MERIT-Infonomics Research Memorandum series

Patterns of inter-sectoral diffusion of technological growth: income, concentration, and public capital stocks

Ute Pieper

2002-010

MERIT – Maastricht Economic Research Institute on Innovation and Technology
PO Box 616
6200 MD Maastricht
The Netherlands
T: +31 43 3883875
F: +31 43 3884905

http://meritbbs.unimaas.nl
e-mail:secr-merit@merit.unimaas.nl

International Institute of Infonomics

PO Box 2606
6401 DC Heerlen
The Netherlands
T: +31 45 5707690
F: +31 45 5706262

http://www.infonomics.nl
e-mail: secr@infonomics.nl

Patterns of inter-sectoral diffusion of technological growth: income, concentration, and public capital stocks

Ute Pieper*

June 2002 (revised version)
Paper prepared for the conference on “The Future of Innovation Studies” at the Eindhoven Centre for Innovation Studies (ECIS), Technische Universiteit Eindhoven, from September 21-23, 2001.

Keywords: technological growth, inter-sectoral diffusion, structural demand composition, income distribution, public capital stock
JEL: O110, O140, O300

Abstract

This paper investigates the existence and character of technological growth diffusion in form of learning spillovers at the sector level of the economy. Based on panel data for 47 countries during the postwar period the evidence suggests robust statistical regularities of inter-sectoral learning resulting from a changing structure of demand. The findings further show differences in the magnitude of productivity spillovers across sectors. In particular, the patterns reveal a distinctive role for upstream production activities esp. manufacturing as a source of diffusion. When the technological growth potential of sectors in low-income economies is compared to high-income countries the empirical evidence does not show a tendency for catching up to occur. However, higher potential for inter-sectoral diffusion of technological growth is associated with (i) low income concentration, and (ii) high public (human and physical) capital stocks.

*MERIT, Economics Department, Maastricht University
P.O. Box 616, 6200 MD Maastricht, The Netherlands
Email: ute.pieper@merit.unimaas.nl

ACKNOWLEDGEMENTS

Comments by Thorsten Block, Duncan Foley, Catherine Saget, Eddy Szirmai, Nick von Tunzelmann, and participants at the Eindhoven Centre for Innovation Studies conference, “The Future of Innovation Studies,” September 21-23, 2001, are gratefully acknowledged. I also wish to thank Duncan Campbell, Eugene Canjels, Philippe Egger, Ajit Ghose, Rolph van der Hoeven, and Pierre Mohnen for helpful discussions and suggestions. Many friends and colleagues have supported this study by providing country data, I am indebted to all of them, especially Luciano Amaral, Matti Hannikainen, Adalmir Marquetti, the Austrian Trade Commission and Österreichisches Statistisches Zentralamt, and last but not least the International Labour Office in Geneva. This research was supported by a *Marie Curie* Fellowship of the European Commission under contract no. HPMF-CT-1999-00204.

Contents

1. Introduction 1

2. Some concepts 3
2.1 Diffusion, productivity spillovers, and technological growth 3
2.2 Conceptualizing the process of technological growth diffusion 6
2.3 A simple model 8

3. A matrix of learning 9
3.1 Data and Methodology 9
3.2 Estimates. 12

4. Inter-sectoral productivity spillovers, income level, and concentration 15
4.1 Inter-sectoral spillovers and catching up 15
4.2 Manufacturing activities as source for growth diffusion 20
4.3 Income concentration. 25

5. Public capital stocks and productivity spillovers 29
5.1 Human capital. 29
5.2 Infrastructure investment and capital stock 33

6. Conclusions 37

Data Appendix. 38
References. 41
Notes. 44

1. Introduction

Doubtless, technological change and its diffusion across time and space is one of the most important factors in understanding long-run economic development and persistent divergence of particularly income per capita. Corresponding stylized facts that have been identified in the growth literature during the past two to three decades further suggest to be more consistent with a technology explanation of growth and income distribution rather than economic models of decreasing returns to capital.[1] Essentially, innovation in firms alone cannot explain observed differences in growth performances across countries. So while the capacity to innovate and to realize the potential of new technologies is one of the main sources of economic growth, it is the diffusion of these new products and processes across firms, industries, and countries that leads to widespread increases in productivity and economic welfare. The economic field of technology spillover, and diffusion more generally, remains under-explored, which may explain in part why recent efforts have not been successful at providing a more fundamental understanding of the processes underlying economic growth.

Similarly, recent attempts of the so-called new growth literature have made an important contribution by emphasizing the importance of the sources of economic growth. However, their success in modeling experienced growth has been limited both for cross-sectional and time-series evidence (Durlauf and Quah, 1999; Jones, 1998; Temple, 1999). As Nelson (1998) has pointed out, this *puzzle* between the predictions of the theory and observed growth may be a consequence of the level of aggregation of (mostly macro-) economic variables under investigation. As a result scholars have recently focused their research efforts on a more disaggregated analysis of the patterns of technical change.[2] Most of the work, however, has been directed at the study of one particular aspect in the process of technological growth namely the generation of new products and processes—inventions and innovations—rather than the spread of novel ideas.

Over long periods it can be expected that productivity improvements are associated with technological growth. The diffusion of technological growth across economic activities can be conceptualized as a process based on learning that leads to positive externalities. In other words, the diffusion of new products and processes throughout the economy by way of learning generates productivity-increasing effects that are realized in economic activities outside the source activity. This argument was first motivated by Allyn Young (1928) and Nicholas Kaldor (1966, 1975) who hypothesized that increasing returns due to learning by doing are a macroeconomic phenomenon as opposed to being restricted to specific (industrial) activity alone.

It is our understanding of the existence of technology diffusion over space and time, that has motivated investigations into underlying processes and their impact on the creation of welfare, the distribution of income and long-term growth and development. In a first step this study attempts to identify statistical regularities of productivity spillover or the diffusion of technological growth between sectors of the economy. More specifically, the question will be asked if changes in the composition of demand (or output) are responsible for observed patterns of sectoral technological growth. A model which essentially represents a modification of the so-called Kaldor-Verdoorn law is proposed and applied to a cross-country panel data set of 47 economies compiled from internationally compatible time-series data at the one-digit level of the *International Standard Industry Classification* (ISIC) codes. In the empirical analysis both parametric as well as nonlinear statistical techniques will be used to identify sectoral regularities of technology spillover and to ensure robustness of the results.

The findings suggest the prevalence of technological growth diffusion at the sector level of the economy. In particular, the evidence confirms a distinctive role for upstream economic activities like manufacturing in generating positive productivity spillovers into all other main sectors of the economy. Most importantly, however, when income levels are accounted for, the estimates do not suggest catching up as a result of technological growth diffusion to occur in low-income economies.

These findings based on the modified Verdoorn model allow for the identification of the diffusion of technological growth that is due to changes in demand and its composition in the economy. In addition to a changing structure of the economy, other factors are expected to influence further the spillover potential of individual sectors. These factors can be thought of as either facilitating or hindering the diffusion of technological growth. In a second step, hypotheses with respect to these types of factors were identified and tested in order to nest the empirical results in more theoretical applications. For instance, criticism has been directed particularly at standard growth accounting exercises that assume perfect substitutability between factors of production and thereby neglect to investigate the fundamentally complementary character of technological change (Felipe, 1999; Nelson and Pack, 1999). Similarly, current work in the field of economic history of technological change by e.g. David et al. (2000) informs us of the necessity to explore the nature of complementarities in understanding the complexity of technologies.

In a first approximation, factors that can be hypothesized as influencing the process of the diffusion of technological growth due to being complementary in their nature are income concentration, human capital and its mobility, and public investment and/or infrastructure capital stocks. This attempt to identify empirical regularities of the behavior of complementary factors that impact on productivity spillover at the sector level of the economy may then help in the modeling of deterministic relationships underlying the development process, and therefore may inform more proactive policy-making.

2. Some concepts

2.1 Diffusion, productivity spillovers, and technological growth

It is, however, not an easy task to conceptualize analytically and measure and test empirically the phenomena that are associated with the process of technology diffusion. At a methodological level the challenge is to disentangle the influences of different factors that are associated with technical change in general and technology diffusion in particular, like e.g. the effects of changing physical and human capital or changes in the structure and organization of production in the economy. This may explain why there has been a recent wave of research activities in the area of technology diffusion, and figure 1 illustrates main concepts and their relationships.

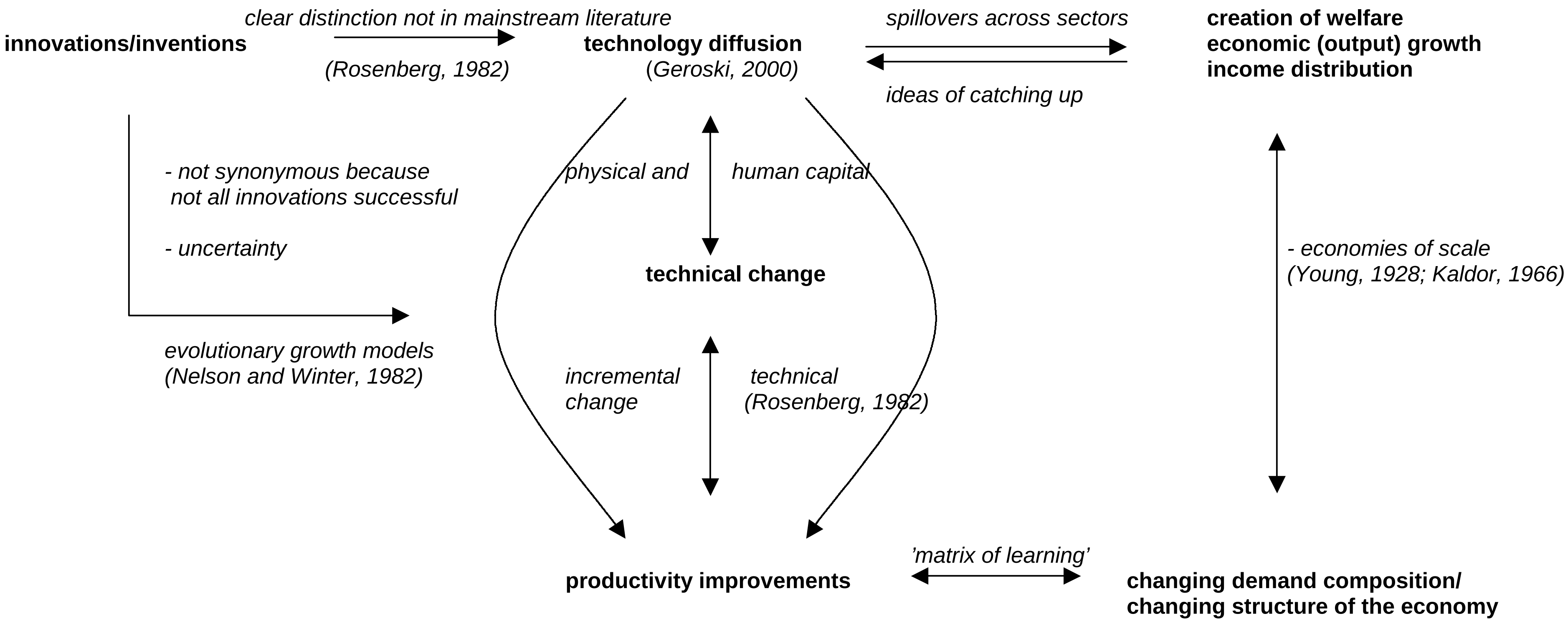
In the original mainstream approach to economic growth, new technologies diffuse instantaneously across total capital, while in later formulations, technology and technical change is limited by its embodiment in capital and therefore determined by the rate of investment (Nelson, 1981). The result is that technological growth is transitory, and for long-run growth to occur exogenous impulses of new technologies are necessary.

But until very recently even outside these mainstream formulations, economists and historians alike have focused their attention foremost on the aspect of invention when studying the question of technical progress. Rosenberg (1982, p. 19) writes: "Indeed, the diffusion process [of new technologies] has often been assumed out of existence. This has been done by identifying the economic impact of an invention with the first date of its demonstrated technological feasibility or—what is hardly the same thing—the securing of a patent." Not surprisingly, in response to this criticism most research initiatives were directed at the inquiry into the diffusion of innovations, which by its nature required a better understanding of the flow of information and learning processes in the economy.

As a result one major strand of research activities in the field of technical change is concerned with explaining the characteristic functional form of observed technology diffusion processes over time, i.e., the so-called S-shaped curve or logistic function. This class of models takes the agent or firm as unit of analysis, and formulations are derived from population dynamics modeling information flows (Geroski, 2000).[3]

Out of a criticism of the mainstream growth literature that not all inventions and/or innovations are adopted successfully, the second major strand of research is concerned with explicitly modeling the inherently uncertain nature of technical change. This class of models in the tradition of evolutionary growth theory, however, does not treat the diffusion process of innovations or more generally technologies explicitly. In fact, in Nelson and Winter's (1982) classical model once a new technology is chosen, the old technology of a firm (or industry) is transformed instantaneously.[4]

Figure 1: The relationship between technology, demand composition, and economic growth



Source: Author.

Where technology diffusion has entered into evolutionary growth modeling it is usually in the form of embodied technical change and (only) in this sense similar to mainstream formulations. This approach utilizes the information of observed patterns of technology diffusion, in which vintage capital is replaced by new equipment and machinery according to Goodwin-type macro-dynamics, to show that stochastic processes of innovation are sufficient to generate long waves of economic activity (Silverberg and Lehnert, 1993). But overwhelmingly, the different approaches have been less clear with respect to the economic frameworks that are implicit in the investigations, and much work in this area of research remains to be done.

2.2 Conceptualizing the process of technological growth diffusion

This study's approach to the question of inter-sectoral diffusion of technological growth takes two concepts as its starting point that are not completely separate. First, it explores the impact of changes in the composition of demand (or output) in the economy on the diffusion of technological growth. Observed changes in production structures of the economy don't behave randomly but rather exhibit systematic behavior associated with the process of economic growth. The empirical investigation therefore proposes to utilize the information underlying changing structural demand specifically at the sector level of the economy.

Second, the so-called Kaldor-Verdoorn law (Kaldor, 1966) will be modified and applied to this information which will generate a matrix of inter-sectoral learning spillovers. The Law in its original presentation identifies a close long-run relationship between the rate of growth of output and productivity growth in a given industry or sector of the economy. When interpreted in light of the classical idea of the reserve army of labor the robust observed patterns suggest a technology explanation of growth due to externalities that are associated with learning by doing. These aspects of learning have long been highlighted in the development literature, and were first reemphasized by Arrow's seminal article *The*

Economic Implications of Learning by Doing (1962). Arrow argued that externalities arising from learning by doing and knowledge spillover positively affect aggregate labor productivity.

A catalog of different forms of learning can be found in Rosenberg (1982). He classified learning by doing as "a form of learning that takes place at the manufacturing stage after the product has been designed, that is, after the learning in the R&D stages [..] has been completed. Learning at this stage, as described by Arrow and others, consists of developing increasing skill in production. This has the effect of reducing real labor costs per unit of output. The significance of this process has been documented in several industries, including airframe production, shipbuilding, machine tools, and textiles" (ibid., p. 121).

Rosenberg further distinguished a related form of learning by doing which again occurs as a by-product of productive activity. This form of learning has recently received a lot of attention and came to be better known as incremental technological change. Direct involvement in the productive process leads to many kinds of productivity improvements that are often individually small but cumulatively very large. It is probably these two types of learning by doing that Kaldor and many authors after him had in mind when applying the Verdoorn law in their empirical investigations.[5]

While the productivity gains from these types of learning activities will be felt where they are undertaken so that they are internal to the productive activity of the firm or industry, there is another form of learning generated in the process of *utilization*. The learning-by-using experience generates two very different kinds of useful knowledge that may either be *embodied* or *disembodied*. Rosenberg (1982, p. 123) writes: "In the former, the early experience with a new technology leads to better understanding of the relationship between specific design characteristics and performance that permit subsequent improvements in design. In the case of disembodied knowledge, the knowledge generated leads to certain alterations in use that require no (or only trivial) modifications in hardware design. Here, prolonged experience with the hardware reveals information about performance and operation characteristics that, in turn, leads to new practices that increase the productivity of the hardware—either by lengthening its useful life or by reducing the operating costs."

These modifications are simultaneously fed by downstream and upstream sources that lie outside the economic activity—say industry or sector—that absorbs them. The steady flow of small improvements will show up as efficiency increases in the production of the absorbing sector. It can be further expected that any one economic activity represents a source as well as an absorber of the consequences of learning by using, which taken together will yield a matrix of inter-sectoral learning. The following section will propose a model that attempts to capture observed patterns of the diffusion of learning between sectors in the economy.

2.3 A simple model

First, it is hypothesized that the Verdoorn law, which in its simplest form states a positive statistical relationship between output growth and the rate of growth of labor productivity over the long run, also extends to inter-sectoral or inter-industry diffusion of learning. In other words, demand or output growth in one sector of the economy positively affects another sector's productivity growth as a result of learning spillovers. In essence, this model therefore captures the impact of technological growth that originates with a changing composition of demand or structure of production in the economy.

Estimations of the modified Verdoorn model are based on three main variables: value added, employment and labor productivity at the sector or industry level of the postwar economy. The relationship is specified as:

$$p_{jkt} = \alpha_0 + \beta q_{ikt}, \text{ with expectation } \beta > 0 \qquad (1)$$

where

q = output growth,

p = productivity growth,

i, j = sector,

k = country, and

t = time.

In words, the output growth in sector i is expected to show a positive relationship with the rate of growth of productivity in sector j over the long run. The estimations of the relationship will provide a matrix of coefficients that measures every sector's potential as source of technological growth resulting from sectoral learning spillover as well as its potential to "absorb" the spillovers from all the other sectors in the economy.

It is necessary to control for the influence of own-sector output growth on the rate of growth of productivity of sector j, that is, the original specification of Verdoorn's (1949) relationship. In order to circumvent the problem of multicollinearity between sectoral output growth rates, the so-called Rowthorn formulation of the Verdoorn law was introduced to the specification. Rowthorn (1975) proposed this formulation of using changes in employment as the regressor on productivity in his debate with Kaldor (1966, 1975) over the accuracy of his interpretation of the Verdoorn law of increasing returns.[6] Mathematically speaking, multiple formulations of the production relation are possible based on the productivity identity ($P \equiv Q/E$). After differentiating the change in productivity is equal to the difference between output growth and the rate of growth of employment. In fact, estimates of alternative formulations would give equivalent results if the association measured is exact or a close fit.

In addition to the hypothesis of a positive long-run relationship between the rate of growth of productivity in sector j and output growth in sector i, it can be expected that the observed behavior of different sectors can be distinguished from one another. Thus further statistical testing is directed at the question of significant differences in spillover potentials of individual sectors.

3. A matrix of learning

3.1 Data and methodology

Estimations of the model are based on a panel data set for the postwar period with a breakdown at the one-digit level of the *ISIC* codes, i.e., 9-10 main economic activities or sectors depending on country data availability. The data sets consist of two main time series on sectoral value added and employment, and sectoral labor productivity levels and growth rates are computed based on the former two data series. The main economic activities covered are: (1) agriculture, forestry and fishing, (2) mining and quarrying, (3) manufacturing, (4) public utilities, (5) construction, (6) wholesale and retail trade and hotel and restaurants (henceforth “commerce”), (7) transport and communication, (8) finance, insurance and real estate (“FIRE”), (9) community, social personal services, and (10) government services.

The panel data set was compiled based on three main international sources which yielded consistent series for 30 low-income and 17 high-income countries. First, the time series for low-income countries come from (1) the *International Labour Office* for sectoral employment data, and (2) *UN National Accounts* for value added with the same sector breakdown. For additional low-income countries national data sources were used (see data appendix for details). The 30 low-income countries cover sub-Saharan Africa, Latin America, South and East Asia for the period from 1975 to the early 1990s.

Since the 1970s the U.N. system of statistics has devised detailed survey guidelines for its collection of national data to ensure consistency for international comparison. This is why the two sets of sectoral data series can be considered to be consistent over time and space. Most importantly for the investigations at hand, however, the two sets of employment and output series are compatible with respect to the sector breakdown according to ISIC codes.

Additionally, a considerable effort was spent in particular on the raw series of the ILO to work on consistency of the sectoral employment data. The majority of the data is from national household or establishment surveys, and was further classified according to its quality based on criteria like for example changing definitions, discrepancies between figures for aggregate employment and the sum of sectoral employment, and obvious measurement errors. Then only country series of medium or high data quality were selected for inclusion in the study. Ultimately it was the sectoral employment series due to overall availability and exclusion based on poor quality that limited the size of the developing country sample to 30 (while consistent value added series at the sector level are more widely available).

Nevertheless, it should be pointed out that it probably represents the best time-series data available for developing country employment at this time.

Table 1: Data coverage of regions and countries

OECD	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom, United States
Sub-Saharan Africa	Botswana, Ghana, Kenya, Malawi, Sierra Leone, South Africa, Zambia, Zimbabwe
Latin America and the Caribbean	Bolivia, Brazil, Chile, Colombia, Costa Rica, Guatemala, Mexico, Panama, Peru, Puerto Rico, Venezuela
South and East Asia	India, Indonesia, Korea, Malaysia, Myanmar, Philippines, Singapore, Sri Lanka, Thailand
Other	Turkey, Jordan

Source: See data appendix for details.

Second, for high-income countries the majority of the historical evidence is from the OECD's *International Sectoral Data Base (ISDB) 1998*; and was supplemented by Leacy and Urquhart (1983), Pilat (1994), Banco de Portugal (1997), and van Ark and Crafts (1996) for data on Canada, Japan, Portugal, and Spain, respectively. For most of the OECD countries data is available from 1950 to the late 1990s. Table 1 shows the regional and country coverage of the resulting country panel.

The time series of value added, employment, and labor productivity were smoothed by taking 5-year log growth rates, which leaves about 100-130 observations per sector sample. It was necessary to eliminate cyclical fluctuations because the modified Kaldor-Verdoorn model is concerned with the long-run relationship of technological growth diffusion between sectors, and it is in this sense not a "proper" panel set up of the data.[7]

The second part of the empirical analysis investigates the question if factors such as income level and concentration, and human and public capital stocks influence the different sectors potential to absorb spillovers from the other sectors in the economy. The theoretical and methodological issues involved are discussed in detail in sections 4 and 5. Additional country data was collected on three main indicators: (i) income inequality, (ii) educational attainment, and (iii) public investment or infrastructure stock variables (see data appendix for sources and coverage).

3.2 Estimates

The results from estimating the modified Kaldor-Verdoorn model which capture the effects of a changing sectoral composition of demand on technological growth diffusion are summarized in table 2. The estimates are based on data for 47 countries after influential outliers were removed from the sample (see table notes for details on techniques used to identify outliers). The left-hand column lists the "source" sector of the technological growth spillover, while the top row indicates the sector receiving or "absorbing" the spillover. The cells of the matrix show the estimates of the partial coefficients (β_{ij}) on sector i's output growth rate and t-statistics.

In accordance with the model's expectation the β_{ij}-coefficient is positive and statistically significant for the majority of cases. The estimates suggest a positive relationship between the rate of growth of output of the source sector and productivity growth in the absorbing sector, and thus support the hypothesis of the prevalence of inter-sectoral diffusion of technological growth.

The findings further show differences in the magnitude of the growth spillover across sectors. The patterns reveal three distinctive groups or classes of sectors that allow us to develop a taxonomy based on their diffusion potential. Most strikingly, *upstream* sectors, i.e., manufacturing, public utilities, construction, and transport and communication, tend to have a higher spillover coefficient than the other sectoral activities. On the other hand, natural resource exploiting or *downstream* sectors (agriculture and mining) show very small potential for technological growth diffusion. Services, like e.g. commerce, FIRE and social and government services, appear to form a third intermediate class of sectoral activities. On average they are not as weak a source for spillover as the downstream sectors yet they are not as strong as compared to upstream sectors.

The estimates suggest similar statistical regularities when the sectors are considered in terms of their capacity to absorb technological spillover from other sectors. Again the natural resource exploiting sectors seem to have a relatively smaller absorptive capacity, while the upstream sectors are not only better sources for spillover but are also better at absorbing them. Services activities particularly social and government services absorb a relatively higher spillover from other services upstream (e.g. commerce, transport and FIRE) than from upstream production activities such as construction and manufacturing.

The finding of stronger learning spillovers being associated with upstream economic activities further suggests an interpretation of the β-coefficient that is more consistent with an explanation of sectoral growth that is due to the diffusion of technological growth. A simple pulling along of downstream activities would show up in a relatively higher β-coefficient to the left of the diagonal in the matrix of table 2 considering that the sectors are arranged from downstream to upstream from left to right. However, higher values of β-coefficients are found on the right hand side of the diagonal of the matrix.

These results remain robust when fixed country and time effects are included in the estimations. One way of interpreting the changes in some of the estimates for individual β-coefficients as compared to the model without fixed effects is that other factors which are important for the diffusion behavior of sectors besides a changing composition of demand have not yet been accounted for. The following sections will take up some of these factors.

Table 2: Inter-sectoral spillovers: β_{ij}-coefficients[a] for 47 countries (t-statistics)

		Absorbing sector									
Source sector	fixed time and country effects	agriculture	mining	manufacturing	public utilities	construction	commerce	transport	FIRE	social services	government services
agriculture	without	NA	0.105 (0.603)	0.069 (0.893)	0.031 (0.325)	0.312*** (3.164)	0.092 (1.209)	-0.102 (-1.457)	0.128* (1.820)	-0.026 (-0.391)	0.047 (0.816)
	included	NA	0.294 (1.583)	0.247*** (3.705)	0.008 (0.091)	0.260*** (2.517)	0.185*** (2.582)	0.024 (0.327)	0.102 (1.348)	0.060 (0.838)	0.104* (1.763)
mining	without	0.017 (0.879)	NA	0.011 (0.467)	0.033 (0.998)	0.012 (0.356)	0.040* (1.650)	0.021 (0.899)	0.020 (0.812)	0.008 (0.384)	0.020 (1.578)
	included	0.035 (1.608)	NA	0.026 (1.160)	0.029 (0.969)	0.029 (0.867)	0.052** (2.383)	-0.002 (-0.083)	0.027 (1.113)	0.016 (0.698)	0.027** (2.085)
manufacturing	without	0.102*** (2.478)	0.297*** (2.609)	NA	0.523*** (8.840)	0.450*** (6.387)	0.526*** (12.080)	0.436*** (10.444)	0.379*** (7.426)	0.262*** (6.273)	0.188*** (4.657)
	included	0.246*** (3.844)	0.154 (0.855)	NA	0.235*** (2.745)	0.268*** (2.716)	0.453*** (7.166)	0.367*** (6.044)	0.256*** (3.418)	0.242*** (3.736)	0.115** (2.073)
public utilities	without	0.034 (0.867)	0.341*** (3.278)	0.324*** (7.151)	NA	0.320*** (4.975)	0.300*** (6.710)	0.146*** (3.269)	0.254*** (5.855)	0.145*** (3.522)	0.156*** (4.856)
	included	0.004 (0.007)	0.445*** (3.677)	0.114** (2.369)	NA	0.043 (0.572)	0.159*** (3.112)	0.034 (0.649)	0.120** (2.246)	0.103** (2.014)	0.101** (2.270)
construction	without	0.092*** (3.950)	0.211*** (2.636)	0.236*** (8.201)	0.177*** (4.876)	NA	0.262*** (9.423)	0.171*** (6.346)	0.185*** (6.394)	0.113*** (4.489)	0.113*** (3.729)
	included	0.119*** (4.290)	0.142 (1.360)	0.151*** (5.707)	0.013 (0.336)	NA	0.191*** (6.534)	0.139*** (4.946)	0.133*** (4.213)	0.106*** (3.781)	0.094** (2.371)
commerce	without	0.063 (1.259)	0.325*** (2.927)	0.447*** (10.266)	0.242*** (3.910)	0.422*** (6.207)	NA	0.311*** (7.198)	0.225*** (4.684)	0.278*** (5.367)	0.155*** (3.006)
	included	0.154** (2.108)	0.288** (2.161)	0.373*** (8.670)	0.133** (2.069)	0.309*** (3.589)	NA	0.231*** (4.695)	0.182*** (3.298)	0.240*** (3.410)	0.153*** (2.873)
transport	without	0.028 (0.575)	0.466*** (3.348)	0.568*** (9.290)	0.481*** (6.340)	0.328*** (3.602)	0.521*** (8.519)	NA	0.387*** (6.270)	0.390*** (8.107)	0.098* (1.736)
	included	0.160** (2.240)	0.369** (2.038)	0.349*** (4.969)	0.201** (2.052)	0.368*** (3.274)	0.366*** (4.921)	NA	0.256*** (3.305)	0.424*** (6.608)	0.058 (0.915)
FIRE	without	0.135*** (3.248)	0.231** (2.092)	0.349*** (7.177)	0.380*** (6.404)	0.170** (2.281)	0.329*** (7.052)	0.274*** (5.973)	NA	0.115*** (2.617)	0.103* (1.698)
	included	0.170*** (3.581)	0.159 (1.326)	0.198*** (4.461)	0.193*** (3.301)	0.056 (0.758)	0.183*** (3.839)	0.145*** (3.021)	NA	0.006 (0.125)	0.062 (1.067)
social services	without	-0.0002 (-0.004)	0.127 (0.934)	0.335*** (5.241)	0.271*** (3.371)	0.137 (1.595)	0.254*** (3.889)	0.389*** (7.340)	0.076 (1.240)	NA	0.114** (2.353)
	included	0.048 (0.772)	0.076 (0.507)	0.242*** (4.022)	0.125 (1.498)	0.200** (2.347)	0.156** (2.420)	0.321*** (5.859)	-0.041 (-0.663)	NA	0.108** (2.228)
government services	without	0.055 (0.557)	0.573* (1.915)	0.214** (2.060)	0.841*** (6.147)	0.330*** (2.810)	0.218** (2.415)	0.070 (0.679)	0.249*** (2.863)	0.354*** (4.281)	NA
	included	0.151 (1.036)	0.442 (0.889)	-0.132 (-0.940)	0.342** (1.802)	-0.022 (-0.131)	0.183 (1.179)	-0.206 (-1.352)	0.055 (0.365)	0.174 (1.304)	NA

Notes:
[a]After removing outliers above 3 standard deviations. The estimates were robust when alternative techniques were applied in identifying influential observations. For instance, *Cook's Distance* was used which tests for the change in an OLS estimate resulting from omitting the i^{th} observation.

*Significant at the 0.10 level (2-tailed).
**Significant at the 0.05 level (2-tailed).
***Significant at the 0.01 level (2-tailed).

Source: Author's calculations. See data appendix for details.

4. Inter-sectoral productivity spillovers, income level, and concentration

4.1 Inter-sectoral spillovers and catching up

The estimation results suggest a substantial role for diffusion of learning across sectors as a source for economic growth, which thus may help in explaining differences in per capita income levels. The applied growth literature identifies a tendency for less developed countries to catch up to the world technological leaders, which implies that productivity growth across countries will be inversely related to their initial productivity levels or income per capita. Convergence of countries to a shared long-run growth path therefore results from productivity to increase faster in countries that are furthest away from the technological frontier than in countries that are already close to it (Abramovitz, 1986).[8]

If there is a general tendency for convergence then it can be further hypothesized that low-income countries show a higher potential for sectoral learning spillovers than high-income countries. In order to test this hypothesis the data sample of 47 countries was divided into two groups according to the World Bank country classification.[9] The two groups consist of 17 high-income and 30 low-income countries where the former happens to coincide with the group labeled OECD countries in table 1.

Table 3 summarizes the results from estimating the modified Kaldor-Verdoorn model for the two country groups. The set up of the table is essentially the same as before where for every source sector the estimates for the low-income and high-income groups are shown in the first and second rows, respectively. Just like the findings from the estimations for the whole sample, when income levels are accounted for the β-coefficient for both country groups support the hypothesis of a positive long-run relationship between the rate of growth of output in sector i and productivity growth of sector j.

Moreover, the estimates show again differences in the magnitude of the learning spillovers across sectors for both country groups. The main findings can be summarized as follows. First and most importantly, the same taxonomy between upstream production activities and downstream natural resource exploiting sectors (agriculture and mining) that are characterized by substantially lower spillover coefficients remains clearly identifiable.

Second, with income levels accounted for an additional distinction can be made between the spillovers from upstream services, i.e. commerce and FIRE, and downstream services (social and government services). Downstream services' spillovers tend to be relatively lower compared to upstream services for the high-income group. The estimates, however, do not suggest a similar distinction for the group of low-income countries.

Third, there is also a difference with respect to the statistical regularities of the absorptive capacity of sectors when income levels are accounted for. As before the natural resource exploiting sectors perform relatively poorly at absorbing spillovers. A notable exception is the mining sector, which shows a high absorptive capacity in the low-income country group. Moreover, upstream production activities, i.e., manufacturing, public utilities, construction and transport and communication, reveal again the highest capacity to absorb spillovers as compared to the other sectoral activities.

Fourth, maybe not surprisingly out of this group of upstream production activities the statistical regularities for learning spillovers are most consistent for manufacturing both as source and absorbing sector. In section 4.2 the question of manufacturing activities as a source for the diffusion of technological growth will be examined in more detail.

Finally, in order to examine the question of cross-country convergence the two country samples are compared based on the taxonomy of inter-sectoral diffusion. On the one hand, there is no apparent difference between low and high-income countries in the magnitude of learning spillovers of both types of downstream activities—natural resource exploitation and social services. On the other hand, an overall tendency for the spillover coefficient to be higher in the high-income group can be found for the two types of upstream activities—services and particularly production sectors. A noteworthy exception among the latter is the transport and communication sector, which tends to generate higher spillovers in low-income countries.

Table 3: Low vs. high per capita income levels (β_{ij}-coefficients[a] and t-statistics)

		Absorbing sector									
Source sector	**income level**	**agriculture**	**mining**	**manufacturing**	**public utilities**	**construction**	**commerce**	**transport**	**FIRE**	**social services**	**government services[b]**
agriculture	**low**	NA	**0.091** (0.386)	**0.127** (1.076)	**0.002** (0.010)	**0.425***** (2.619)	**0.181** (1.588)	**-0.097** (-0.839)	**0.135** (1.101)	**-0.107** (-1.006)	--
	high	NA	**0.160** (0.578)	**0.018** (0.214)	**0.107** (0.823)	**0.226**** (2.066)	**-0.005** (-0.055)	**-0.113** (-1.234)	**0.156**** (2.017)	**0.092** (1.144)	**0.047** (0.816)
mining	**low**	**0.031** (0.911)	NA	**0.068** (1.512)	**0.084** (1.379)	**0.131*** (1.746)	**0.110**** (2.494)	**0.031** (0.627)	**0.094*** (1.738)	**0.006** (0.131)	--
	high	**0.003** (0.149)	NA	**-0.026** (-1.163)	**0.003** (0.074)	**-0.038** (-1.335)	**0.007** (0.296)	**0.018** (0.798)	**-0.023** (-1.183)	**0.007** (0.321)	**0.020** (1.578)
manufacturing	**low**	**0.105*** (1.753)	**0.393**** (2.502)	NA	**0.473***** (4.876)	**0.321***** (2.654)	**0.473***** (7.145)	**0.489***** (7.550)	**0.448***** (4.881)	**0.255***** (3.714)	--
	high	**0.090** (1.502)	**0.126** (0.731)	NA	**0.588***** (8.143)	**0.582***** (8.516)	**0.578***** (10.285)	**0.358***** (6.121)	**0.297***** (5.741)	**0.279***** (5.590)	**0.188***** (4.657)
public utilities	**low**	**-0.034** (-0.574)	**0.503***** (3.718)	**0.293***** (4.216)	NA	**0.242**** (2.175)	**0.276***** (3.979)	**0.151**** (2.047)	**0.286***** (3.722)	**0.098** (1.390)	--
	high	**0.118**** (2.253)	**0.087** (0.512)	**0.266***** (4.708)	NA	**0.410***** (6.476)	**0.301***** (5.388)	**0.123**** (2.231)	**0.219***** (4.970)	**0.210***** (4.623)	**0.156***** (4.856)
construction	**low**	**0.091***** (3.067)	**0.262***** (2.605)	**0.201***** (5.309)	**0.115**** (2.272)	NA	**0.218***** (5.923)	**0.162***** (4.226)	**0.182***** (4.107)	**0.109***** (3.014)	--
	high	**0.089**** (1.967)	**0.060** (0.406)	**0.247***** (4.101)	**0.405***** (6.623)	NA	**0.425***** (8.148)	**0.200***** (4.151)	**0.203***** (4.933)	**0.127***** (3.109)	**0.113***** (3.729)
commerce	**low**	**0.102** (1.313)	**0.373***** (2.713)	**0.376***** (6.203)	**0.135** (1.491)	**0.311***** (2.993)	NA	**0.280***** (4.332)	**0.214***** (2.797)	**0.321***** (3.649)	--
	high	**0.011** (0.171)	**0.167** (0.804)	**0.498***** (6.322)	**0.513***** (5.612)	**0.632***** (6.918)	NA	**0.445***** (6.253)	**0.260***** (4.234)	**0.222***** (3.793)	**0.155***** (3.006)
transport	**low**	**0.070** (0.983)	**0.618***** (3.587)	**0.600***** (7.210)	**0.480***** (4.198)	**0.337**** (2.336)	**0.496***** (5.766)	NA	**0.494***** (5.153)	**0.416***** (5.528)	--
	high	**-0.039** (-0.492)	**0.167** (0.667)	**0.347***** (4.042)	**0.473***** (4.307)	**0.359***** (3.374)	**0.549***** (6.118)	NA	**0.155**** (2.000)	**0.351***** (5.286)	**0.098*** (1.736)
FIRE	**low**	**0.152***** (2.816)	**0.300**** (2.392)	**0.326***** (5.356)	**0.349***** (4.381)	**0.113** (1.055)	**0.311***** (5.226)	**0.287***** (4.601)	NA	**0.083** (1.292)	--
	high	**0.127** (1.472)	**-0.027** (-0.105)	**0.313***** (3.370)	**0.503***** (4.123)	**0.448***** (3.922)	**0.362***** (3.681)	**0.183**** (2.031)	NA	**0.242***** (3.155)	**0.103*** (1.698)
social services	**low**	**-0.011** (-0.147)	**0.068** (0.383)	**0.367***** (3.909)	**0.236*** (1.895)	**0.143** (1.047)	**0.300***** (3.171)	**0.443***** (5.615)	**0.057** (0.548)	NA	--
	high	**0.035** (0.461)	**0.336** (1.432)	**0.242***** (3.259)	**0.352***** (3.282)	**0.174*** (1.771)	**0.172**** (1.969)	**0.267***** (3.572)	**0.160**** (2.364)	NA	**0.114**** (2.353)
government services	**low**	--	--	--	--	--	--	--	--	--	NA
	high	**0.055** (0.557)	**0.573*** (1.915)	**0.214**** (2.060)	**0.841***** (6.147)	**0.330***** (2.810)	**0.218**** (2.415)	**0.070** (0.679)	**0.249***** (2.863)	**0.354***** (4.281)	NA

Notes:
[a]See table 2.

[b]No government services data available for low-income countries.

Source: Author's calculations. See data appendix for details.

The upstream production activities esp. manufacturing, public utilities and construction also perform relatively better as absorbing sectors in high-income countries. Transport and communication is again an exception with higher absorptive capacity in low-income countries. Regarding the downstream natural resource exploiting sectors there is no difference in the absorption of learning spillovers for agriculture. However, mining receives substantially more spillover in low-income countries. With respect to downstream and upstream services the estimates do not show a clear tendency for better absorption of spillovers in both country groups.

Based on these findings there appears to be no evidence supporting the hypothesis of low-income country convergence. In fact, the identified diffusion patterns in particular of upstream activities are more consistent with a tendency for low-income economies to fall behind the group of high-income countries. Stated slightly differently it appears that low per capita income is associated with relatively lower potential for the diffusion of technological growth.

Next in order to test for statistical robustness of this tendency the pairs of estimates of sectoral β-coefficients were compared for the two income groups. The results from testing for statistically significant differences between sector estimates are shown in table 4a. Critical values were calculated to test the null hypothesis of equality between a pair of β-coefficients for the same source sector i in the two country groups. The findings can be summarized following the identified taxonomy of sectoral learning spillovers. For downstream service activities the null hypothesis of equality between coefficients on output growth of sector i could not be rejected for the majority of sector pairs. Similarly, the test results show no statistically significant differences for agriculture in the class of downstream natural resource exploiting sectors. On the other hand, when income levels are controlled for mining as source sector for learning spillovers shows significant differences for four out of eight absorbing sectors with bigger (though low in magnitude) coefficients for the group of low-income countries. As mentioned above mining performs also better as absorbing sector in low-income countries.

Out of the class of upstream production activities about half of the sector pairs show significantly higher spillover coefficients for high-income countries. Moreover, the results from testing for significantly higher β-coefficients of upstream service activities are also in favor of the high-income group. The transport and communications sector is an exception in the class of upstream production activities because the learning spillovers are substantially higher for the low-income group in three out of eight sector pairs.

In sum, the statistical tests found significant differences in spillover coefficients between sector pairs of the two income groups. These differences, however, do not lend support to the hypothesis of cross-country convergence in income per capita levels because there is no general tendency for low-income countries to have higher learning spillovers. Instead, based on our understanding of the importance of upstream production activities where high-income countries tend to have significantly higher inter-sectoral learning spillovers the findings suggest the possibility of falling behind due to comparatively less diffusion of technological growth across sectors in low-income countries.

Table 4: Significant differences between main sectors' spillovers (critical values)[a]

(a) comparing country groups with low vs. high per capita income levels

	Absorbing sector									
Source sector	agriculture	mining	manufacturing	public utilities	construction	commerce	transport	FIRE	social services	government services[b]
agriculture	NA	--	--	--	--	--	--	--	1.50*	--
mining	--	NA	**1.88****	--	**2.11****	**2.04****	--	**2.03****	--	--
manufacturing	--	--	NA	--	1.88**	--	**1.50***	**1.43***	--	--
public utilities	1.91**	**1.92****	--	NA	1.32*	--	--	--	1.34*	--
construction	--	--	--	3.65***	NA	3.24***	--	--	--	--
commerce	--	--	--	2.94***	2.32**	NA	1.71**	--	--	--
transport and communication	--	**1.49***	**2.12****	--	--	--	NA	**2.75*****	--	--
FIRE	--	--	--	--	2.14**	--	--	NA	1.59*	--
social services	--	--	--	--	--	--	**1.62***	--	NA	--
government services	--	--	--	--	--	--	--	--	--	NA

(b) comparing country groups with low vs. high income concentration

Source sector	Absorbing sector									
	agriculture	mining	manufacturing	public utilities	construction	commerce	transport	FIRE	social services	government services
agriculture	NA	**1.30***	--	**2.33****	--	--	--	**1.39***	--	--
mining	--	NA	1.54*	--	1.62*	--	--	2.39***	--	--
manufacturing	--	1.42*	NA	**2.26****	**1.60***	--	--	--	--	--
public utilities	**2.85*****	2.25**	--	NA	**3.51*****	--	--	**1.35***	**1.88****	--
construction	--	--	--	**5.45*****	NA	**2.19****	**1.47***	**3.46*****	--	--
commerce	--	--	**2.59*****	**3.59*****	**1.89****	NA	--	**1.41***	--	--
transport and communication	--	1.64*	--	**2.04****	--	--	NA	--	--	--
FIRE	--	2.18**	1.53*	1.54*	--	1.86**	3.25***	NA	1.79**	--
social services	1.37*	--	--	**1.51***	1.72**	--	2.36**	--	NA	--
government services	--	--	--	--	--	--	--	--	**1.44***	NA

Notes:
[a]Under the assumption of normal distribution, $\beta_i \sim N(\beta_i, V(\beta_i))$, to test whether two regression coefficients, β_1 and β_2, drawn from samples of sizes n_1 and n_2, differ significantly from each other, critical values ($z_{1,2}$) are computed as follows. With $\beta_1 - \beta_2 \sim N(\beta_1 - \beta_2, V(\beta_1) + V(\beta_2))$,

$$z_{1,2} = \frac{\beta_1 - \beta_2}{\sqrt{V(\beta_1) + V(\beta_2)}} \sim N(0, 1).$$

The null hypothesis H_0: $\beta_1 = \beta_2$ and H_1: $\beta_1 > \beta_2$. The following are critical values ($z_{1,2}$) from the t-statistic (1-tailed):
*Significant at the 0.10 level z > 1.30
**Significant at the 0.05 level z > 1.67
***Significant at the 0.01 level z > 2.39

The tables show only values of sector pairs for which the null hypothesis could be rejected. Highlighted values in (a) or (b) indicate that the β-coefficient is higher for the country group with low income level or low income concentration, respectively.

[b]No government services data available for low-income countries.

Source: Author's calculations.

4.2 Manufacturing activities as source for growth diffusion

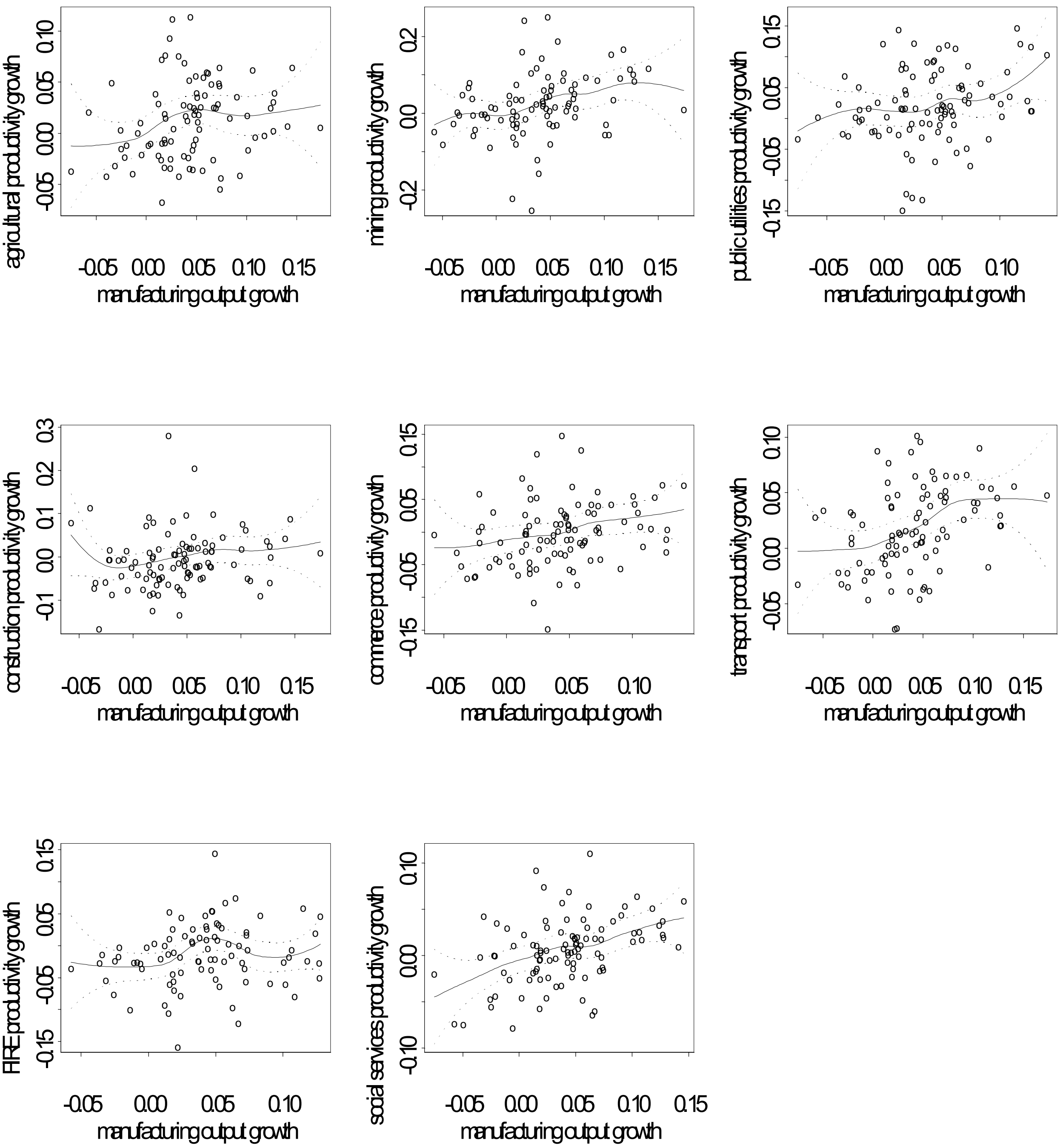
In a historical account Amsden (2001) has recently studied the group of countries (labeled "the rest") that was successful at converging to the world technological frontier during the postwar period. She argues that the success of competing in world markets of the late-industrializing economy crucially depends on previously accumulated experience in manufacturing.[10] More generally, most research work in the area of technological change and growth focuses its attention more or less explicitly on the role of the manufacturing sector in the development process. In particular, manufacturing activities have been at the core of the study of inventions and innovations and their diffusion. However, it is not at all clear how they are interlinked with overall growth of the economy. This section takes a closer look at the modified Kaldor-Verdoorn relation in the manufacturing sector as a possible source for either divergence or convergence of countries.

As mentioned above the estimation results suggest manufacturing as the sector that is most consistently linked with all other main activities in the economy. The statistical regularities reported in tables 2 and 3 show a robust long-run association for manufacturing both as a source of as well as a receiving sector for learning spillovers. The panels of figures 2 and 3 plot the β-coefficients on manufacturing output growth regressed on productivity growth for all other sectors of the low and high-income countries, respectively.

Every panel contains the smooth curve for the receiving sector (solid line) based on local regression fitting, as well as sample observations and standard error of the regression fit (dotted lines). A smooth fit is sensitive to the range of observations or "bandwidth" used in the local regressions. A bandwidth of alpha equal to .7 appeared to not oversmooth the curve. Techniques of nonlinear data smoothing allow us to relax the unnecessarily restrictive assumption of linearity of the statistical relationship under investigation. They also have the advantage of providing additional information as compared to linear fitting regarding the robustness of the estimates by tracing the data closely. In particular, through visualization of the statistical relationship a nonlinear estimation may reveal influential data points and/or heterogeneity of the samples.

The nonlinear fits confirm the findings from the linear estimations reported in the previous section. For both per capita income groups they show a stable positive relationship between the rate of growth of manufacturing output and productivity growth in all other sectors of the economy suggesting the prevalence of learning spillovers originating from manufacturing activity.

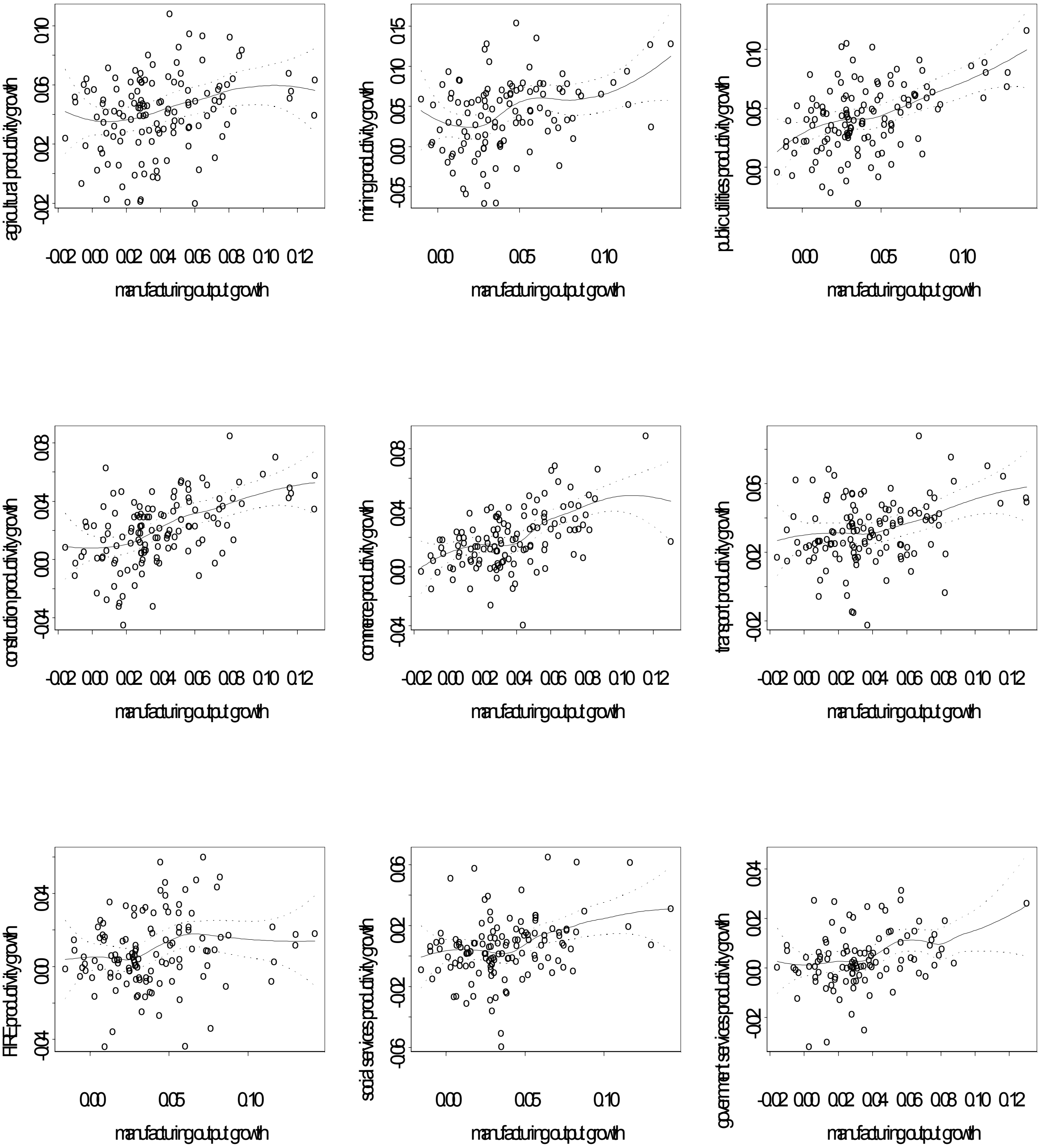
Figure 2: Manufacturing spillover into main sectors of the economy: low-income countries



Note:
Smooth fits for manufacturing spillover are predicted based on low-income country data with a bandwidth of alpha equal .7. Solid curve and dotted lines show smooth fit and standard error, respectively.

Source: Author’s computations.

Figure 3: Manufacturing spillover into main sectors of the economy: high-income countries



Note:
Smooth fits for manufacturing spillover are predicted based on high-income country data with a bandwidth of alpha equal .7. Solid curve and dotted lines show smooth fit and standard error, respectively.

Source: Author's computations.

As already mentioned in section 4.1 statistical tests indicated significant differences in the β-coefficients on manufacturing output growth between the two income groups. The question that hasn't been looked at yet is whether there are also differences across the two country groups in the statistical regularities of the sectors receiving spillovers from manufacturing.

Tables 5a and 5b show critical values for testing the null hypothesis of equality between the β-coefficients for manufacturing on absorbing sector j. By definition, either small or large sector estimates have a relatively higher probability for the null hypothesis to be rejected than sectors with average coefficients. Most strikingly, the results find fewer differences across absorbing sectors in low-income countries as compared to absorbing sectors in high-income countries. In other words, diversity in spillover behavior across sectors is associated with high per capita income levels.

What the two country groups have in common is that natural resource exploiting sectors (agriculture and mining) and downstream services (social and government services) show most significant differences with the other main activities in the economy. This again confirms the taxonomic regularities of sectoral activities. Additionally, in high-income economies FIRE and transport and communication show significant differences in their absorptive capacities compared to the other sectors.

Table 5: Manufacturing spillover in low and high per capita income countries (critical values)[a]

(a) manufacturing as source sector in low-income countries[b]

Absorbing sector	transport and communication	commerce	public utilities	FIRE	mining	construction	social services	agriculture
transport and communication	NA	--	--	--	--	--	2.47***	4.34***
commerce	--	NA	--	--	--	--	2.28**	4.13***
public utilities	--	--	NA	--	--	--	1.83**	3.23***
FIRE	--	--	--	NA	--	--	1.68**	3.12***
Mining	--	--	--	--	NA	--	--	1.71**
construction	--	--	--	--	--	NA	--	1.60*
social services	2.47***	2.28**	1.83**	1.68**	--	--	NA	1.64*
agriculture	4.34***	4.13***	3.23***	3.12***	1.71**	1.60*	1.64*	NA

(b) manufacturing as source sector in high-income countries

Absorbing sector	public utilities	construction	commerce	transport and communication	FIRE	social services	government services	mining	agriculture
public utilities	NA	--	--	2.49***	3.28***	3.53**	4.86***	2.48***	5.31***
construction	--	NA	--	2.51***	3.33***	3.59***	4.99***	2.47***	5.43***
commerce	--	--	NA	2.73***	3.68***	3.98***	5.67***	2.50***	5.95***
transport and communication	2.49***	2.51***	2.73***	NA	--	--	2.41***	1.30*	3.21***
FIRE	3.28***	3.33***	3.68***	--	NA	--	1.66*	--	2.61***
social services	3.53**	3.59***	3.98***	--	--	NA	1.42*	--	2.42***
government services	4.86***	4.99***	5.67***	2.41***	1.66*	1.42*	NA	--	1.36*
Mining	2.48***	2.47***	2.50***	1.30*	--	--	--	NA	--
agriculture	5.31***	5.43***	5.95***	3.21***	2.61***	2.42***	1.36*	--	NA

Notes:
[a,b]See table 4.

Source: Author's calculations.

4.3 Income concentration

The analysis which so far has focused on the effect of a changing structure of demand on the behavior of inter-sectoral learning spillovers will now be extended to other factors that may positively or negatively affect the diffusion of technological growth. One such factor that can be hypothesized as hampering the diffusion of technologies—both embodied, and disembodied in the form of learning spillovers—is the concentration of resources and particularly of income in the economy.

At the macroeconomic level of the analysis the distribution or concentration of income has traditionally played a fundamental role in classical models of the determination of growth and technological change. Furthermore, the findings of recent empirical investigations into observed patterns of growth have emphasized the importance of income concentration by presenting a strong significant negative relation between the two for both historical panel data and postwar cross-section evidence (Perotti, 1992; Persson and Tabellini, 1994).

Beginning with the economic history work of the 1960s concentration has also played a key role in explaining growth and the spread of new technologies at the micro level—sector or industry—of the economy. The relationship is often explored either in association with the size of the investments required for the adoption of the new technology (Mansfield, 1968), or changes in relative factor prices (David, 1966). For instance, in his influential study about technology diffusion David found that the spread of a particular capital good in agriculture (for example the reaper in the American Midwest from the 1830s through the 1850s) was a function of farm size. Only farms that were above a certain threshold in terms of their size adopted the new production technique embodied in the capital equipment early on, while the diffusion of the new technique was delayed for small family-sized farms. In other words, the concentration of resources hampers the widespread adoption of a new harvest technique or the diffusion of new technologies more generally.

This section will apply these ideas in the context of the modified Kaldor-Verdoorn law. The question is whether income concentration has an effect on the regularities of learning spillovers identified above. In arriving at a statistically testable hypothesis, first a few words on the methodology and data applied. There are a number of different indicators of the concentration or the distribution of income. Invariably, however, these tend to be at the aggregate level of the economy. More disaggregated statistical measures at the sector level are not available least for a large panel of countries. This investigation relies on the most common indicator for income distribution, the Gini coefficient of income inequality. Based on average Gini coefficients for the period between the early 1950s and the mid-

1990s the 47 countries included in the sectoral panels were classified into low vs. high income concentration groups.[11]

Table 6 summarizes the estimation results for the β-coefficients of the 10 sectors based on the income concentration classification. First, the estimates for both country groups support the prediction of the modified Kaldor-Verdoorn model of a positive relationship between the rate of growth of output in sector i and productivity growth in sector j.

Second, the previously identified sector taxonomy is also apparent when the country sample is grouped according to income concentration. Thus, the natural resource exploiting sectors (agriculture and mining) again show least potential for learning spillovers. At the other extreme upstream production activities (manufacturing, public utilities, construction, and transport and communication) have the biggest sectoral spillover coefficients. Similarly, the dichotomy for services activities is also repeated with comparably higher diffusion originating from upstream FIRE and commerce than from the downstream services.

In addition to supporting the taxonomy the classification of countries based on income concentration reveals further regularities in inter-sectoral spillovers compared to the findings from the previous two estimations of the model (whole sample, and country groupings according to income level). In particular, the estimates suggest that learning spillovers are comparably higher in source sectors of countries with low income concentration.

The null hypothesis of equality between sector regression coefficients from the two country groups was investigated using the same statistical test as described above. Critical values were calculated for comparing pairs of corresponding β-coefficients for sectors of low vs. high income concentration. The results are presented in table 4b.

In particular, the upstream production activities of manufacturing, public utilities and construction show significantly higher inter-sectoral learning spillovers in countries with low income inequality. Similarly, higher spillovers from commerce as source sector are associated with low income inequality.

Table 6: Low vs. high income concentration (β_{ij}-coefficients[a] and t-statistics)

		Absorbing sector									
Source sector	**income concentration**	**agriculture**	**mining**	**manufacturing**	**public utilities**	**construction**	**commerce**	**transport**	**FIRE**	**social services**	**government services**
agriculture	**low**	NA	**0.400** (1.458)	**0.041** (0.400)	**0.344**** (2.335)	**0.217*** (1.648)	**0.117** (1.047)	**-0.036** (-0.385)	**0.271***** (2.762)	**-0.035** (-0.366)	**0.085** (1.430)
	high	NA	**-0.052** (-0.232)	**0.090** (0.853)	**-0.109** (-0.856)	**0.370***** (2.659)	**0.099** (0.949)	**-0.124** (-1.219)	**0.074** (0.719)	**-0.010** (-0.106)	**0.120** (0.995)
mining	**low**	**0.016** (0.686)	NA	**-0.026** (-0.981)	**0.020** (0.471)	**-0.034** (-0.988)	**0.020** (0.698)	**0.021** (0.856)	**-0.032** (-1.290)	**0.011** (0.437)	**0.020*** (1.652)
	high	**0.018** (0.530)	NA	**0.046** (1.197)	**0.048** (0.933)	**0.079** (1.305)	**0.072*** (1.864)	**0.045** (1.086)	**0.089**** (2.027)	**0.012** (0.323)	**0.071** (1.120)
manufacturing	**low**	**0.088*** (1.876)	**0.142** (0.955)	NA	**0.663***** (9.083)	**0.494***** (7.058)	**0.497***** (9.431)	**0.388***** (7.121)	**0.327***** (5.283)	**0.245***** (5.080)	**0.178***** (4.171)
	high	**0.114** (1.570)	**0.471***** (2.642)	NA	**0.392***** (4.111)	**0.259**** (2.005)	**0.545***** (7.415)	**0.461***** (6.502)	**0.392***** (4.654)	**0.304***** (4.280)	**0.061** (0.721)
public utilities	**low**	**0.138***** (3.190)	**0.130** (0.920)	**0.338***** (6.003)	NA	**0.508***** (8.309)	**0.318***** (5.818)	**0.150***** (2.858)	**0.308***** (6.186)	**0.237***** (5.233)	**0.143***** (4.294)
	high	**-0.089** (-1.329)	**0.582***** (4.078)	**0.227***** (3.274)	NA	**0.069** (0.626)	**0.252***** (3.507)	**0.094** (1.263)	**0.190***** (2.643)	**0.079** (1.120)	**0.028** (0.312)
construction	**low**	**0.082**** (2.108)	**0.180** (1.403)	**0.269***** (4.334)	**0.501***** (8.246)	NA	**0.364***** (7.335)	**0.230***** (5.022)	**0.332***** (7.993)	**0.150***** (3.599)	**0.096***** (3.173)
	high	**0.093***** (2.934)	**0.265**** (2.547)	**0.190***** (5.321)	**0.078*** (1.646)	NA	**0.229***** (6.363)	**0.143***** (3.892)	**0.129***** (3.107)	**0.107***** (3.108)	**0.022** (0.253)
commerce	**low**	**0.081** (1.367)	**0.341*** (1.866)	**0.593***** (8.132)	**0.568***** (5.688)	**0.568***** (5.658)	NA	**0.360***** (4.906)	**0.315***** (4.324)	**0.293***** (4.755)	**0.114**** (2.093)
	high	**0.051** (0.603)	**0.368*** (2.638)	**0.353***** (6.203)	**0.101** (1.206)	**0.310***** (3.327)	NA	**0.262***** (4.354)	**0.174**** (2.564)	**0.268***** (3.168)	**0.181** (1.583)
transport	**low**	**0.019** (0.320)	**0.238** (1.174)	**0.511***** (5.750)	**0.674***** (6.452)	**0.450***** (4.381)	**0.512***** (6.699)	NA	**0.317***** (3.625)	**0.383***** (6.578)	**0.052** (0.880)
	high	**0.053** (0.640)	**0.686***** (3.767)	**0.534***** (6.320)	**0.360***** (3.181)	**0.231** (1.627)	**0.500***** (5.315)	NA	**0.418***** (4.730)	**0.412***** (5.259)	**0.167** (1.022)
FIRE	**low**	**0.133***** (3.293)	**0.042** (0.328)	**0.251***** (5.164)	**0.293***** (4.222)	**0.087** (1.183)	**0.243***** (4.722)	**0.108**** (2.082)	NA	**0.051** (1.078)	**0.107** (1.606)
	high	**0.141** (1.520)	**0.534***** (2.870)	**0.408***** (4.558)	**0.489***** (4.575)	**0.164** (1.087)	**0.431***** (4.950)	**0.426***** (5.102)	NA	**0.222***** (2.678)	**0.014** (0.164)
social services	**low**	**-0.065** (-1.064)	**0.243** (1.305)	**0.250***** (3.175)	**0.418***** (3.913)	**0.001** (0.013)	**0.213**** (2.409)	**0.208***** (2.820)	**-0.001** (-0.013)	NA	**0.117**** (2.418)
	high	**0.080** (0.931)	**0.075** (0.391)	**0.380***** (4.247)	**0.177** (1.486)	**0.282**** (2.183)	**0.243**** (2.516)	**0.460***** (5.973)	**0.139** (1.480)	NA	**-0.112** (-0.547)
government services	**low**	**0.064** (0.639)	**0.546*** (1.700)	**0.238**** (2.200)	**0.889***** (6.137)	**0.339***** (2.738)	**0.205**** (2.229)	**0.078** (0.731)	**0.257***** (3.005)	**0.374***** (4.366)	NA
	high	**0.858** (1.249)	**1.612** (1.714)	**0.299** (0.699)	**0.243** (0.294)	**0.056** (0.082)	**0.542** (0.762)	**0.043** (0.077)	**0.298** (0.347)	**-0.266** (-0.612)	NA

Notes:
[a]See table 2.

Source: Author's calculations. See data appendix for details.

The results for the natural resource exploiting sectors are most notable. While agriculture shows substantially higher inter-sectoral spillovers in countries with low concentration of income, mining performs significantly better both as source as well as absorbing sector in countries with high concentration of income. Another exception to the general tendency for stronger diffusion of technological growth to be associated with low income inequality is FIRE for which the findings suggest that it generates significantly higher spillovers in concentrated economies.

5. Public capital stocks and productivity spillovers

5.1 Human capital

The following two sections will focus on the role of public capital—both human and physical—for productivity spillovers between sectors in the economy. In particular, human capital has been given a lot of attention in models of technical change and measures of human capital have been applied in numerous cross-section and time-series studies of both the augmented Solow approach or endogenous growth models. There are important lessons to be learned from the different approaches, however, only the main arguments can briefly be summarized here.[12] First, the most important result of the study of observed growth is that models based on human or knowledge capital overpredict technical change and therefore growth rates of income per capita. Statistics show that human capital and research intensity in advanced countries have increased dramatically over time, yet per capita income growth rates have roughly remained constant (Jones, 1998). Second, similar to other explanatory variables human capital measures in particular human capital investments have been shown to have problems of robustness when used in cross-country growth regressions (Wolff, 2000). Thus while it has been widely accepted that human capital plays an important role for technical change and long-run development more generally, it is probably now also accepted that the nature of the interrelation with long-term growth performance is complex.

For instance, commonly in the framework of the augmented Solow model the effects are captured by introducing human capital in form of an additional input into the aggregate production function, which assumes constant elasticity of substitution of factor inputs. However, more disaggregated analyses are better suited for the conceptualization of alternative, more realistic channels through which human capital interacts with growth. Especially sector, industry or firm models that attempt to capture ideas of the diffusion of technological growth over space and time lend themselves for the analysis of the flow or mobility of resources between economic activities. Human capital, i.e., skill and knowledge, is, of course, *embodied* in people, and the migration of labor between economic activities was identified by classical development economists like W. Arthur Lewis and Simon Kuznets as one of the most important stylized facts in the development process. However, the mobility of labor was not merely seen as a result of changing factor prices but rather as structural shifts that coincide with fundamental socio-economic transformations like e.g. the declining importance of agricultural activities along with intensive urbanization, or the development of the welfare state.

While some of these earlier transformations are not yet completed in many parts of the world we may already be faced with similar dramatic changes of what has been labeled the "knowledge-based economy." Only time will tell of the extend of the recent changes, but what the early development work has taught us is that the role of mobility or flow of human capital for technological growth diffusion goes beyond mere factor substitution and requires an understanding of co-evolving social and economic institutions.

Human capital or education may thus play a complementary role, and only its co-evolution or the combination with other necessary factors may facilitate successful development.[13] A slightly different but related way of thinking about human capital is the already mentioned and widely accepted idea of social capabilities (simply a broader definition of human capital) which have to be in place for successful development to occur (Abramovitz, 1986). This premise that the state of education facilitates economic performance will be examined by applying human capital indicators to the modified Kaldor-Verdoorn model. It is expected that the state of human capital in the economy is associated positively with learning spillovers between sectors.

The methodology of applying human capital to the idea of spillovers is limited by the availability of suitable data at the sector level for a broad number of countries. In particular, there is no consistent evidence on the flow of human capital between sectors. Further, due to the mentioned robustness problems with indicators of human capital investments in cross-sectional studies this investigation relies on a composite index that measures stocks of human capital in the country.[14] The countries covered in the sample were grouped according to an index of human capital stocks using the country median as the cutoff for countries with low levels vs. countries with high levels of educational attainment.

The main findings can be summarized as follows (see table 7). First, the results confirm the sector taxonomy of productivity spillovers due to learning identified in sections 3.2 and 4.1. The upstream production sectors and here again manufacturing activities show the strongest learning spillovers.

The pattern of unsubstantial spillovers for the downstream resource exploiting sectors also does not change as compared to the earlier results when educational attainment is accounted for. Similarly the estimation results for the upstream services activities particularly FIRE suggest higher spillovers compared to the downstream service sectors.

Second, the findings support the hypothesis of a positive association between the productivity spillover of a given sector and the stock of human capital in the economy. The estimates suggest an overall tendency of the sectoral spillovers to be higher for the group of countries with high educational attainment. The hypothesis of systematic differences between sector pairs of spillover coefficients from the two country groups was tested for statistical significance. Table 8a shows critical values for those cases for which the null hypothesis of equality between coefficients could be rejected.

Sector pairs with significantly bigger β-coefficients for the country group with comparably high educational attainment are highlighted in the table. They clearly outnumber the cases for which the spillover coefficients are significantly bigger in countries with low human capital stocks. Most strikingly, significantly stronger productivity spillovers of the upstream production activities (manufacturing and public utilities) are associated with high educational attainment. But also agriculture, commercial services and upstream FIRE activities show a significant tendency for productivity spillovers to be stronger in countries with high human capital stocks. In sum, these findings suggest an overall positive association between human capital and productivity spillovers at the sector level.

Table 7: Low vs. high educational attainment (β_{ij}-coefficients[a] and t-statistics)

		Absorbing sector									
Source sector	**educational attainment**	**agriculture**	**mining**	**manufacturing**	**public utilities**	**construction**	**commerce**	**transport**	**FIRE**	**social services**	**government services[b]**
agriculture	**low**	NA	**-0.097** (-0.408)	**0.117** (1.019)	**-0.072** (-0.500)	**0.430*** ** (2.598)	**0.063** (0.600)	**-0.104** (-0.946)	**0.185** (1.582)	**-0.025** (-0.231)	--
	high	NA	**0.379** (1.391)	**-0.025** (-0.225)	**0.208** (1.471)	**0.030** (0.255)	**0.105** (0.888)	**-0.081** (-0.801)	**0.056** (0.609)	**-0.004** (-0.043)	**0.047** (0.816)
mining	**low**	**-0.012** (-0.281)	NA	**0.031** (0.657)	**0.104** (1.627)	**0.078** (1.011)	**0.072*** (1.695)	**0.016** (0.319)	**0.148*** ** (2.597)	**-0.008** (-0.156)	--
	high	**0.021** (1.070)	NA	**-0.012** (-0.450)	**-0.004** (-0.115)	**-0.027** (-0.959)	**0.018** (0.638)	**0.028** (1.160)	**-0.032** (-1.477)	**0.022** (0.969)	**0.020** (1.578)
manufacturing	**low**	**0.117** (1.531)	**0.450*** * (2.503)	NA	**0.445*** ** (4.008)	**0.296*** * (2.190)	**0.400*** ** (5.640)	**0.435*** ** (5.960)	**0.353*** ** (3.481)	**0.282*** ** (3.741)	--
	high	**0.084*** (1.770)	**0.126** (0.830)	NA	**0.606*** ** (9.160)	**0.615*** ** (10.042)	**0.656*** ** (12.476)	**0.428*** ** (8.189)	**0.408*** ** (8.021)	**0.261*** ** (5.240)	**0.188*** ** (4.657)
public utilities	**low**	**-0.081** (-1.052)	**0.558*** ** (3.742)	**0.266*** ** (3.462)	NA	**0.146** (1.133)	**0.221*** ** (2.999)	**0.077** (0.942)	**0.276*** ** (3.383)	**0.025** (0.309)	--
	high	**0.123*** ** (2.929)	**0.204** (1.426)	**0.372*** ** (6.316)	NA	**0.472*** ** (8.421)	**0.370*** ** (6.485)	**0.208*** ** (3.904)	**0.213*** ** (4.337)	**0.262*** ** (5.935)	**0.156*** ** (4.856)
construction	**low**	**0.117*** * (2.283)	**0.230*** (1.771)	**0.223*** ** (3.829)	**0.203*** * (2.767)	NA	**0.226*** ** (4.444)	**0.192*** ** (3.506)	**0.289*** ** (4.589)	**0.127*** * (2.333)	--
	high	**0.063*** ** (2.607)	**0.208*** * (1.998)	**0.234*** ** (7.250)	**0.167*** ** (4.078)	NA	**0.284*** ** (7.803)	**0.168*** ** (5.499)	**0.127*** ** (4.250)	**0.112*** ** (4.208)	**0.113*** ** (3.729)
commerce	**low**	**-0.068** (-0.597)	**0.388*** * (2.520)	**0.322*** ** (4.752)	**0.038** (0.381)	**0.278*** * (2.387)	NA	**0.229*** ** (3.257)	**0.133** (1.588)	**0.278*** * (2.469)	--
	high	**0.119*** * (2.421)	**0.293*** * (1.796)	**0.638*** ** (9.786)	**0.528*** ** (6.657)	**0.631*** ** (8.201)	NA	**0.441*** ** (7.360)	**0.373*** ** (6.604)	**0.284*** ** (5.391)	**0.155*** ** (3.006)
transport	**low**	**0.063** (0.692)	**0.864*** ** (4.563)	**0.551*** ** (5.561)	**0.447*** ** (3.352)	**0.338*** * (2.044)	**0.432*** ** (4.707)	NA	**0.410*** ** (3.723)	**0.450*** ** (5.306)	--
	high	**0.027** (0.476)	**0.089** (0.468)	**0.489*** ** (6.173)	**0.535*** ** (5.864)	**0.371*** ** (4.164)	**0.602*** ** (7.210)	NA	**0.332*** * (4.624)	**0.348*** ** (6.005)	**0.098*** (1.736)
FIRE	**low**	**0.163*** ** (2.638)	**0.375*** ** (2.764)	**0.263*** ** (3.915)	**0.294*** ** (3.559)	**0.079** (0.704)	**0.236*** ** (3.977)	**0.222*** ** (3.312)	NA	**0.097** (1.420)	--
	high	**0.104** (1.591)	**-0.172** (-0.886)	**0.558*** ** (6.736)	**0.585*** ** (5.833)	**0.467*** ** (4.512)	**0.593*** ** (6.816)	**0.422*** * (5.518)	NA	**0.204*** ** (2.926)	**0.103*** (1.698)
social services	**low**	**0.049** (0.508)	**0.094** (0.468)	**0.373*** ** (3.362)	**0.082** (0.571)	**0.069** (0.427)	**0.228*** * (2.285)	**0.451*** ** (5.327)	**0.121** (1.083)	NA	--
	high	**-0.026** (-0.459)	**0.232** (1.263)	**0.302*** ** (4.050)	**0.431*** ** (4.576)	**0.269*** ** (3.247)	**0.268*** ** (3.076)	**0.302*** ** (4.342)	**0.025** (0.372)	NA	**0.114*** * (2.353)
government services	**low**	--	--	--	--	--	--	--	--	--	NA
	high	**0.055** (0.557)	**0.573*** (1.915)	**0.214*** * (2.060)	**0.841*** ** (6.147)	**0.330*** ** (2.810)	**0.218*** * (2.415)	**0.070** (0.679)	**0.249*** ** (2.863)	**0.354*** ** (4.281)	NA

Notes:
[a]See table 2.

[b]No government services data available for countries with low educational attainment.

Source: Author's calculations. See data appendix for details.

5.2 Infrastructure investment and capital stock

Similarly to the treatment of human capital as a source for development the problem of public capital, more specifically the accumulation of public investment or stocks of infrastructure has received a lot of attention in the theoretical and empirical literature on long-run growth and technical change. Considerable controversy remains as regards the relative importance of public and private physical capital in the economic growth process. Aschauer (1989) was the first to demonstrate strong positive effects of public capital on economic performance. In contrast, Barro (1991) finds that public capital investment and private capital investment have similar effects on growth based on a cross-section of 98 countries. In another cross-section study Easterly and Rebelo (1993) identify an important role for particular infrastructure capital in the area of transport and communication.[15]

A corollary issue of the question over the relationship between public capital and economic performance has also recently been treated in the literature. This work addresses the question over the importance of the effectiveness, or "efficiency," of public capital to the growth process (Hulten, 1996). In a cross-country study Aschauer (2000) has merged these related aspects and finds evidence that both the amount of public capital accumulated and its efficiency have significant positive effects on output per worker.[16]

Without doubt these are important findings not least for the formulation of economic development policies. However, overwhelmingly, these investigations into the relationship between public capital and growth performance and technical change remain at the aggregate level of the economy. Most importantly, both theoreticians and practitioners understand that fiscal policy may introduce sectoral biases, in particular the disproportionate support of urban economic activities.[17] Thus more directed development policies may benefit from disaggregated analysis into the relationship between public capital and the performance of different sectors in the economy.

Table 8: Public capital (critical values for significant differences between main sectors' spillovers)[a]

(a) comparing country groups with low vs. high educational attainment

Source sector	Absorbing sector									
	agriculture	mining	manufacturing	public utilities	construction	commerce	transport	FIRE	social services	government services[b]
agriculture	NA	**1.31***	--	**1.39***	1.98**	--	--	--	--	--
mining	--	NA	--	1.45*	--	--	--	2.95***	--	--
manufacturing	--	1.38*	NA	**1.30***	**2.15****	**2.89*****	--	--	--	--
public utilities	**2.33****	1.71**	--	NA	**2.32****	**1.60***	**1.34***	--	**2.60*****	--
construction	--	--	--	--	NA	--	--	2.32**	--	--
commerce	**1.52****	--	**3.36*****	**3.84*****	**2.54****	NA	**2.30****	**2.36****	--	--
transport and communication	--	2.89***	--	--	--	**1.37***	NA	--	--	--
FIRE	--	2.30**	**2.77*****	**2.24****	**2.54*****	**3.40*****	**1.97****	NA	--	--
social services	--	--	--	**2.03****	--	--	1.35*	--	NA	--
government services	--	--	--	--	--	--	--	--	--	NA

(b) comparing country groups with low vs. high infrastructure capital

Source sector	Absorbing sector									
	agriculture	mining	manufacturing	public utilities	construction	commerce	transport	FIRE	social services	government services[b]
agriculture	NA	--	2.65***	1.99**	1.41*	1.91**	--	2.84***	--	--
mining	--	NA	--	1.99**	--	--	--	--	--	--
manufacturing	--	--	NA	--	--	**2.28****	--	--	--	--
public utilities	--	--	--	NA	--	--	--	--	**2.16****	--
construction	--	1.68**	1.31*	2.69***	NA	--	1.90**	3.51***	--	--
commerce	--	1.82**	2.49***	2.18**	2.29**	NA	--	--	--	--
transport and communication	--	--	--	--	1.60*	--	NA	--	--	--
FIRE	--	--	**2.25****	**2.38****	--	**2.79*****	**2.57*****	NA	**1.40***	--
social services	--	--	--	--	--	--	--	--	NA	--
government services	--	--	--	--	--	--	--	--	--	NA

Notes:
[a]See table 4.

The tables show values only for sector pairs for which the null hypothesis could be rejected. Highlighted values in (a) or (b) indicate that the β-coefficient is higher for the country group with high educational attainment or high infrastructure capital stock, respectively.

[b]No government services data for (a) countries with low educational attainment, and (b) countries for which infrastructure capital data is available.

Source: Author's calculations.

The same data methodology as in the previous sections is applied here to explore the effect of investment and accumulation of physical public capital on the diffusion of technological growth. The countries in the sample were classified according to indicators of public capital. It is expected that similar to the findings for the aggregate economy public investment and stocks of public capital have a positive effect on inter-sectoral productivity spillovers. And similar to Hulten's (1996) and Aschauer's (2000) analyses, evidence on public investment, physical public capital stocks, and measures of the efficiency of public capital are utilized.[18]

The data for public investment in percent of GDP is taken from the World Bank (Pfeffermann et al., 1997). Measures for the latter two aspects of physical public capital—amount and efficiency—are also from the World Bank (1994). They cover the following infrastructure areas: (i) power, (ii) telecommunications, (iii) paved roads, (iv) water, and (v) railways. Based on these public capital indicators the countries in the sample were classified into two groups.[19] The country group with relatively high public capital in terms of quantity and quality is expected to show higher productivity spillovers between sectors than the group of countries with low public capital.

Table 9 presents the estimation results for the matrix of inter-sectoral spillovers. The taxonomy of productivity spillovers between sectors remains robust when public capital is accounted for. The upstream production activities of manufacturing, public utilities, construction, and transport and communication exhibit again higher spillover coefficients than the downstream activities of the natural resource exploiting sectors. And also the upstream services sectors, in particular FIRE, suggest higher spillover potential than downstream service activities, like for example the social services.

In addition, there is now a sharp distinction between the high spillover sectors associated with high public capital development and the high spillover sectors associated with low public capital development (cf. table 8b). Based on testing for statistical differences between sectors FIRE shows the clearest pattern of significantly higher sectoral β-coefficients for the country group with relatively higher public capital. In contrast, for three sectors, agriculture, construction and commercial services, the estimates suggest that significantly higher productivity spillovers are associated with comparatively less public capital development.

Table 9: Low vs. high infrastructure capital (β_{ij}-coefficients[a] and t-statistics)

		Absorbing sector									
Source sector	**infra-structure capital stock**	**agriculture**	**mining**	**manufacturing**	**public utilities**	**construction**	**commerce**	**transport**	**FIRE**	**social services**	**government services[b]**
agriculture	**low**	NA	**0.292** (0.832)	**0.421***** (2.627)	**0.271** (1.310)	**0.579**** (2.503)	**0.372***** (2.616)	**0.042** (0.267)	**0.484***** (2.925)	**-0.026** (-0.159)	--
	high	NA	**-0.132** (-0.411)	**-0.189** (-1.142)	**-0.307** (-1.495)	**0.129** (0.588)	**-0.068** (-0.374)	**-0.191** (-1.228)	**-0.184** (-1.104)	**-0.197** (-1.361)	--
mining	**low**	**0.031** (0.728)	NA	**0.116*** (1.680)	**0.172*** (1.977)	**0.241**** (2.384)	**0.140**** (2.464)	**0.078** (1.052)	**0.180** (1.654)	**0.034** (0.523)	--
	high	**0.048** (0.911)	NA	**0.027** (0.455)	**-0.072** (-0.084)	**0.070** (0.067)	**0.095** (1.409)	**0.010** (0.150)	**0.053** (0.795)	**-0.025** (-0.440)	--
manufacturing	**low**	**0.145**** (2.118)	**0.561***** (2.687)	NA	**0.422***** (2.944)	**0.369**** (2.233)	**0.361***** (4.505)	**0.448***** (6.110)	**0.396***** (2.816)	**0.200**** (2.093)	--
	high	**0.175** (1.527)	**0.210** (0.871)	NA	**0.506***** (3.484)	**0.311**** (1.859)	**0.669***** (6.132)	**0.534***** (4.432)	**0.490***** (3.669)	**0.365***** (3.536)	--
public utilities	**low**	**-0.027** (-0.364)	**0.551***** (2.812)	**0.271**** (2.543)	NA	**0.325**** (2.045)	**0.248***** (2.890)	**0.104** (1.084)	**0.326***** (2.924)	**-0.023** (-0.232)	--
	high	**0.033** (0.324)	**0.484**** (2.467)	**0.311***** (3.382)	NA	**0.249*** (1.712)	**0.289**** (2.535)	**0.186** (1.598)	**0.237**** (2.080)	**0.280***** (2.814)	--
construction	**low**	**0.168***** (3.450)	**0.489***** (3.023)	**0.286***** (3.686)	**0.313***** (3.560)	NA	**0.248***** (4.170)	**0.257***** (4.141)	**0.441***** (5.543)	**0.116***** (1.632)	--
	high	**0.098**** (2.604)	**0.140** (1.079)	**0.169***** (3.974)	**0.027** (0.442)	NA	**0.192***** (3.811)	**0.107**** (2.196)	**0.104*** (1.957)	**0.108***** (2.651)	--
commerce	**low**	**0.175** (1.502)	**0.932***** (2.822)	**0.716***** (4.747)	**0.537***** (2.629)	**0.733***** (3.052)	NA	**0.411***** (2.839)	**0.312** (1.533)	**0.340**** (2.288)	--
	high	**0.148** (1.377)	**0.271*** (1.805)	**0.311***** (4.964)	**0.043** (0.430)	**0.133** (1.271)	NA	**0.239***** (3.321)	**0.203**** (2.416)	**0.320***** (2.917)	--
transport	**low**	**0.210**** (2.255)	**0.767**** (2.272)	**0.658***** (4.517)	**0.578***** (2.813)	**0.626***** (2.746)	**0.430***** (3.468)	NA	**0.465**** (2.342)	**0.437***** (3.561)	--
	high	**0.068** (0.596)	**0.631***** (3.038)	**0.559***** (5.492)	**0.408***** (2.712)	**0.172** (1.020)	**0.535***** (4.463)	NA	**0.512**** (4.459)	**0.439***** (4.553)	--
FIRE	**low**	**0.186***** (3.535)	**0.273**** (1.960)	**0.238***** (3.185)	**0.209**** (2.006)	**0.138** (1.061)	**0.208***** (3.096)	**0.196***** (2.633)	NA	**0.033** (0.394)	--
	high	**0.153** (1.111)	**0.546**** (2.274)	**0.541***** (4.838)	**0.621***** (4.510)	**0.180** (0.949)	**0.562***** (5.219)	**0.537**** (4.880)	NA	**0.228**** (2.062)	--
social services	**low**	**0.048** (0.519)	**0.306** (1.053)	**0.267*** (1.691)	**0.144** (0.696)	**0.055** (0.246)	**0.286**** (2.200)	**0.382***** (3.298)	**-0.043** (-0.248)	NA	--
	high	**0.033** (0.254)	**-0.070** (-0.296)	**0.434***** (3.750)	**0.282*** (1.790)	**0.269*** (1.750)	**0.336**** (2.499)	**0.480***** (4.525)	**0.106*** (0.811)	NA	--
government services	**low**	--	--	--	--	--	--	--	--	--	NA
	high	--	--	--	--	--	--	--	--	--	NA

Notes:
[a]See table 2.

[b]No government services data for countries for which infrastructure capital stock data is available.

Source: Author's calculations. See data appendix for details.

One plausible way of interpreting this latter finding in particular for the agricultural sector is that the infrastructure measures utilized here, like e.g. power and water supply, roads and phone lines, essentially capture the fiscal policy bias already mentioned above. It is fair to say that in less developed countries a bias towards urban economic activities appears to dominate. This may explain why agriculture shows significantly higher productivity spillovers in countries where infrastructure capital stocks are relatively smaller, which in turn may represent less skewed fiscal policies. Of course, this is not to say that the agricultural sector does not benefit from public capital development.

6. Conclusions

While it is widely accepted that the diffusion of technological growth across time and space is an important source of economic performance, this research area continues to be under-explored. This paper investigated the existence and character of technological growth diffusion in form of sectoral learning spillovers. Learning represents an essential component in the process of diffusion of technological change. Many scholars have stressed that the fundamental nature of technological growth is the result of incremental changes, often individually small but cumulatively very large. Two related forms of learning—learning by doing and learning by using—have been identified in the literature, and the proposed extension of the Kaldor-Verdoorn model utilizes the ideas of the latter.

The production process of a given economic sector is simultaneously fed technical modifications originating in downstream and upstream activities. The steady flow of small improvements will show up as efficiency increases in the production of the sector that absorbs them. In terms of the extended Kaldor-Verdoorn model, it can be expected that the rate of growth of output or demand in one sector of the economy positively affects another sector's productivity growth. In essence, this model captures the impact of technological growth that results from a changing composition of demand. It can further be expected that any one economic activity represents a source as well as an absorber of the consequences of learning by using, which taken together will yield a matrix of inter-sectoral learning.

Based on panel data for 47 countries during the postwar period the identified statistical regularities support the hypothesis of the diffusion of technological growth as a result of a changing structure of demand. The evidence further suggests robust differences across sectors in the magnitude of productivity spillovers. In particular, the patterns reveal a distinctive role for upstream production activities, especially manufacturing, as a source of technological growth diffusion.

No significant differences in these patterns were found between low and high-income countries. Thus, the estimated spillover potential of sectors in low-income economies does not suggest a tendency for catching-up to occur. However, higher potential of technological growth diffusion at the sector level was found to be associated with (i) low income concentration, and (ii) high public (human and physical) capital stocks.

Data Appendix

A. *Data sources for low-income countries*

Value added at constant prices

The country data for value added used in the paper is taken from the annual series "Gross Domestic Product by Kind of Activity (at constant prices)" of the *U.N. National Accounts* which was provided by the United Nations Statistics Division, New York. The data is in national currency and is arranged according to the International Standard Industry Classification (ISIC) code at the one-digit level, i.e. it covers nine main "activities" or sectors. The sum total of these nine sectors' real value added (excluding "producers of government services") gives the gross domestic product (GDP) at factor prices. For most countries, the series covers the period from the mid-1970s to 1993.

For Brazil, sectoral output data is taken from *Estatísticas Historicas do Brasil: Series Economicas, demograficas e sociais de 1550 a 1988*, 2nd ed., Instituto Brasileiro de Geografia e Estatística (IBGE) 1990.

Employment

The country data for sectoral employment was provided by the International Labour Office, Geneva, also published in *Yearbook of Labour Statistics*. It is an annual series that covers (at maximum) the period from 1975 to 1993. The data is disaggregated at the one-digit level of the *ISIC* codes, the very same level of disaggregation as the country series from the *U.N. National Accounts*.

Due to a smaller country coverage of the employment series additionally national data sources were used for Peru (Compendio Estadístico), and Mexico (Sistema de Cuentas Nacionales de México).

Labor productivity

Sectoral labor productivity for the countries was computed by combining the two data series of sectoral value added and employment described above. In other words, sectoral productivity is defined as sectoral value added (here in national currency) divided by the number of persons employed in the sector.

Table A.1: Low-income country coverage

Sub-Saharan Africa	Botswana, Ghana, Kenya, Malawi, Sierra Leone, South Africa, Zambia, Zimbabwe
Latin America and the Caribbean	Bolivia, Brazil, Chile, Colombia, Costa Rica, Guatemala, Mexico, Panama, Peru, Puerto Rico, Venezuela
South and East Asia	India, Indonesia, Korea, Malaysia, Myanmar, Philippines, Singapore, Sri Lanka, Thailand
Other	Turkey, Jordan

B. *Data sources for high-income countries*

Value added at constant prices and employment

The main source for both the data series of real value added at the sector level and sectoral employment is the *International Sectoral Data Base* (ISDB) published by the OECD in 1998. Additional data sources were used for Austria, Canada, Germany, Japan, Portugal, and Spain.

Table B.1: High-income country data sources and coverage

Country	Sectoral data series	
	value added at constant prices	employment
AUSTRALIA	OECD (1998)	OECD (1998)
AUSTRIA	ÖSTAT (1995)	ÖSTAT (1995)
BELGIUM	OECD (1998)	OECD (1998)
CANADA	Leacy and Urquhart (1983); OECD (1998)	Leacy and Urquhart (1983); OECD (1998)
DENMARK	van Ark (1996); OECD (1998)	van Ark (1996); OECD (1998)
FINLAND	OECD (1998)	OECD (1998)
FRANCE	OECD (1998)	OECD (1998)
GERMANY	van Ark (1996)	van Ark (1996)
ITALY	OECD (1998)	OECD (1998)
JAPAN	Pilat (1994); OECD (1998)	Pilat (1994); OECD (1998)
NETHERLANDS	van Ark (1996); OECD (1998)	van Ark (1996); OECD (1998)
NORWAY	OECD (1998)	OECD (1998)
PORTUGAL	Pinheiro (1997)	Pinheiro (1997)
SPAIN	van Ark (1996)	van Ark (1996)
SWEDEN	OECD (1998)	OECD (1998)
UNITED KINGDOM	OECD (1998)	OECD (1998)
UNITED STATES	OECD (1998)	OECD (1998)

Labor productivity

Same definition as above.

C. *Data sources for income concentration and public (physical and human) capital stocks*

Income distribution

Gini coefficients and top to bottom income share ratios are from Deininger and Squire (1996). See source article for details on methodology and country and time period covered. Additional data is from *Human Development Report* (UNDP). The Gini for Myanmar is from 1958 Burma.

Here "high" income inequality is defined by a Gini coefficient that is higher than the average Gini coefficient for the world, i.e., equal or greater than 36.12, and denoted by 1 (0 otherwise). For the ratio of top quintile's share of income to bottom quintile's share the cutoff rate between high and low inequality is defined by the sample's average ratio of 7.8.

Public investment and capital stocks

(1) *Public investment*

Public investment data (in percent of GDP) for developing countries in 1975 and 1985 is from Pfeffermann, Kisunko, and Sumlinski (1997). Missing data is filled in from Easterly, Rodriguez and Schmidt-Hebbel (1994).

(2) *Infrastructure stocks*

Measures of infrastructure stocks are from *World Development Report* (World Bank, 1994) covering the following indicators:

(a) power supply in percent of total households in 1984;
(b) power system losses in percent of total output in 1990;
(c) telephone mainlines per 1000 persons in 1990;
(d) faults per 100 mainlines per year;
(e) road density in km per million persons in 1988;
(f) access to safe water in percent of total population in 1990;
(g) losses in percent of total water provision;
(h) rail traffic in km per million US$ GDP in 1990.

(3) *Human capital indicator*

Educational attainment data for 1980-1985 is from *Human Development Report* (UNDP, 1991). The educational attainment index measures human capital stocks for a broad number of countries. It is based on a weighted average of literacy rates and mean years of schooling defined as the average number of years of school attained by the population aged 15 and above.

The individual human capital stock indicators included in the index are similar to the educational attainment measures collected for the human capital database by Barro and Lee (2001). The advantage of UNDP's data, however, is that it provides a ready to use composite index of human capital stocks for consistent cross-country comparison.

REFERENCES

Abramovitz, Moses A, “Catching Up, Forging Ahead, and Falling Behind,” *Journal of Economic History*, June 1986, vol. 46, no. 2, pp. 385-406.

Amsden, Alice H., *The Rise of “The Rest”—Challenges to the West from Late-Industrializing Economies*, Oxford: Oxford University Press, 2001.

Ark, Bart van, “Sectoral Growth Accounting and Structural Change in Post-War Europe,” Chapter 3, pp. 84-164, in *Quantitative Aspects of Post-War European Economic Growth*, Bart van Ark and Nicholas Crafts (eds.), Cambridge: Cambridge University Press, 1996.

Arrow, Kenneth J., “The Economic Implications of Learning by Doing,” *Review of Economic Studies*, June 1962, vol. 29, no. 3, pp. 155-173.

Aschauer, David Alan, “Is Public Expenditure Productive?” *Journal of Monetary Economics*, March 1989, vol. 23, no. 2, pp. 177-200.

Aschauer, David Alan, “Public Capital and Economic Growth: Issues of Quantity, Finance, and Efficiency,” *Economic Development and Cultural Change*, January 2000, vol. 48, no. 2, pp. 391-406.

Barro, Robert J., “Inequality and Growth in a Panel of Countries,” *Journal of Economic Growth*, March 2000, vol. 5, no. 1, pp. 5-32.

Barro, Robert J., “Economic Growth in a Cross Section of Countries,” *Quarterly Journal of Economics*, May 1991, vol. 106, no. 2, pp. 407-443.

Barro, Robert J., and Jong-Wha Lee, “International Data on Educational Attainment: Updates and Implications,” *Oxford Economic Papers*, July 2001, vol. 53, no. 3, pp. 541-563.

David, Paul A., “The Mechanization of Reaping in the Ante-Bellum Midwest,” in *Industrialization in Two Systems: Essays in Honor of Alexander Gerschenkron*, Henry Rosovsky (ed.), New York: Wiley, 1966.

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole, “Is Public R&D a complement or substitute for Private R&D? A Review of the Econometric Evidence,” *Research Policy*, April 2000, vol. 29, no. 4-5, pp. 497-529.

Deininger, Klaus, and Lyn Squire, “A New Data Set Measuring Income Inequality,” *World Bank Economic Review*, 1996, vol. 10, no. 3, pp. 565-591.

Dosi, Giovanni, “Technological Paradigms and Technological Trajectories,” *Research Policy*, 1982, vol. 11, pp. 147-162.

Durlauf, Steven N., and Danny T. Quah, “The New Empirics of Economic Growth,” in *Handbook of Macroeconomics*, Volume 1A, John B. Taylor and Michael Woodford (eds.), Netherlands: Elsevier Science Publishers, 1999, pp. 235-308.

Easterly, William R., and Ross Levine, “It’s Not Factor Accumulation: Stylized Facts and Growth Models,” *World Bank Economic Review*, 2001, vol. 15, no. 2, pp. 177-219.

Easterly, William R., and Sergio Rebelo, “Fiscal Policy and Economic Growth,” *Journal of Monetary Economics*, December 1993, vol. 32, no. 3, pp. 417-458.

Easterly, William R., Carlos A. Rodriguez, and Klaus Schmidt-Hebbel (eds.), *Public Sector Deficits and Macroeconomic Performance*, New York: Oxford University Press, 1994.

Felipe, Jesus, “Total Factor Productivity Growth in East Asia: A Critical Survey,” *Journal of Development Studies*, April 1999, vol. 35, no. 4, pp. 1-41.

Geroski, Paul A, “Models of Technology Diffusion,” *Research Policy*, April 2000, vol. 29, no. 4-5, pp. 603-625.

Hulten, Charles R., “Infrastructure Capital and Economic Growth: How Well You Use It May Be More Important than How Much You Have,” NBER working paper no. 5847, Cambridge, MA, December 1996.

Jones, Charles I., *Introduction to Economic Growth*, New York: W. W. Norton, 1998.

Kaldor, Nicholas, *Causes of the Slow Rate of Economic Growth in the United Kingdom*, Cambridge: Cambridge University Press, 1966.

Kaldor, Nicholas, “Economic Growth and The Verdoorn Law—A Comment on Mr. Rowthorn’s Article,” *Economic Journal*, December 1975, vol. 85, no. 340, pp. 891-896.

Leacy, Frank H. and Malcolm C. Urquhart (eds.), *Historical Statistics of Canada*, Second Edition, Toronto: Macmillan, 1983.

Malerba, Franco, and Luigi Orsenigo, “Technological Regimes and Sectoral Patterns of Innovative Activities,” *Industrial and Corporate Change*, 1997, vol. 6, no. 1, pp. 83-117.

Mansfield, Edwin, *Industrial Research and Technological Innovation*, New York: W.W. Norton.

Nelson, Richard R., “Research on Productivity Growth and Productivity Differences: Dead Ends and New Departures,” *Journal of Economic Literature*, September 1981, vol. 19, no. 3, pp. 1029-1064.

Nelson, Richard R., “The Agenda for Growth Theory: A Different Point of View,” *Cambridge Journal of Economics*, September 1998, vol. 22, no. 3, pp. 497-520.

Nelson, Richard R., and Howard Pack, “The Asian Miracle and Modern Growth Theory,” *Economic Journal*, July 1999, vol. 109, no. 457, pp. 416-436.

Nelson, Richard R., and Bhaven N. Sampat, “Making Sense of Institutions as a Factor Shaping Economic Performance,” *Journal of Economic Behavior and Organization*, January 2001, vol. 44, no. 1, pp. 31-54.

Nelson, Richard R., and Sidney G. Winter, *An Evolutionary Theory of Economic Change*, Cambridge, MA: The Belknap Press of Harvard University Press, 1982.

OECD, *International Sectoral Data Base*, Paris: OECD, 1998.

Österreichisches Statistisches Zentralamt, *Republik Österreich: 1945-1995*, Vienna: ÖSTAT, 1995.

Pavitt, Keith, “Sectoral Patterns of Technical Change,” *Research Policy*, 1984, vol. 13, pp. 343-373.

Perotti, Roberto, “Income Distribution, Politics, and Growth,” *American Economic Review*, May 1992, vol. 82, no. 2, pp. 311-316.

Persson, Torsten, and Guido Tabellini, “Is Inequality Harmful for Growth?” *American Economic Review*, June 1994, vol. 84, no. 3, pp. 600-621.

Pfeffermann, Guy P., Gregory V. Kisunko, and Mariusz A. Sumlinski, "Trends in Private Investment in Developing Countries: Statistics for 1970-97,” Washington, DC: International Finance Corporation, 1997.

Pieper, Ute, "Sectoral Regularities of Productivity Growth in Developing Countries—A Kaldorian Interpretation," *Cambridge Journal of Economics*, 2003, forthcoming.

Pilat, Dirk, *The Economics of Rapid Growth*, England: Edward Elgar Publishing, 1994.

Pinheiro, Maximiano (ed.), *Séries Longas para a Economia Portuguesa, Pós II Guerra Mundial*, vol. I, Series Estatísticas, Lisbon: Banco de Portugal, 1997.

Rosenberg, Nathan, *Inside The Black Box*, Cambridge: Cambridge University Press, 1982.

Rowthorn, Robert E., "A Reply to Lord Kaldor's Comment," *Economic Journal*, December 1975, vol. 85, no. 340, pp. 897-901.

Silverberg, Gerald, and Doris Lehnert, "Long Waves and 'Evolutionary Chaos' in a Simple Schumpeterian Model of Embodied Technical Change," *Structural Change and Economic Dynamics*, 1993, vol. 4., no. 1, pp. 9-37.

Sturm, Jan Egbert, Gerard H. Kuper, and Jacob de Haan, "Modelling Government Investment and Economic Growth on a Macro Level: A Review," in *Market Behavior and Macroeconomic Modelling*, Steven Brakman, Hans van Ees, and Simon K. Kuipers (eds.), London: Macmillan, 1998.

Temple, Jonathan, "The New Growth Evidence," *Journal of Economic Literature*, March 1999, vol. 37, no. 1, pp. 112-156.

United Nations Development Programme, *Human Development Report*, various years, New York: Oxford University Press.

Verspagen, Bart, "A New Empirical Approach to Catching Up or Falling Behind," *Structural Change and Economic Dynamics*, 1991, vol. 2, no. 2, pp. 359-380.

Verdoorn, Petrus Johannes, "Fattori che regolano lo sviluppo della produttivitá del lavoro," *L'industria*, 1949, vol. 1, pp. 3-10. [English translation by Anthony P. Thirlwall in *National Income and Economic Progress: Essays in Honour of Colin Clark*, Duncan Ironmonger et al. (eds.), London: Macmillan, 1988.]

Wolff, Edward N., "Human Capital Investment and Economic Growth: Exploring the Cross-Country Evidence," *Structural Change and Economic Dynamics*, December 2000, vol. 11, no. 4, pp. 433-472.

World Bank, *World Development Report*, New York: Oxford University Press for the World Bank, various years.

World Bank, "Estimation of Internationally Comparable per Capita Income Numbers for Operational Purposes," Washington, DC: The World Bank, 2001.

Young, Allyn A., "Increasing Returns and Economic Progress," *Economic Journal*, December 1928, vol. 38, no. 152, pp. 527-542.

Notes

[1]Cf. Easterly and Levine (2001) for recent empirical investigations of the stylized facts of economic growth.
[2]See for example the classic study by Pavitt (1984) on sectoral patterns of technical change using survey data on main innovations in postwar Britain. Cf. also for recent work Dosi (1982) on technological growth regimes, and Malerba and Orsenigo (1997) for a taxonomy on industry-specific characteristics of innovative activities.
[3]A detailed survey is beyond the scope of this paper. See Geroski (2000) for a recent overview of models of the dynamic processes of technology diffusion.
[4]Nelson (1998) provides a comprehensive survey of the important theoretical issues.
[5]For an overview of this body of literature, see e.g. the symposium in the *Journal of Post-Keynesian Economics* (1983). Pieper (2003) offers a recent re-examination of this relationship applying new nonlinear statistical techniques.
[6]Kaldor (1966) interpreted the close statistical association between the long-run rate of growth of productivity and output of the Verdoorn law as technological growth due to learning. He therefore specified long-run productivity growth as a function of the rate of growth of demand—which he argued was the independent variable—and not changes in employment. Cf. Pieper (2003) for a recent discussion of the debate in the context of observed patterns of sectoral productivity growth in 30 developing economies.
[7]Using the data set for low-income economies in another paper Pieper (2003) computes 5 as well as 10-year growth rates to estimate the Kaldor relationship. Since there were no significant differences between the estimates and in the interest to preserve degrees of freedom, here 5-year averages were also taken because they appear to smooth these data series appropriately.
[8]Since it became clear that the predictions of the so-called *convergence* literature have been supported only by experienced growth of a limited number of countries, subsequent research has pointed out the importance of other factors that may help explain the catching up of some countries over others. These types of factors, like e.g. *social capabilities* (Abramovitz, 1986), that attempt to measure a country's potential to assimilate technological knowledge tend to be introduced to the models as exogenous variables. See Verspagen (1991) for a critique of the convergence framework and an explicit treatment of the possibility of falling behind of countries.
[9]Data for GNP per capita in US dollars for 1975, 1985, and 1990 and the per capita income classification is taken from *World Tables*, The World Bank, various volumes. Income groups are defined for 1975 (1985; 1990) as follows: Low-income countries are those with a GNP per capita of less than \$4500 (\$6850; \$7620); and high-income countries are those with a GNP per capita of \$4500 (\$6850; \$7620) or more.

The World Bank country classification attempts to provide comparative estimates of economic capacity. Per capita income thresholds are calculated by finding a stable relationship between a summary measure of well-being such as poverty incidence and infant mortality on the one hand and economic variables including per capita GNP estimated based on the World Bank's *Atlas methodology* on the other. The thresholds are updated every year to incorporate the effect of international inflation, which is measured by the average inflation of the G-5 countries ("SDR deflator"). Thus, the thresholds remain constant in real terms over time. See World Bank (2001) for a discussion on estimating internationally comparable per capita income numbers.
[10]This group of countries "the rest"—which had elsewhere been called the "convergence club"—comprising of China, India, Indonesia, South Korea, Malaysia, Taiwan, and Thailand in Asia; Argentina, Brazil, Chile, and Mexico in Latin America; and Turkey in Europe—had acquired enough manufacturing experience in the production of silk, cotton textiles, foodstuffs, and light consumer goods to move into mid-technology and later high-technology sectors (Amsden, 2001).
[11]A Gini coefficient is an index based on household survey data measuring income inequality between 0 and 100, where the latter represents highest possible inequality. Data is from the World Bank data set by Klaus Deininger and Lyn Squire. Cf. Deininger and Squire (1996) for details on methodology and country and time period covered. Additional data is from *Human Development Report*, UNDP, various years. See data appendix for details on methodology to classify countries. It turns out that the country classification based on Gini coefficients coincides with other measures of income concentration like for example the ratio of top quintile's share of income to bottom quintile's share.
[12]See Durlauf and Quah (1999) and Temple (1999) for comprehensive critical reviews. Also cf. Jones (1998) on observed growth and associated problems with time-series predictions of endogenous growth models.

[13]For instance Nelson and Sampat (2001) argue that economic performance depends crucially on the co-evolution of different types of “social technologies” with physical technologies.
[14]See data appendix for details. The individual human capital stock indicators included in the index are similar to the educational attainment measures collected for the human capital database by Barro and Lee (2001). The advantage of this data, however, is that it provides a ready to use composite index of human capital stocks for consistent cross-country comparison.
[15]There are numerous empirical studies testing whether public investment or public capital have a stimulating effect on the performance of economies. For a review of the literature see Sturm et al. (1998).
[16]One other issue is the importance of the means of financing government spending for economic growth. For instance, Aschauer (2000) finds that financing physical capital accumulation out of public debt is negatively associated with growth in output per capita. This aspect will not be pursued further.
[17]There are of course examples where fiscal policies (at least in part) target the agricultural sector and thereby rural areas of economies. Note for instance the European Union, which has subsidized European agriculture throughout the postwar period.
[18]Unfortunately, evidence on quantities of physical public capital and/or its efficiency is only available for a limited number of countries. The most comprehensive comparable data was collected by the World Bank (1994). Public investment data for 1975 and 1985 is from Pfeffermann et al. (1997). The public capital data covers only low and medium income countries from 1984 until 1990, which leaves essentially the 30 non-OECD countries of table 1. Cf. the data appendix for more details.
[19]The data appendix provides more detailed information about the individual indicators. The individual indicator’s country coverage was overall good. For the country classification factor analysis was used to reduce the number of variables. According to the commonly used standard for eliminating components with no explanatory power, three of the variables were sequentially removed with factor loadings of < .5 (i.e., public investment, railways, paved roads, respectively). The factor analysis was restricted to one factor score. Note that missing values were replaced by sample means in the factor analysis.