon	12.5	14.5
Bicol	6.8	7.5
Western Visayas	8.9	8.0
Central Visayas	7.6	7.1
Eastern Visayas	5.4	4.7
Western Mindanao	5.1	5.2
Northern Mindanao	6.1	5.7
Southern Mindanao	7.3	7.4
Central Mindanao	4.5	5.3
Sector		
Agriculture	47.3	36.8
Mining	0.8	1.1
Manufacturing	7.0	7.2
Utilities	0.5	0.5
Construction	4.9	7.1
Trade	8.0	10.4
Transportation	6.1	9.2
Finance	1.8	2.1
Services	12.1	11.1
Unemployed	11.4	14.4

Source: Authors' estimates, based on Family Income and Expenditure Survey data.

of the labour force in 2000, has consistently had the lowest mean living standard among all sectors. Manufacturing and trade have an income level almost twice that of agriculture's mean living standard. Utility and services have more than twice agriculture's mean expenditure. Finance, the richest sector, has more than four times agriculture's level.

The large income disparity between Luzon and the rest of the country, as well as between urban and rural areas, has attracted much attention in policy discussions. A common theme emerging from these discussions is that the spatial income disparity is largely responsible for the high income inequality in the country, implying that much of the inequality would be reduced by policy reforms aimed at closing the income gaps



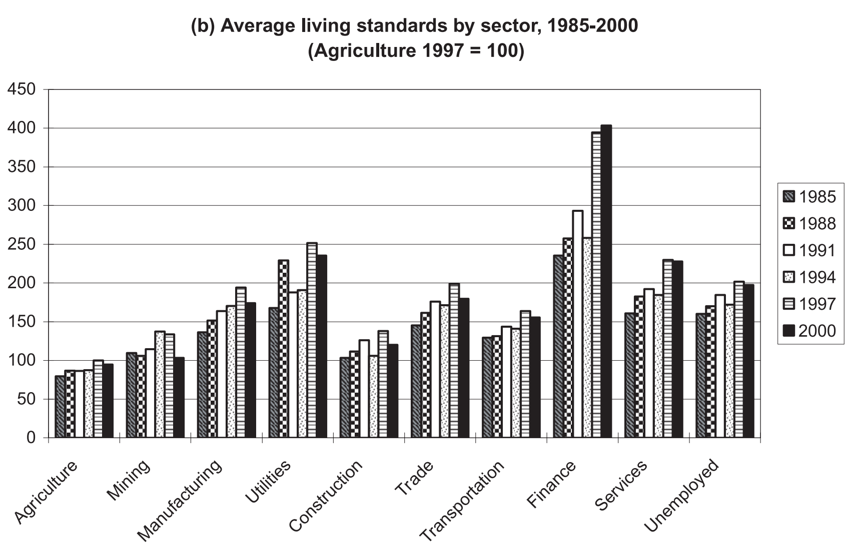


Figure 10.2 Average living standards by region and by sector, 1985–2000.
Note: Per capita consumption expenditure adjusted for provincial cost-of-living differences. Average living standards in 1997 for urban areas, Metro Manila and agriculture were P31,657, P42,367 and P14,886, respectively.
Source: Family Income and Expenditure Survey.

Table 10.4 Decomposition of expenditure inequality indices (Theil-T)

	1985	1988	1991	1994	1997	2000
National inequality	0.330	0.298	0.363	0.302	0.376	0.368
Within-group contribution to aggregate inequality (%)						
Locality (urban/rural)	85.1	85.0	86.7	86.9	86.3	86.3
	(14.9)	(15.0)	(13.3)	(13.1)	(13.7)	(13.7)
Region	86.5	88.1	84.8	87.5	86.7	86.9
	(13.5)	(11.9)	(15.2)	(12.5)	(13.3)	(13.1)
Sector	83.7	81.6	82.4	81.5	82.1	80.4
	(16.3)	(18.4)	(17.6)	(18.5)	(17.9)	(19.6)

Note: Figures in parentheses are between-group contributions to aggregate inequality.
Source: Authors' estimates, based on Family Income and Expenditure Survey data.

among regions and between rural and urban areas. Table 10.4 suggests, however, that this claim is not quite accurate. Although regional differences in the mean living standards are substantial, the contribution of the between-group (region) component to overall inequality is rather small (15 per cent). This implies that removing between-group inequality by equalizing all the regional mean expenditures (but keeping within-group inequality constant by equiproportionately changing the expenditures of all members of that region) would reduce overall inequality by 15 per cent. Conversely, removing within-region inequality by making everyone's expenditure within a region equal to the mean for that region would reduce overall inequality by 85 per cent.

3.2. Sources of inequality changes

As observed in Table 10.3, the changes in the living standards are accompanied by population shifts (i.e. relative changes in population shares), as well as changes in inequality within population subgroups. Thus, the change over time in the relative importance of between-group and within-group components cannot be ascertained directly from the results given in these tables. Based on Tsakloglou's methodology (1993), which is a dynamic analogue of the (static) inequality decomposition approach, the change in Theil-T can be decomposed into three components: (a) the effects of intertemporal changes in within-group inequality, holding population shares and relative mean expenditures of the subpopulation groups constant; (b) the effects of changes in population shares on within-group inequality and on relative mean expenditures; and (c) the effects of changes in the relative group means on overall inequality.

Table 10.5 Decomposition of the change in inequality (Theil-T index)

Period		Change in inequality owing to change in			
		Within-group inequality	Population share	Mean group expenditure	Total change
1985–1988	Locality	–2.60 (81.97)	–0.07 (2.09)	–0.51 (15.95)	–3.18
	Region	–2.30 (72.56)	–0.01 (0.45)	–0.86 (27.00)	–3.18
	Sector	–3.38 (104.99)	–0.11 (3.43)	0.27 (–8.42)	–3.18
1988–1991	Region	4.33 (66.83)	–0.02 (–0.37)	2.17 (33.54)	6.48
	Sector	5.26 (80.96)	0.06 (0.95)	1.18 (18.09)	6.48
1991–1994	Locality	–5.02 (82.58)	–0.02 (0.30)	–1.04 (17.13)	–6.08
	Region	–4.43 (72.76)	–0.02 (0.37)	–1.64 (26.87)	–6.08
	Sector	–5.11 (84.04)	–0.06 (1.04)	–0.91 (14.92)	–6.08
1994–1997	Locality	6.23 (84.12)	–0.18 (–2.37)	1.35 (18.26)	7.40
	Region	5.99 (80.74)	0.08 (1.14)	1.34 (18.12)	7.40
	Sector	5.71 (76.93)	0.11 (1.55)	1.60 (21.52)	7.40

Note: Absolute changes in inequality indices are multiplied by 100. Figures in parentheses are percentage contributions to total change.
Source: Authors' estimates, based on Family Income and Expenditure Survey data.

Table 10.5 shows the results of the decomposition for the Theil-T index using three subpopulation groupings: (1) locality (i.e. urban or rural); (2) region; and (3) sector of employment.[4] When disaggregation is based on the location of residence, the change in within-group inequality contributes about three-quarters of the total change in overall inequality during the entire period. Note, however, that during the 1988–1991 period the estimate may have been biased by the reclassification of geographical areas.

Disaggregation by region tells us almost the same thing, with the change in within-group inequality still contributing the largest share (although less than three-quarters) to the total inequality change. When disaggregated by sector, the change in within-group inequality contributes from three-quarters (1994–1997) to the entire (1985–1988) total change in overall inequality. We thus observe that the changes in overall

inequality from 1985 to 1997 came mainly from changes *within* geographical boundaries and not from changes in relative mean group expenditures, in relative population shares, or both.

3.3. The relative importance of spatial inequality: A regression-based inequality decomposition approach

Although the above decomposition approach provides (at best) an indication of the contribution of a set of factors – location- and household-specific attributes – to inequality, the approach is rather cumbersome in the cases where many of these factors have to be treated jointly rather than individually. In the next step in our enquiry, therefore, we follow a regression-based inequality decomposition approach in order systematically to explore the contributions of each of these factors to the observed variation in household welfare (or living standards). Following Fields (2002),[5] we estimate a standard set of regressions of the Mincerian form and use the parameter estimates to calculate the relative contribution of each factor to the differences in living standards. The regression is of the form:

$$\ln y_{it} = \alpha_t + \beta_t X_{it} + \varepsilon_{it}, \tag{10.1}$$

where the subscript i refers to the household, t refers to year, y is the living standard (defined as per capita household expenditure adjusted for provincial cost-of-living differences) and X_{it} is a vector of explanatory variables.[6] This is a standard formulation of the earnings function in the human capital literature (see Mincer 1974; Atkinson 1983). In this specification, the relative contribution of each factor (jth covariate) to the inequality in household living standards (as measured by the variance of the logarithm of per capita household consumption expenditures)[7] can then be estimated as (with time subscript t omitted):

$$S_j = \text{cov}[a_j Z_j, Y]/\sigma^2(Y) = a_j * \sigma(Z_j) * \text{cor}[Z_j, Y]/\sigma(Y), \tag{10.2}$$

where S_j is the relative contribution of the jth covariate, a_j is the jth element of the coefficient vector (α, β_j), Z_j is the jth element of the vector of explanatory variables plus a constant $(1, X)$ and Y is log y.[8]

Table 10.6 shows the shares accounted for by the location- and household-specific attributes in the total variance explained by the model, for the period between the 1985 and 2000 FIES.[9] Location (rural–urban disparity and regional disparities taken together) accounted for 19 per cent of the total variation in per capita consumption expenditure in 1985; of this, 5 per cent was explained by urban–rural disparity

Table 10.6 The relative contribution of spatial and household attributes to the variance in living standards

	1985	1988	1991	1994	1997	2000
Household attributes						
Family size	10.8	11.3	10.4	12.3	14.2	15.9
Household type	0.4	0.4	0.5	0.5	0.5	0.3
Child dependency ratio	10.2	10.8	9.7	10.8	9.7	10.3
Employment ratio	1.3	2.0	1.5	2.3	3.3	2.4
Spouse employed	0.0	0.1	0.3	0.3	0.7	0.4
Skill and experience of household head	0.8	0.4	0.4	0.7	0.4	0.1
Gender of household head	0.7	0.6	0.6	0.7	0.7	0.6
Marital status of household head	–0.4	–0.5	–0.2	–0.3	–0.4	–0.4
Educational level of household head	33.4	33.6	30.5	33.7	34.1	33.6
Economic sector						
Labour class of household head	3.5	4.3	5.4	4.5	6.5	5.5
Employment sector of household head	0.8	3.4	3.2	3.8	2.7	4.9
Infrastructure						
Electricity	19.7	16.9	18.7	18.2	17.2	15.3
Location						
Urban	5.1	6.2	4.4	4.0	3.2	3.8
Region	13.6	10.4	14.8	8.5	7.1	7.4

Note: The estimation takes into account sampling design effects, i.e. stratification and weights. For brevity, details of regression results are not shown (but are available from the authors upon request). The relative contributions of "class of worker (household head)", of "sector of employment" and of "region" are each the sums of the contribution of a set of dummy variables representing 9 sectors of employment, 10 classes of worker and 13 regions of residence, respectively.
Source: Authors' estimates, based on Family Income and Expenditure Survey data.

and 14 per cent by the regional dummies. The rest of the nationwide variation in mean expenditure (81 per cent) was explained by the combination of intraregional factors such as education of the household head, household composition, sector of economic activities and access to electricity. Household composition and the household head's attributes, taken together, explain half of the variance. Among those, the educational attainment of the household head contributes by far the largest share (over 33 per cent). Infrastructure, represented by access to electricity, is another major contributor to the variance explained by the regression model,[10] accounting for 15–20 per cent. On the other hand, the employment sector contributes only a very small proportion (less than 10 per cent) of the variance explained by the model throughout the period,

although its share increased rapidly in the 1990s.[11] This suggests that it is differences in welfare levels within a sector, rather than differences in mean welfare levels between sectors, that account for a significant proportion of the variation in household welfare nationally. The relatively low level of spatial inequality as a share of total inequality appears to be roughly in line with the findings from other countries, for example, (rural) Ecuador, Madagascar and Mozambique (Elbers et al. 2003), although a similar study from Viet Nam found a much higher share of total inequality (as high as 42 per cent) being explained by spatial inequality (Heltberg 2003).

In addition, the relative contribution of regional disparities to nationwide inequality declined between 1985 and 2000, from 14 per cent to 7 per cent. What was behind this decline, however, is not immediately clear. On the one hand, some village-level studies in the 1990s suggest that the spread of non-agricultural growth to lower-income regions may have been a factor (see, for example, Hayami and Kikuchi 2000). Manasan and Chatterjee (2003), on the other hand, argue that high growth in the agricultural sector reduced regional income disparities because lower-income regions have mainly agriculture-based economies. In the next section we will focus directly on the process of change in regional income disparities based on neoclassical growth convergence analysis.

4. Is provincial income disparity increasing in the Philippines? Income convergence analysis

In the previous section, we observed that spatial income inequality is a sizeable but *not* an overwhelming source of nationwide income inequality in the Philippines, accounting for at most 20 per cent of the total variation. Nevertheless, if spatial inequality were on the rise, then this inequality could become an increasingly important source of income inequality at the national level. In this section we examine whether spatial income inequality was increasing between the late 1980s and the late 1990s. We address this question by asking whether mean income (as measured by consumption expenditures) across provinces in the Philippines was converging.[12]

4.1. Absolute convergence among provinces

How does regional income inequality tend to evolve? According to the (simple) neoclassical growth model (owing to its assumption of diminishing returns to capital), the lower the starting level of real per capita in-

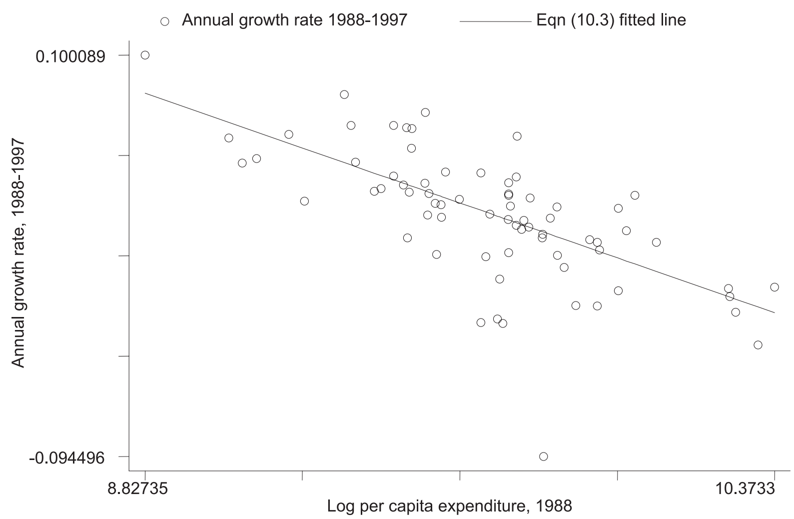


Figure 10.3 Absolute convergence of provincial income growth, 1988–1997.
Note: The outlier observation (middle bottom) is that of the province of Sulu.
Source: Family Income and Expenditure Survey.

come, the higher is the predicted growth rate (the convergence property). Whereas such convergence can occur in only a conditional sense across countries because national economies differ considerably – in terms of the propensities to save or to have children, willingness to work, access to technology, and government policies – "absolute convergence" is more likely to be observed within an economy because those factors are relatively similar across different parts of the country. Indeed, empirical studies of the historical experience in currently developed countries suggest that such absolute convergence within countries is in fact common (Barro and Sala-i-Martin 1992, 1995).

Does the pattern of spatial income disparity in the Philippines follow this prediction of neoclassical growth theory? Figure 10.3 shows the relationship between per capita expenditure in 1988 and the average annual growth rate of per capita expenditure between 1988 and 1997 in the Philippines.[13] The unit of observation here is each of the 72 provinces (excluding Metro Manila, which, as Figure 10.2 shows, is a clear outlier). We can observe a clear pattern of absolute convergence during the period. Following Barro and Sala-i-Martin (1995: Chapter 11) we estimated the following equation by non-linear least squares estimation:

$$(1/T)\log(\mathrm{PCEXP97}_i/\mathrm{PCEXP88}_i)$$
$$= a - [(1 - e^{-\beta T})/T]\log(\mathrm{PCEXP88}_i) + u_i, \quad (10.3)$$

where T is the number of years between the two data points (in our case $T = 9$), $PCEXP88_i$ is the level of per capita expenditure (as a proxy for per capita income) for province i in the initial year (1988), $PCEXP97_i$ is the level of per capita expenditure for province i in the end year (1997), and u_i is the error term.[14] The β is the ''beta convergence'' coefficient indicating the annual rate of convergence.[15] Our estimated beta convergence coefficient for the Philippines during the period 1988–1997 is 0.107.[16]

Table 10.7 compares our estimate from the Philippines with the estimated rates of convergence from historical data in the United States, Japan and Europe as reported in Barro and Sala-i-Martin (1995: Chapter 11). As we can see from the table, compared with these historical beta convergence coefficient estimates in currently developed countries, the estimates from the Philippines appear to be quite high; the only historical episode where the rate of convergence comes close to our Philippine case is in Japan in the period 1970–1975. The magnitude of the difference in the rate of convergence between our estimate from the Philippines and those from the historical experiences of the United States, Japan and Europe is quite striking. With an annual rate of convergence (β) of 2.0 per cent, the number of years required to close the gap between the initial income and the steady-state income by up to a half is 35 years; with a β value of 10.7 per cent, it would take only 6 years. Without similar estimates from other time periods, however, it remains to be seen whether this high rate of convergence is a longer-term trend or was an exceptional episode within the history of Philippine economic development like the Japanese episode of the 1970–1975 period, since historical experiences from currently developed countries indicate that the rates of convergence fluctuate quite substantially over time. In addition to the very high rate of beta convergence, we also find that the standard deviation of the log of per capita expenditures across provinces fell from 0.303 in 1988 to 0.239 in 1994 (sigma convergence).[17]

In sum, we find that mean income tended to grow faster (slower) in the provinces where the initial level of mean income was lower (higher), thereby exhibiting a pattern of provincial income convergence, and that the rate of this convergence was indeed quite high. Thus, the dynamic patterns of spatial income inequality (in the sense of the disparity in mean income levels across provinces) in the Philippines were operating in the direction of *reducing* overall income inequality at the national level during the period between the late 1980s and the late 1990s.

4.2. Conditional convergence: Provincial growth regression results

We have observed a general pattern of absolute income convergence across provinces, as predicted by the neoclassical growth theory. The

Table 10.7 Estimated beta convergence coefficients of regional income growth

Country and period	Estimated beta coefficient
Philippines	
1988–1997	0.107[a]
	(0.114[b])
United States	
1880–1990	0.0174
1880–1900	0.0101
1900–1920	0.0218
1920–1930	−0.0149
1930–1940	0.0141
1940–1950	0.0431
1950–1960	0.0190
1960–1970	0.0246
1970–1980	0.0198
1980–1990	0.0011
Japan	
1930–1990	0.0279
1930–1955	0.0358
1955–1990	0.0191
1955–1960	−0.0152
1960–1965	0.0296
1965–1970	−0.0010
1970–1975	0.0967
1975–1980	0.0338
1980–1985	−0.0115
1985–1990	0.0007
European regions	
1950–1960	0.018
1960–1970	0.023
1970–1980	0.020
1980–1990	0.010

Notes:
[a] Estimate based on all provinces except Metro Manila and Sulu.
[b] Estimate based on the full sample of all provinces.
Sources: The Philippines – authors' estimates; the United States, Japan and European regions – Barro and Sala-i-Martin (1995).

same theory also predicts that income disparity could persist to the extent that the steady-state level of income differs across provinces. If we could identify the determinants of such steady-state income levels, then appropriate policies could potentially be formulated that would reduce spatial inequality in income. In this subsection, we seek to identify such sources of the differential steady-state income levels by applying the familiar

growth regression framework. Following Barro's exposition (1997: 8), the basic model is:

$$Dy = f(y, y^*), \tag{10.4}$$

where Dy is the annual growth rate of per capita income, y is the initial level of per capita income (as measured by per capita consumption expenditure) in 1988, and y^* represents the long-run or steady-state level of per capita income. The convergence property based on neoclassical growth models predicts that the relationship between y and Dy will be negative.[18] The "target value" y^* presumably depends on an array of variables representing the initial conditions (economic and political/institutional) and policy choices. Here we discuss the growth regression results reported earlier (Balisacan and Fuwa 2003), explaining the differential rates of consumption expenditure growth across provinces by estimating the following equation:

$$\text{GRPCEXP}_i = a + b \log(\text{PCEXP88}_i) + \Sigma c_k X_{ik} + u_i, \tag{10.5}$$

where GRPCEXP is the annual average growth rate of per capita expenditures between 1988 and 1997, X_k is a set of additional explanatory variables consisting of initial conditions and policy variables,[19] and u_i is the error term. The descriptive statistics are shown in Table 10.8 and the estimation results are shown in Table 10.9. Among the initial economic conditions, the estimated coefficients on mortality rate, land distribution inequality and "dynasty" were found to be significantly different from zero. Among the policy variables, only the change in the implementation of the Comprehensive Agrarian Reform Program (CARP) was found to have coefficients significantly different from zero. In the final model reported in column (2), all the variables whose estimated coefficients are not significantly different from zero are dropped.

As we saw earlier, provincial expenditure growth exhibits a strong convergence property; controlling for the factors affecting the steady-state level of per capita expenditure, the estimated conditional rate of convergence is 8.5 per cent per year (whereas the unconditional rate of convergence was 10.7 per cent). This suggests not only that conditional convergence is occurring, given the steady-state level of expenditure for each province, but also that steady-state expenditure levels were converging. Whereas the neoclassical convergence effects (presumably owing to the diminishing returns to capital) account for 8.5 percentage points of the 10.7 per cent rate of annual absolute expenditure convergence, the rest (2.2 percentage points) is accounted for by the change in the steady-state expenditure levels, which in turn is determined by

Table 10.8 Descriptive statistics for the provincial income growth regression

Variable name	Description	Mean	Standard deviation	Min.	Max.	No. of observations
GRPCEXP	Average annual growth rate of per capita expenditures	0.023	0.032	–0.090	0.105	71
Initial conditions						
PCEXP	Per capita expenditures	16,598.38	5,133.67	6,818.22	31,993.09	71
Land Gini	Gini coefficient of farm distribution	54.16	6.55	36.49	75.77	72
Mortality rate	Mortality rate per 1000 children aged 0–5	84.99	14.71	55.92	121.12	72
Literacy rate	Simple adult literacy rate	87.57	7.37	56.7	96.6	72
Irrigation area	Share of irrigated farm area	0.27	0.22	0.015	0.95	66
Dynasty	Proportion of provincial officials related by blood or affinity	0.815	0.199	0.0	1.0	72
Time-varying variables						
Chg. CARP	Change in CARP implementation	1.340	1.089	0.4730	4.6851	72
Chg. road density	Change in road density	0.0820	0.0839	–0.2141	0.4047	72
Chg. ag. terms of trade	Change in agricultural terms of trade	0.4481	0.0784	0.24	0.58	72
Chg. electricity	Change in the share of households with electricity	11.3789	12.9160	–21.0	61.8	72

Sources: GRPCEXP and PCEXP – Family Income and Expenditure Survey (National Statistical Office); Land Gini – Census of Agriculture (National Statistical Office); Mortality rate – 1990 Women & Child Health Indicators (National Statistical Coordination Board); Literacy rate – Functional Literacy, Education, and Mass Media Survey (National Statistical Office); Irrigation area – Census of Agriculture (National Statistical Office); Dynasty – collected by the authors in interviews; Chg. CARP – Department of Agrarian Reform; Chg. road density – Department of Public Works and Highway; Chg. ag. terms of trade – Regional Accounts of the Philippines (National Statistical Coordination Board); Chg. electricity – Family Income and Expenditure Survey (National Statistical Office).

Table 10.9 Determinants of provincial growth regression results: Instrumental variable estimation results

Independent variables	Model (1)[b]	Model (2)[b]
Log (per capita expenditure 1988)[a]	−0.088**	−0.085**
	(10.24)	(11.51)
Mortality rate	−0.001**	−0.0007**
	(3.04)	(−4.37)
Literacy rate	0.0001	
	(0.16)	
Dynasty	−0.026**	−0.022**
	(2.24)	(2.17)
Irrigation area	0.002	
	(0.14)	
Land Gini	0.001**	0.001**
	(3.05)	(3.41)
Chg. CARP	0.006**	0.006**
	(2.11)	(3.15)
Chg. electricity	−0.00003	
	(0.13)	
Chg. ag. terms of trade	0.016	
	(0.52)	
Chg. road density	0.018	
	(0.64)	
Constant	0.849**	0.833**
	(8.52)	(10.59)
Adj. R^2	0.6799	0.6967
Sample size	65[c]	70

Notes: Dependent variable = annual growth rate of mean consumption per capita. Figures in parentheses are *t*-ratios.
[a] Per capita income used as instrument (see note 18 in text).
[b] Outlier observation (province of Sulu), as well as Metro Manila, excluded.
[c] Five provinces had to be dropped because one or more of the right-hand-side variables were missing for those provinces.
** indicates statistical significance at 5% level.
Sources: See Table 10.8.

human capital stock, political competitiveness, land distribution inequality and land reform implementation.

Among the initial economic conditions, the initial level of human capital stock as measured by the child mortality rate (but not by the literacy rate) has significant effects in raising the "target" income level y^*: on average, one standard deviation reduction in the mortality rate raises the annual per capita growth rate by 0.9 of a percentage point. Furthermore, we find significantly *positive* effects of the initial inequality in farm distribution: on average, one standard deviation increase in the Gini co-

efficient of land distribution is associated with a 0.7 percentage point increase in growth rates.[20] Our finding thus suggests that there may be a disturbing trade-off between social equity and growth.[21] The ''dynasty'' variable (measuring the proportion of provincial officials related by blood or affinity) has significantly negative effects on subsequent growth. The lack of a competitive political system is one of the major themes in much of the literature on Philippine politics, and this political characteristic has generally been seen among observers as one of the major factors leading to suboptimal policy choices in the Philippine government and, thus, to the Philippines' relatively poor economic performance compared with that of its Asian neighbours (e.g., Balisacan et al. 2005).

Among what we regard as policy variables, only the increase in CARP implementation is found to have estimated coefficients significantly different from zero (Table 10.9, column 1); on average, one standard deviation increase in the implementation of land redistribution is associated with a 0.7 percentage point increase in annual growth in per capita expenditures.[22] The positive correlation between land reform implementation and growth seems to contradict our finding above that inequality in farm distribution is positively related to growth. One possible interpretation of these results, however, is that land reform could affect growth through non-agricultural routes; land reform redistributed income from landowners to former tenants, who subsequently invested in education and non-agricultural activities, which, in turn, emerged as the main source of the income growth in rural Philippines (e.g. Estudillo and Otsuka 1999; Hayami and Kikuchi 2000). Alternatively, the CARP implementation could be seen as endogenous; it was not random across regions, but rather progressed faster in the areas with greater growth potential. Indeed, Otsuka (1991) found that a higher increase in agricultural yields was a major determinant of the implementation of the agrarian reform programme in the period between 1970 and 1986.

4.3. Was non-agricultural sector growth a source of convergence?

The high rate of convergence across provincial incomes raises a question: what are the processes behind provincial income convergence? Although a full investigation of this question would be beyond the scope of this chapter, we made a few initial attempts to explore this question. Village-level studies in Luzon Island (mainly on the outskirts of the Metro Manila region), for example, document the spread of rural industries after the late 1980s (e.g. Hayami and Kikuchi 2000), suggesting that the gradual spread of (rural) industrialization to lower-income provinces might have been part of the process behind the regional catching-up. We find that the growth convergence pattern of non-agricultural incomes is quite

similar to the convergence pattern of total income, with an estimated beta coefficient (based on equation (10.1)) of 0.106 (s.e. 0.0189); the relationship is much less clear in the case of agricultural income growth, with an estimated beta coefficient of 0.0211 (s.e. 0.0098).[23] Furthermore, we find a moderate but statistically significant negative relationship between the initial *total* income level and the growth of the *share* of non-agricultural income (as measured by the ratio of the share of non-agricultural income in 1997 to its share in 1988), possibly indicating the gradual spread of industrialization toward lower-income provinces in the 1990s.

In order to examine further how the growth in the share of non-agricultural income affects the rate of provincial income convergence, we re-estimated equation (10.3) by including an interaction term between the log initial income and the growth in the non-agricultural income share.[24] Surprisingly, the coefficient on the interaction term is positive and significant, indicating that the growth in the non-agricultural income share reduces (rather than increases) the rate of convergence, although the quantitative magnitude of this impact is quite small. Thus, although we can observe the gradual spread of industrialization to lower-income provinces and also the positive (though modest) effects of the growth in the non-agricultural income share on total income growth, this process does not appear to account for the high rate of provincial income convergence.[25] We will further investigate the processes behind the provincial income convergence in future work.

5. Conclusions

The primary purpose of this study has been to establish some basic facts about income inequality in the Philippines, with a special focus on the importance of spatial income inequality. Despite major fluctuations in macroeconomic performance, national-level income inequality remained quite stable during the period 1985–2000. In 2000, the disparity in mean incomes between the highest (Metro Manila) and the lowest (Western Mindanao) of the 13 regions was roughly three-to-one. Our findings suggest that spatial inequality accounts for a sizeable but not an overwhelming portion of national-level income inequality, and that the relative importance of spatial inequality was declining over time. Our regression analysis found, for example, that spatial inequality (the urban–rural disparity and mean income disparity across 13 regions) accounted for roughly 20 per cent of the overall variation (explained by the model) in per capita incomes in 1985, but the share declined to 11 per cent in 2000. The rest of the variation was explained by such factors as the education

of the household head, household composition, the economic sector of income sources and access to infrastructure (electricity). We further examined whether spatial income inequality has been increasing or decreasing in the Philippines. We found that mean income levels across provinces were converging at a much faster rate than that observed in currently developed countries. Provincial income disparity in the Philippines has been declining, possibly as a result of neoclassical convergence effects (diminishing returns to capital) and also of some convergence in steady-state income levels, which are affected by the human capital stock, political competition and land distribution, among others.

Based on our findings, it is tempting immediately to conclude that spatial inequality should not be high on the policy agenda. However, Kanbur (2002) cautions that such a policy conclusion should not be drawn before careful comparisons of policy instruments for addressing spatial (between-group) inequality and those addressing within-group inequality have been made to examine which policy instruments could have a larger impact on inequality per dollar of public expenditure.[26] Apart from this caveat, a major focus in attacking high inequality in the Philippines should perhaps be the sources of within-region inequality – human capital stock, demographic composition and infrastructure access are major factors in within-region income disparity.

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Notes

1. No household data for poverty comparison are available from 1972 to 1984. Although summary tables of nationwide household surveys are available for 1961, 1965 and 1971, these are not strictly comparable with those for the 1980s and 1990s.
2. According to Balisacan (1999: Figure 4), the mean logarithmic deviation increased slightly between 1985 and 1994 when no economies of scale are assumed (i.e. the "scale elasticity" has value 1.0, which means that simple per capita expenditure is used) whereas the trend reverses once a scale elasticity of values smaller than around 0.8 is assumed.
3. Tracking progress in the living standard in rural areas is not as straightforward as it seems, however. For example, rural poverty indicators constructed from the FIES for

the 1980s are not comparable with those for the 1990s owing to the urban–rural reclassification problem. Balisacan (1993b) demonstrated that the failure to take account of the ''shifting of physical areas'' arising from the reclassification of villages would distort the overall picture of the actual performance of rural areas from the late 1980s to the early 1990s. The sampling frame for the 1985 and 1988 FIES was based on the 1980 population census, and that for the 1991 FIES was based on the 1990 census. Both censuses applied the same set of criteria in classifying villages into ''urban'' and ''rural'' areas. Nevertheless, inter-year comparison within a decade is valid since the sampling frame and the rural–urban classification of geographical areas are common for these years.

4. Decomposition analysis based on the Theil-L index was also conducted but the results were very similar.
5. Additional applications of the same approach include Heltberg (2003) and Ravallion and Chen (1999).
6. The explanatory variables included are: age and age squared of household head (HH), sex of HH, marital status dummy of HH, educational dummies of HH (elementary, high school, college), family size, child dependency, number of household members employed, access to electricity, and dummy variables representing sector of employment (9 sectors), class of worker (10 classes), region of residence (13 regions) and urban residence.
7. It is well known, however, that the variance of the logarithm (''varlog'') has an undesirable property as an inequality measure: it violates the ''Pigou–Dalton transfer axiom'' at high income levels (e.g. Sen 1993).
8. Fields (2002), as well as Ravallion and Chen (1999), invokes the axiomatic results of Shorrocks (1982) in arguing that the *same* relative shares as obtained by the inequality decomposition above are applicable not only to the ''varlog'' measure but also to a broad class of inequality measures satisfying the conditions specified by Shorrocks (1982) as well. This ''generality result'' by Fields (2002), however, has been disputed by Morduch and Sicular (2002) and Wan (2002). Our use of Fields' (2002) approach in this chapter is based on its practical appeal and addressing the methodological controversy is beyond the scope of this chapter. A potentially promising approach could be to apply the ''Shapley value decomposition'' recently developed by Shorrocks (1999), which will be pursued in our future work.
9. The estimation takes into account sample design effects, i.e. stratification and weights assigned to each observation.
10. The relatively large effect of the electricity variable cannot be interpreted literally as the effect of electricity access per se; since the availability of electricity is likely to be highly correlated with other infrastructure development (such as roads) and other infrastructure variables are not available, we should perhaps interpret this vaguely as the effect of better infrastructure (leading to greater economic opportunities).
11. As seen in Figure 10.2, the sectoral income disparities increased in the 1990s; especially notable is the rapid increase in the income of the finance sector.
12. This section draws heavily on Balisacan and Fuwa (2003).
13. Although we have 2000 FIES data on per capita consumption expenditures, some of the right-hand-side variables in the regression analysis discussed in the next section are not yet available at the time of writing. As a result, we restrict our analysis of provincial income convergence to the 1988–1997 period.
14. The potential bias owing to the possible correlation between the initial income and the unobserved provincial-specific effects here is likely to be less serious than in cross-country estimates, since the main sources of such heterogeneity (technologies, tastes, etc.) tend to be similar within a country. Furthermore, Caselli et al. (1996) show such

bias to be unambiguously downward. Thus, our main qualitative finding of a high convergence rate would not be affected (but, rather, enhanced).

15. $\beta > 0$ would mean that provinces with low initial incomes grow faster (i.e. convergence of provincial income) whereas $\beta = 0$ would mean no convergence.
16. In estimating equation (10.3) we excluded the province of Sulu, which appears to be an outlier (see Figure 10.3). If we include Sulu, the estimated beta convergence coefficient is 0.114.
17. Nor do we find an indication of twin-peakedness by inspecting the kernel density of the per capita expenditures between 1988 and 1994, in contrast with Quah's (1996) observations based on cross-country data.
18. As is often the case in this type of regression analysis, the initial per capita expenditures and the dependent variable come from the same set of variables and thus there is a potential that the common measurement errors contained in both the dependent and the independent variables could lead to spurious correlation. In order to address this potential problem, we used instrumental variable estimation with household income per capita as the instrument for the initial per capita expenditure variable.
19. We included as initial economic conditions: child mortality rate, simple adult literacy rate, proportion of irrigated farm area, Gini ratio of farm distribution, political "dynasty" (proportion of key provincial officials related to each other by blood or affinity). Our (time-varying) policy variables are: agricultural terms of trade, electricity access, road density, and Comprehensive Agrarian Reform Program (CARP) implementation.
20. Since this result runs directly counter to the recent conventional wisdom that "initial inequality hurts subsequent economic growth" (e.g. Persson and Tabellini 1994), we examined the robustness of this relationship. It turns out that the significantly positive coefficient on the "land Gini" variable tends to be quite stable among various specifications with various combinations of explanatory variables. In addition, we experimented with alternative measures of land distribution, such as the ratio of large to small landholdings, but we tend to find that an initially higher share of small or medium-sized farm holdings is negatively related to subsequent growth, and an initially higher share of large farm holdings is positively related to subsequent growth (the results are not reported here but are available from the authors upon request). We find no evidence of the conventional wisdom and a rather robust positive relationship between high inequality in farm distribution and subsequent income growth.
21. See Balisacan and Fuwa (2003) for further discussions on this disturbing finding.
22. We must note here, however, that this variable is defined only at the level of the "region", which is a higher-level aggregation of provinces (owing to the absence of provincial-level observations of the land reform accomplishment), whereas our basic unit of observation is at the provincial level; thus, our results show that provinces within the regions of broader land reform implementation tend to grow faster.
23. Here, agricultural income includes agricultural self-employment and wage incomes, and non-agricultural income similarly includes self-employment and wage incomes from industrial and service sector activities. Neither category includes rental, transfer (including remittances) or capital incomes.
24. The detailed results are not reported here but are available from the authors upon request.
25. We also re-estimated equation (10.3) with an additional interaction term between initial income and one of the other initial conditions (i.e. mortality rate, literacy, land inequality, political dynasty and irrigation), one at a time, in separate regressions. None of these additional terms, however, is found to be statistically significant.
26. See Elbers et al. (2003) for an additional cautionary note.

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11

Spatial inequality and development in central Asia

Kathryn H. Anderson and Richard Pomfret

Introduction

The five Central Asian states – Kazakhstan, the Kyrgyz Republic, Tajikistan, Turkmenistan and Uzbekistan – emerged as new independent countries during the second half of 1991 with the dissolution of the USSR. They were, together with Azerbaijan, the poorest Soviet republics, although human development indicators, such as almost universal literacy and life expectancies of 66–69 years, were high (World Bank 1993). Assessments of economic performance since independence have focused on outcomes at the national level or on the distribution of household expenditures. By the end of the 1990s output had not recovered its 1991 level, and inequality and poverty were substantially higher than in 1991.[1]

This chapter focuses on an intermediate unit of analysis, oblasts and regions within Kazakhstan, the Kyrgyz Republic, Tajikistan, Turkmenistan and Uzbekistan.[2] Regional inequality is an important area of research and policy development. Inequality in income and consumption is a logical outcome in a market-based economic system; labour is rewarded for its productivity, and inherent individual differences in ability and skill are associated with variation in income. When investment in human capital is not rewarded, macroeconomic performance suffers. In many cases, however, economic inequality is not primarily the result of differences in skill or performance but is the result of barriers to entry into good jobs or labour markets, unequal access to productive resources, and other constraints on competitive market interaction. If inequality within countries

exists because of these barriers to competition, then inequality can foment internal tension, and economic and social development within countries is negatively affected.

Central Asia has experienced large changes in its political, social and economic institutions since independence in the early 1990s. In this chapter, we document how these changes affected the distribution of public and private resources across and within countries in Central Asia. We attribute part of these regional adjustments to inequality in human capital and dependency but find that most of the inequality is the result of regional differences within countries. These differences are large and growing over time and are not simply owing to rural–urban disparities. Regional inequality is reinforced by the public sector in the allocation of public services. Our analysis of spatial inequality in the distribution of public and private resources could guide the development of public policies in the Central Asian region to redress, to a certain extent, the inequalities we measure. To our knowledge, there is little published information on the spatial dimension of inequality in Central Asia. The Central Asian region is of increasing political importance, and an understanding of its people and the problems they face is essential to the development of regional stability.

The opening section provides background information by describing the main ethnic, sub-ethnic and supranational groups. Section 2 presents evidence on spatial inequality within the five economies. The third section offers explanations of the level of and trends in spatial inequality. Section 4 analyses the consequences of spatial inequality. The final section draws some conclusions.

1. Background

None of the five countries had any previous history as a nation-state. Although some have tried to create legitimacy by harking back to past rulers, the link is far from direct and the territory is different.[3] The current borders are those of the eponymous Soviet republics, which had been established by the delimitation of 1924, and by subsequent revisions, which were essentially completed by 1936.

The delimitation by Stalin is a source of controversy. In broad terms, dividing the Turkestan Autonomous Soviet Republic (established in 1918 as a successor to the Tsarist Governor Generalship) into smaller units was a case of divide and rule aimed at discouraging any sense of a unified Turkestan. That policy was successful, insofar as there has been no serious PanTurkic pressure in the region since the defeat of the *basmachi* movement in the early 1920s.

Whether the details of republic boundaries were aimed to cause discord is more debatable. Some Central Asian nationalists are convinced of a conspiracy theory. Tajiks see a plot in the separation of their Soviet republic from their chief historical cities of Samarkand and Bukhara. The Khorezm oasis was divided between Uzbekistan and Turkmenistan, leaving a concentrated Uzbek minority in the Dashkhoguz oblast of Turkmenistan. The densely populated and ethnically intermingled Ferghana Valley posed the most difficult problem, which was dealt with by convoluted borders separating the Kyrgyz, Tajik and Uzbek republics and by creating three small enclaves as part of the Uzbek republic but surrounded by Kyrgyz territory.[4] Although the outcome was messy, some outside observers conclude that "the Russian linguists, anthropologists, and politicians had done fairly competent work" in determining republic boundaries (Soucek 2000). The ethnic groups were intermingled, in particular where urban and surrounding rural populations differed and in the Ferghana Valley, so that any solution would be imperfect.[5]

During the Soviet era the issue became more complex because the USSR was treated in many respects as a single unit, with republican boundaries having little real significance, and yet there was a growth of identity among the titular nationalities. Several waves of migration increased the ethnic complexity. During the 1930s, many fled from Central Asia in response to forced collectivization and political purges, and many more died. During the 1941–1945 war, Stalin deported groups whom he considered untrustworthy to Central Asia from regions near the front line, notably Volga Germans and Crimean Tatars from the west and Koreans from the east of the USSR. There was also an ongoing pattern of political prisoners being exiled to Central Asia. During the 1950s Khrushchev organized the Virgin Lands programme, which brought many new settlers to northern Kazakhstan, reinforcing a pattern that had existed since Tsarist times of Europeans from within the empire moving to fertile land in northern Kyrgyzstan and in Kazakhstan.

Despite the rhetoric of comradeship, ethnic antagonisms existed beneath the Soviet surface. After a soccer game in Tashkent in May 1969, Uzbek and Russian youths fought in the streets following chants of "Russians go home" from the Uzbeks, in reaction to the granting of housing privileges to Russians involved in the reconstruction following the 1966 earthquake. The deal made by Brezhnev was to leave the Uzbek first secretary with a fairly free hand in return for maintenance of political stability. Sharof Rashidov, first secretary during 1959–1983, died just before Andropov and Gorbachev launched the anti-corruption campaign in which the Uzbek élite was the prime target. Despite official demonization of Rashidov for corruption, he remained a local hero for channelling billions of roubles surreptitiously into the republic, and, after independence,

a major street in Tashkent was named after him.[6] Attempts by Gorbachev to establish first secretaries loyal to Moscow failed and in 1989 he appointed a local technocrat, Islam Karimov, who owed nothing to the central government and who appropriated much of the opposition's Uzbek nationalism when he became president of Uzbekistan in 1991.

A similar pattern occurred in Kazakhstan, the other populous Central Asian republic. The powerful Kazakh leader Dinmukhamed Kunaev, who had been first secretary since 1960, was dismissed by Gorbachev in 1986 for corruption. After the appointment of a Russian as his replacement, a large demonstration in the Kazakh capital was dispersed by force, leaving two people dead. Subsequently, Gorbachev backed down, and in 1989 he appointed Nursultan Nazarbayev as first secretary, a Kazakh whose career had been promoted by Kunaev and who metamorphosed into president of Kazakhstan.[7] Under Kunaev, Kazakhization of the political and administrative system was substantial and Kazakhs were favoured in access to higher education, so that by 1989 a national identity had been forged and this was promoted by Nazarbayev (Melvin 1995: 106). Today a prominent statue in Almaty commemorates the nationalist martyrs of December 1986.

Inter-ethnic tensions became more open in the final years of the USSR, although never on the scale of events in the Caucasus. The most serious clashes in Central Asia occurred in June 1990 when the border between the Uzbek and Kyrgyz republics had to be closed to prevent an armed mob of about 15,000 Uzbeks from crossing into the Kyrgyz Republic to assist their co-ethnics involved in land disputes in the neighbourhood of Osh. The political fall-out from the Osh riots was severe enough to lead to the fall of the Kyrgyz first secretary and his replacement by the head of the Kyrgyz Academy of Sciences, Askar Akaev, who became the most liberal president in the region after 1991. The area around Osh, and indeed the whole Ferghana Valley, remains a potential tinderbox of ethnic disputes, exacerbated by the concentration of the most avid Islamist groups in this densely populated area.[8]

The ethnic composition has changed in important respects since the 1989 census. Many non-Central Asian groups emigrated in the early 1990s. People with a claim to German blood "returned" to Germany, and this group has almost disappeared from Kazakhstan and the Kyrgyz Republic. Slavs had a more difficult choice; many had lived in Central Asia for several generations and felt divided loyalties, but over 1 million Russians emigrated between 1990 and 1996 (Olcott 1996). Kazakhstan encouraged the return of ethnic Kazakhs who had moved to Mongolia or western China earlier in the twentieth century,[9] but this was on a smaller scale and since 1991 the net effect in Kazakhstan (and to a lesser extent the Kyrgyz Republic) has been substantial emigration, amounting

Table 11.1 Ethnic composition of the Kyrgyz Republic, 1979, 1989 and 1999

Ethnic group	1979 Number ('000)	1979 Per cent	1989 Number ('000)	1989 Per cent	1999 Number ('000)	1999 Per cent
Kyrgyz	1,687	47.9	2,230	52.4	3,128	64.9
Uzbek	426	12.1	550	12.9	665	13.8
Russian	912	25.9	917	21.5	603	12.5
Dungan	27	0.8	37	0.9	52	1.1
Ukrainian	109	3.1	108	2.5	50	1.0
Uigur	30	0.8	47	0.9	47	1.0
Tatar	72	2.0	70	1.6	45	0.9
Kazakh	27	0.8	37	0.9	43	0.9
Tajik	23	0.7	34	0.8	43	0.9
Turkish	5	0.1	21	0.5	33	0.7
German	101	2.9	101	2.4	21	0.4
Korean	14	0.4	18	0.4	20	0.4
Other	89	2.5	98	2.3	72	1.5
Total	**3,523**		**4,258**		**4,823**	

Source: National Statistical Committee of the Kyrgyz Republic, 1979, 1989 and 1999 censuses (National Statistical Committee 2000: 26).

to almost 10 per cent of the 1989 population (Heleniak 1997). Net emigration has roughly been balanced by natural increase in the Kyrgyz Republic, but in Kazakhstan the population dropped from 17.1 million at independence to 15.4 million in 1999 (ESCAP 2000). The selective effect of emigration on the ethnic composition of the remaining population is illustrated by the 1999 census in the Kyrgyz Republic (Table 11.1), where the combined share of Russians, Ukrainians and Germans dropped from almost a third in 1979 to a seventh of the total in 1999, and Uzbeks displaced Russians as the largest minority group. There has also been economic migration from Central Asia, especially by Tajiks since the late 1990s, although it is unclear how many of these are temporary migrants and how many have left their country permanently.[10]

Sub-ethnic divisions are also important in Central Asia, and some observers believe they are more important than the ethnicities defined by Stalin in the 1920s. In Kazakhstan, the Kyrgyz Republic and Turkmenistan, where the titular nationality has a relatively more recent nomadic past, tribal groupings remain strong. Turkmenistan's national flag incorporates five carpet designs belonging to the main tribes (Akhal Teke, Yumot, Salar, Ersari and Kerki), and the country's oblasts approximate tribal boundaries. Although the Akhal Teke, whose territory includes the national capital, have been dominant, President Niyazov styles him-

self Turkmenbashi (head of all Turkmen) and emphasizes the motherland as the prime locus of loyalty (Akbarzadeh 1999). However, it is unclear to what extent the Yumot in Balkan and Dashkhoguz oblasts or Ersari and Kerki in Lebap accept national over tribal allegiance. Kazakhs owe allegiance to the Great Horde (2 million in 1989), Middle Horde (3 million in 1989) or Little Horde (1.5 million in 1989), and there are tensions between President Nazarbayev as leader of the Great Horde and the leaders of the Middle Horde, which had been pre-eminent before the 1960s. Askar Akaev, President of the Kyrgyz Republic, represents the northern region and the Sary Bagysh tribe, so that Kyrgyz (as well as Uzbeks) in the south of the country feel excluded. In Tajikistan, the civil war that waged throughout most of the 1990s pitted three Tajik groups (from Leninabad in the north, Gulab in the south and Garm in the east) against one another; the Pamiri people in the Gorno-Badakhshan Autonomous Oblast (GBAO) are distinct.[11] In Uzbekistan, which contains the non-nomadic heart of the region, the élite is divided into geographical factions, identified with Samarkand/Bukhara in the centre/west, Kashkadarya in the south, Tashkent in the north and Ferghana in the east; the Samarkand group is currently dominant.

The present situation consists of overlapping loyalties, which remain fluid. Despite the lack of genuine historical legitimacy, the five Soviet republics created some degree of national consciousness, which has been strengthened since independence in all except Tajikistan. At the same time, ethnic and sub-ethnic ties remain strong, and they have a geographical dimension that makes spatial inequalities potentially inflammatory. At the supranational level, concerns about pan-Turkism have proven unfounded, and Tajik links to co-linguist Iran are even weaker. On the other hand, Islam is the common religion, although here too there are distinctions.

The hold of Islam is much weaker in the northern and traditionally more nomadic or pastoralist parts of Central Asia; i.e. Kazakhstan, Karakalpakstan, Turkmenistan and northern Kyrgyz Republic. In Uzbekistan, President Karimov is committed to establishing a secular state accommodating its Islamic heritage. In 1992 he took the oath of office on the Koran, but he has increasingly staked his legitimacy on being a bulwark against religious extremism. In 1997, riots in Namangan left several policemen dead, and the severed head of one of them was displayed by the rebels in the town centre. In February 1999, bombs, ostensibly aimed at the president himself, killed several people in the centre of Tashkent. The most serious battles have occurred in the Ferghana Valley, where Islamic Movement of Uzbekistan (IMU) incursions in the summers of 1999 and 2000 led to Uzbek planes bombing terrorist targets in Tajikistan and the Kyrgyz Republic and to the laying of mines along the border.[12]

The protracted civil war in Tajikistan from 1992 until (and, by some accounts, beyond) the June 1997 peace agreement is generally seen as a regional conflict, driven by competition for resources rather than over beliefs. Nevertheless, the war had a religious component, with Islamic groups supporting the United Tajik Opposition (UTO); moreover, growing poverty reinforced the politicization of Islam.[13] The UTO and the IMU are succoured by supporters in Afghanistan, and the governments of Uzbekistan and Tajikistan are involved in supporting co-ethnic groups fighting in the northern alliance in the Afghanistan conflict. Heightened instability in Afghanistan could easily spill over into Tajikistan and Uzbekistan.

The regional, sub-ethnic or tribal, ethnic, national and supranational sources of tension often merge in practice. Kyrgyz and Tajik protests over Uzbek bombing and mining of their territory are partly driven by concerns that Uzbekistan's territorial designs are being hidden behind an anti-terrorist rhetoric. In November 1998, Makhmud Khudoberdyev, an ethnic Uzbek who had been an army colonel in Tajikistan before splitting with President Rakhmanov of Tajikistan and fleeing to Uzbekistan, led a military force that occupied Khudjand before being driven out by Tajikistan government forces. President Rakhmanov initially denounced this as a coup attempt supported by Uzbekistan with the intention of promoting secession by Leninabad oblast, although later both governments downplayed the incident. The first explicit attempt to revise the national borders occurred in the winter of 2000/2001, when Uzbekistan started pressing for territory to provide corridors to its enclaves in the Kyrgyz Republic's portion of the Ferghana Valley and reinforced its claim by cutting off gas supplies to the Kyrgyz Republic.[14]

2. Descriptive evidence

Income levels varied across Soviet republics and also within them. Since independence, intra-republic differentials appear to have widened. In general, the people in the capital cities were best able to benefit from the opportunities of the market economies or best able to protect themselves from the huge negative shocks. In Kazakhstan, proximity to Russia also seems to have been a positive factor because the northern part of the country did relatively well.

Table 11.2 presents conceptually comparable measures of GDP per capita at purchasing power parity (PPP) for the oblasts of Kazakhstan, the Kyrgyz Republic and Uzbekistan, as reported in the various national *Human Development Reports* prepared under the aegis of local UNDP offices. They illustrate the significantly higher income levels in Kazakh-

Table 11.2 Real per capita GDP by region: Kazakhstan, Kyrgyz Republic and Uzbekistan

(a) Kazakhstan, 1994–1999

	Real GDP per capita (PPP$)					
Oblys	1994	1995	1996	1997	1998	1999
Akmola (incl. Astana)	3,153	3,420	3,061	3,218	3,710	4,066
Almaty	2,008	2,263	2,919	2,942	2,671	2,437
Almaty City	6,725	5,188	9,369	10,980	10,730	11,935
Aqtöbe	4,804	4,977	4,204	5,311	5,639	5,246
Atyrau	8,031	9,988	11,096	12,155	9,807	14,677
East Kazakhstan	5,224	5,063	4,394	4,826	5,238	4,811
Karaganda	8,950	7,444	5,257	5,836	5,718	6,176
Mangistau	10,623	11,894	13,571	10,461	7,967	10,130
North Kazakhstan	5,928	5,790	6,405	4,986	3,620	4,334
Pavlodar	8,456	8,488	7,376	5,439	10,822	10,235
Qostanay	5,494	4,320	4,019	5,721	5,137	4,603
Qyzylorda	2,174	2,662	3,155	3,206	2,712	2,838
South Kazakhstan	1,336	1,611	2,304	2,333	2,127	2,080
West Kazakhstan	2,897	2,962	2,693	4,100	4,091	5,438
Zhambyl	1,638	1,556	2,501	2,178	1,983	1,952

(b) Kyrgyz Republic, 1996–1999

	Real GDP per capita (PPP$)			
Oblast	1996	1997	1998	1999
North				
Bishkek	3,663	3,762	4,231	4,340
Chuy (excl. Bishkek)	3,651	3,927	3,617	3,776
Centre (mountain region)				
Issyk-Kul	1,577	2,734	3,372	3,517
Naryn	1,890	2,200	2,131	2,218
Talas	1,766	1,794	1,656	1,718
South				
Jalal-Abad	1,470	1,424	1,380	1,421
Osh	1,117	1,088	997	1,024
Batken			1,010	1,039

(c) Uzbekistan, 1999

	Real GDP per capita, 1999	
Oblast	PPP$	As % of national average
Uzbekistan	2,994	100
Northern Uzbekistan		
Karakalpakstan	2,023	85
Khorezm	3,148	105

Table 11.2 (cont.)

(c) Uzbekistan, 1999	Real GDP per capita, 1999	
Oblast	PPP$	As % of national average
Central Uzbekistan		
Bukhara	3,863	129
Dzhizak	2,278	76
Navoi	3,948	132
Samarkand	2,464	82
Syrdarya	3,100	104
Southern Uzbekistan		
Kashkadarya	2,458	82
Surkhandarya	2,225	74
Eastern Uzbekistan		
Andijan	2,796	93
Fergana	3,106	104
Namangan	1,965	66
Tashkent	3,165	106
Tashkent City	5,543	185

Sources: UNDP (2000b: 56–57; 2000c: 64–65; 2000d: 60).

stan and more equal spatial distribution in Uzbekistan, as well as bringing out some of the major intra-country variations. As measures of well-being, however, these data must be treated with caution. There are substantial data problems, including both the reliability of the raw data and the choice of PPP conversion rates. Moreover, because they are output measures they may not reflect final claims on resources; this is especially true of Kazakhstan, where the western oblasts of Atyrau and Mangistau produce most of the oil but the economic benefits accrue elsewhere, especially in the commercial centre, Almaty. Unfortunately, similar measures are not reported in the national *Human Development Reports* prepared in Tajikistan or Turkmenistan.

The best distributional evidence comes from data from the Living Standards Measurement Study (LSMS) surveys, conducted under the aegis of the World Bank, which are in the public domain for three of the Central Asian countries. These are high-quality household survey data, which can be analysed to estimate the determinants of household expenditure, including the role of location.[15] The data for our analysis are obtained from four LSMS surveys: the 1993 and 1997 Kyrgyz Republic surveys, the 1996 Kazakhstan survey, and the 1999 Tajikistan survey. For Uzbekistan, we use data on households collected in the Fergana oblast in 1999 as a pilot study for the redesign of the national Household

Budget Survey.[16] The sample sizes are 1,926 households in 1993 and 2,618 in 1997 for the Kyrgyz Republic, 1,890 households for Kazakhstan, 1,983 households for Tajikistan and 542 households for Uzbekistan.[17]

Despite the four countries' historical, cultural and geographical similarities, there are differences in the samples. The differences largely reflect the higher incomes and more ''European'' culture of Kazakhstan, and the more traditionally Central Asian society in Tajikistan and the Fergana oblast of Uzbekistan. The Kazakhstan sample is the most urban, with 44 per cent of households living in rural communities, which is fewer than in the Kyrgyz Republic (57 per cent in 1993 and 62 per cent in 1997), the Fergana oblast of Uzbekistan (72 per cent) or Tajikistan (73 per cent). Households in Kazakhstan are less likely than households in the Kyrgyz Republic, Tajikistan or the Fergana oblast of Uzbekistan to be headed by a man and the head is less likely to be married. Finally, household heads in Kazakhstan are older (46 years), on average, than heads in the Kyrgyz Republic (40–41), Tajikistan (40), and Uzbekistan (39).

Households are smaller in Kazakhstan than in Tajikistan, Uzbekistan or the Kyrgyz Republic. In 1996 the average household in Kazakhstan contained 3.6 members, which is less than in the Kyrgyz Republic (4.9 in 1993 and 5.6 in 1997), Uzbekistan (6.0) and Tajikistan (7.0). The average number of children in a household in Kazakhstan is 1.3, which is less than in the Kyrgyz Republic (1.8 in 1993 and 2.2 in 1997), Uzbekistan (2.9) or Tajikistan (3.5); the number of elderly household members is similar in each country (0.4–0.5). The number of children is substantially higher than in European transition economies or elsewhere in the Confederation of Independent States.

The education variables indicate the high education level, relative to income levels, of these countries. Over two-fifths of household heads in each country have post-secondary education. In Kazakhstan the proportion with university education is slightly higher than in Tajikistan or the Fergana oblast of Uzbekistan. The Kyrgyz surveys, especially that of 1997, report substantially higher proportions of college-educated heads, and fewer heads having other post-secondary education than in the other countries, and there is also a sharp increase in the proportion of household heads completing secondary education and a drop in those with incomplete secondary education between 1993 and 1997.[18] The other human capital variable, reported health of the household head, also has implausible variations, with very poor reported health in Kazakhstan and very good in the Kyrgyz Republic.

Comparison of the samples' characteristics suggests that, in many respects, households in the Kyrgyz Republic and Kazakhstan are more similar to each other than to households in Tajikistan and the Fergana oblast

of Uzbekistan. In the Kyrgyz Republic and Kazakhstan, compared with the other two countries, households are more likely to be headed by women or by an unmarried head, heads are younger and better educated, and households are less likely to be in rural areas. In addition, households are smaller and contain fewer dependants in Kazakhstan and the Kyrgyz Republic than in Tajikistan or the Fergana oblast of Uzbekistan.

In the next section of the chapter, we examine whether differences in these characteristics explain the variation in living standards that we observe within and across countries in Central Asia. Our measure of well-being is household per capita expenditure. We examine regional differences in expenditures that cannot be accounted for by differences in the measurable characteristics of households in our samples. Residual regional inequality is related to the ethnic, cultural, religious and social differences described in section 2.

3. Model and variables

We estimate a human capital model in which the per capita expenditure of households is affected by the level of human capital, the number of household members and other demographic characteristics of the household, and the location of the household (see Anderson and Pomfret 2000 for a more detailed discussion of the expenditure model). The dependent variable is household expenditure per capita, based on a headcount of household members and reported expenditures on goods (excluding vehicles), food, health, education and other services, housing, utilities, communication, and transportation.[19] Because the log of expenditure more closely follows a normal distribution, we estimate semi-logarithmic regressions of the log of per capita expenditure on the household characteristics.

To capture household human capital, we include measures of the education and health of the household head. For all countries we use dummy variables for college education, other post-secondary training and completed secondary education, with incomplete secondary schooling as the omitted education category. For Kazakhstan, we include two non-college post-secondary training variables, differentiating between professional-technical training (PTU) and Tecnikum education.[20] Health is measured by a subjective assessment of the head's health status; the dummy variable is equal to one if the head reports good or very good health and equal to zero if health is average, poor or very poor.

Household composition is measured by three variables describing the number of children under the age of 18, the number of elderly and the number of non-elderly adults in the household. An adult is defined as

elderly if he or she is eligible for a state pension, normally at age 60 for a man and age 55 for a woman. The other demographic characteristics include the age (measured in years), gender and marital status of the head of the household. Gender and marital status are captured by dummy variables, respectively equal to one if the head is a man and zero if the head is a woman, and equal to one if the head is married or cohabiting with a partner and equal to zero otherwise.

Location of the household is measured by the interaction of a rural–urban residence dummy variable (1 = rural, 0 = urban) with region-specific variables for the Kyrgyz Republic, Kazakhstan and Tajikistan. In the Kyrgyz Republic, we classify households into four groups: resident in Bishkek and other urban areas of Chuy oblast; resident in rural Chuy; resident in the rural or urban areas of the southern oblasts of Osh or Jalal-Abad; and resident in the rural or urban areas of the mountain oblasts of Issyk-Kul, Naryn or Talas. We divide Kazakhstan into six regions: Almaty;[21] rural and urban areas of the southern oblasts other than Almaty; and rural and urban residence in the northern, central, western and eastern oblasts. We divide Tajikistan into five regions: Gorno-Badakhshan in the east; Leninabad in the north-west;[22] Khatlon in the south-west; and Dushanbe and the Rayons of Republican Subordination (RRS) in the central western area. We differentiate between the rural and urban areas of all regions of Tajikistan with the exception of the capital, Dushanbe. In each of these three countries, the omitted category for regional location is the largest city (Bishkek and other urban areas of Chuy oblast; Almaty; and Dushanbe). In Uzbekistan, we include only the rural–urban variable because a single oblast was sampled.

In addition to the national-level analysis, we compare the Fergana oblast of Uzbekistan in 1999 with the parts of the Kyrgyz Republic in 1997 and Tajikistan in 1999 also located in the Ferghana Valley.[23] The Ferghana region of the Kyrgyz Republic is defined as the Osh and Jalal-Abad oblasts; the Ferghana region of Tajikistan is the Leninabad oblast.

4. Results

The results of the ordinary least squares regressions are presented in Tables 11.3 (Kazakhstan), 11.4 (the Kyrgyz Republic, 1993–1997) and 11.5 (Tajikistan). The pooled model for the Kyrgyz Republic regresses the log of real per capita expenditures on the explanatory variables, with 1993 as the base year (price index = 100) and a 1997 price index equal to 369. In Table 11.6, we present results from expenditure models for the Fergana oblast of Uzbekistan and for the Ferghana Valley regions of the Kyrgyz Republic and Tajikistan.[24] The explanatory power of the models

for the Kyrgyz Republic and Kazakhstan are reasonable, with an R^2 of about .3. The Tajikistan and Uzbekistan models are weaker, with an R^2 for each country of about .18.

4.1. Household location

The locational variables in Tables 11.3–11.6 are dummies, and the omitted category is the capital city, with the exception of Uzbekistan. In both the Kyrgyz Republic and Tajikistan, a household in the capital had sig-

Table 11.3 Expenditure model: Kazakhstan, 1996

	Ln expenditure	
Variables	Coefficient	*t*-statistic
Intercept	**8.570**	93.19
Demographic traits		
Head is male	0.040	1.15
Age of head	–0.001	–1.04
Head is married	0.043	1.07
Education/health of head		
College graduate	**0.213**	4.99
Tecnikum	**0.112**	2.78
Professional-technical training	0.076	1.49
Completed secondary	–0.009	–0.23
Head in good health	–0.026	–0.86
Location of household		
Rural*central	0.100	1.64
Urban*central	–0.037	–0.67
Rural*south	**–0.357**	–5.72
Urban*south	**–0.431**	–7.29
Rural*west	0.024	0.30
Urban*west	**0.222**	3.10
Rural*north	**0.437**	7.62
Urban*north	**0.289**	5.06
Rural*east	**0.200**	3.47
Urban*east	0.002	0.03
Household composition		
Number of children	**–0.169**	–13.47
Number of elderly	**–0.114**	–3.74
Number of non-elderly adults	**–0.055**	–3.91
R^2	.303	
F-statistic	**38.69**	
Sample size	1,890	

Note: Bold numbers indicate significance at the 5% level.
Source: Data obtained from the 1996 Living Standards Measurement Survey.

Table 11.4 Expenditure model: Kyrgyz Republic, 1993–1997

	Ln expenditure		Ln expenditure, 1993		Ln expenditure, 1997	
Variables	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	**5.195**	61.21	**4.863**	30.48	**7.547**	93.82
Demographic traits						
Head is male	–0.017	–0.39	0.104	1.31	**–0.179**	–4.16
Age of head	0.00007	0.07	–0.0006	–0.28	0.001	0.76
Head is married	0.036	0.93	0.083	1.12	0.062	1.74
Education/health of head						
College graduate	**0.187**	4.96	**0.221**	3.29	**0.135**	3.51
Post-secondary	0.067	1.58	0.110	1.54	–0.073	–1.55
Completed secondary	–0.077	–1.93	–0.149	–1.88	–0.071	–1.87
Head in good health	0.032	0.71	0.111	1.22	–0.002	–0.06
Household location						
Rural Chuy	**–0.288**	–6.63	**–0.272**	–3.49	**–0.317**	–7.44
Rural south	**–0.744**	–18.28	**–0.694**	–8.72	**–0.839**	–22.91
Urban south	**–0.417**	–9.11	**–0.237**	–2.79	**–0.648**	–15.07
Rural mountain	**–0.940**	–23.10	**–0.853**	–9.80	**–1.048**	–29.99
Urban mountain	**–0.553**	–10.61	–0.185	–1.69	**–0.804**	–18.08
Household composition						
Number of children	**–0.128**	–15.01	**–0.123**	–7.03	**–0.125**	–16.61
Number of elderly	**–0.052**	–2.96	**–0.085**	–2.37	0.020	1.16
Number of non-elderly	**–0.028**	–3.35	0.002	0.10	**–0.085**	–9.69
Year						
1997	**0.666**	24.62				
R^2	.319		.15		.537	
F-statistic	**131.57**		**22.34**		**201.45**	
Sample size	4,515		1,913		2,618	

Note: Bold numbers indicate significance at the 5% level.
Source: Data obtained from Living Standards Measurement Surveys for 1993 and 1997.

Table 11.5 Expenditure model: Tajikistan, 1999

	Ln expenditure	
Variables	Coefficient	*t*-statistic
Intercept	**9.911**	113.64
Demographic traits		
Head is male	0.017	0.30
Age of head	−0.001	−0.87
Head is married	0.069	1.49
Education/health of head		
College graduate	**0.339**	7.15
Post-secondary	**0.166**	4.08
Completed secondary	0.043	1.06
Head in good health	−0.009	−0.32
Household location		
Rural RRS	−0.066	−1.25
Urban RRS	0.048	0.54
Rural Leninabad	**−0.315**	−6.21
Urban Leninabad	**−0.327**	−5.55
Rural Khatlon	**−0.324**	−6.51
Urban Khatlon	**−0.366**	−5.65
Gorno-Badakhshan	**−0.585**	−7.82
Household composition		
Number of children	**−0.087**	−12.73
Number of elderly	**−0.048**	−2.74
Number of non-elderly	−0.005	−0.59
R^2	.177	
F-statistic	**24.93**	
Sample size	1,983	

Note: Bold numbers indicate significance at the 5% level.
Source: Data were obtained from the 1999 Living Standards Measurement Survey.

nificantly higher per capita expenditure, *ceteris paribus*, than a household elsewhere in the country. In Tajikistan (Table 11.5) the difference is not significant between the capital Dushanbe and the surrounding Rayons of Republican Subordination (RRS), but on average a household in the north or the south is about one-third poorer and one in the Gorno-Badakhshan autonomous region is almost 60 per cent poorer than an equivalent household in Dushanbe. Rural–urban differences in expenditures are small within RRS, Leninabad and Khatlon.

The results from the Kyrgyz Republic (Table 11.4) are even starker, and of special interest because this is the only country for which we have more than one survey set. In 1993, before the transition to a market economy was far under way, locational differences were already signifi-

Table 11.6 Expenditure model: Ferghana Region of Uzbekistan, Kyrgyz Republic and Tajikistan

	Uzbekistan		Kyrgyz Republic		Tajikistan	
Variables	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
Intercept	**8.067**	32.56	**6.890**	53.95	**9.732**	67.90
Demographic traits						
Head is male	0.0005	0.00	–0.012	–0.172	–0.108	–0.98
Age of head	**0.010**	2.60	0.0005	0.33	0.001	0.65
Head is married	0.049	0.33	–0.060	–1.03	–0.011	–0.12
Education/health of head						
College graduate	**0.439**	3.12	0.110	1.73	**0.237**	2.63
Post-secondary	0.169	1.31	**–0.175**	–2.33	**0.180**	2.44
Completed secondary	0.127	1.01	–0.075	–1.19	0.044	0.60
Head in good health			–0.076	–1.11	0.064	1.28
Household location						
Rural community	**–0.530**	–6.63	**–0.234**	–6.26	0.047	0.89
Household composition						
Number of children	**–0.105**	–4.27	**–0.114**	11.43	**–0.106**	–7.31
Number of elderly	**0.106**	2.24	**0.057**	2.08	–0.056	–1.85
Number of non-elderly adults	–0.026	–0.91	**–0.071**	–5.63	**–0.030**	–1.96
R^2	.187		.342		.14	
F-statistic	**12.16**		**42.73**		**8.760**	
Sample size	541		915		603	

Note: Bold numbers indicate significance at the 5% level.
Source: Data were obtained from Living Standards Measurement Study surveys for the Kyrgyz Republic 1997 and Tajikistan 1999 and the 1999 pilot study for the redesigned Household Budget Survey in Uzbekistan.

cant, with a household in rural Chuy (the province surrounding the capital, Bishkek) 27 per cent poorer, households in the south 24 per cent (urban) and 69 per cent (rural) poorer, and households in the mountain region across the middle of the country 18 per cent (urban) and 85 per cent (rural) poorer than a household with the same characteristics in Bishkek. In 1997, when the transition to a market economy was well established, these locational differences had widened to 32 per cent (rural Chuy), 65 per cent (urban south), 84 per cent (rural south), 80 per cent (urban mountain), and 105 per cent (rural mountain) relative to Bishkek and the urban north. In all regions and in both 1993 and 1997, rural households were worse off than urban households.

The Kazakhstan results (Table 11.3) differ insofar as the largest city (and capital at the time), Almaty, was not the richest region. Thus, the locational coefficients are positive for the north and west and negative for the south and centre, and only the north and south coefficients are significantly different from zero. If the poorest region had been the base, the regional differences would appear at least as strong as those in the Kyrgyz Republic. In addition, we find that rural households are better off than urban households in the east, the north and the south, but rural households are worse off than urban households in the west. There is no difference in the well-being of rural and urban households in the central oblasts.

The pattern of regional inequality in Kazakhstan is clear both from the tables and from anecdotal evidence. The oil-producing oblasts by the Caspian Sea (Atyrau and Mangistau) have relatively high, but volatile, per capita GDP – a phenomenon shared by Almaty City, which is believed to be the major beneficiary of petrodollars. The other high-GDP oblast is Pavlodar in the north, which together with its neighbours, East and North Kazakhstan, is the centre of Russian settlement and separatist tendencies. In contrast, the four southern oblasts, Zhambyl, South Kazakhstan, Qyzylorda and Almaty, are the poorest, and by quite a large margin. The gap between north and south is substantial in the raw output data of Table 11.2 and, if anything, even stronger in the locational effects reported in Tables 11.3–11.5 when adjustment is made for demographic and human capital attributes. Although primarily Kyrgyz, the south contains the Uzbek minority; whether the latter is driven to secessionist thoughts by economic inequality may, however, depend upon comparison with neighbouring regions of Uzbekistan (Tashkent, Syrdarya and Dzhizak) rather than with distant parts of Kazakhstan. In the Kyrgyz Republic, per capita GDP differences have widened, with Bishkek and the surrounding Chuy oblast enjoying an increase between 1996 and 1999 whereas the poor oblasts of the south became poorer. The relatively sparsely populated mountain oblasts had mixed fortunes, driven in part

by minerals (especially the Kumtor gold project, which accounted for four-fifths of national GDP by the end of the 1990s), and, as in Kazakhstan, the benefits from the higher output accrued in part in the capital and commercial centre (Bishkek). This phenomenon is reflected in the household expenditure analyses for 1993 and 1997, which show households everywhere becoming worse off than identical households in Bishkek, and the mountain region has the largest locational disadvantage.

The data from the other three countries are less rich, but they appear to have less spatial inequality than the relatively rapidly reforming Kazakhstan and the Kyrgyz Republic. In Tajikistan, incomes fell substantially during the 1992–1997 civil war and, although they have recovered on average since then, poverty rates remain very high and Tajikistan is clearly the poorest country in Central Asia. The sparsely populated and mountainous Gorno-Badakhshan Autonomous Oblast has long been the poorest part of the country and that is reflected in Table 11.5. The similarity of the coefficients for Leninabad and Khatlon is a little surprising, but this may reflect the higher human capital and other more favourable demographic variables in the northern oblast, which is generally viewed as the most developed part of the country. Khatlon is more rural and the centre of cotton cultivation in Tajikistan, and has suffered relative decline as a result of the droughts, which hurt cotton harvests in 2000 and 2001. The central region has benefited from the main raw material and industrial complex built around the aluminium smelter of Tursunzade, whose output has been much reduced since independence but which remains the major foreign exchange earner.

Spatial inequality appears to have been least in Uzbekistan. In Table 11.2, the high-end outliers are as elsewhere the capital city (Tashkent) and a mineral-rich underpopulated region (Navoi). Otherwise, although the southern oblasts near the Afghanistan border (Kashkadarya and Surkhandarya) and the autonomous republic of Karakalpakstan are poorer and Bukhara richer, the gaps are not extreme. The relative equity is reinforced by a government that has maintained public revenue collection and apparently targeted its social expenditures effectively (Pomfret 2000a,b).

Turkmenistan is the most difficult country to analyse owing to the tight control exerted by the government, including controlled access to data.[25] The government has an active programme to create a national road and rail network and has invested in large industrial plants in Lebap and Balkan oblasts, but observation suggests that most of the wealth in the country is concentrated in the capital, Ashgabat. Social indicators are, as in most of the region, worse for rural areas, and the northern oblast of Dashkhoguz appears to be particularly badly off.[26]

4.2. Household composition

In all four countries, household composition is an important determinant of per capita household expenditures. The costs of large households are substantial. A recurring result is that additional children lower per capita household expenditure (9 per cent in Tajikistan, 12 per cent in Kyrgyzstan, 17 per cent in Kazakhstan) by a larger amount than do additional elderly or non-elderly adults (respectively 5 per cent and 3 per cent in Tajikistan and Kyrgyzstan, 12 per cent and 6 per cent in Kazakhstan).[27] Unsurprisingly, the costs of additional children, in terms of the negative impact on per capita household expenditure, are larger in the urban areas.

When we compare the Ferghana regions of Uzbekistan, Tajikistan and the Kyrgyz Republic (Table 11.6), we find similarities and differences. In all three countries, an additional child lowers per capita household expenditure by about 11 per cent. The presence of a pensioner has no effect on per capita household expenditure in the Ferghana region of Tajikistan, but it increases per capita household expenditure by 6 per cent in the Ferghana region of the Kyrgyz Republic and by 11 per cent in the Fergana oblast of Uzbekistan.[28] In contrast, non-elderly adults have no impact on per capita household expenditures in the Fergana oblast of Uzbekistan, but reduce expenditures in the Ferghana regions of Tajikistan and the Kyrgyz Republic in 1997. This suggests that, in the Ferghana Valley, the labour market provides enough income to cover the average expenditures of adults in Uzbekistan, but cannot cover the expenditure needs of adults in the poorer countries of Tajikistan and the Kyrgyz Republic.

4.3. Education and health of household head

In all four countries, having a college-educated head positively affects household living standards. In Kazakhstan and in the Kyrgyz Republic in 1993, per capita expenditure is 22 per cent higher in households with a college-educated head than in households whose heads failed to complete secondary school.[29] In the Kyrgyz Republic, the effect of college education drops significantly during the transition period, to 14 per cent in 1997. The effect of a college-educated head is larger in Tajikistan (34 per cent higher per capita household expenditure than in households whose head failed to complete secondary education), and larger still in the Fergana oblast of Uzbekistan (44 per cent).[30] Overall, general high-skilled training has substantially helped household heads improve their families' standard of living.

4.4. Demographic traits

The demographic traits in our model – age, gender and marital status of the head – are generally not significant determinants of household expenditures.

4.5. Year

Table 11.4 presents estimation of the pooled expenditure regression for the Kyrgyz Republic (1993–1997). We find that real per capita expenditure is 67 per cent higher in 1997 than in 1993, holding other determinants of household expenditure constant. Households are better off in the later transition period than in the early period after independence once we control for changes in education, region, household composition and the demographic characteristics of the household. Hyperinflation ended, production in mining and agriculture increased, and the economy experienced an increase in income after the turbulent early transition years.

4.6. Summary

In summary, the most important explanations for the variation in expenditures per capita in the region are household location, household composition and education. We find large variation in per capita expenditure by location within each country, and the differences go beyond the simple rural–urban distinction. Family structure is also important; an increase in the number of children in a household reduces household expenditure, and the cost of a child to the household exceeds the cost of an extra working or non-working adult.[31] The human capital variables yield one strong conclusion. In all countries, having a university-educated household head significantly improves household welfare; expenditures are higher in these households than in households with less-educated heads. Other levels of education, relative to the benchmark of incomplete secondary schooling, do not consistently have a positive impact on material well-being. The effects of education dominate the effects of health on household consumption, but this may be owing to the limited nature of the subjective measure of health that we use.

5. Distribution of public services

Inequality in income and expenditures of households within a country can be mediated by government intervention and the provision of public

services. Governments could, for example, provide more public services to the lowest-income communities in which households are less able to purchase these goods on their own. In this case, we would expect to find more equality in the provision of schools, health clinics and other public goods than in the distribution of income or expenditures.

In this section, we use data on the availability of public services at the local community level in the Kyrgyz Republic (1997), Kazakhstan (1996) and Tajikistan (1999) to determine whether the provision of public goods reinforces or offsets the regional inequality in expenditures that we described in section 4. The public services we examine are classified into three groups: education, health care and other services. The education indicators are: good schools (good teachers in the Kyrgyzstan survey), adequate school supplies, adequate heating in the schools, adequate books, adequate furniture, sufficient buildings, access to secondary school, access to gymnasiums, access to kindergarten, and the percentage of eligible children enrolled in school in the community. The healthcare indicators are: location of hospital, clinic, obstetrician/gynaecologist, paediatrician or pharmacy in the community and the percentage of residents who have been vaccinated. The other services are: post office, hard roads, public water service, sewerage service, garbage collection, and the percentage of households with a telephone service. We have 121 communities in Tajikistan, 230 in Kyrgyzstan and 130 in Kazakhstan. The Kazakhstan survey does not include information on all of the services listed above, but does include more enquiry into the health care of the community.

We tabulated by region the proportion of communities in these countries that have these services. We tested whether the region and service availability are independent events for each service in each country, and rejected the null hypothesis of independence. To determine where the regional differences are largest, we estimated robust linear probability regression models of service availability in the community and regression models of school enrolment and vaccination rates in which the independent variables are the regional dummy variables. We control for rural–urban regional differences where possible. In some cases, there was no variation in service availability within a region or between the rural and urban areas of a region; in those cases the regions were dropped from the analysis. The regression results are given in Tables 11.7 (Kazakhstan), 11.8 (Kyrgyzstan) and 11.9 (Tajikistan).

We find considerable regional variation in the availability of services within each country but less inequality in service distribution in Kazakhstan than in the other countries. In Kazakhstan (Table 11.7), there is no measured inequality in education services with one exception – the rural

Table 11.7 Public service regressions: Regional inequality in Kazakhstan, 1996

		North		Central		South		West	
Service	Rural east	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Education									
Kindergarten	**−0.357**	0.060	−0.135	−0.000	0.032	−0.049		−0.079	−0.057
Secondary[a]									
Adequate books	**−0.405**	0.012	0.040	−0.143	−0.238	−0.071	−0.259	−0.016	−0.271
% in school, age 6–10	−0.638	0.300	−0.075	0.069	−0.200	−0.271	−0.033	0.157	−0.367
% in school, age 11–14	−1.167	0.100	0.044	−0.438	−0.4	0.100	0.100	0.100	0.100
% in school, age 15–18	−1.078	−4.586	−4.149	−0.364	−1.078	−0.221	−3.864	−8.078	0.636
Health care									
Hospital	**−0.492**	0.036	**−0.437**	0.071	**−0.714**	0.186	**−0.464**	−0.241	
Clinic	−0.206	−0.095	−0.095	−0.146		−0.082		**−0.484**	−0.229
Obstetrician/gynaecologist	**−0.294**	−0.155	**−0.516**	−0.071	**−0.460**	0.329	**−0.384**	−0.016	**−0.371**
Paediatrician	**−0.373**	−0.195		−0.124		0.271	**−0.366**	−0.218	
Pharmacy	−0.325	0.119	−0.214	0.068		−0.022		0.063	**−0.514**
Lack inst.	0.127	**−0.295**		−0.214	0.016	−0.229	−0.116	−0.095	−0.029
Lack drugs	**0.302**	0.190	0.246	**0.314**		0.257	**0.295**	0.246	0.157
Low knowledge		0.052	0.080	0.040	0.080	0.046		**0.232**	
Bad care	**−0.302**	0.226	−0.079	0.000	0.024	−0.057	−0.045	0.198	**−0.357**
Poor organization	0.198	0.143	0.143	0.000	−0.024	−0.157	0.018	0.087	0.143
Inadequate primary care	−0.095	−0.012	0.071	0.071	−0.095	−0.229	−0.179	0.016	−0.029
Other services									
Hard roads		−0.008		−0.005		0.010		0.020	
Water		−0.079		0.057		−0.120		−0.128	
Sewerage	**−0.349**	−0.271		**0.217**	**−0.460**	−0.264		**−0.361**	

Notes: Bold numbers indicate significance at the 5% level. A blank cell indicates no estimable rural–urban difference in the region.
[a]Insufficient regional variation to estimate a model.
Source: Data were obtained from the 1996 Living Standards Measurement Study survey.

Table 11.8 Public service regressions: Regional inequality in Kyrgyzstan, 1997

	Chuy		Mountain		South	
Service	Rural	Urban	Rural	Urban	Rural	Urban
Education						
Kindergarten	**−0.287**	0.141	**−0.432**	−0.070	**−0.473**	0.071
Secondary	**0.072**	0.020	0.037	−0.075	**0.072**	0.047
Gymnasium	−0.029	**0.445**	0.007	**0.177**	0.013	**0.202**
Good-quality teachers	**−0.336**	−0.101	**−0.291**	**−0.409**	**−0.390**	−0.120
Adequate buildings			−0.104		**−0.153**	−0.093
Adequate supplies	0.112	0.010	−0.198	−0.062	−0.163	**−0.196**
Adequate furniture	−0.052	−0.038	**−0.170**	**−0.133**	−0.106	−0.086
Adequate books	**0.316**	**0.394**	−0.003	0.047	0.063	**0.258**
Adequate heating	−0.020	0.050	**−0.401**	**−0.216**	−0.207	−0.116
% in school	**−8.913**	−4.176	**−6.949**	**−9.207**	**−9.513**	**−5.788**
Health care						
Hospital	0.000	**0.667**	0.060	**0.461**	−0.013	**0.385**
Clinic	−0.129	**0.418**	−0.137	**0.235**	**−0.369**	**0.214**
Obstetrician/ gynaecologist	−0.020	**0.474**	−0.063	**0.256**	−0.100	0.144
Paediatrician	0.165	**0.460**	0.065	**0.271**	0.045	**0.309**
Pharmacy	**−0.290**	−0.009	**−0.385**	−0.104	**−0.437**	**−0.136**
% vaccinated	−0.209	0.005	0.022	**−0.336**	−0.022	**−0.192**
Other services						
Post office	0.032	0.127	−0.019	−0.150	−0.008	−0.007
Hard roads	**−0.380**	0.034	**−0.721**	**−0.325**	**−0.793**	−0.008
Water			**−0.195**	**−0.157**	**−0.380**	−0.030
Sewerage	**−0.353**	−0.040	**−0.584**	0.028		
Garbage collection	**−0.565**	0.049	**−0.791**	**−0.310**	**−0.819**	−0.099

Notes: Bold numbers indicate significance at the 5% level. A blank cell indicates no estimable rural–urban difference in the region.
Source: Data were obtained from the 1997 Living Standards Measurement Study survey.

east region is less likely to report kindergartens and adequate school books than are other regions. We also find little variation in access to other public services, with the exception of sewerage services, which are less available in the central, urban west and rural east regions of the country. In contrast, there is significant regional inequality in the distribution of healthcare services, and we find fewer healthcare services in the rural areas of each region than in the urban areas. Specifically, the rural areas report fewer hospitals and physicians than other areas of the country.

In Kyrgyzstan (Table 11.8), significant regional differences exist in education, healthcare and other services. For education services, we find that the mountain and southern areas of the country have fewer kinder-

Table 11.9 Public service regressions: Regional inequality in Tajikistan, 1999

		RRS		Leninabad		Khatlon	
Service	Gorno	Rural	Urban	Rural	Urban	Rural	Urban
Education							
Kindergarten	−0.418	**−0.434**		−0.049		**−0.455**	
Secondary		**0.072**	0.020	0.037	−0.075	**0.072**	0.047
Gymnasium		−0.256		−0.119	**0.485**	−0.304	0.095
Good-quality schools		−0.290		−0.226	0.121	−0.310	
Adequate buildings	**0.509**	**0.524**		**0.373**	**0.818**	**0.538**	**0.784**
Adequate supplies		−0.229	0.061	−0.201	0.000	−0.225	
Adequate furniture		**−0.523**		**−0.164**		−0.437	
Adequate books		**0.316**	**0.394**	−0.003	0.047	0.063	**0.258**
Adequate heating		0.055	0.214	0.024	**0.517**		
% in school		**−8.913**	−4.176	**−6.949**	**−9.207**	**−9.513**	**−5.788**
Health care							
Hospital	0.350	**0.404**		**0.494**		**0.517**	
Clinic	0.150	0.288		**0.468**		0.215	
Obstetrician/gynaecologist	0.350	0.519		0.519		0.415	
Paediatrician	−0.036	0.171		**0.338**		0.068	
Pharmacy	−0.225	0.183		0.298		0.096	
% vaccinated		−0.209	0.005	0.022	**−0.336**	−0.022	**−0.192**
Other services							
Post office		0.084		**0.494**		0.000	
Hard roads	**−0.55**	−0.173		−0.16		−0.076	
Water	−0.408			**−0.038**		**−0.103**	
Sewerage	**−0.578**	**−0.647**	−0.111	**−0.393**		**−0.692**	−0.153
Garbage collection	−0.425	**−0.538**	0.042	**−0.411**	0.284	**−0.454**	0.125

Notes: Bold numbers indicate significance at the 5% level. A blank cell indicates no estimable rural–urban difference in the region.
Source: Data were obtained from the 1999 Living Standards Measurement Study survey.

gartens, lower-quality teachers, inadequate facilities and lower enrolment in school than the northern areas of Chuy and Bishkek. Within each region, the rural areas tend to have fewer services than the urban areas. For the healthcare indicators, we find that the urban areas of Chuy, the south and the mountain regions are more likely to report a hospital, clinic or physician than are the rural areas or Bishkek, and pharmacies are less available in rural areas. Finally, of the other services, hard roads, water, sewerage and garbage services are unequally distributed. The mountain oblasts have fewer of these services than the other regions, and, within each region, rural areas are less likely to have services than urban areas. In all cases, services are more available in the north (Chuy and Bishkek) than in the mountainous regions or the southern agricultural area.

In Tajikistan (Table 11.9), education, healthcare and other services differ significantly across regions, but the distributional pattern is less obvious than in Kyrgyzstan. Among education services, kindergartens are less likely but secondary schools are more likely in rural than in urban areas. School enrolment in rural and urban areas of Leninabad, RRS and Khatlon is lower than in Dushanbe, but Dushanbe has inadequate school buildings and an inadequate supply of school books in comparison with other regions. Leninabad seems to have more availability of healthcare facilities (hospitals, clinics and paediatricians) than other regions, and vaccination rates are high in all regions but lowest in urban areas of Leninabad and Khatlon. For other services, we find greater access to hard roads, water, sewerage and garbage collection in Dushanbe than in other regions, and the rural regions have less access to these services than do the urban areas.

This evaluation of the distribution of public services in the three countries suggests that provision of public goods reinforces the regional inequality patterns in expenditures that we measured among households. The poorest households are likely to live in communities with the lowest access to public services. We try to determine why these regional differences exist by looking at the effect of community characteristics on the availability of these services. The community characteristics measure the employment base of the community, income, population, ethnicity and regional isolation. In general, the most important determinant of service location is rural–urban residence: rural communities are less likely to have services than are urban communities, and, within rural and urban areas, large population areas seem to have greater access to many public services. We also find some evidence that the ethnic composition of the community does influence service location, generally in favour of Slavic communities in each country. The results from this analysis of community characteristics are available from the authors on request.

6. Conclusions

In Central Asia, although international migration took place on a large scale, internal migration did not. In the Kyrgyz Republic, which probably has the most liberal labour and housing markets in the region, there has been internal migration but it has been primarily within regions, from rural areas in the northern oblasts of Chuy, Talas, Naryn and Issyk-Kul to urban centres, especially Bishkek, with little migration from the poorer south to the richer north. The LSMS evidence establishes that even in what are the three least-regulated economies there is not a national labour market. Given the tighter control over the economy and over internal mobility in Uzbekistan and Turkmenistan, it is safe to conclude that labour mobility is not reducing spatial inequality to any great extent in the Central Asian countries. This is somewhat surprising insofar as we might have expected the move to a market economy to be followed by establishment of national labour markets, with people relocating in response to economic incentives. Two main sets of explanations can be offered for why this did not happen: the economies are not physically integrated, and social factors discourage mobility. The infrastructure prevents a national economy being established.[32] The Soviet transport network ignored republic boundaries and many regions were better connected to the Tashkent rail hub or, in the case of northern Kazakhstan, to Russian cities than to their republic's capital. In the south-east, physical boundaries are formidable, with the Ferghana Valley blocked from the rest of Uzbekistan, northern and southern Kyrgyz Republic separated, and many parts of Tajikistan cut off by snow in winter.[33] Since independence, all five countries have aimed to create national transport networks, with Turkmenistan devoting most resources to the specific task and impoverished Tajikistan and the Kyrgyz Republic suffering from acute resource constraints.

The extended family is very strong in Central Asia. Buckley (1998: 72) has argued that these ties are so strong that people will prefer to remain in their place of birth within the family than to move elsewhere for higher economic returns. The international migration has largely concerned non-Central Asian groups such as Germans and Slavs, whereas Central Asian groups have not relocated. Central Asian groups have not tended to migrate across borders; in particular, there have not been cross-migrations of people to their "ethnic homeland" (e.g. Turkmen to Turkmenistan and Uzbeks to Uzbekistan in the Khorezm/Dashkhoguz region) as happened between Azerbaijan and Armenia in the early 1990s.

There are limits to non-mobility. In the dire economic conditions of Tajikistan in the late 1990s migration did increase, although this consisted mainly of males moving to Russia in search of work (and sending

remittances to their families) rather than internal migration. Tajiks and Uzbeks (and others) have fled from Afghanistan and live as refugees in border areas of Tajikistan and Uzbekistan, although the economic impact of these movements is secondary.

The lack of price integration in the national labour markets implies economic inefficiency, in the sense that moving labour from low- to high-wage locations could increase national output. However, the welfare implications of the two explanations of the spatial differentials matter. In the first case, infrastructural improvements yield a clear benefit in terms of allocative improvement. On the other hand, if people choose not to move owing to the non-pecuniary benefits of staying put, then improved infrastructure will have less welfare benefit. How does spatial inequality align with ethnic or other divisions? In our econometric work on the LSMS data, ethnicity has very little independent impact as a determinant of per capita household expenditure. Nevertheless, given the regional clustering of ethnic minorities, ethnicity is likely to become associated with spatial inequalities.

The Slavs and other Europeans tend to be concentrated in the largest cities, apart from in Kazakhstan and the Kyrgyz Republic where there are also large rural communities in the north of each country. In general, the Slavs and Europeans are located in the more economically flourishing regions. In the Kyrgyz Republic, however, there is an implicit commonality of interest between the Slavs and the Kyrgyz in the north, and the major divide is north–south. Moreover, many of the Slavs and Europeans emigrated during the 1990s, and presumably included the most discontented and most dynamic members of those ethnic groups. Given the relatively high human capital endowment of these groups and an age distribution among migrants that tended to be relatively concentrated in working-age adults, this emigration was a serious economic cost to the countries concerned, although it contributed to political stability by increasing ethnic homogeneity. The only real remaining source of tension is in northern Kazakhstan, where Russian communities are still large and concentrated in areas contiguous to the Russian Federation, and their relative wealth may make them fearful of what they might perceive as a rapaciously redistributing central government dominated by Kazakhs.

Perhaps of more concern are potential tensions among native Central Asian ethnic groups, especially where these tensions could fuel irredentist claims. The Uzbek minorities, for example, are concentrated near to the borders of Uzbekistan in South Kazakhstan, in southern parts of the Kyrgyz Republic, in the Dashkhoguz oblast of Turkmenistan and in the Leninabad oblast (and small pockets in the western parts of RRS) in Tajikistan. The first three of these locations are among the poorest parts

of the countries concerned. If they feel disadvantaged within their current country, the Uzbek minorities might yearn for secession, although this is more likely if they live in poorer countries (Tajikistan and the Kyrgyz Republic) than if they live in Kazakhstan. Regional differentiation can also fuel other conflicts. The densely populated Ferghana Valley oblasts of Uzbekistan (Fergana, Namangan and Andijan) and the neighbouring regions of the Kyrgyz Republic (Jalal-Abad, Osh and Batken) are fertile grounds for Islamic extremists and will become more so if these regions continue to lag economically.[34]

This chapter measures the existence and persistence of regional inequality in household resources and public goods. It does not offer a policy solution to the inequality we observe in the 1990s in Central Asia. A high degree of persistent inequality can exacerbate internal political and social problems and promote regional instability; economic growth and performance can be negatively affected by inequality. The government has a responsibility to address the concerns of all citizens and can use its resources to balance, to a certain extent, regional differences in resource availability. The governments of these countries have not as yet equalized access to schools, hospitals and other services that are vital to growth. Policy should focus more resources on correcting these imbalances; regional stability may hinge on the success of redistributive policy actions.

Appendix 1

Table 11A.1 Administrative divisions

(a) Kazakhstan[a]

Oblast	Capital	Population, 1999
Almaty	Almaty (Alma-Ata)	1,560
Almaty City		1,129
Akmola	Astana (Akmolinsk/Tselinograd)	837
Astana		318
Aqtöbe	Aqtöbe (Aktiubinsk)	683
Atyrau	Atyrau (Gurev)	439
East Kazakhstan	Öskemen (Ust-Kamenogorsk)	1,533
Karaganda	Karaganda	1,414
Mangistau (Mangyshlak)	Aqtau (Shevchenko)	316
North Kazakhstan	Petropavl (Petropavlovsk)	727
Pavlodar	Pavlodar	807
Qostanay	Qostanay (Kustanai)	1,022
Qyzylorda	Qyzylorda (Kzyl-Orda)	596
South Kazakhstan	Shymkent (Chimkent)	1,974
West Kazakhstan	Oral (Uralsk)	618
Zhambyl	Zhambyl (Dzhambul)	984

Table 11A.1 (cont.)

(b) Kyrgyz Republic[b]

Oblast	Capital	Population, 1999	
		No. ('000)	People/km^2
Chuy	Bishkek (Frunze)	771	38
Issyk-Kul	Karakol (Przhevalsk)	413	10
Jalal-Abad	Jalal-Abad	869	26
Naryn	Naryn	249	6
Osh	Osh	1,176	34
Talas	Talas	200	17
Batken	Batken	382	
Bishkek City		762	6,215

(c) Tajikistan[c]

Viloyat	Capital	Population, 2000	
		No. ('000)	People/km^2
Khatlon	Gulab	2,151	87
Leninabad (Sughd)	Khujand	1,870	72
RRS	Dushanbe	1,338	47
Dushanbe (Stalinabad)		562	4,390
Viloyati avtonomi			
Gorno-Badakhshan	Khorugh (Khorog)	206	3

(d) Turkmenistan[d]

Velayat	Capital	Population
Akhal	Ashgabat (Ashkhabad)	n.a.
Balkan	Nebitdag	n.a.
Dashkhoguz	Dashkhoguz (Tashauz)	n.a.
Lebap	Turkmenabat (Charjew/Chardzhou)	n.a.
Mary	Mary	n.a.

(e) Uzbekistan[e]

Oblast	Capital	Population, 2000	
		No. ('000)	People/km^2
Andijan	Andijan (Andizhan)	2,195	522
Bukhara	Bukhara	1,424	35
Dzhizak	Dzhizak	979	46
Fergana	Fergana	2,672	399
Kashkadarya	Qarshi (Karshi)	2,179	76
Khorezm	Urgench	1,330	217
Namangan	Namangan	1,933	261
Navoi	Navoi	786	7
Samarkand	Samarkand	2,680	160

Table 11A.1 (cont.)

(e) Uzbekistan[e]

Oblast	Capital	Population, 2000 No. ('000)	Population, 2000 People/km^2
Syrdarya	Gulistan	644	150
Surkhandarya	Termez	1,746	87
Toshkent	Toshkent (Tashkent)	2,356	290
Tashkent City		2,142	
Autonomous Republic Karakalpakstan	Nukus	1,510	9

Notes: Names in parentheses are former names or alternative spellings.
[a] In 1994 the parliament approved transfer of the capital from Almaty to Akmola, which was subsequently renamed Astana. After a preliminary inauguration in November 1997, the new capital was officially inaugurated in June 1998.
[b] Bishkek is the national capital as well as capital of Chuy oblast. In 2000, Osh oblast was subdivided into two, and a new oblast created with its capital at Batken.
[c] Dushanbe, the national capital, is located in the Rayons of Republican Subordination (RRS), but is the only one whose executive is directly subordinate to the national government. Khatlon viloyat was formed in early 1993 by amalgamating Gulab and Kurgan-Teppe oblasts.
[d] Ashgabat is the national capital as well as capital of Akhal velayat.
[e] Tashkent is the national capital as well as capital of Tashkent oblast.
Sources: Kazakhstan: population data from UNDP (2000b). Kyrgyzstan: population data from 1999 census; density data are preliminary estimates from UNDP (2001). Tajikistan: population data from UNDP (2000a: 17, 107). Uzbekistan: population data from *Uzbekistan Economic Trends*, January–March 2001.

In Tables 11.3, 11.4 and 11.5, household location is measured by a region-specific dummy variable interacted with a rural–urban residence variable. In each of the three countries, the omitted category for regional location is the largest city (Almaty, Bishkek and Dushanbe). Kazakhstan is divided into six regions:

- Almaty, the capital at the time of the LSMS survey, and the manufacturing and financial centre of the country.
- Southern oblasts other than Almaty – the south is the poorest part of Kazakhstan; it is an agricultural, cotton-growing region, and a manufacturing area producing intermediate goods.
- Central oblasts – the central region produces heavy metals such as chrome, lead and zinc, has coalmines, and grows wheat and other grains.
- Northern oblasts – the north is the main wheat-producing area of the country, and also specializes in metallurgy and heavy industry such as steel.
- Western oblasts – the west is the oil-producing region.
- Eastern oblasts – in the east, hydroelectric power is important as well as the mining of light metals and the production of heavy equipment.

In the Kyrgyz Republic, we classify households into four regions:

- Bishkek.
- Chuy, but not Bishkek – rural Chuy is a primarily agricultural region, but prox-

imity to Bishkek makes it relatively affluent and one of the higher-growth areas of the country.

- The southern oblasts of Osh and Jalal-Abad – the south is the main cotton-growing region but also contains Osh, which is the second-largest city in the country and a manufacturing centre. The south is the most deeply Islamic part of the country.
- The mountain oblasts of Issyk-Kul, Naryn and Talas – the mountain region was known for pastoral farming during the early transition period, but agriculture has developed into more vegetable production and less sheep production during the later transition years in this region.

We divide Tajikistan into five regions:

- Dushanbe.
- Rayons of Republican Subordination (RRS) in the central western area – although the region is less poor than Khatlon or Leninabad, in Dushanbe and the surrounding RRS agricultural production is depressed, many state enterprises (cement, refrigerators, for example) have shut down or significantly reduced their production, and unemployment remains high in both the agricultural and non-agricultural regions.
- Leninabad in the north-west – the Leninabad oblast is the centre of much of Tajikistan's manufacturing, as well as lake areas for recreation.
- Khatlon in the south-west – a heterogeneous province, with conflicts between more established groups and groups arriving from central and eastern Tajikistan during the cotton expansion of the 1950s and 1960s. The western part (Qurghon Teppa) is the centre of cotton production, while the eastern part (Gulab) is poorer. Khatlon also has to deal with the illegal drug trade from bordering Afghanistan.
- Gorno-Badakhshan in the east – the Gorno-Badakhshan region is sparsely populated and separated from the rest of the country by rugged mountains; it is the poorest region and also culturally distinct.

Appendix 2

Table 11A.2 Summary statistics

	Kazakhstan	Kyrgyz Republic		Tajikistan	Fergana (Uzbekistan)
Variables	1996	1993	1997	1999	1999
Per capita expenditure					
(National currency units)	4,863.76 (3,515.27)	144.61 (140.26)	782.00 (921.11)	15,636 (13,095)	4,099.36 (3869.45)
Demographic traits					
Male head (%)	61.6	81.8	86.9	91.3	93.9
Head is married (%)	72.1	77.5	77.3	85.5	90.8
Age of head (years)	46.326 (14.218)	41.337 (13.722)	39.751 (12.642)	39.850 (11.047)	38.760 (10.444)

Table 11A.2 (cont.)

Variables	Kazakhstan 1996	Kyrgyz Republic 1993	Kyrgyz Republic 1997	Tajikistan 1999	Fergana (Uzbekistan) 1999
Education of head					
College graduate (%)	18.2	25.1	32.7	14.8	14.4
Post-secondary (%)	23.2	24.5	10.8	34.6	29.4
Post-secondary – contd. (%)	10.6				
Completed secondary (%)	25.5	16.9	43.8	36.0	45.3
Incomplete secondary (%)	22.5	33.5	12.7	14.6	10.9
Health of head					
Head in good health (%)	28.9	90.7	90.5	69.3	
Location of household					
Rural community (%)	43.6	57.1	62.6	72.8	71.5
Capital city (%)	9.4	18.4	15.1	8.9	
Region 1 (%)	20.7	22.7	13.9	4.0	
Region 2 (%)	18.1	39.1	35.0	21.5	
Region 3 (%)	8.5	19.8	36.0	30.4	
Region 4 (%)	22.3			35.2	
Region 5 (%)	21.0				
Household composition					
Number of children	1.263	1.822	2.239	3.515	2.850
	(1.228)	(1.690)	(1.740)	(2.071)	(1.601)
Number of elderly	0.414	0.511	0.507	0.492	0.492
	(0.676)	(0.731)	(0.732)	(0.733)	(0.742)
Number of non-elderly adults	1.914	2.603	2.846	3.065	2.643
	(1.119)	(1.800)	(1.472)	(1.812)	(1.395)
Sample size (households)	1,890	1,926	2,618	1,983	541

Notes: Standard deviations of continuous variables are in parentheses. For Kazakhstan, post-secondary education is divided between Tecnikum and professional-technical training. The regions are: Kazakhstan 1 = Central, 2 = South, 3 = West, 4 = North, 5 = East (excluding Almaty); Kyrgyz Republic 1 = Chuy, 2 = South, 3 = Mountain; Tajikistan 1 = Gorno-Badakhshan, 2 = RRS, 3 = Leninabad, 4 = Khatlon.

Source: Data were obtained from the Living Standards Measurement Study surveys for 1993 and 1997 in the Kyrgyz Republic, 1996 in Kazakhstan and 1999 in Tajikistan and from the 1999 pilot study for the redesign of the Household Budget Survey in Uzbekistan.

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Notes

1. Pomfret and Anderson (2001) review this literature. For general background on the Central Asian countries' economies, see Pomfret (1995) and Islamov (2001).
2. The oblasts are listed in Table 11A.1. Although the official name for these administrative units has been changed in some of the successor states, the Russian term ''oblast'' remains in common usage.
3. For Tajikistan, ''the Samanid Empire (874–1005 AD) marked the formation of the Tajik nation, with a common language, territory and culture'' (UNDP 2000a: 41). In Tashkent, the main statue of Karl Marx was replaced by one of the Emir Timur (Tamerlaine) in 1993. These forerunners governed territory far beyond the present boundaries of Tajikistan and Uzbekistan.
4. Most of the Ferghana Valley is in Uzbekistan, but the uplands are in the Kyrgyz Republic, which controls vital water supplies, and the mouth of the valley is in Tajikistan.
5. Before 1917 the urban population was often divided into European and Sart (or ''native''), a general term for all Central Asian groups. As mentioned, however, Bukhara and Samarkand were considered to be Tajik cities, Tashkent was an Uzbek (and Russian) city surrounded by Kazakh countryside, and Osh and Jalal-Abad were towns with Uzbek majorities surrounded by countryside of mixed, but dominantly Kyrgyz, ethnicity.
6. This popularity appears to be fairly general, despite the awful practices of some of Rashidov's associates in this quasi-feudal regime (Rumer 1989: 144–159), and is a sign of the growth of Uzbek national consciousness during the Rashidov era. In their study of the Uzbek city, Koroteyeva and Makarova (1998) provide evidence from Samarkand that during the 1960s, with the satisfaction of basic needs and the rise of consumerism, Central Asians began to reassert traditional consumption patterns, notably in connection with major life event ceremonies such as circumcision, marriage or death.
7. The catalyst for change was the ethnic riots in June 1989 in Novy Uzen in the south-west of the republic, but little is known about the scale of these disturbances. The Kazakh republic was the only Central Asian republic in which major demonstrations against the Soviet Union occurred in 1989–1991, but these focused on environmental issues, especially the dumping of nuclear waste in the republic, rather than on ethnic issues.
8. In November 1991 an Islamic Centre was established in Namangan and that oblast (one of three in the Uzbekistan part of the Ferghana Valley) was under Islamic control until

suppressed by the Uzbekistan security forces, successors to the Soviet KGB, in March 1992 (Ro'i 2004).

9. The *Human Development Report Kazakhstan 2000* (UNDP 2000b: 6) estimates that repatriates numbered 360,000 by the end of the 1990s. This was part of a conscious policy to improve the Kazakh population balance. In 1994, the parliament approved the transfer of the capital of Kazakhstan, and the new capital, Astana, was officially inaugurated in June 1998; one motive for this expensive move was to bring the centre of government closer to the Russian belt.
10. There is also a much-publicized trafficking in women, which appears mainly to involve Kyrgyz citizens being tempted to the Gulf states.
11. The Pamiri people are the only group in the region that follows the Ishmaeli branch of Islam, recognizing the Aga Khan as their spiritual leader. Within the GBAO, Tajik is the official language, but Shugnan, Rushan, Vahan, Yazgulam, Russian and Kyrgyz are also used as languages of instruction in secondary schools. The civil war initially confronted factions from Gulab and Leninabad, supported by Russia and Uzbekistan, against Garmis and Badakhshanis, but around 1994 the apparent victors fell out as the Gulab group, which had done most of the fighting, and the Leninabad group, which had been dominant in the Soviet era, disagreed over how to share power.
12. Both Tajikistan and the Kyrgyz Republic protested against the 1999 bombings, which killed citizens of both countries. Dozens of people in Tajikistan, mainly children, have died from landmines. According to *The Economist* (27 January 2001) over 30 Kyrgyz and at least 200 Uzbek soldiers died repelling IMU incursions in 2000.
13. In this sense it mirrored the situation in Afghanistan, where regional groups fought for the succession after the withdrawal of Soviet troops. There the outcome was an extreme Islamist regime.
14. The Kyrgyz Republic and Tajikistan note that Uzbekistan seems to be in no hurry to complete demarcation of indeterminate boundary areas with them, but is progressing with demarcation of the border with its larger neighbour, Kazakhstan. When the USSR was dissolved in late 1991, assets such as military equipment or civilian aircraft were taken over by the successor state on whose territory they were to be found, and Uzbekistan inherited the strongest army in the region because Tashkent was the centre of the Soviet Central Asian military command.
15. The data estimation and results are described more fully in Pomfret and Anderson (2001), and in more depth for the Kyrgyz Republic in Anderson and Pomfret (2000). Atkinson and Micklewright (1992) describe the limitations of the household budget surveys designed in the Soviet era and still used in Central Asia throughout the 1990s. The LSMS surveys are far superior, although they still have limitations (Falkingham 1999; Kandiyoti 1999).
16. The administrative unit in the USSR was the oblast, which is equivalent to counties or provinces. After independence the structure was maintained and, although new nomenclatures were adopted, oblast remains a universally recognized term. We use the names and jurisdictions at the time of the surveys and ignore administrative changes that occurred later (such as the relocation of Kazakhstan's capital from Almaty to Astana, the subdivision of the Osh oblast in the Kyrgyz Republic, or the renaming of the Leninabad oblast in Tajikistan).
17. Summary statistics for each survey are given in Table 11A.2.
18. This last change is implausibly large, even allowing for the change in sample composition. The 1997 numbers for incomplete/complete secondary schooling appear more plausible than those for 1993, when compared with the shares in the neighbouring Fergana oblast. In the econometric estimation the coefficient for completed secondary education is not statistically significant apart from in the Kyrgyz Republic.

19. Expenditure is preferred to income because the arrears problem in former Soviet republics during the 1990s meant that income often came in lumps, and many households reported zero income during the two-week survey period. We also expected underreporting to avoid tax or other impositions to be less prevalent for expenditure. Non-purchased items, such as food grown on household plots, are valued and included in expenditure.
20. Tecnikum education is more academic, providing generic skills related to, say, computer science, rather than the narrower vocational training provided by PTUs. It includes artistic, musical, medical and technical education. PTU education is less general or professional and is linked to secondary education.
21. Almaty was the capital at the time of the LSMS survey and is the manufacturing and financial centre of Kazakhstan.
22. The Leninabad oblast was renamed Sughd in 2000.
23. The Ferghana Valley is the most fertile and most densely populated area of Central Asia. In the 1920s and 1930s, the Ferghana Valley was divided between the Kyrgyz, Tajik and Uzbek republics of the USSR with economically meaningless borders.
24. The Uzbekistan pilot and the Ferghana samples are too small for meaningful quantile regression analysis. The Tajikistan national survey is also ill-suited to quantile regression, because a large proportion of households is in bad financial shape.
25. Turkmenistan has held an LSMS survey but refuses to release results or make the raw data available to researchers. Its economic data are the most questionable in the region (Pomfret 2001).
26. Dashkhoguz, like Karakalpakstan, Qyzylorda and, to a slightly lesser extent, Khorezm, suffers from the ecological disaster of the desiccation of the Aral Sea, which has been associated with increased morbidity and mortality. In this chapter we say little about environmental issues, but they impinge strongly on feelings of regional well-being. They are especially important in oblasts affected by the Aral Sea disaster and in areas such as East Kazakhstan, where radiation from Soviet tests is high and where radioactive waste has been dumped since independence.
27. Use of an equivalence scale (such as $E^* = E/n^\theta$, where E is household expenditure and n is family size) allowing for lower consumption by children would soften the main conclusion, but it is uncertain which equivalence scale would be appropriate. The numerical results are sensitive to the implicit assumption of no scale economies in the provision of household services, but similar studies have found that the qualitative results are not sensitive to this assumption; for example, Jovanovic (2001: 253) reports that varying θ within a plausible range did not alter his results "in any significant way".
28. This is consistent with the evidence that Uzbekistan has been relatively successful in maintaining its social policies during the transition from central planning (Pomfret 2000b) and that public service provision broke down in Tajikistan.
29. The independent impact of having a college-educated head is lower in the capital cities than in the country as a whole. The difference is small in Kazakhstan, but for Bishkek and Dushanbe the coefficient on the college graduate variable, although positive, is not significant at the 5 per cent level.
30. The Uzbekistan estimate is especially striking in light of the smaller than national average impact in the Ferghana region of Tajikistan and the absence of any significant effect of college education on household expenditure in the Ferghana region of the Kyrgyz Republic.
31. In the Kyrgyz Republic in 1997 and in the Ferghana regions of the Kyrgyz Republic and Tajikistan, pensioners cost the household less than working-age adults, and in the Fergana oblast of Uzbekistan the presence of an extra elderly adult significantly increases per capita household expenditure.

32. In the product market context, Aghion and Schankerman (1999) emphasize the role of improved infrastructure in reducing transactions costs and hence increasing competition, and their argument is supported by the convergence of infrastructure in Poland, Hungary and the Czech Republic towards West European standards; in all three countries the degree of competition appears to have been increasing. Similar causality works in labour markets; an oft-cited example is the impact of US road-building in eastern Thailand during the 1960s in creating a national labour market and contributing to the rapid economic growth in Thailand during the final quarter of the twentieth century.
33. Tajikistan's main north–south road from Dushanbe to Khujand (Leninabad) is riddled with potholes and key passes are controlled by local warlords such as Rahmon Sanginov, whose *nom de guerre* is Hitler and who is treated as a Robin Hood figure by his admirers and as a terrorist by the government. The highest pass on this road is closed from October to May, but tunnels begun in the Soviet era remain unfinished. In July 2001 the approach road to the tunnel, which was off-limits to foreigners, showed no sign of construction activity.
34. In March 2001 a Batken schoolteacher commented, "It's the same everywhere. The villages are empty of young men – either they have gone to Russia to look for work or they join Namangani [leader of the IMU fighters] because at least he pays them" (Rashid 2001: 29).

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Part III

Poverty in Asia

12

Decomposing spatial differences in poverty in India

Shatakshee Dhongde

1. Introduction

India has long faced a problem of widespread poverty, and reduction in poverty levels has always been a major policy concern. India has the largest concentration of poor people in the world, with nearly 300 million people living in absolute poverty. However, since the economic reforms in the early 1990s, India has become one of the fastest growing economies of the world. Throughout the past decade, GDP per capita has grown at a rapid rate of about 4 per cent per year. The rise in the average income levels has also led to a decline in income poverty in the country. Many recent studies show that the all-India level of poverty declined considerably over the 1990s (Datt and Ravallion 2002; Dhongde 2005). However, in a vast country such as India, poverty at the national level does not reflect significantly different poverty levels across different regions. For example, during 1999–2000 the all-India headcount ratio of poverty was about 25 per cent. But in rural Orissa, the headcount ratio was as high as 41 per cent, whereas in rural Punjab it was as low as 8 per cent.

Given the vast differences in poverty levels across the country, it is important to understand the reasons underlying these differences. Do poverty levels across states differ because states have different mean income levels? If so, what would have been the poverty levels in the states if each state had experienced the same all-India mean income level? On the other hand, if the distribution of income also matters in determining poverty, then what would have been the poverty levels in the states if

each state had a similar relative distribution of income, say the all-India distribution? In other words, what explains the difference in poverty levels across states – the difference in the mean level of income or the difference in the distribution of income? This chapter tries to answer these important questions.

In order to analyse the differences in poverty levels across the country I decompose the differences in poverty levels. There have been some attempts in the past to decompose the total change in poverty over a period of time (Kakwani and Subbarao 1990; Datt and Ravallion 1992; Dhongde 2005). In this chapter, however, I decompose differences in poverty levels across states within a country for the first time.[1] At a given point in time (1999–2000), I decompose the total difference between state and national poverty levels and measure how much of this difference is owing to the difference between state and national mean income levels and how much of it is owing to the difference between state and national distributions of income. The decomposition of poverty contributes important information that is relevant to the ongoing debate about the impact on poverty levels of the rise in mean income levels and of changes in the distribution of income. It enables us to quantify the relative significance of the differences in state and national mean income levels, as compared with the differences in state and national distributions of income, in explaining the differences in state and national poverty levels.

My analysis concludes that, in India, differences in poverty levels across the states were largely the result of differences in their mean income levels. Differences in the distribution of income were much less important. The results imply that states with poverty levels higher than the all-India level could have reduced poverty significantly by raising the state mean income level to the all-India mean income. On the other hand, if the poorer states were to redistribute their income such that the distribution of income resembled the all-India income distribution, without changing their mean income levels, poverty in these states would have increased further. On the whole, spatial differences in poverty were chiefly explained by spatial differences in mean income levels rather than by differences in the distributions of income.

Another novel feature of the chapter is the use of non-parametric kernel density to estimate poverty levels. The non-parametric method estimates income distribution directly, without assuming any particular functional form for the true distribution. The chapter contains a brief discussion of the use of this new technique in estimating poverty.

The chapter is organized as follows. Section 2 explains the concepts involved in the decomposition of poverty. Section 3 briefly discusses the non-parametric technique used to estimate poverty levels. The details of the data used in the study are given in section 4. The results of the

analysis are discussed in section 5. Section 6 contains a summary of the conclusions.

2. The decomposition of poverty

The conventional notion of income poverty defines the poor as those people who earn income less than or equal to a benchmark level of income called the poverty line. Income poverty can be written as a function, $P(z, m, l)$, where z is the poverty-line benchmark, m is the mean income level and l is the relative distribution of income, represented by the Lorenz curve.[2] Assuming a fixed poverty line, the poverty level in any state is given by $P(m_0, l_0)$, where m_0 is the mean income level of the state and l_0 is the Lorenz curve representing the relative distribution of income in the state.[3] Similarly, the poverty level of the nation as a whole is given by $P(m_1, l_1)$, where m_1 is the mean income level of the nation[4] and l_1 is the Lorenz curve representing the income distribution of the nation. Note that any poverty measure thus defined is independent of the number of people since the scale of the population affects neither the mean income level nor the distribution of income, i.e. the Lorenz curve. The difference between poverty at the national and state levels is simply:

$$\Delta P = P(m_1, l_1) - P(m_0, l_0).$$

The total difference in poverty at the two levels occurs because of a difference between the national and state mean income levels and/or a difference between the national and state distributions of income.

The decomposition analysis helps us understand how much of the total difference in national and state poverty levels can be attributed to a difference between the two mean income levels and how much of it can be attributed to a difference between the two distributions of income. In order to conduct the decomposition, we need to construct ''hypothetical'' poverty levels. $P(m_1, l_0)$ tells us what a state's poverty level would have been if the state's mean income level had been the national mean, without any change in its distribution of income. On the other hand, $P(m_0, l_1)$ tells us what a state's poverty level would have been if there had been no change in the state's mean income level but its distribution of income had been the income distribution at the national level. Using these hypothetical poverty levels, the total difference between state and national poverty can be decomposed in different ways. One way is first to change the state's mean income level and then to change its distribution of income:

$$P(m_0, l_0) \rightarrow P(m_1, l_0) \rightarrow P(m_1, l_1).$$

Another way is first to change the state's distribution of income and then to change its mean income level:

$$P(m_0, l_0) \to P(m_0, l_1) \to P(m_1, l_1).$$

The components of the decomposition obtained by following the first sequence will differ from those obtained by following the second sequence. Since there is no compelling reason to prefer one sequence to the other, we can take an average of their components. Thus, the difference between the national and state poverty levels arising purely from a difference between their mean income levels is given by:

$$\Delta P(m) = \frac{P(m_1, l_0) - P(m_0, l_0)}{2} + \frac{P(m_1, l_1) - P(m_0, l_1)}{2},$$

where an average is taken of two components. The first component gives the difference in poverty owing to changes in mean income when the distribution of income is held fixed at the state level. The second component gives the difference in poverty owing to changes in mean income when the distribution is held fixed at the national level. Similarly, the difference between the national and state poverty levels arising purely from a difference between their distributions of income is given by:

$$\Delta P(l) = \frac{P(m_1, l_1) - P(m_1, l_0)}{2} + \frac{P(m_0, l_1) - P(m_0, l_0)}{2},$$

where an average is taken of two components. The first component gives the difference in poverty owing to changes in the distribution of income when mean income is held fixed at the national level. The second component gives the difference in poverty owing to changes in the distribution of income when mean income is held fixed at the state level. By taking averages of the two components, the decomposition no longer depends on the sequence in which the mean income level and the distribution of income are changed; i.e. the decomposition becomes path independent. Also, the changes in the mean income level and the changes in the distribution of income fully explain the total change in the poverty level; i.e. the decomposition is exact and has no residual.[5] Thus, the total difference in poverty can be decomposed into a mean component and a distribution component:

$$\Delta P = \Delta P(m) + \Delta P(l).$$

The following example illustrates the decomposition procedure explained above. In 1999–2000, in the rural sector of Bihar the headcount ratio of poverty $P(m_0, l_0)$ was 40.62 per cent whereas the all-India headcount ratio $P(m_1, l_1)$ was 25.19 per cent. If Bihar had raised its mean income levels to the all-India income level, keeping the state distribution of income fixed, the headcount ratio in Bihar $P(m_1, l_0)$ would have declined to nearly 17.19 per cent. On the other hand, if Bihar had adopted the all-India distribution of income, keeping its mean income level constant, the headcount ratio $P(m_0, l_1)$ would have increased to 47.62 per cent. Thus the total difference between the national headcount ratio and Bihar's headcount ratio was:

$$\Delta P = 25.19\% - 40.62\% = -15.43\%.$$

Out of this total difference, the average contribution of the mean component was:

$$\Delta P(m) = \frac{17.19\% - 40.62\%}{2} + \frac{25.19\% - 47.62\%}{2} = -22.93\%.$$

The average contribution of the distribution component was:

$$\Delta P(l) = \frac{25.19\% - 17.19\%}{2} + \frac{47.62\% - 40.62\%}{2} = 7.50\%.$$

3. Non-parametric estimation of poverty

The headcount ratio is the most common measure of poverty and the easiest to interpret.[6] It gives the proportion of the population earning income less than or equal to the poverty-line income level. The headcount ratio can be obtained as a cumulative sum of the density of population earning income below the poverty line. Thus to calculate the headcount ratio of poverty one needs to estimate the distribution of income, which I do by using the non-parametric technique.

Given data on individual income levels in each state, one can estimate the income distribution by specifying a parametric functional form, typically a lognormal distribution. A disadvantage of the parametric method is the need to assume that the actual income density is indeed lognormal or some such function. This may not always be true. For example, most of the studies on India have employed a two-parameter lognormal distri-

bution to fit income distribution (Minhas et al. 1987). But the lognormal distribution tends to overcorrect the positive skewness of the income distribution and, thus, fits poorly to the actual data (Kakwani and Subbarao 1990). The non-parametric approach instead estimates distribution directly from the given data, without assuming any particular form.

Let x_i $(i = 1, 2, \ldots, n)$ be a continuous random variable representing income. The density at any income level x, given by $f(x)$, is estimated by the probability that x_i lies in an interval around x, say, $[x - (h/2)] \leq x_i \leq [x + (h/2)]$, where h is the width of the interval. Let $\phi_i = (x_i - x)/h$, then the interval can be rewritten as $(-1/2 \leq \phi_i \leq 1/2)$. A simple way to measure the headcount ratio of poverty is by plotting the histogram. The histogram is a naïve estimate of income distribution and is given by:

$$\hat{f}_1(x) = \frac{1}{nh}\sum_{i=1}^{n} I\left(-\frac{1}{2} \leq \phi_i \leq \frac{1}{2}\right),$$

where I is an indicator function. I takes the value one if ϕ_i lies in the above interval and takes the value zero otherwise. However, the histogram contains jumps at each income interval and so gives a discontinuous estimate of income distribution.

In order to obtain a continuous estimate of the distribution in a non-parametric way, a kernel is often used. The Rosenblatt–Parzen kernel estimate of the distribution is given by:

$$\hat{f}_2(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\phi_i),$$

where K is a real positive kernel function satisfying the property $\int_{-\infty}^{\infty} K(\phi)\, d\phi = 1$ and $K(\phi)$ is small for large values of $|\phi_i|$. Since the properties that a kernel function is required to satisfy are similar to those satisfied by a density function, kernels are often chosen to be well-known density functions. In this chapter, we choose the standard normal density function as the kernel:

$$K(\phi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\phi^2\right).$$

Optimal h is chosen such that $\hat{f}(x)$ is as close as possible to the true density, $f(x)$. The most common criterion is to minimize the integrated mean squared error given by $E[\int_{-\infty}^{\infty} (\hat{f}(x) - f(x))^2\, dx]$. Using the criterion of minimizing the integrated mean square error to choose the optimal

window width h, we approximate h as $h \cong 1.06\sigma n^{-1/5}$, where σ denotes the standard deviation of income and n denotes the sample size.[7] Thus, we estimate income density by using the non-parametric kernel method. The headcount ratio of poverty is obtained as the sum of the estimated densities, until the poverty-line income level is reached. Tables 12.4 and 12.5 (below) show the estimated headcount ratios for each state in the rural and urban sectors respectively.

4. The data

The difference between the national and state headcount ratios is decomposed for a given point in time, namely for the year 1999–2000. I chose this year because it is the latest year for which National Sample Survey (NSS) data are available. The National Sample Survey Organization is a unified agency under the Department of Statistics, Government of India, and is one of the chief agencies providing reliable data since 1972.

Although in the discussion in this chapter I use income levels, NSS data are in fact available on consumer expenditure levels. Hence, when estimating poverty, income is replaced by consumption expenditure. Not only is the expenditure series more stable than the income series but the difference between the income and the expenditure series narrows considerably for the poor. I use the per capita consumption expenditure data from the 30-day recall schedule of the fifty-fifth round of the NSS, which are available separately for the rural and urban sectors of each state.[8] Out of a total of 26 states, my analysis covers 15 major states (Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal),[9] which account for nearly 97 per cent of the total population of the country.

The data record per capita expenditure in each state at nominal values. However, at any given point in time, prices differ significantly across states,[10] and, hence, nominal expenditure levels cannot be compared directly. In order to make meaningful comparisons across the states I adjust nominal expenditure levels by using the poverty-line price deflator; i.e. the nominal expenditure levels in each state are scaled by the ratio of the state poverty line to the all-India poverty line. Table 12.1 gives the price deflators used to convert nominal expenditure levels to real expenditure levels for each state in each sector. Since expenditure levels across states are made comparable at the national level, the all-India poverty line is used to measure the headcount ratio in each state. An all-India rural poverty line of Rs 327 per capita per month is used to measure poverty in the rural sector of every state, and an all-India urban

Table 12.1 Poverty-line price deflators used for inter-state price comparisons, 1999–2000

State	Rural poverty line	Deflator	Urban poverty line	Deflator
Andhra Pradesh	262.94	0.80	457.40	1.01
Assam	365.43	1.12	343.99	0.76
Bihar	333.07	1.02	379.78	0.84
Gujarat	318.94	0.97	474.41	1.04
Haryana	362.81	1.11	420.20	0.93
Karnataka	309.59	0.95	511.44	1.13
Kerala	374.79	1.14	477.06	1.05
Madhya Pradesh	311.34	0.95	481.65	1.06
Maharashtra	318.63	0.97	539.71	1.19
Orissa	323.92	0.99	473.12	1.04
Punjab	362.68	1.11	388.15	0.85
Rajasthan	344.03	1.05	465.92	1.03
Tamil Nadu	307.64	0.94	475.60	1.05
Uttar Pradesh	336.88	1.03	416.29	0.92
West Bengal	350.17	1.07	409.22	0.90
All India	**327.56**	**1.00**	**454.11**	**1.00**

Source: All the poverty lines have been prescribed by the Planning Commission of India (〈http://planningcommission.nic.in〉). The deflator is the ratio of the state poverty line to the all-India poverty line.

poverty line of Rs 454 per capita per month is used to measure poverty in the urban sector of every state.[11]

Table 12.2 shows the ranking of the states in terms of real mean expenditure levels. In both the rural and the urban sectors, Punjab, Haryana and Tamil Nadu were among the richest states, whereas Bihar, Orissa and Madhya Pradesh were among the poorest states. Compared with the urban sector, the rural sector had a greater number of states with mean income levels higher than the all-India average.

Table 12.3 shows the ranking of the states in terms of the Gini coefficient of the distribution of expenditure. The Gini coefficients are estimated from the raw data because no price adjustment is required for calculating the coefficients. In Assam, Gujarat, Haryana and Rajasthan, the distribution of income was fairly equal in both sectors, whereas Kerala, Maharashtra, Tamil Nadu and Karnataka had a relatively unequal distribution of income as measured by the Gini coefficient. It is rather surprising that Kerala had one of the highest Gini coefficients, especially in the rural sector (0.32), although it also had high mean income levels and low poverty levels.[12] Kerala has often been cited for its commendable achievements in the fields of education and health care, but it is rather

Table 12.2 Mean per capita expenditure levels across the states, 1999–2000

State	Rural mean (Rs)	State	Urban mean (Rs)
Punjab	725	Assam	1,117
Kerala	712	Punjab	1,105
Haryana	657	Haryana	1,044
Tamil Nadu	613	West Bengal	1,008
Andhra Pradesh	604	Tamil Nadu	952
Gujarat	592	Kerala	913
Karnataka	583	Gujarat	850
Rajasthan	547		
Maharashtra	534		
All India	**515**	**All India**	**841**
Uttar Pradesh	485	Andhra Pradesh	808
West Bengal	471	Maharashtra	808
Madhya Pradesh	463	Rajasthan	789
Orissa	415	Karnataka	786
Assam	405	Bihar	776
Bihar	404	Uttar Pradesh	751
		Orissa	676
		Madhya Pradesh	676

Source: Author's calculations of real mean levels using NSS data after adjusting for inter-state price differences.

Table 12.3 Gini coefficient of expenditure levels across the states, 1999–2000

State	Rural Gini	State	Urban Gini
Kerala	0.32	Tamil Nadu	0.40
Tamil Nadu	0.31	West Bengal	0.36
		Maharashtra	0.35
All India	**0.28**	**All India**	**0.34**
Karnataka	0.28	Bihar	0.34
Maharashtra	0.27	Kerala	0.34
Madhya Pradesh	0.27	Karnataka	0.34
Punjab	0.27	Andhra Pradesh	0.33
Orissa	0.26	Orissa	0.33
Uttar Pradesh	0.26	Uttar Pradesh	0.33
Andhra Pradesh	0.26	Madhya Pradesh	0.33
West Bengal	0.26	Assam	0.31
Gujarat	0.24	Gujarat	0.30
Haryana	0.24	Rajasthan	0.30
Bihar	0.23	Punjab	0.29
Rajasthan	0.23	Haryana	0.28
Assam	0.22		

Source: Author's calculations of Gini coefficients using NSS data.

Table 12.4 Decomposition of the headcount ratio in the rural sector, 1999–2000

State	Headcount ratio (%)	Total difference	Mean component	Distribution component
Orissa	40.96	−15.77	−18.95	3.18
Bihar	40.62	−15.43	−22.93	7.50
Assam	37.46	−12.27	−21.38	9.11
Madhya Pradesh	32.96	−7.77	−9.54	1.77
West Bengal	28.35	−3.16	−4.87	1.71
Uttar Pradesh	27.43	−2.24	−5.54	3.30
All India	**25.19**	**0.00**	**0.00**	**0.00**
Maharashtra	21.96	3.23	1.79	1.44
Tamil Nadu	18.98	6.21	10.23	−4.03
Karnataka	16.38	8.81	7.58	1.23
Rajasthan	12.98	12.21	3.33	8.88
Kerala	12.88	12.31	17.41	−5.11
Gujarat	12.40	12.79	7.79	5.00
Andhra Pradesh	11.76	13.43	9.43	4.00
Haryana	8.40	16.79	12.90	3.90
Punjab	7.91	17.28	16.71	0.57

Note: Total difference is the difference between the all-India and the state headcount ratios.
Source: Author's calculations of decomposition values using the equations in section 2.

surprising that there has been no mention in the literature of the high levels of income inequality prevalent in the state.

Overall, in the rural sector, mean income levels were positively correlated with the Gini coefficients (+0.5), indicating that poorer states had a more equal distribution of income compared with the richer states. In the urban sector, the correlation was weak. It was only slightly negative (−0.2), suggesting that richer states also had lower income inequality.

5. Decomposition results

Table 12.4 shows the decomposition of the headcount ratio across the states in the rural sector, and Table 12.5 shows the decomposition of the headcount ratio across the states in the urban sector.

5.1. Worse-performing states in the rural sector

In the rural sector, 6 out of the 15 states (Assam, Bihar, Madhya Pradesh, Orissa, Uttar Pradesh and West Bengal) experienced poverty levels higher than the all-India poverty level. The decomposition of the differ-

Table 12.5 Decomposition of the headcount ratio in the urban sector, 1999–2000

State	Headcount ratio (%)	Total difference	Mean component	Distribution component
Orissa	36.71	−11.73	−11.00	−0.72
Madhya Pradesh	36.47	−11.49	−13.23	1.74
Uttar Pradesh	29.88	−4.90	−5.98	1.08
Bihar	29.42	−4.43	−4.15	−0.29
Maharashtra	28.68	−3.69	−1.83	−1.86
Karnataka	27.20	−2.22	−3.15	0.93
Andhra Pradesh	26.35	−1.37	−1.95	0.58
All India	**24.98**	**0.00**	**0.00**	**0.00**
Tamil Nadu	23.81	1.17	2.92	−1.75
Rajasthan	21.39	3.59	−3.09	6.68
Kerala	20.25	4.74	3.73	1.00
Gujarat	17.82	7.16	0.54	6.63
West Bengal	16.49	8.49	8.45	0.04
Assam	9.54	15.44	10.38	5.06
Haryana	8.61	16.38	7.31	9.06
Punjab	6.90	18.08	9.90	8.18

Note: Total difference is the difference between the all-India and the state headcount ratios.
Source: Author's calculations of decomposition values using the equations in section 2.

ence between the state and national poverty levels shows that the main reason underlying the high levels of poverty in these states was the low level of mean income compared with the all-India mean income. If these states had raised their mean income levels to the all-India level without changing the distribution of income, poverty in these states would have declined below the all-India poverty level. On the other hand, if these states had changed the distribution of income to the all-India distribution without raising their mean income levels, poverty in these states would have risen above the actual poverty levels.

For example, consider the state of Bihar (Table 12.4). The rural headcount ratio in Bihar was 40.62 per cent, compared with the all-India ratio of 25.19 per cent. If Bihar had raised its mean income level to the all-India income level, keeping the state distribution of income fixed, the headcount ratio in Bihar would have declined from 40.62 per cent to nearly 17.19 per cent, which is lower than the all-India headcount ratio. On the other hand, if Bihar had adopted the all-India distribution of income, keeping its mean level constant, the headcount ratio would have increased to 47.62 per cent, which is above the actual headcount ratio in Bihar. Thus, in this sense, Bihar had a better distribution of income than did all-India and the high levels of poverty in the state were mainly the

result of low levels of income. In fact, like Bihar, all the other poorer, worse-performing states had a better distribution of income than did all-India and their high poverty levels were chiefly the result of low mean income levels.

5.2. Worse-performing states in the urban sector

In the urban sector, 7 out of the 15 states (Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Orissa and Uttar Pradesh) experienced poverty levels higher than the all-India poverty level. All these states had mean income levels lower than the all-India level. Poverty in these states would have declined significantly had these states achieved the all-India mean income level. However, instead of raising income to the all-India levels, had these states changed their distribution of income so that it resembled the all-India distribution, poverty in these states would have increased. Thus, although the states had low income levels, in terms of distribution most of the states were ''better off'' than all-India.

Note that a lower value of the Gini coefficient does not imply a lower value of the headcount ratio of poverty. For example, Orissa's Gini coefficient was lower than that for all-India. Given this fact, one would be tempted to think that, if Orissa had adopted the all-India distribution of income, poverty in Orissa would have increased. On the contrary, the decomposition analysis reveals that poverty in Orissa would have declined if it had adopted the all-India distribution of income without changing its mean income level. This is because the Gini coefficient is a summary measure of inequality and it depends on the shape of the entire Lorenz curve, whereas the headcount ratio of poverty is calculated using only one segment of the Lorenz curve. In order to answer the counterfactual question of what the poverty levels would have been for different distributions of income, we need to calculate hypothetical poverty levels.

On the whole, in both the rural and the urban sectors, a rise in the poorer states' mean income level to the all-India level would have reduced the gap between the state and national poverty levels. If, instead, the poorer states had adopted the all-India distribution of income without changing their mean income levels, the gap between the state national poverty levels would in most cases have increased further.

5.3. Better-performing states in the rural sector

In the rural sector, 9 out of the 15 states (Andhra Pradesh, Gujarat, Haryana, Karnataka, Kerala, Maharashtra, Punjab, Rajasthan and Tamil Nadu) had poverty levels lower than the all-India poverty level. All of these states had mean income levels higher than the all-India mean in-

come. In most of the states, their high mean income levels explained more than 50 per cent of the total difference between the state and national poverty levels. Most of these states also had a more equal distribution of income than all-India, in the sense that, if the states' distributions of income had changed to the all-India distribution, keeping the mean income constant, poverty in these states would have increased.

Important exceptions were the states of Kerala and Tamil Nadu. Had these rich states changed their distribution of income to the all-India distribution, without changing their mean income levels, poverty in these states would have declined. Thus, despite being richer than all-India, these states would have reduced their poverty levels further by adopting the all-India distribution of income.

5.4. Better-performing states in the urban sector

In the urban sector, 8 out of the 15 states (Assam, Gujarat, Haryana, Kerala, Punjab, Rajasthan, Tamil Nadu and West Bengal) had poverty levels lower than the all-India poverty levels. All of these states, except for Rajasthan, had mean income levels higher than the all-India mean income. But in richer states such as Punjab, Haryana and Gujarat the high level of mean income was not the only reason for the low level of poverty. The distribution component of the decomposition was equally important. In other words, a substantial part of the difference between the state and national poverty levels was accounted for by the difference between the state and national distributions of income. Thus, as noted earlier, the rich states also had a better distribution of income compared with the all-India distribution.

Another example where the distribution of income played an important role was in the state of Rajasthan. The mean income level in urban Rajasthan was lower than the all-India mean income. Yet poverty in this state was also lower than all-India poverty, owing to a fairly equal distribution of income. Thus, in both the rural and the urban sectors, the better performance of the states in terms of poverty levels was explained mainly because these states had higher-than-average mean income levels. In the urban sector, the lower poverty levels were also partly explained by a better distribution of income compared with the all-India distribution.

6. Conclusion

The performance of the states in terms of mean income levels, the distribution of income and poverty levels varies significantly across India.

In this chapter I conducted, for the first time, a spatial decomposition of poverty to measure how much of the total difference in state and all-India poverty levels is the result of a difference between their mean income levels, and how much of it is the result of a difference between their distributions of income.

I found that the difference between the state and national levels of poverty is largely explained by a difference in the state and national mean income levels. In all cases, except urban Rajasthan, higher-than-average mean income levels imply lower-than-average poverty levels, and vice versa. On the whole, differences between the state and all-India distributions of income were less important in explaining differences in poverty levels. However, there were a few important exceptions. Especially in the urban areas of Punjab, Haryana and Gujarat, low levels of poverty were the result not only of higher income levels but also of a "better" distribution of income.

The analysis has interesting implications. In 1999–2000, many states in India had a higher incidence of poverty compared with the all-India ratio. The number of poor in these states would have declined significantly had these states raised their mean income levels to the all-India level without altering the distribution of income. In contrast, had these states adopted the all-India distribution of income without changing their mean income levels, poverty in most of the states would have increased. Of course, the question of whether the required changes in the mean income level and the distribution of income were politically feasible in each state remains open. Nevertheless, the decomposition analysis provides important information by revealing the fact that, in India, differences in the state and national mean income levels were relatively more significant than differences in the distributions of income in explaining the differences in state and national poverty levels.

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Notes

1. The paper by Kolenikov and Shorrocks (2003) is based on a similar decomposition of poverty across the regions in Russia.

2. A Lorenz curve gives the relationship between the cumulative proportions of the population to the cumulative proportion of income received when the population is arranged in ascending order of income.
3. Henceforth, for the sake of convenience, I shall drop the word "relative" and simply use the term "distribution of income". However, the reader is urged to note that a change (no change) in the distribution of income is to be understood as a change (no change) in the Lorenz curve representing the relative distribution of income.
4. The national mean income level is equal to the population-weighted average of the state mean income levels.
5. Shorrocks (1999) shows the links between this method of decomposition and the Shapley value solution in cooperative game theory. Note 3 therein asserts that this method of decomposition satisfies the following requirements: the decomposition be path independent; the decomposition be complete; and the components of the decomposition be given by the marginal effect of changing one factor, holding all other factors constant.
6. Although my analysis focuses on the headcount ratio of poverty, it can easily be extended to include other poverty measures such as the poverty gap or the squared poverty gap.
7. Software packages that implement non-parametric density estimation (SAS, Shazam, STATA) use $h \cong 1.06\sigma n^{-1/5}$ as the default window width. For a detailed discussion on the choice of optimal kernel and window width, see Pagan and Ullah (1999).
8. The raw data of the 55th NSS round for the year 1999–2000 were made available by UNU-WIDER, Helsinki.
9. In late 2000, the states of Bihar, Madhya Pradesh and Uttar Pradesh were restructured to form six states: Bihar, Chattisgarh, Jharkhand, Madhya Pradesh, Uttar Pradesh and Uttaranchal. This chapter refers to the three states prior to restructuring.
10. Prices, especially those of food grains, may differ widely across states because the free trade of agricultural products across state boundaries can be restricted by state governments by enforcing the Essential Commodities Act (1955).
11. These poverty lines have been prescribed by the Planning Commission of India.
12. The high Gini coefficient in rural Kerala is not a peculiarity of the data collected for 1999–2000, but is seen consistently over the past few years. The Gini coefficient in rural Kerala was one of the highest in 1993–1994 and was recorded as 0.3 in Dreze and Sen (2002). In 1983, too, rural Kerala's Gini coefficient was as high as 0.37 (see Mishra and Parikh 1997). However, note that all the estimates of the Gini coefficient quoted above are based on the per capita consumption expenditure data of the NSS. Hence, the relatively widespread provision of public goods in Kerala compared with the other states is not accounted for, so the Gini estimates of inequality are likely to be biased upwards.

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13

Commune-level estimation of poverty measures and its application in Cambodia

Tomoki Fujii

1. Introduction

Cambodia is still suffering from the legacy of civil conflict after more than a decade. With over one-third of the population living below the poverty line, poverty remains one of the most serious problems in Cambodia. A number of governmental bodies, local and international non-governmental organizations (NGOs), and international organizations operating in Cambodia have made eradicating poverty a priority and have established many social programmes to this end. In designing such programmes, the efficient allocation of resources is essential for making poverty alleviation more cost-effective. Targeting is often helpful for this purpose because one can avoid wasting resources on the non-poor, which would occur in the absence of targeting. If targeting were costless and consumption poverty were at issue, it would be desirable to formulate a targeting policy such that the gap between current consumption and the poverty line were just filled.

In reality, such social intervention is unlikely to be possible for at least two reasons. First, targeting is not costless because there are administrative, political and other costs. Van de Walle (1998) argues that hidden costs associated with targeting may undermine its benefits and these need to be evaluated. Second, there are two types of errors in targeting. One is the error of exclusion, in which intended beneficiaries cannot benefit from the intervention. The other is the error of inclusion, in which an intervention reaches individuals who were not intended to be beneficiaries

(Hoddinott 1999). These errors are commonly known as Type I and Type II errors, respectively, and these two error types cannot usually be eliminated altogether.

The question policy makers face is whether and what type of targeting policy would make anti-poverty programmes more efficient. One of the obvious ways of targeting is to move resources according to geographical information. Such targeting is called geographical targeting. Geographical targeting is relatively easy to monitor and administer, and local institutions and NGOs can greatly assist in implementing the programmes. Moreover, geographical targeting has relatively little influence on a household's behaviour because it is difficult and costly for a household to change its place of residence (Bigman and Fofack 2000a). Furthermore, geographical targeting can be combined with other targeting mechanisms or criteria. For example, a food-for-work programme for local road construction is a combination of geographical targeting and self-targeting. Such a programme may be best targeted to poor areas with insufficient road access.

As a powerful tool to identify the location of the poor and to enable a more efficient allocation of resources through geographical targeting, poverty mapping has increasingly drawn the attention of researchers and practitioners in the development community. Poverty maps may be combined with other maps to derive even more valuable information by overlaying maps using geographical information systems (GIS). For example, the targeting policy of a basic medical care programme may be better formulated by choosing poor areas where indicators show low health status. Irrigation systems may be most beneficial in poor areas that are drought prone. Such targeting would be difficult or impossible without poverty maps.

This study has two purposes. The first purpose is to present in the form of maps the commune-level estimates of poverty measures using the small-area estimation technique developed by Elbers et al. (2000, 2002, 2003), which allows for explicit treatment of the standard errors. The maps are helpful in identifying target areas and formulating efficient and effective programmes and policies to reduce poverty. Furthermore, they provide a basis for promoting coordination within and between donors and implementing organizations in addressing poverty.

The second purpose of this study is to illustrate the application of poverty mapping. Though poverty maps per se are useful for formulating targeting policies, it is not clear whether a particular social sector intervention programme is suitable for certain areas. Using the school meals programme as an example, I shall discuss how best other maps may be combined with the poverty maps to identify the target areas for social sector intervention programmes.

This chapter is organized as follows. Section 2 reviews the relevant literature. Section 3 explains the theory of poverty mapping. Section 4 describes the data used in this study. Some known problems with the data set are also discussed. It should be noted that the extensive use of geographical data characterizes this study. The implementation of poverty mapping is provided in section 5, followed by the results in section 6. Section 7 illustrates the application of poverty mapping to school meals programmes, and section 8 concludes.

2. Review of the literature

2.1. Motivation of poverty mapping

Socio-economic surveys have been widely used to analyse poverty in developing countries. Cambodia is no exception. Three successive Cambodian socio-economic surveys (CSES), carried out in 1993/1994, 1997 and 1999, respectively, have been used to generate poverty estimates. They have provided valuable information for policy makers (Prescott and Pradhan 1997; MoP 1998, 2001). However, the sampling designs of these surveys impose severe limitations on the geographical level of disaggregation at which the poverty estimates are reliable. None of the three surveys can provide a reliable estimate of poverty rates even at the provincial level.[1]

However, as is often the case, what policy makers really need is information that is geographically disaggregated. They may want poverty estimates at the district or even commune level. If policy makers want to deliver food to poor people, knowing poverty rates at the provincial level may not be very useful, because too many non-poor might benefit owing to the error of inclusion. Baker and Grosh (1994) examined the efficiency gains from targeting in Mexico, and showed that only small improvements over uniform transfers of money can be made if the programme is targeted at the state level, but the improvement is significant if the programme is targeted at the district or neighbourhood level.

Whether detailed targeting is possible depends on the information available to policy makers. Poverty maps allow for a reduction of informational constraints, which are one of the central issues concerning the formulation of targeting policies (Ravallion and Chao 1989; Kanbur 1987). They help policy makers to find pockets of poverty, or poor areas surrounded by non-poor areas, which cannot be identified from the socio-economic surveys alone. Hence, poverty maps are useful for formulating geographical targeting policies to move assistance to the neediest people in a more efficient and transparent manner.

2.2. Household unit small-area estimation

Poverty maps can be created by a number of methodologies, including small-area estimation, a multivariate weighted basic needs index, a combination of qualitative information and secondary data, and extrapolation from participatory approaches. Davis (2002) overviews these various poverty mapping methods and their applications, and discusses their merits and limitations. Small-area estimation is a statistical technique that combines survey and census data to derive statistics for geographically small areas such as communes and districts.

There are two variants: the household unit-level method and the community-level data method, depending on the level at which the census records are available. The basic idea for these methods is that the welfare measure at the household level or community level is regressed on a set of variables that are common between the census and the socioeconomic survey. Then the welfare measure is imputed in each record in the census. The advantage of running regression at the household level is that the standard errors associated with poverty estimates can be evaluated through regression, it is often easier to access the community-level census data, and the computational burden is substantially lower. Viet Nam has a poverty map based on the community-level data method (Minot 2000). Other examples include Bigman et al. (2000) for Burkina Faso, and Bigman and Fofack (2000b) for India.

The household unit-level method was first applied to Ecuador (Hentschel et al. 2000). Its statistical properties were rigorously studied and various estimation strategies were discussed by Elbers, Lanjouw and Lanjouw (2003; hereafter ELL). The ELL approach has been applied to a number of countries. Alderman et al. (2002) studied the case in South Africa and found that the income derived from census data provides only a weak proxy for the average income or poverty rates either at the provincial level or at lower levels of aggregation. Demombynes et al. (2002) compared the experience of poverty mapping in Ecuador, Madagascar and South Africa. Cambodia is the first country in Asia to which the ELL technique has been applied.

3. The methodology of poverty mapping

To measure the welfare of people, I use household consumption expenditure, defined as goods and services bought on the market, received in kind or produced by the household. Although the consumption measure captures only certain aspects of poverty, it is a commonly used and

widely studied welfare measure, and it has a relatively straightforward interpretation. All of the consumption items in the CSES questionnaire, including food items and non-food items, are aggregated to arrive at the consumption aggregate for the household. To derive per capita consumption, household consumption is simply divided by the number of individuals in the household. I report the Foster–Greer–Thorbecke (FGT) poverty measures with parameter 0, 1 and 2, which are commonly called the poverty rate, the poverty gap and poverty severity. The poverty lines used in this study to derive five FGT poverty measures are given in section 5.

The concepts behind poverty mapping are straightforward. First, the survey data are used to estimate a consumption model. This model describes the relationship between consumption and right-hand-side (rhs) variables. Right-hand-side variables are restricted to those variables that can also be found in the census or in a tertiary data set that can be linked to both the census and the survey. A GIS data set is used as tertiary data. The census data are then fed into the model with the parameter estimates to derive the small-area statistics of interest. It should be noted that I assume the models estimated from the survey data to be applicable to census records. The theoretical underpinnings of this methodology are given in detail in a series of papers by Elbers et al. (2000, 2002, 2003). One of the important contributions of their study is that they rigorously examined the properties of the small-area statistics. In what follows, I shall briefly present the features of the theory. Per capita household consumption, y_h, for household h is related to a k-vector of observable characteristics, $\mathbf{x}_h$, through the following model:

$$\ln y_h = \mathbf{x}_h^T \beta + u_h, \tag{13.1}$$

where β is a k-vector of parameters and u_h is a disturbance term; u_h satisfied $E[u_h|\mathbf{x}_h] = 0$. As described in section 5, the disturbance term is decomposed into the location, or cluster-specific, effect and the household-specific effect to allow for spatial autocorrelation and heteroscedasticity among households in application. The parameter β is estimated through regression using the household survey data. The empirical distribution of the residual terms is also obtained from the regression. This regression will be referred to as the first-stage regression.

For the purpose of poverty maps, it is not the consumption of each household that is of interest but rather the various welfare measures at a certain level of aggregation. In this chapter, I chose commune-level aggregation because such a level of aggregation is *useful* and the estimate at that level is *acceptable*. Welfare estimates at a more aggregated level,

such as the district or provincial level, are more accurate and, depending on the purpose, accuracy may be more important than the level of disaggregation.

The problem we face in this exercise is that we know only $\mathbf{x}_h^T$, but would like to estimate a commune-level welfare measure W derived from y_h for households in the commune. A natural way to compute W is to impute y_h using the parameters estimated in the first-stage regression and to use the imputed values. Such an estimate is subject to statistical errors. Elbers et al. (2002) showed that the error can be decomposed into the idiosyncratic error, model error and computation error, and studied their properties.

The magnitude of idiosyncratic error is approximately inversely proportional to the size of the population in the target area. Hence, there is a practical limit to the degree of disaggregation possible. This is precisely the reason I did not produce the estimates at the village level. The model error in general depends solely on the standard errors of the first-stage coefficients and the sensitivity of the indicators to deviations in household consumption. The computation error depends upon the computational method used. Using simulation methods with sufficient computational resources and time, this error can be made arbitrarily small.

4. Data sets

To produce the poverty maps, I used four distinct data sets – two socio-economic survey data sets, a census data set and a GIS data set.

4.1. The CSES data sets

The consumption model is built upon the two socio-economic surveys, namely, the CSES 1997 and the CSES 1999. For reasons discussed later, the CSES 1999 was used only for auxiliary purposes. The CSES 1997 was conducted by the National Institute of Statistics of the Ministry of Planning (MoP), funded by the United Nations Development Programme (UNDP) and the Swedish International Development Agency, and executed by the World Bank. The questionnaires for CSES 1997 comprised three substantive components: a village questionnaire, a core questionnaire for households, and a social sector household module. Only the core questionnaire was used in this study.

The sample design for the CSES 1997 treated villages as the primary sampling units and households as secondary sampling units. A sampling frame developed for the 1996 socio-economic survey of Cambodia 1996 was updated with newly available information to use as the sampling

frame for the CSES 1997 survey. In the CSES 1997, there were three sampling strata: Phnom Penh, "other urban", and "rural". The total sample size of the CSES 1997 was 6,010 households in 474 villages. In the Phnom Penh stratum, a sample was taken from 120 villages with 10 households from each village; in the "other urban" stratum, 10 households were sampled in each of 100 villages; in the "rural" stratum, 15 households were sampled in each of 254 villages. For each of the three sampling strata, a consumption model for small-area estimation was constructed.[2]

The CSES 1999 is similar to the CSES 1997 in design, and was carried out in two rounds between January and March 1999 and between June and August 1999 to capture seasonal variations in consumption. Although the CSES 1999 also had three components, I used only the core questionnaire. The CSES 1999 has 10 sampling strata defined from the urban and rural sectors within each of five zones (Phnom Penh, Plain, Tonle Sap, Coastal and Plateau).[3] The CSES 1999 is more attractive for my purposes in terms of the sampling design than the CSES 1997, but the inconsistencies in measured consumption between the two rounds of the survey indicate the potential presence of widespread and systematic measurement error (MoP 2001). Since the reliability of the consumption measure is critical in this study, I decided to use the CSES 1997 for the most part of my analyses.

Owing to security concerns and access restrictions, some parts of Cambodia were not covered in the sampling frame of the CSES 1997 and the CSES 1999. In terms of the number of households, 11.6 per cent of the rural areas and 2.6 per cent of the urban areas were not covered in CSES 1997. The corresponding figures for the CSES 1999 were substantially smaller: 3.8 per cent for the rural areas and 0.3 per cent for the urban areas. Hence, I decided to take advantage of the better geographical coverage of the sampling frame for CSES 1999 to see if the consumption model holds for those households outside the CSES 1997 sampling frame but inside the CSES 1999 sampling frame.

To do so, I took the following steps. First, using data from NIS (1997), I identified the villages in the CSES 1999 that were excluded from the CSES 1997 sampling frame. Then I estimated the parameters of the consumption model using the CSES 1999 data. Second, I assigned each record in the CSES 1999 data set the corresponding stratum code of the CSES 1997. Ideally, two regressions with the same set of regressors should be run separately for the areas inside and outside the sampling frame of CSES 1997 to test the hypothesis that the estimated parameters for those two areas are the same. However, the sample sizes for the excluded areas were too small to allow the generation of meaningful results. Instead, I took an alternative approach. I first ran a regression with-

out the excluded areas and the coefficient β_0 was estimated. Then I ran another regression with the excluded areas and estimated the coefficient β_1. I tested the hypothesis $\beta_0 = \beta_1$. The rejection of this hypothesis would suggest that, if the CSES 1997 had included the excluded areas, the consumption model would have been different.

It should be noted that, in the procedure described above, the CSES 1999 data set does not affect the estimated parameters used in the simulation. This is because there is concern about the quality of the CSES 1999 data set. However, as was observed in MoP (2001), there were some common patterns between the two rounds. This seems to suggest that the overall pattern of consumption was not altered to the extent to render the test described above invalid. The tests were carried out with CSES 1999 round 1, CSES 1999 round 2, and both rounds pooled.

4.2. The census data set

The Cambodian national population census was conducted over a period of 10 days in March 1998. It was the first population census to be conducted in Cambodia since 1962 and was done on a de facto basis. The census covered all people staying in Cambodia, including foreigners, at the reference time, which was midnight on 3 March 1998. Foreign diplomatic corps and their families were, however, excluded. The census questionnaire consisted of two forms, Form A (the house list) and Form B (the household questionnaire). The construction material of walls, roof and floors of each house was observed by the enumerator and recorded on Form A, together with other information. Form B had four parts: part 1 collected information on the usual household members present and absent on the census night as well as visitors present on the census night; part 2 gathered specific information on each usual household member and visitors present on the reference night, including full name, relationship to the head of household, sex, age, marital status, mother tongue, religion, birth place, migration, literacy, education and employment; part 3 contained questions on the fertility of females ages 15 and over; and part 4 contained housing characteristics, conditions and other facilities.

The geographical frame for the census followed the defined structure of province, district, commune and village in descending order of aggregation. There are 24 provinces in Cambodia, including the municipality of Phnom Penh and the towns of Kep, Sihanoukville and Krong Pailin. Because of military operations, 15 communes with an estimated population of 45,000 were not covered in the census. Since it is not possible to estimate poverty measures for these areas, I analysed only the 1,594 communes included in the census.[4]

Prior to the computer simulation, I applied two treatments to the census data set. First, I excluded special settlements. Special settlements are groups of people who were found together on the census night. These people are transitional and may not necessarily live in the commune. Hence, they were not included for the calculation of the poverty estimates.

Second, there is a practical inconsistency between the definitions of household used in the census and in the survey data sets. Even though the census data set distinguishes between usual members of the household and visitors in Form A, part 2 of Form B includes both if they were present on the reference night and makes no distinction between them. This means that the data user has to take the usual members of the household as well as visitors present on the census night as the household. The survey, however, asks questions about the usual members of the household, including those absent at the time of the survey. Moreover, there were households that did not appear to be regular households. For example, there were households with more than 100 people. Hence a decision was made to deal with this issue. Only those households whose size was fewer than 16 and whose number of visitors was fewer than 10 were used for the analysis.[5] The original data set contained 2,162,086 regular households, and, as a result of this treatment, it was reduced to 2,150,235 households. Admittedly, the decision may have been somewhat arbitrary. However, it seemed more reasonable to make such a distinction than to ignore the issue. More importantly, the exclusion does not affect the main findings of this study significantly because much less than 1 per cent of the data set was dropped.

4.3. The geographical information system data set

A set of geographically derived indicators was also used in this analysis. These indicators included distance calculations, land-use and land cover information, climate indicators, vegetation, agricultural production, and flooding. A number of data sets from various sources were compiled into a GIS and the geographical indicators were generated for all villages and communes in Cambodia. Very coarse resolution data were summarized at the commune level, and high-resolution data were attributed to individual villages. Distances from villages to roads, other towns, health facilities and major rivers were calculated. Indicators based on satellite data with varying temporal resolutions included land use within the commune (agricultural, urban, forested, etc.), a vegetation greenness indicator to proxy agricultural productivity, and the degree to which the area benefited from night-time lighting as a proxy of urbanization. Relatively stable indicators, including soil quality, elevation and various 30-year av-

erage climatological variables, were also generated from other composite data sets.

The sources as well as the spatial and temporal dimensions of the data sets vary. Some data sets were assumed not to have changed greatly over time. Others, where multi-temporal data were available, included both yearly and monthly indicators as well as change and long-term average indicators. Road, river, village location and administrative boundary data were obtained under a project of the United Nations Transitional Authority in Cambodia and updated in 1996 by the Department of Geography under a UNDP-sponsored Cambodian Resettlement and Rehabilitation Programme (CARERE) project. Latitude and longitude locations of health facilities were provided by the World Health Organization. Land-use and land cover data were obtained from the Landsat Thematic Mapper satellite for 1993 and 1997 at 50 metre resolution. Agricultural production data at the commune level were taken from the commune-level crop assessment database prepared by the World Food Programme (WFP). NASA's Advanced Very High Resolution Radiometer (AVHRR) satellite data at 7 km resolution were used to generate the normalized differential vegetation index (NDVI). A 19-year monthly series of AVHRR-derived NDVI data, covering 1981–2000 and compiled by Clark Labs, was used to generate the NDVI values. NDVI indicators included monthly values, 19-year average and standard deviation, and coefficient of variation.

A global digital elevation model at 1 km resolution, GTOP030, was used for elevation values. GTOP030 was developed under the coordination of the US Geological Survey in collaboration with NASA, the United Nations Environment Programme Global Resource Information Database, the United States Agency for International Development and others. City lights satellite data at 1 km resolution were collected during 1994–1995 by the Defense Meteorological Satellite Programme and obtained from the National Geophysical Data Center. The soil-quality data are based on a reclassification of the Soils Map of the World (Food and Agriculture Organization of the United Nations and United Nations Educational, Scientific and Cultural Organization – FAO/UNESCO), which contains 106 soil-type classes. The United States Department of Agriculture Natural Resources Conservation Service and the University of Puerto Rico overlaid the FAO/UNESCO map with a global climate data set and, using the combined climate and soils data, reclassified the soils map according to suitability for food production. The University of East Anglia Climatic Research Unit's Global Climate data set was obtained from the Intergovernmental Panel on Climate Change. These 30-year monthly averages, interpolated into 5° grids, are based on daily weather station data collected during 1961–1990.

5. Implementation of the poverty mapping

5.1. The choice of consumption aggregate and poverty line

Using the CSES 1997 to define the consumption aggregate was not as straightforward as it initially seemed. There were two possible alternatives. One was to use the adjusted consumption aggregate derived by Knowles (1998); the other was the unadjusted consumption aggregate defined in MoP (2001). When MoP (1998) was published, the data set contained errors that necessitated the use of the adjusted consumption aggregate. The mistakes were subsequently corrected and hence the adjustments made by Knowles are unnecessary for this chapter. I therefore follow the definition of unadjusted consumption given in MoP (2001).

To ensure comparability with the publicized benchmark national poverty rate of 36.1 per cent, I redefined the poverty line so that the same poverty rates could be reproduced using the unadjusted consumption aggregate for each of the three strata. As a result, the poverty lines, in terms of consumption per capita per day, employed in this analysis are 1,629 riels for Phnom Penh, 1,214 riels for the other urban stratum and 1,036 riels for the rural stratum.[6]

By construction, the poverty rate for each stratum in this chapter is the same as given in MoP (1998). However, there is no guarantee that the poverty gap and the severity of poverty are the same. Hence checking these indices provides an indication of how important the choice between the adjusted and unadjusted measures is. In this chapter, the poverty gap was estimated at 8.9 per cent and poverty severity at 3.2 per cent. The corresponding figures in MoP (1998) were 8.7 per cent and 3.1 per cent, respectively. Although these numbers are not exactly the same, the differences are small enough to be considered random errors. This seems to suggest that the analysis presented in this chapter will be robust with respect to the choice of consumption aggregate.

5.2. The consumption model

This section provides details of the implementation of the ELL approach in Cambodia. I followed the implementation described in Elbers et al. (2002) whenever possible. As was discussed above, the CSES 1997 has three strata and is intended to be representative at that level. Thus, I have constructed three consumption models, one for each stratum. Hereafter, subscripts v and h are used to denote a village and a household, respectively.

The first step in creating a poverty map is to develop an accurate empirical model of household consumption.[7] It should be noted that my in-

terest here is not in the description of causal relationship but in the prediction of household consumption. I estimate the following consumption model:

$$\ln y_{vh} = E[y_{vh}|\mathbf{x}_{vh}^T] + u_{vh} = \mathbf{x}_{vh}^T\beta + \eta_v + \varepsilon_{vh}, \tag{13.2}$$

where y_{vh} is the per capita consumption and u_{vh} is the disturbance term, which is the sum of the location-specific component η_v and the idiosyncratic component ε_{vh}. These two components, η_v and ε_{vh}, are assumed to be independent of each other and uncorrelated with observable household characteristics $\mathbf{x}_{vh}$. This specification allows for an intra-cluster (i.e. intra-village) correlation in the disturbances and heteroscedasticity in ε_{vh}. Explicit treatment of the location effects is important because some of the effects of location may remain unexplained even with a rich set of regressors, including a number of geographical variables. The household characteristics $\mathbf{x}_{vh}$ in this model are not limited to variables that are specific to the household. They can also include the characteristics of the village in which the household is located. For example, $\mathbf{x}_{vh}$ can include the village-level means of the census data and the GIS data, which capture a part of the location effects. Cross-terms between a household-level variable and a GIS variable were also included.[8] For notational convenience, the variance of a random variable will hereafter be denoted as $\sigma_{\cdot}^2 \equiv Var[\cdot]$. When $\cdot$ has a subscript s, it is expressed using a comma as $\sigma_{\cdot,s}^2 \equiv Var[\cdot_s]$.

Elbers et al. (2002) point out that, for any given disturbance variance $\sigma_{u,vh}^2 = \sigma_{\eta,v}^2 + \sigma_{\varepsilon,vh}^2$, the greater the fraction owing to the common component, the less one enjoys the benefits of aggregating over more households within a country. To assess the performance of the consumption model, a number of diagnostic statistics are checked, and important ones are reported in Table 13.1.[9] In all three models, R^2 statistics are reasonably high, with the urban stratum performing the best. Since unexplained location effects reduce the precision of poverty estimates, I tried to explain the variation in consumption owing to location as far as possible with the choice and construction of $\mathbf{x}_{vh}$. Location means of household-level variables derived from the census data are particularly useful for this purpose. The importance of location effects as measured by $\hat{\sigma}_\eta^2/\hat{\sigma}_u^2$ is quite small for the Phnom Penh and other urban strata, but is relatively high in the rural stratum.[10]

In constructing the models, I also need to be careful not to overfit the data. Although the model error can grow as the number of indicators used in the model increases, overfitting is still a concern. To address this issue, I carried out random dropping and confirmed the robustness of the coefficients, as was done in Elbers et al. (2002). Random dropping was

Table 13.1 Diagnostic statistics

Description	Phnom Penh	Other urban	Rural
No. of observations	1,200	1,000	3,810
No. of clusters	120	100	254
No. of household-level rhs variables	22	10	17
No. of census mean variables	9	13	35
First stage: No. of GIS variables	0	5	11
Regression: No. of cross-terms between household-level and GIS variables	7	12	12
R^2	.481	.700	.538
$\hat{\sigma}_\eta^2/\hat{\sigma}_u^2$	0.047	0.008	0.139
Residual: No. of rhs variables	29	23	34
Regression R^2	.121	.066	.045

Source: Author's calculations.

tried not only at the individual level but also at the village level, because, when too many village-level indicators are included in the model, one is just fitting the village-level means.[11] Once the consumption models are specified, the next step is to estimate each component of the disturbance term. First, the residual term $\hat{u}$ was derived from the ordinary least squares regression. The common component η_v was estimated non-parametrically at the average of $\hat{u}$ in the cluster as follows:

$$\hat{u} = \hat{u}_{v.} + (\hat{u}_{vh} - \hat{u}_{v.}) = \hat{\eta}_v + e_{vh}, \tag{13.3}$$

where $\hat{u}_{v.}$ is the average of $\hat{u}$ over the households in the same village. To model heteroscedasticity in the idiosyncratic part of the residual, a restricted number of household characteristics, z_{vh}, that best explain variation in e_{vh} out of potential explanatory variables, their squares and interactions were chosen. The following logistic model of the variance of ε_{zh} conditional on z_{vh}, bounding the prediction between zero and a maximum, $A \equiv 1.05 \times \max_{v,h}\{e_{vh}^2\}$, was estimated:

$$\ln\left[\frac{e_{vh}^2}{A - e_{vh}^2}\right] = z_{vh}^T\alpha + r_{vh}. \tag{13.4}$$

Letting $B \equiv \exp\{z_{vh}^T\hat{\alpha}\}$ and using the delta method, the model implies a household-specific variance estimator for ε_{vh} of:

$$\hat{\sigma}_{\varepsilon,vh}^2 = \left[\frac{AB_{vh}}{1 + B_{vh}}\right] + \frac{1}{2}\hat{\sigma}_r^2\left[\frac{AB_{vh}(1 - B_{vh})}{(1 + B_{vh})^3}\right]. \tag{13.5}$$

Once $\hat{\sigma}^2_{\varepsilon,vh}$ is computed, the household residuals are standardized as follows:

$$e^*_{vh} = \frac{e_{vh}}{\hat{\sigma}_{\varepsilon,vh}} - \left[\frac{1}{H}\sum_{vh}\frac{e_{vh}}{\hat{\sigma}_{\varepsilon,vh}}\right], \tag{13.6}$$

where H is the number of households in the survey. Before proceeding to conduct the simulation, the estimated variance-covariance matrix $\hat{\sum}$ was weighted by the population expansion factor to obtain generalized least squares estimates of the first-stage parameters, $\hat{\beta}_{GLS}$, and their variance $Var(\hat{\beta}_{GLS})$.

5.3. Simulations

From the consumption model, α, β_{GLS}, and their associated variance-covariance matrices as well as the empirical distribution of e^*_{vh} and $\hat{\eta}_v$ are obtained. Assuming multivariate normal distribution, $\tilde{\alpha}^R$ and $\tilde{\beta}^R$ are drawn for each Rth simulation. Once $\tilde{\alpha}^R$ is drawn, the household-specific variance of the household component of disturbance, $(\tilde{\sigma}^2_{\varepsilon,vh})^R$, is estimated for each census household. Then the error terms are drawn in two stages to take clustering into account. The location-specific error $\tilde{\eta}^R_v$ is drawn from the empirical distribution of $\hat{\eta}_v$. Then the household component $\tilde{\varepsilon}^R_{vh}$ is obtained with a draw from the empirical distribution of e^*_{vh} in the corresponding cluster (i.e. village) and $(\tilde{\sigma}^2_{\varepsilon,vh})^R$. The simulated value of consumption $\hat{y}^R_{vh}$ for household h in village v is, therefore:

$$\hat{y}^R_{vh} = \exp(\mathbf{x}^T_{vh}\tilde{\beta}^R + \tilde{\eta}^R_v + \tilde{\varepsilon}^R_{vh}). \tag{13.7}$$

The full set of simulated $\hat{y}^R_{vh}$ is used to compute the Rth estimate of poverty measures for each commune except for some outliers. For example, the Rth estimate of poverty incidence for commune c, $\hat{I}^R_c$, is computed as follows:

$$\hat{I}^R_c = \frac{1}{n_c}\sum_{v\in V_c}\sum_{h\in H_v}\mathrm{Ind}(\hat{y}^R_{vh} < z)\cdot n_{vh}, \tag{13.8}$$

where V_c denotes the set of villages in commune c, H_v the set of households in village v, n_{vh} the size of household h in village v, z the poverty line, n_c the population of commune c, and $\mathrm{Ind}(\cdot)$ is an indicator function. For this chapter, the simulation was repeated 100 times. The mean and standard deviation of the estimates of poverty measures from each simulation were computed to arrive at the commune-level estimates of pov-

erty measures and their associated standard errors. In a similar manner, poverty measures at more aggregated levels, such as district, province and stratum, were estimated.

6. Results

6.1. Creating poverty maps

Once the commune-level estimates of poverty measures are computed, it is straightforward to create poverty maps. The polygon data for communes are combined with poverty estimates by the GIS. The map presented in Figure 13.1 is the map for the poverty rate. The darker areas are poorer and the hatched areas are outside the sampling frame of CSES 1997.

6.2. Are the villages excluded from the CSES 1997 sampling frame different?

As noted before, the sampling coverage of the CSES 1997 is smaller than that of the CSES 1999. I therefore used the CSES 1999 data to check if the consumption model applies to those areas that were excluded from the CSES 1997 sampling frame but included in the CSES 1999 sampling frame. Table 13.2 provides a summary of the sampling frame of 1997. Unfortunately, the number of samples from the excluded areas was too small to compare the equality of the coefficients for the included and excluded areas meaningfully. Hence, as discussed before, the hypothesis that the estimated regression coefficients with and without excluded areas are the same was tested.

If the relationship between the right-hand-side variables and consumption is kept intact in each round, in principle the same conclusion should be derived. However, the results obtained in this study are mixed. For the ‘‘other urban'' stratum, the hypothesis was rejected at the 1 per cent significance level when round 1 data or pooled data (i.e. round 1 and round 2) were used. However, the hypothesis could not be rejected even at the 10 per cent significance level when round 2 data were used. For the ‘‘rural'' stratum, the pooled sample could not reject the hypothesis but, with the round 1 and round 2 data, both sets rejected it when used separately. Hence the results are inconclusive.

How one should deal with the excluded areas depends on the objective of the policy maker. If one wants to reduce the Type I error and the budget is severely limited, these areas may be best avoided. On the other hand, if the policy maker is concerned about lives in the heavily mined

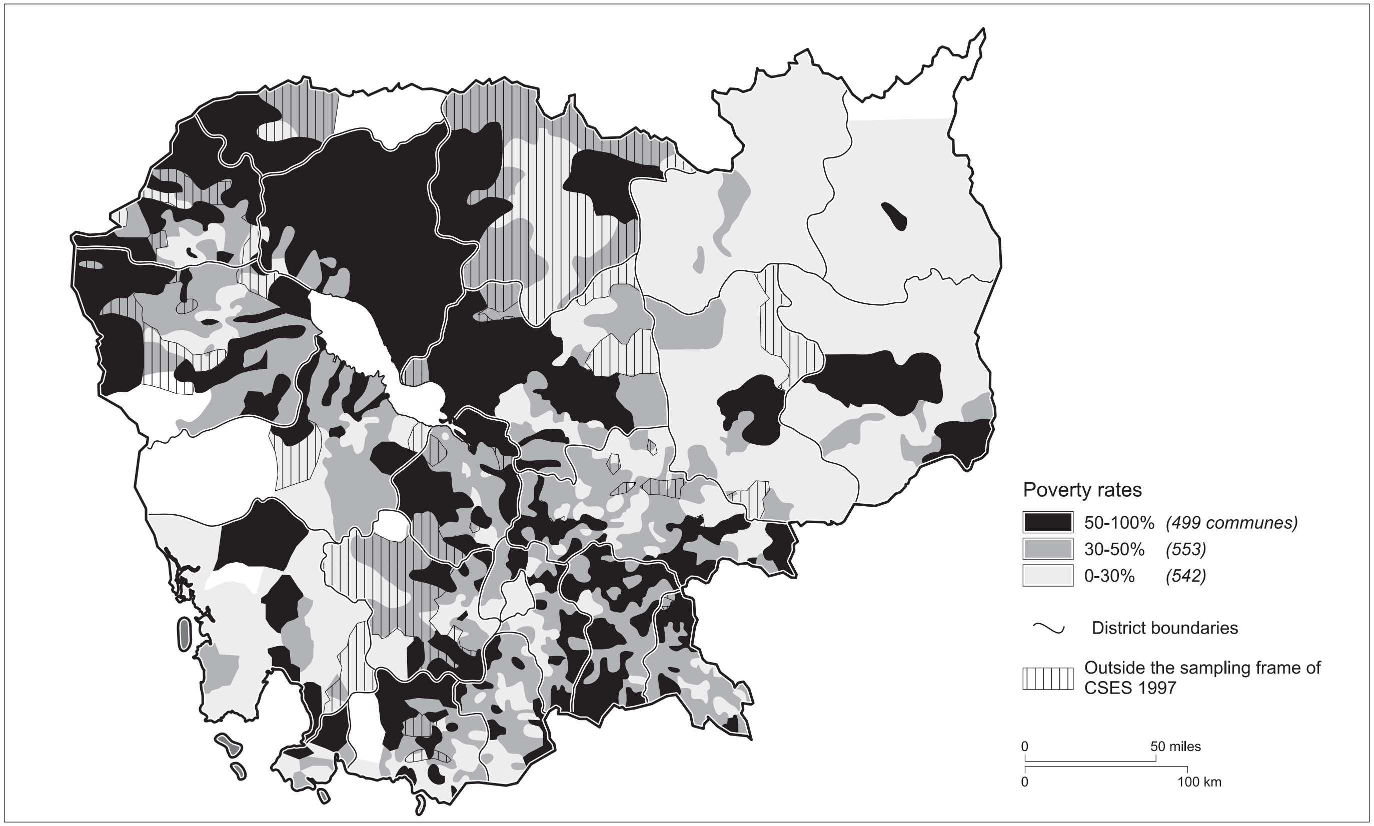

Figure 13.1 Commune-level poverty rate of Cambodia.
Source: Author.

Table 13.2 Summary of the number of villages in CSES 1999 included and excluded from the sampling frame of CSES 1997

	Round 1		Round 2		Total	
Stratum	Excluded	Included	Excluded	Included	Excluded	Included
Phnom Penh	0	600	0	600	0	1,200
Other urban	50	810	10	850	60	1,660
Rural	180	1,360	110	1,430	290	2,790
Cambodia	230	2,770	120	2,880	450	5,650

Source: Author's calculations.

Table 13.3 Stratum-level comparison of estimates of poverty rates (per cent)

Stratum	CSES only	CSES plus census
This study		
Phnom Penh	11.1 (1.8)	11.9 (1.2)
Other urban	29.9 (3.3)	30.0 (1.0)
Rural	40.1 (2.0)	43.0 (1.1)
WFP (2001) model 2		
Phnom Penh	9.7	12.5
Other urban	25.2	26.7
Rural	40.1	49.4

Note: Standard errors are in parentheses. The standard errors for CSES take into account only clustering and expansion factors.
Source: Author's calculations and WFP (2001).

areas, which roughly correspond to the excluded areas, they could use the estimates in the initial stages of targeting area selection. Irrespective of how the policy maker decides to use the excluded-area estimates, they should bear in mind that there is a good reason for caution in using these estimates.[12]

6.3. How accurate are the estimates?

To have an idea about the accuracy of the estimates, I compared my results with the preliminary poverty map (WFP 2001) constructed by combining the survey and census. Because WFP (2001) uses a different combination of data sets from that used in this study and because it does not record standard errors, it is not possible to compare the commune-level estimates directly. It makes more sense to conduct a comparison at the stratum level, because it is possible to use the poverty measures in poverty profiles as benchmarks. Table 13.3 compares the stratum-level poverty rates obtained in WFP (2001) and in this study for survey data

estimates (CSES only) and for estimates obtained by combining the survey and census (CSES plus census). The latter estimates are created at the stratum level and consistent with the poverty maps. For the sake of comparison, WFP (2001) model 2 was used because it also has a consumption model for each of the three CSES 1997 strata.

Two observations can be made. First, the patterns of poverty rates in this chapter and in WFP (2001) are quite similar irrespective of the data sets used. The poverty rate in Phnom Penh is around 10–12 per cent, "other urban" is 25–30 per cent and "rural" is 40–50 per cent. Second, when the differences between CSES only and CSES plus census for this chapter and for WFP (2001) are compared, there are much smaller discrepancies for this chapter. The difference between CSES only and CSES plus census for this chapter is small enough to be attributed to the random error.

The level of accuracy of the commune-level estimates varies from commune to commune. For example, the standard errors associated with commune-level estimates range between 0.1 per cent and 22.6 per cent. Table 13.4 provides summary statistics on the standard errors. The first column (mean standard error) is the simple average of the standard errors. Urban areas have lower standard errors. The median of standard errors is presented in the second column (median standard error). The third column (standard error ratio) is the average of the ratio of the standard error to the point estimate (i.e. coefficient of variation). The fourth (average number of households) and fifth (number of communes) columns provide the average number of households in the commune and the number of communes in the stratum respectively.

The first three columns provide a general picture of the levels of accuracy. The standard errors are low enough for the results to be useful as proxies, but are high for a number of communes, so policy analysts should treat the estimates with caution. At the same time, it should be noted that none of the summary statistics is perfect. For example, a relatively high level of standard error may not matter if the point estimates

Table 13.4 Summary statistics of the standard errors associated with commune-level poverty rate estimates

	Mean SE	Median SE	SE ratio	Average no. of households	No. of communes
Phnom Penh	4.0	3.5	35.7	2,169	76
Other urban	5.0	4.9	23.8	1,345	159
Rural	7.9	7.6	27.4	1,289	1,359
Cambodia	7.4	7.2	27.4	1,337	1,594

Source: Author's calculations.

are high enough. A commune with a point estimate of the poverty rate of 95 per cent and standard error of 15 per cent is clearly a very poor commune. On the other hand, even if the ratio of the standard error to the point estimate is high, it does not matter when the absolute value of the standard error is low. If the point estimate and standard error are both 0.1 per cent, then the commune is not a poor commune while the ratio is 100 per cent. In practical terms, the size of the commune is also important. Provided that the cost of a programme increases in proportion to the size of the commune, mis-targeting for small communes is a relatively minor issue in terms of the efficient use of resources. The statistics above do not incorporate the size of the commune.

One way to address some of these issues is to define a poor commune and non-poor commune by the ratio of the difference between the poverty estimate and a reference level to the standard error. If a poor commune is defined as a commune whose point estimate is higher than the national poverty rate by at least two times the standard error, and if a non-poor commune has the opposite definition, then 48 per cent of all communes can be classified as either poor or non-poor. When a commune cannot be classified, the communes can be aggregated to make the standard error smaller.

Although the magnitudes of the standard errors are not small enough to be ignored, and can be quite high for some communes, the commune-level estimate is accurate enough to make the difference from the national poverty rate statistically significant for half of the communes. Even for the other communes, the estimates provide useful information for targeting, especially when several communes are taken together. It is likely, for example, that the net gains from targeting poorer-than-national-average communes will be positive. Although the usefulness of the estimates depends upon the purpose to which they are put, commune-level estimates with this level of accuracy are still very useful given that reliable poverty estimates have previously been produced only at the stratum level. Even when the estimates need to be made at a more aggregated level such as district or even province to reduce standard errors, the usefulness of the estimates from this exercise will not be undermined because no other reliable estimates are available at this level.[13]

6.4. Extensions

The focus so far has been on poverty measures for the entire population. It is possible to create maps with other measures, such as inequality measures, that can be derived from consumption. It is also possible to derive poverty maps for specific target groups if the census weight for these groups is known. For example, poverty maps for women and children

can be derived by using the number of females and the number of children under the age of 5, respectively, instead of the total household size as the census weight (see WFP 2002).

7. Applying the poverty map to educational programmes

7.1. The education of children and poverty in Cambodia

The poverty map is very useful not only for identifying the location of the poor but for a variety of other purposes. In this section, I discuss an application of the poverty map to educational programmes. I argue that the poverty map is helpful, *inter alia*, for formulating targeted policies for educational programmes such as school meals programmes. The education of children is imperative in Cambodia. However, the current situation is not very encouraging. Education policies, like other policies, have been subject to arbitrary political influences. Ayres (2000: 459) says:

> the provision of formal education in Cambodia has been embraced to build a nation-state that looks modern, yet is concerned almost exclusively with sustaining the key tenets of the traditional polity, where leadership is associated with power and where the nature of the state is perceived to be a function of that power. The result, in terms of education, has been an educational crisis: a significant disparity between the education system and the economic, political, and cultural environments it has been intended to serve.

Educational statistics highlight the abysmal situation in Cambodia. As of 2001, the net enrolment rates (NER) at the primary level for boys and girls are 89 per cent and 83 per cent, respectively. At the secondary level, the statistics are even worse, with an NER of 26 per cent for boys and 16 per cent for girls (World Bank 2004). As Bray (1999) argues, Article 68 of Cambodia's constitution, which declares that "the state shall provide free primary and secondary education to all citizens in public schools", must be taken as a declaration of aspiration rather than reality.

The result of badly planned and poorly implemented education policies, coupled with a lack of resources for education, is the high private cost of public schooling. Bray (1999) studied the private costs of public schooling in Cambodia. Many schools charge fees and other forms of cash payment, for example demanding per-pupil payments for construction, repairs and equipment. Teachers often charge their students fees because salaries are very low. Bray's study shows that households' direct and opportunity costs of schooling are significant factors both for non-enrolment and for drop-outs. His findings are consistent with those of Fujii and Ear (2002). They found that children are more likely to attend

school if their parents are from a wealthier and more educated household. These findings have important intergenerational implications: children from poor and uneducated households, especially from households with poor and uneducated spouses, are less likely to go to school, which in turn implies that they are more likely to reproduce poor and uneducated children.

To cut this vicious cycle, appropriate education programmes are critical. For example, school meals programmes, which supply schoolchildren with nutritious food and are designed to provide parents with incentives for schooling and to enhance the nutritional status of children, would be worth considering. Such programmes are also expected to increase the effectiveness of learning, since improved nutritional status results in better concentration in class.

7.2. Finding potential areas for targeting

Education programmes, such as school meals programmes, must be appropriately targeted to those areas in which people are poor and the standard of education is low. This is particularly the case when the budget for education programmes is severely limited. To identify potential areas for targeting, the poverty map is of great use. One can overlay the education map on the poverty map, and take the intersection between poor areas and low education areas.

To overlay the education map on the poverty map, I first need to create the education map. The Education Information Management System 2001 data set was used in order to create the education map. The data are collected annually at school level by the Ministry of Education, Youth and Sport (MoEYS) and the Department of Planning with support from UNICEF (the UN Children's Fund), and contain net enrolment rates at the primary level among other indicators. MoEYS distributes questionnaires to directors of provincial offices of education, youth and sport (PDEYS), and, at the provincial level, the PDEYS provides training on data collection to chiefs of district education offices. At the district level, again, the chief of the district education office arranges training on data collection for directors of all schools within their administrative boundaries. The results are shown in Figure 13.2. Since we are looking for poor areas with a low level of education, we can place priority on the dark and hatched areas. However, it should be emphasized that these are not necessarily the best areas for targeting, because the map shows only the areas that are most lacking in resources. When targeting school meals programmes, other factors should be taken into consideration. Such factors would include the cost of procuring and delivering food, economies of scale and the capacity of the regional staff.

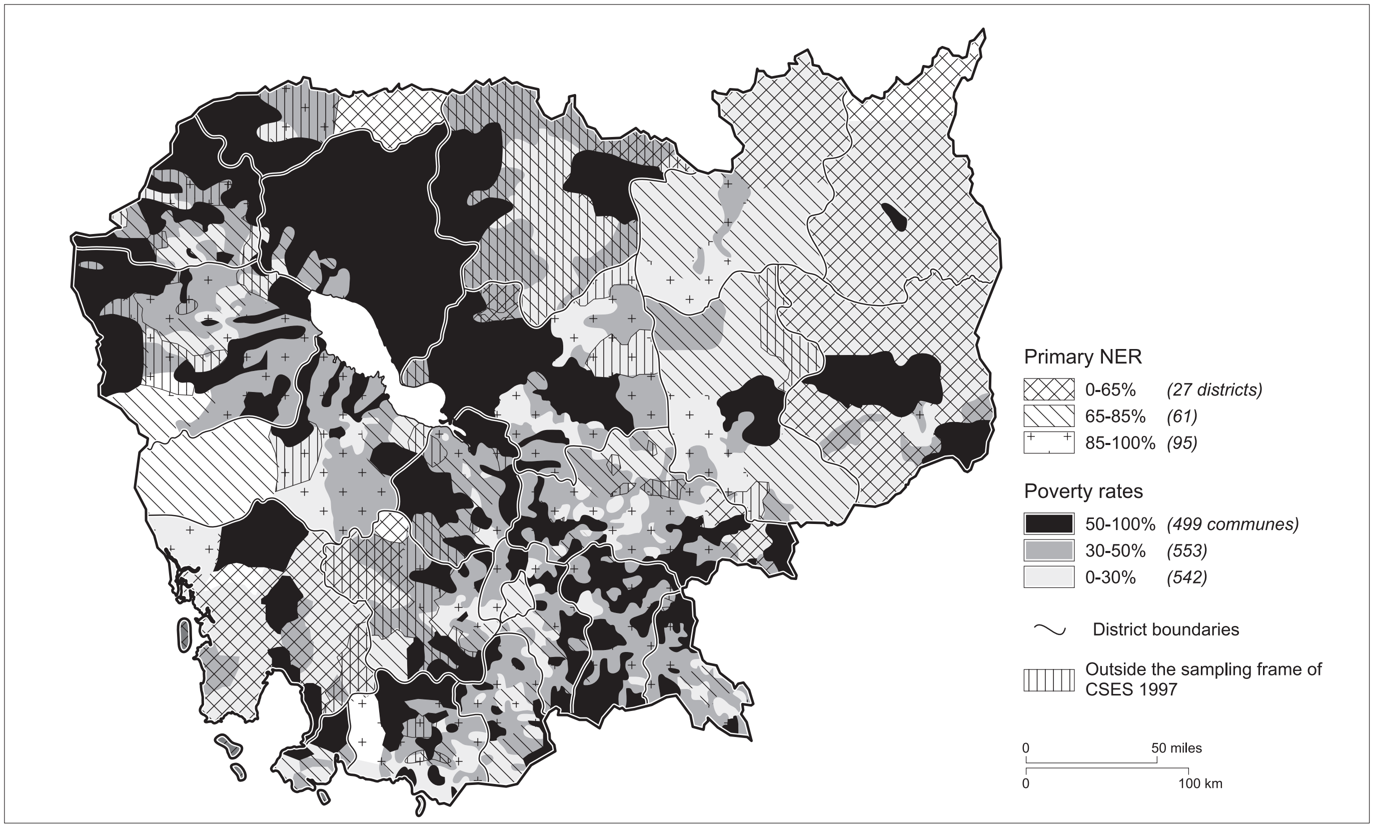

Figure 13.2 Basic education index map overlaid on poverty map.
Source: Author.

8. Conclusion

The poverty maps provide invaluable information to policy makers. When there is no reliable information for identifying the poor, targeted policies, if they exist at all, are likely to be inefficient and subject to arbitrary political influences. To deliver assistance to those most in need, policy formulation should be based upon reliable information. The poverty maps presented in this chapter give such information at the commune level. Moreover, the power of poverty maps is multiplied when they are combined with other maps such as the education map using GIS.

As I have discussed in section 7, by superimposing the education map on the poverty map a policy maker can identify the areas where poverty seems to prevent children from going to school. I have argued that school meals programmes, for instance, are most likely to be successful if targeted toward such areas, and the method I have presented in this study is useful for finding such areas.

The commune-level estimates of poverty rates presented in this chapter are reliable enough to be useful. This study has successfully applied the ELL technique to Cambodia and contributed to the empirical evidence of the applicability of the technique. However, it should also be noted that there are errors associated with the estimates and they may be very large for a number of communes. Moreover, the picture depicted here reflects the conditions as of 1998. It should be remembered that analysis of poverty is never static and thus efforts to acquire up-to-date information and monitor changes in poverty will be indispensable for the efficient, effective and timely delivery of assistance. Hence, policy makers should not be misled by the intuitive appeal of poverty maps. The maps presented here can serve as a sound basis for the formulation of targeted policies, but they cannot and should not be taken as the sole basis. Other maps and data sources, as well as observations from the field, should be incorporated in the analysis whenever possible. This is particularly true for the areas outside the sampling frame of CSES 1997.

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Notes

1. In Cambodia, there are four levels of administrative division: province, district, commune and village, in descending order of aggregation.
2. For further details of CSES 1997, see NIS (1998).
3. For further details of CSES 1999, see NIS (2000a).
4. Further information on the implementation of the census can be found in NIS (2000b).
5. The maximum household size is 14 in CSES 1997 data. I allowed for a margin of 1. CSES 1997 does not contain information on visitors. I excluded households with clearly too many visitors.
6. The average official exchange rate in 1998 was US$ = 3807.8 riels.
7. The detailed regression results in this section are omitted to save space. They are given in WFP (2002), and are also available from the author upon request.
8. Although the fact that the cross-terms increased the predictive power of the model justifies their inclusion in the model, it is plausible that the interaction term indeed affects the welfare measure. For example, the potential of good soil quality may be more efficiently exploited by those with better education or experience, which results in a positive and significant coefficient on the relevant cross-term.
9. WFP (2002) provides a complete list of the diagnostic statistics I used.
10. See Elbers et al. (2002) for the derivation of $\hat{\sigma}_\eta^2/\hat{\sigma}_u^2$.
11. I used stepwise regression to reduce the number of candidate variables included in the model. I determined the final models taking into consideration the diagnostic statistics and the concern for overfitting.
12. For example, Krong Pailin was the poorest province on the map. It is, however, generally considered to be a non-poor area. This may be because Krong Pailin was out of the sampling frame of the CSES 1997.
13. Commune-, district- and provincial-level estimates are available in WFP (2002).

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