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Working Paper Series

#2007-026

**The productivity effects of internal and external R&D:
Evidence from a dynamic panel data model**

Boris Lokshin, René Belderbos & Martin Carree

The productivity effects of internal and external R&D: Evidence from a dynamic panel data model

Boris Lokshin¹, René Belderbos², Martin Carree³

Abstract

We examine the impact of internal and external R&D on labor productivity in a 6-year panel of Dutch manufacturing firms. We apply a dynamic linear panel data model that allows for decreasing or increasing returns to scale in internal and external R&D and for economies of scope. We find complementarity between internal and external R&D, with a positive impact of external R&D only evident in case of sufficient internal R&D. These findings confirm the role of internal R&D in enhancing absorptive capacity and hence the effective utilization of external knowledge. The scope economies due the combination of internal and external R&D are accentuated by decreasing results to scale at high levels of internal and external R&D. The analysis indicates that on average productivity grows by increasing the share of external R&D in total R&D.

Keywords: R&D, Innovation, Complementarity, Panel data

JEL classification: O32, O33, D24

UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research and training centre on Innovation and Technology,
UNU-MERIT

UNU-MERIT Working Papers intend to disseminate preliminary results of research carried out at the Centre to stimulate discussion on the issues raised.

Acknowledgements: The empirical part of this research uses micro-level data provided by CEREM/Statistics Netherlands, drawing on the MICRONOOM data integration project at Statistics Netherlands supervised by Bert Diederer. The views expressed in this paper are those of the authors and do not necessarily reflect the policies of Statistics Netherlands. We are grateful to Pierre Mohnen, participants of the 2005 EARIE conference in Porto, two anonymous referees, and Christopher Bowdler for comments on earlier drafts.

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1. Introduction

The growing technological diversification of companies and high demands on their portfolio of competencies makes successful integration of new external knowledge into the innovation process increasingly important. Such successful integration fosters innovation performance, while the effective use of external R&D strategies ultimately leads to higher profitability of the firm. Academic research in the fields of management and industrial economics has been focusing on these themes for some time now (Arora et al., 2001; Chiesa et al., 2004). Moreover, some authors have argued that the trend of utilizing external sources of knowledge is accelerating due to technological convergence, declining transaction costs of acquiring external R&D inputs, and shortening product cycle times (Grandstrand et al. 1992b; Narula, 2001). This development is accompanied by a parallel decrease of the presence of internal R&D departments (Chesbrough 2003; Howells et al., 2004) and is especially pronounced in research intensive industries (Bönte, 2003). Firms are therefore increasingly confronted by the issue of management of internal and external innovation strategies and have to decide what technologies should be developed in-house and which can be sourced externally.

It has been argued that to absorb externally acquired knowledge, an effective ‘absorptive capacity’ to understand and effectively utilize this knowledge is essential (Cohen and Levinthal, 1989, Griffith et al., 2004). In-house R&D activities are often required to create sufficient absorptive capacity, which suggests a complementarity between internal R&D and external technology acquisition. Empirically, the effective balance between internal R&D and external sourcing and interaction between these two strategies has however remained relatively unexplored and has been hampered by a lack of adequate data. Cassiman and Veugelers (2006) find that firms combining ‘make’ and ‘buy’ strategies are more innovative, but have to treat ‘make’ and ‘buy’ as discrete practices in their research. Audretsch et al. (1996) suggest that external and internal R&D are alternatives for firms in medium and low tech industries, but not in high tech industries. Fernandez-Bagues (2003) analyses the impact of the number of R&D projects started in-house and under outsourcing agreements in a panel of pharmaceutical firms and finds a negative relationship between ‘make’ and ‘buy’.

The objective of the present paper is to contribute to the empirical literature by examining the joint impact of internal and external R&D expenditures on productivity in a panel of innovating firms in the Netherlands. This is one of the first empirical studies that explore a panel data set to examine these effects at the firm level. Earlier work had to rely on cross sectional data, which hampered separation of complementarity effects from the effect of time-invariant and time-variant heterogeneity (Fernandez-Bagües, 2003). Our study's inferences are based on a dynamic panel data model, which allows us to control for persistence (fixed effects) in productivity levels and differences among firms. We look at the productivity effects of external and internal R&D strategies as opposed to looking at the correlation (adoption) structure, a method that was shown to have measurement problems and inference difficulties (Arora, 1996). Instead of analyzing the effect of discrete practices ('make' versus 'buy') or counts of practices, our analysis is of actual expenditures on internal and external R&D, allowing us to examine scale and scope (dis)economies in R&D.

The results of our dynamic panel data model are robust to different estimation techniques and show that combining internal and external R&D significantly contributes to productivity growth. This finding is consistent with the frequent joint adoption of internal and external R&D strategies and provides evidence of complementarity between the two innovation strategies. A positive impact of external R&D is only present in case of sufficient internal R&D in line with the absorptive capacity argument.

The remainder of the paper is organized as follows. The next section reviews previous research on "make" and "buy" R&D strategies and discusses in greater detail the potential for competing hypotheses on the combination of external and internal R&D. In section three we present the model and discuss our estimation methodology. The following section presents the data. In section five we discuss the results and section 6 concludes.

2. External and internal R&D

Several studies suggest that there is a trend towards increasing reliance on external sources of knowledge in innovation, as Chesbrough's 'open innovation' paradigm suggests (Chesbrough, 2003; UNCTAD,

2005). In an industry-level longitudinal study, Bönnte (2003) cites evidence from the National Science Foundation that for the most industries the share of external R&D gradually increased since the 1980s into the mid 1990s. UNCTAD (2005) notes that the contract R&D sector is growing rapidly in the United States, in particular in the pharmaceutical industry. To an extent this is seen as part of the more general trend towards outsourcing non-core business operations (e.g. IT services, wage administration) to outside service providers. R&D outsourcing, however, is not limited to standard research or development tasks but includes strategic research projects where partner firms and partner institutions possess complementary technological capabilities not available in-house (e.g. Pisano, 1990; Bönnte, 2003; Chesbrough, 2003). The combination of external technology sourcing and internal R&D can allow firms to benefit from research complementarities through involvement in multiple technological trajectories, research directions that cannot be developed simultaneously (at sufficient speed) in-house, and external development skills exploiting in-house research activities more effectively. Access to complementary research and development activities performed externally, hence, can improve the performance effects of internal R&D efforts (Cassiman and Veugelers, 2006). The rise of external technology sourcing has been attributed to a growing complexity, speed, and uncertainty of technological developments, combined with greater codification of R&D processes that has facilitated R&D contracting and segmentation of R&D activities (e.g. Grandstrand et al. 1992; Narula, 2001).

Although there is a clear suggestion that internal R&D can be successfully complemented by external R&D and knowledge sourcing, the findings of the empirical literature have painted a mixed picture.⁴ Audretsch et al. (1996) analyze a cross-section of Dutch manufacturing firms reporting internal and external R&D activity and find that in low and medium technology industries external R&D is a substitute for internal R&D, while the reverse was true in high-technology industries. The authors left open the question why this may be the case. Veugelers and Cassiman (1999) in a cross-section of Belgian

⁴ The theoretical literature on this subject is scarce. In one of the few contributions, Gans and Stern (2000) show that the relationship between in-house R&D and external technology sourcing is theoretically ambiguous. In their model of technological competition and licensing, incumbent firms consider entrants' R&D as a strategic substitute for own in-house R&D when the license fee is not very high.

firms find that these are likely to restrict themselves to either a “make” or a “buy” strategy, possibly reflecting scarcity of the internal capabilities to manage both. On the other hand, larger more resourceful firms have a propensity to combine the strategies. Later research in Cassiman and Veugelers (2006) suggests that firms combining make and buy strategies show superior innovative performance. Piga and Vivarelli (2004) model the decision to outsource R&D jointly with the decision on internal R&D. They find evidence that firms that have larger internal R&D expenditures and pursue broader R&D objectives related to both process and product innovation have a greater propensity to engage in external R&D. Blonigen and Taylor (2000), in contrast, find an inverse relationship between R&D intensity and acquisition activity in high-tech industries, suggesting that firms opt for either a 'make' or a 'buy' strategy.

A number of papers have examined the performance effects of internal R&D and external technology sourcing more specifically. Basant and Fikkert (1996) use a panel of Indian firms to estimate the impact of own R&D and technology purchases on their productivity. They find a robust relation that holds across different specifications suggesting that own R&D and technology purchase expenditures are substitutes, with licensing lowering the marginal productivity of internal R&D.⁵ Bönnte (2003) analyzes the productivity impact of internal and external R&D using an industry-level panel data set and finds a positive relationship between the share of the external R&D and productivity. Beneito (2006) examines the impact of internal and external R&D on firms’ patent output in Spanish firms. Her results suggest that contracted R&D improves patent application performance only if it is combined with internal R&D. Griffith and co-authors (2004, 2003) make a recent contribution to the discussion about two functions performed by R&D. The first role is being a direct stimulus for the productivity growth, while the second role is to increase the absorptive capacity facilitating technology transfers from other countries. By examining the productivity growth at the industry level across a panel of OECD countries, the authors find that R&D expenditure by the business sector increases such technology transfer and allows countries that

⁵ In contrast, Deolalikar and Evenson (1989), Katrak (1985), and Mohnen and Lepine (1991) find a complementary relation between licensing purchases and internal R&D. Basant (1993) discusses in more detail methodological problems related to these previous studies.

are behind the technological frontier to catch up with technology leaders. They find this catch up to be conditional on a minimum absorptive capacity represented by business R&D expenditures.⁶

Summarizing, the previous literature suggests that absorptive capacity play an important role in ensuring that firms can benefit from externally acquired technological knowledge. In balance, however, the literature is not conclusive about the complementarity between internal and external technology sourcing. We explore these two issues by examining the impacts of internal and external R&D on productivity in a dynamic panel data model.

3. Modeling Framework and Econometric Specification

We derive a modeling framework that allows estimating labor productivity as a function of internal and external R&D from an augmented Cobb-Douglas production function for firm i at time t :

$$Y_{it} = \alpha_i L_{it}^\beta C_{it}^\delta K_{it}^\gamma e^{\sigma_{it}} \quad (1)$$

where Y is output, L is labor input, C is the physical capital stock and K is the knowledge stock. The parameters β , δ , and γ are elasticities with respect to labor, physical capital, and the knowledge stock.⁷ The parameter α is a firm-specific efficiency parameter. Dividing both sides by labor, taking logarithms and differencing the resulting equation in two consecutive periods, we obtain the equation in the growth form:

$$\Delta q_{it} = (\beta - 1)\Delta l_{it} + \delta\Delta c_{it} + \gamma\Delta k_{it} + \Delta \sigma_{it} \quad (2)$$

⁶ Other related studies have examined the effects of R&D within and outside an industry on firm performance within the industry. Geroski (1991) finds that the effect on productivity of the outside-industry innovations is 3.7 times larger compared to the effect of ‘produced’ innovations (p. 1441).

⁷ The multiplicative constants α_i may represent firm-specific capabilities. They drop out when taking first differences in (2).

where $q_{it} = \log(Y_{it}) - \log(L_{it})$ denotes labor productivity, with lower case letters denoting variables in logarithms. We assume that the change in firm-specific efficiency levels is a function of past productivity, in order to allow for a gradual convergence in efficiency levels between firms.⁸

$$\Delta c_{it} = \theta q_{it-1} + \varepsilon_{it} \quad (3)$$

Firms that are behind the productivity frontier are more likely to be able to record strong productivity growth through technology spillovers from frontier firms. We expect θ to fall within the interval $[-1,0]$. If θ is zero there is no gradual convergence between leading firms and lagging firms; if θ is -1 complete convergence materializes in one period. To allow unobserved firm-level heterogeneity in efficiency growth and an impact of common macro-economic efficiency shocks, the error term ε_{it} in equation (3) includes firm specific fixed effects μ_i and year-specific intercept λ_t in addition to serially uncorrelated measurement errors v_{it} :

$$\varepsilon_{it} = \lambda_t + \mu_i + v_{it} \quad \text{for } i = 1, \dots, N; t = 1, \dots, T \quad (4)$$

We can transform the knowledge stock portion of the specification (cf. Griffith et al., 2004, p.7; Jones, 2002, p. 233) as follows:

$$\gamma \Delta k_{it} \approx \frac{\partial Y}{\partial K} \frac{K_{i,t-1}}{Y_{i,t-1}} \frac{\Delta K_{it}}{K_{i,t-1}} \approx \varphi \frac{\Delta K_{it}}{Y_{i,t-1}} \quad \text{with } \varphi = \frac{\partial Y}{\partial K} \quad (5)$$

The change in the knowledge capital stock is assumed to be a function of investments in both internal and external R&D:

$$\Delta K_{it} / Y_{i,t-1} = f(R_{i,t-1}^{int} / Y_{i,t-1}, R_{i,t-1}^{ext} / Y_{i,t-1}) = f(r_{i,t-1}^{int}, r_{i,t-1}^{ext}) \quad (6)$$

We approximate the unknown function (6) with a second-order polynomial in R&D investment.⁹

If the depreciation rate of the knowledge stock is small¹⁰ we can write:

⁸ Klette (1996), for instance, shows that the empirically observed persistent productivity differences between firms require a model specification that allows for gradual convergence.

$$\gamma \Delta k_{it} = \varphi [\eta_1 r_{it-1}^{int} + \eta_2 r_{it-1}^{ext} + \eta_3 (r_{it-1}^{int})^2 + \eta_4 (r_{it-1}^{ext})^2 + \eta_5 r_{it-1}^{int} r_{it-1}^{ext}] \quad (7)$$

The equation includes linear terms, quadratic terms, and the interaction term between internal and external R&D. Although in previous research the quadratic terms have often been suppressed (e.g. Basant and Fikkert, 1996), exclusion of the quadratic terms is certainly not trivial.¹¹ Earlier empirical studies have provided evidence of the existence of decreasing returns to R&D (e.g. Acs and Isberg, 1991). Cohen and Klepper (1996) argue that larger R&D budgets lead larger firms to also pursue marginal R&D projects with lower innovation impact. This is profitable because larger firms can apply the results of R&D projects (or: spread the costs of R&D) over a larger output (Cohen and Klepper, 1996, p. 933). In addition, Henderson and Cockburn (1996) in a pioneering study of pharmaceutical research productivity, have provided strong evidence that there are economies of scope in pursuing various R&D projects simultaneously. Hence, there are priori strong reasons to allow for (dis)economies of scale at the same time as testing for (dis)economies of scope (substitutability or complementarity). If the process of augmentation of the knowledge capital stock is characterized by declining returns to scale and if high R&D intensive firms engage in both internal and external R&D, the interaction term between internal and external R&D may be confounded as negative as it picks up the declining marginal impact of R&D. Precisely in the presence of declining returns to internal and external R&D one may expect firms to avoid this by combining R&D strategies. A full specification with quadratic terms is required to explore this. In the empirical analysis, we will estimate the productivity effects of internal and external R&D using (7). In

⁹ Flexible functional forms previously used in the literature can be viewed as linear-in-parameters expansions which approximate an arbitrary function. See Fuss et al. (1978) for known functional forms of such approximations. Adopting a Generalized Leontief Linear functional form (e.g. as in Basant and Fikkert, 1996) gives similar results.

¹⁰ Higher depreciation rates lead to an upward bias of the estimate on the rate of return (Mairesse and Sassenou, 1991). We could expand the approximation of changes in the knowledge stock by including more lags of R&D. However, findings in previous studies, e.g. Pakes and Schankerman (1984), Hall et al. (1986) and Klette and Johanson (1998), suggest that the most significant effect of R&D on productivity occurs with a one-year lag.

¹¹ The rationale for omitting quadratic terms has usually been the difficulty in estimating both the linear and quadratic terms simultaneously given the collinearity between them. Estimation of our model also suffers from this problem, but the availability of panel data reduces this impact.

order to show the importance of using a more general specification, we will also report the results of models with quadratic terms suppressed.

Sufficiently long enough series of capital investments are not available to us in order to construct the capital stock variable with the perpetual inventory method. Instead we approximate the log-growth in the capital stock Δc_{it} with the log-growth in fixed capital investment. In steady state the proportional change in the capital stock can be approximated by the proportional change in fixed capital investments (Jones, 2002).

Combining equations (2), (3), and (7), writing $\Delta q_{it} = q_{it} - q_{it-1}$ and bringing the lagged productivity term to the right hand side, we arrive at the dynamic panel equation:

$$q_{it} = (1 + \theta)q_{it-1} + (\beta - 1)\Delta I_{it} + \epsilon \Delta i_{it} + \varphi[\eta_1 r_{it-1}^{int} + \eta_2 r_{it-1}^{ext} + \eta_3 (r_{it-1}^{int})^2 + \eta_4 (r_{it-1}^{ext})^2 + \eta_5 r_{it-1}^{int} r_{it-1}^{ext}] + \lambda_t + \mu_i + v_{it} \quad (8)$$

The model allows for firm fixed effects and the persistence of performance differences between firms, both emphasized to be important in the empirical productivity literature (Klette, 1996; Blundell and Bond, 2000). The optimal share of external R&D in total R&D given a certain level of internal R&D can be derived by taking the first derivative of q_{it} with respect to $r_{i,t-1}^{ext}$:

$$\partial q_{it} / \partial r_{i,t-1}^{ext} = (\eta_2 + \eta_5 r_{i,t-1}^{int}) / (-2\eta_4) = 0 \quad (9)$$

This implies an optimal ratio of external R&D over total R&D of:

$$r_{i,t-1}^{ext} / (r_{i,t-1}^{int} + r_{i,t-1}^{ext}) = (\eta_2 + \eta_5 r_{i,t-1}^{int}) / [\eta_2 + (\eta_5 - 2\eta_4) r_{i,t-1}^{int}] \quad (10)$$

We carry out the estimation of equation (8) with several panel data estimation techniques that provide consistent estimators, of which several are available when the number of firms is large and the number of years is small. We utilize difference GMM as well as system GMM. System GMM has been found to be more efficient, compared to difference GMM (Blundell and Bond, 1998). System GMM has also been shown to perform well in the presence of heteroskedasticity in a production function setting with a small time-series dimension. Instruments that have been chosen are reported in the footnote to Table 3. Although recent developments in GMM estimation make it a standard choice for estimation of a dynamic panel data model, it requires a non-trivial decision on the number of instruments. A potential drawback is that its performance may be unsatisfactory due to weak instruments (Blundell and Bond, 2000). Hence, alternatively, we use recently proposed fixed-effects and random-effects maximum likelihood estimators (MLE) for dynamic panel data models (Hsiao et al., 2002) based on the transformed likelihood function. The advantage of GMM over MLE estimators is that the former allows for weakly endogenous explanatory variables, while the latter assumes that the explanatory variables are weakly exogenous.

4. Data

The empirical analysis makes use of annual R&D surveys in the Netherlands in combination with the Netherlands census of manufacturers, both provided by Statistics Netherlands. The R&D surveys contain information on type and amount of R&D expenditures, and the census data contain information on value added, labor, and fixed capital investments. These merged establishment level databases provided us with a balanced panel of 304 manufacturing firms covering the years 1996-2001. The firms are distributed over industries as follows: Food (34), Textile (9), Paper (15), Printing (5), Petroleum and chemicals (41), Rubber and plastic (19), Metallurgy (5), Metal products (37), Machines & equipment (62), Electronics (28), Cars and Transport (22), and Miscellaneous industry (27).

The dependent variable, labor productivity, is net value added per employee at constant prices. Internal R&D is defined as a firm's expenditure on intramural R&D while external R&D is the

expenditure on contracted R&D. Investment growth is the percentage growth in gross fixed capital investments between $t-1$ and t , and employment growth is the percentage growth in employment.

Table 1 provides descriptive statistics on the variables used in estimation and Table 2 reports propensities (five year means) to engage in external and internal R&D in five different R&D intensity classes. An inverse relationship emerges between R&D intensity and purely in-house R&D. Almost half of the firms in the lowest R&D intensity class report only internal R&D, but in the upper R&D intensity classes (6% and more) this number drops to about a third of the firms. On the other hand, the difference in the share of external in total R&D between the lowest and top intensity classes is not very large.

5. Empirical results

The results of the dynamic panel estimation of equation (8) are reported in Table 3. The four consistent estimators agree on the signs and magnitudes of most of the coefficients, while the system GMM estimator generates a higher F-value than difference GMM.¹² The Hansen test of over-identifying restrictions does not reject the validity of the instruments for the GMM models, with the exception of the linear system GMM model in column (2).¹³ Arellano-Bond AR tests also indicate that there are no problems relating to serial correlation of the error terms. The Hausman test, however rejects the random effects MLE in favor of fixed effects.

Columns (1)-(4) of Table 3 present the estimates from a specification restricting $\gamma_3 = \gamma_4 = 0$, hence excluding quadratic terms. Internal R&D is significant in all models, while external R&D is (marginally) significant in the system GMM model only. The estimated rate of return on the internal R&D (ρ_1) is in the range of 0.14 - 0.30 depending on the estimator. This rate of return is in line with other studies that use a similar production function framework (Mairesse and Sassenou, 1991, Fors, 1998,

¹² GMM results are from the two-step variant of the estimator, which is more efficient than the one-step. The two-step estimates of the standard errors tend to be downward biased (Arellano and Bond 1991; Blundell and Bond 1998). The standard errors are corrected via a finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005). Use of lagged right hand side values as instruments in the difference GMM estimation restricts the panel to 4 years and reduces the number of observations by 304.

¹³ The rejection is at a significance level of 0.08. Omitting industry dummies from the instrument set does not change this result.

Basant and Fikkert, 1996). The rate of return on external R&D (φ_2) in the system GMM model is higher, at 0.82. The interaction term between internal and external R&D is insignificant in all models. These results do not support the absorptive capacity hypothesis but equally do not suggest (cf. Basant and Fikkert, 1996; Blonigen and Taylor, 2000; Fernandez-Bagues, 2004) that there are diseconomies of scope in investing in internal and external R&D simultaneously.

The most efficient (system GMM and MLE fixed effects) estimates for the lagged dependent variable, reflecting movements in and out of equilibrium, indicates a convergence parameter θ of -0.18 to -0.27, implying that about a fifth to a fourth of the productivity lead is neutralized by the next period.¹⁴ The growth of employment and investment variables are positive and significant, the coefficient on labor growth is about -0.3 - -0.4, implying a positive effect of growth on productivity of about 0.6 - 0.7, in line with other studies using similar production function framework (e.g. Fors, 1998).

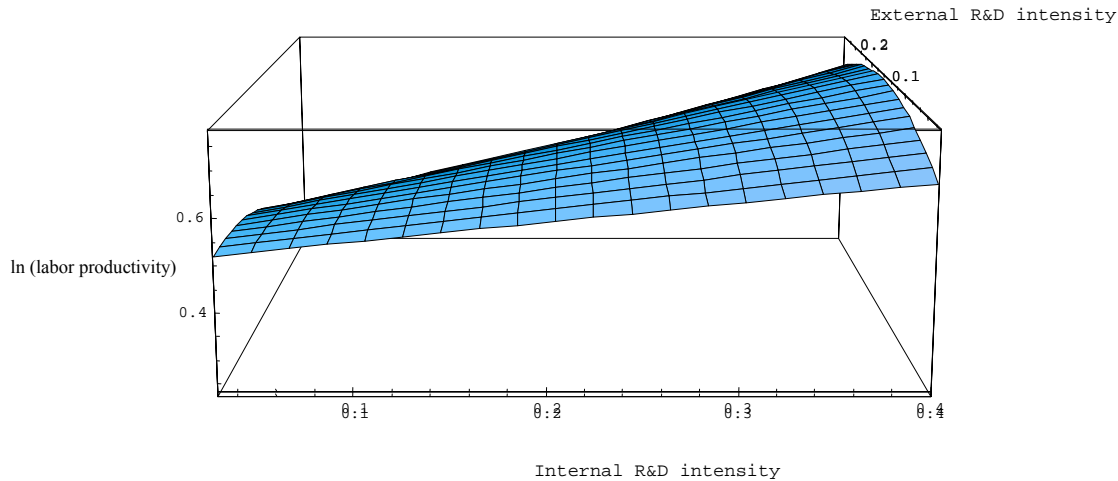
Columns (5) - (8) in Table 3 report the estimates of equation (8) with quadratic terms included, allowing for diseconomies of scale in internal and external R&D. The different estimation methods produce fairly close estimates. Overall the results clearly suggest that there are diseconomies of scale in both internal and external R&D with the squares term of both internal and R&D negative and significant. This is in line with Cohen and Klepper's (1996) R&D cost-spreading argument suggesting that R&D productivity declines with firm size. Furthermore, while the estimated coefficients for the linear term of internal R&D are large and significantly positive, the coefficients of the linear term of external R&D are insignificant in all models. On the other hand, allowing for diseconomies of scale leads to substantially higher and significantly positive estimates for the coefficient of the interaction term between internal and external R&D. The exception in these results is the MLE fixed effects model, which produces smaller and insignificant coefficients for the square term of external R&D and the interaction term between internal and external R&D. Overall, the results provide evidence for the existence of economies of scope in combining both types of R&D. This supports the notion of the importance of absorptive capacity (e.g.

¹⁴ Other research (e.g. Blundell and Bond, 2000; Klette, 1996) using GMM techniques find similar values for the lagged productivity term in production function equations.

Griffith et al. 2004) and suggests that a prerequisite for benefiting from external R&D is that the firm undertakes in-house R&D.

To illustrate the impact of internal and external R&D on labor productivity, Figure 1 plots value added per employee as a function of internal and external R&D intensity based on the estimated coefficients in the system GMM equation. The figure plots labor productivity for a broad range of internal R&D (0-0,4) and external R&D (0-0,2), but it should be noted that the larger majority of firms (80 percent) has R&D intensities in the 0,1-0,1 range. The figure illustrates that an allocation that sets one type of R&D to zero and maximizes the other is not optimal. At low levels of internal R&D intensity (internal R&D expenditures over value added), an increase in external R&D intensity (external R&D over value added) has a relatively small impact on productivity. Productivity levels increase initially steeper along the ‘internal’ R&D axis, followed by a yet steeper increase if R&D is allocated in the ‘external’ direction. Hence, conditional on a sufficient level of internal R&D firm can achieve higher productivity gains by switching from a purely internal R&D strategy to a combination with external R&D. If external R&D is increased further, diseconomies of scale start to reduce its marginal impact on productivity. Higher values of internal R&D intensity allow firms to benefit most from increases in external R&D. Equation (10) can be used to estimate the optimal share of external R&D in total R&D. If we take internal R&D at the sample average of 0.085 and using system GMM estimates, we find an optimal share of external R&D of 37 percent, which is considerably larger than the average share (see Table 2). This suggests that productivity gains can be reaped by increasing the share of external R&D.

Figure 1. Labor productivity as a function of internal and external R&D intensity (estimates of model 6 in Table 3)



6. Conclusions

This paper has produced micro-level econometric evidence that there are productivity gains for firms combining internal and external R&D strategies. Using a dynamic panel data model derived from an augmented production function framework, our analysis of labor productivity in a sample of 304 innovating firms in the Netherlands during 1996-2001 revealed complementarity between internal and external R&D in combination with decreasing returns to scale for both internal and external R&D (Cohen and Klepper, 1996). A positive impact of external R&D was only found conditional on a sufficient level of internal R&D expenditures. These findings support the notion of a dual role played by internal R&D emphasized in recent research (e.g. Griffith et al. 2004; Cohen and Levinthal, 1989). The first role of in-

house research and development activity is in stimulating innovation and productivity. The second role, no less important, is its role to enhance absorptive capacity of the firm needed to derive benefits from the externally acquired R&D. The results also show that the average share of external R&D is considerably below the optimal share of external R&D in relation to productivity. This suggests that there are productivity gains to be reaped by increasing the share of external versus internal R&D.

The findings were robust across a number of dynamic panel data estimation techniques. In contrast, a linear variant of the dynamic model that does not allow for decreasing returns to scale in R&D did not produce clear evidence of economies of scope in combining internal and external R&D. These results suggest that empirical studies examining complementarities between continuously measured practices should adopt more general non-linear specifications to allow for correct inferences.¹⁵

The model presented in this paper assumed constant parameter values across manufacturing industries. A more refined analysis that allows rates of return on R&D to differ across individual industries could not be performed due to the limited number of observations per industry in our sample. This issue could be tackled in the near future as longer times series of data drawn from R&D and Innovation surveys become available. Other interesting avenues for future research are the impact on performance of the technological diversity and coherence of in-house and outsourced R&D activities (e.g. Nesta and Saviotti, 2005) and the potentially differential roles of foreign vs. domestic R&D outsourcing. Despite the need for further extensions, we believe the analysis presented in the paper serves as a tractable contribution to our understanding of the impact of internal and external R&D on firm-level productivity.

¹⁵ In addition, our findings suggest caution in interpreting a negative interaction term in a linear model as decisive evidence against complementarity (e.g. Basant and Fikkert, 1996).

References

- Acs, Z.J. and S.C. Isberg, 1991, Innovation, Firm Size and Corporate Finances. *Economics Letters*, 35, 232-326.
- Arora, Ashish and Alfonso Gambardella. 1990. Complementarity and external linkages: the strategies of the large firms in biotechnology. *Journal of Industrial Economics* 38, 361-79.
- Arora, Ashish, 1996, Testing for complementarities in reduced form regressions. *Economics Letters*, 50, 51-55.
- Audretsch, David, Albert Menkveld and Roy Thurik, 1996, The decision between internal and external R&D. *Journal of Institutional and Theoretical Economics*, 152(3), 519-530.
- Basant, Rakesh and Brian Fikkert, 1996, The effects of R&D, foreign technology purchase, and domestic and international spillovers on productivity in Indian firms. *Review of Economics & Statistics*, 78(2), 187-199
- Beneito, Pilar, 2006, The innovative performance of in-house and contracted R&D in terms of patents and utility models. *Research Policy*, 35, 502–517.
- Bönte, Werner, 2003, R&D and productivity: internal vs. external R&D – evidence from West German manufacturing industries. *Economics of Innovation and New Technology*, 12(4), 343-360.
- Blonigen, Bruce and Christopher Taylor, 2000, R&D intensity and acquisitions in high-technology industries: evidence from the US electronic and electrical equipment industries. *The Journal of Industrial Economics*, 48, 47-70.
- Blundell, Richard and Stephen Bond, 2000, GMM estimation with persistent panel data: an application to production functions. *Econometrics Reviews*, 19(3), 321-340.
- Blundell, Richard and Stephen Bond, 1998, Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics*, 87, 115-143.
- Cassiman, B. and R. Veugelers, 2006, In search of complementarity in innovation strategy: Internal R&D, cooperation in R&D and external technology acquisition. *Management Science*, 52 (1), 68-82.
- Chesbrough, Henry, 2003, The era of open innovation. *Sloan Management Review*, 44(3), p35-41.
- Chiesa, Vittorio, Raffaella Manzini, and Emauele Pizzurno, 2004, The externalization of R&D activities and the growing market of product development services. *R&D Management*, 34(1), 65-75.
- Cohen, Wesley and Steven Klepper, 1996, A reprise of size and R&D. *Economic Journal* 106, 925-951.
- Cohen, Wesley and David Levinthal, 1989, Innovation and Learning: two faces of R&D. *Economic Journal* 99, 569-596.
- Deolalikar, Anil B, Evenson, Robert E., 1989, Technology production and technology purchase in Indian industry: an econometric analysis. *Review of Economics & Statistics*, 71(4), 687-93

Fernandez-Bagües, Manuel, 2004, Complementarity in innovation strategies: evidence from pharmaceutical dynamic panel data. Paper presented at the 30th EARIE conference in Helsinki.

Fors, G., 1996, Utilization of R&D results in the home and foreign plants of multinationals. *Journal of Industrial Economics*, 45, 3, 341-358.

Fuss, Melvyn, Daniel McFadden, and Yair Mundlak, 1978, A survey of functional forms in the economic analysis of production, in M. Fuss and D. McFadden (eds.), *Production Economics: a dual approach to theory and applications*, Vol. 1, Amsterdam: North-Holland, 219-268.

Gans, Joshua and Scott Stern, 2000, Incumbency and R&D incentives: licensing the gale of creative destruction. *Journal of Economics and Management Strategy*, 9(4), pp. 485-511.

Geroski, Paul, 1991, Innovation and the sectoral sources of UK productivity growth. *The Economic Journal*, 101, pp. 1438-1451.

Granstrand, Ove, Erik Bohlin, C. Oskarson, N. Sjöberg, 1992, External technology acquisition in large multitechnology corporations. *R&D Management*, 22(2), pp. 111-113.

Griffith, Rachel, Stephen Redding, and John van Reenen, 2003, R&D and absorptive capacity: theory and empirical evidence. *Scandinavian Journal of Economics*, 105(1), 99-118.

Griffith Rachel, Stephen Redding, John Van Reenen, 2004, Mapping The Two Faces Of R&D: Productivity Growth In A Panel Of OECD Industries. *Review of Economics and Statistics*, 86(4), 883-895.

Griliches, Z. and F. Lichtenberg, 1984a, Inter-industry knowledge flows and productivity growth. *Review of Economics and Statistics*, 66, 324-329.

Hall, Bronwyn H., Zvi Griliches, and Jerry Hausman, 1986, Patents and R&D: is there a lag? *International Economic Review*, 27(2), 265-83.

Henderson, R., Cockburn, I., 1996. Scale, scope, and spillovers: the determinants of research productivity in drug discovery. *Rand Journal of Economics* 27, 32–59.

Howells, Jeremy, Andrew James, and Khaleel Malik, 2004, Sourcing external technological knowledge: a decision support framework for firms. *International Journal of Technology Management*, 2004, 27(2/3), 143-155.

Hsiao, C., Pesaran, H. and Tahmiscioglu A. (2002) Maximum likelihood estimation of fixed effects dynamic panel data models covering short time periods. *Journal of Econometrics*, 109, 107-150.

Jones, Charles, 2002, Sources of U.S. economic growth in a world of ideas, *American Economic Review*, 92(1), 220-239.

Katrak, Homi, 1985, Imported technology, enterprise size and r & d in a newly industrializing country: the Indian experience. *Oxford Bulletin of Economics & Statistics*, 47(3), pp. 213-30

Klette, Tor Jacob, and Frode Johansen, 1998, Accumulation of R&D capital and dynamic firm performance: a not-so-fixed effect model. *Annales d'Économie et de Statistique*, 49/50, 389-419.

Klette, Tor Jacob, 1996, R&D, scope economies and plant performance. *The RAND Journal of Economics* 27(3), 502- 522.

Lee, Chang-Yang, 2003, A simple theory and evidence on the determinants of firm R&D. *Economics of Innovation and New Technology*, 12(5), pp. 385-395.

Love, James and Stephen Roper, 1999, The determinants of innovation: R&D, technology transfer and networking effects. *Review of Industrial Organization* 15, pp. 43-64.

Love, James and Stephen Roper, 2002, Internal vs. external R&D: a study of R&D choice with sample selection. *International Journal of Economics and Business*, 9(2), pp. 239-55.

Mairesse, Jacques and Mohammed Sassenou, 1991, R&D and productivity: a survey of econometric studies at the firm level, NBER working paper No 3666, Cambridge, MA.

Mohnen, Pierre and Normand Lepine, 1991, R&D, R&D Spillovers and Payments for Technology: Canadian Evidence. *Structural Change and Economic Dynamics*, 2(1), pp. 213-28.

Narula, Rajneesh, 2001, Choosing between internal and non-internal R&D activities: some technological and economic factors. *Technology Analysis and Strategic Management*, vol 13(3), pp. 365-387.

Nesta, Lionel and Pier Saviotti, 2005, Coherence of the knowledge base and the firm's innovative performance: evidence from the U.S. pharmaceutical industry, *Journal of Industrial Economics*, 53(1), 123-42.

Pakes, Ariel and Mark Schankerman, 1984, The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources, in Z. Grilliches (eds.) *R&D, Patents, and Productivity*, pp. 73-88, University of Chicago Press

Piga, Caludio, and Marco Vivarelli, 2004, Internal and external R&D: a sample selection approach. *Oxford Bulletin of Economics and Statistics*, 66(4), 457-482.

Pisano, G.P., 1990. The R&D boundaries of the firm : an empirical analysis. *Administrative Science Quarterly* 35, 153–176.

Scherer, F. 1982, Inter-industry flows and productivity growth. *Review of Economics and Statistics*, 64(4), pp. 627-34.

Veugelers, Reinhilde and Bruno Cassiman, 1999, Make and buy in innovation strategies: evidence from Belgian manufacturing firms. *Research Policy*, 28, 63-80.

Windmeijer, Frank, 2005, A finite sample correction for the variance of linear efficient two-step GMM estimators, *Journal of Econometrics*, 126, 25-51.

Table 1 Descriptive statistics

Variable	Mean	S.D.	Description
Productivity	3.921	0.483	Net value added divided by employees in constant prices, in logarithm
Δ Labor	0.015	0.187	Log growth in the number of employees
Δ Investment	-0.069	4.061	Log growth in Fixed Capital Investment in constant prices
R&DINT ^{int}	0.085	0.209	Expenditure on in-house R&D divided by net value added
R&DINT ^{ext}	0.015	0.059	Expenditure on contracted R&D divided by net value added

Table 2 Internal and External R&D by R&D intensity quintile

R&D intensity quintile	Number of observations	Percentage internal R&D only	Average share of external in total R&D (in %)
$\leq 3\%$	525	47.2	12.5
3% - 6%	352	49.3	9.5
6% - 9%	199	38.2	10.7
9% - 12%	120	40.8	10.3
$\geq 12\%$	324	25.9	15.3

Table 3: Dynamic Panel Data Estimates of Equation (8)

	GMM (difference)	GMM (system)	MLE FE	MLE RE	GMM (difference)	GMM (system)	MLE FE	MLE RE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Productivity ₋₁	0.581*** (0.117)	0.823*** (0.059)	0.719*** (0.060)	0.522*** (0.042)	0.628*** (0.128)	0.762*** (0.062)	0.813*** (0.055)	0.494*** (0.038)
ΔLabor	-0.361*** (0.057)	-0.424*** (0.060)	-0.381*** (0.042)	-0.334*** (0.037)	-0.408*** (0.068)	-0.401*** (0.058)	-0.432*** (0.043)	-0.338*** (0.036)
Δinvestment	0.009* (0.005)	0.010** (0.005)	0.009* (0.005)	0.008* (0.004)	0.008* (0.004)	0.011* (0.006)	0.008* (0.004)	0.007* (0.004)
R&DINT ^{int}	0.304** (0.112)	0.299** (0.129)	0.307*** (0.053)	0.137*** (0.042)	1.318*** (0.466)	0.432** (0.194)	1.229*** (0.194)	0.230** (0.125)
R&DINT ^{int} squared					-0.182*** (0.069)	-0.050* (0.027)	-0.166*** (0.031)	-0.041** (0.020)
R&DINT ^{ext}	0.602 (0.690)	0.819* (0.483)	0.297 (0.368)	0.188 (0.271)	0.994 (0.749)	0.126 (0.615)	0.461 (0.397)	0.201 (0.298)
R&DINT ^{ext} squared					-3.486* (1.893)	-3.466*** (1.295)	-1.736 (1.160)	-2.530*** (0.977)
R&DINT ^{int} * R&DINT ^{ext}	0.142 (0.251)	0.061 (0.164)	0.004 (0.155)	0.064 (0.121)	2.004* (1.207)	2.581*** (0.801)	0.862 (0.753)	1.668*** (0.634)
Wald(df) /LL	162.57	547.75	-82.33	-332.96	345.68	353.84	-57.01	-314.35
Hansen test (df), p-value	16.11(20) (0.71)	50.50(34) (0.08)			14.90(21) (0.83)	35.34(27) (0.13)		
AR(1) test (p-value)	-4.96(0.00)	-6.98(0.00)			-4.63(0.00)	-6.95(0.00)		
AR(2) test (p-value)	-0.32(0.75)	0.20(0.84)			-0.09(0.93)	0.21(0.83)		
N. Obs.	1216	1520	1216	1520	1216	1520	1216	1520

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. System GMM and MLE random effects models include industry dummies. All models include year dummies. Instruments for the difference GMM equations are industry dummies and lagged values of the right hand side variables; the extra lag restricts the panel to 4 years and reduces the number of observations by 304. Instruments for the level equations are industry dummies and differenced values of the right hand side variables. Robust standard errors are in parentheses. For GMM estimates, the finite-sample correction to the two-step covariance matrix derived by Windmeijer (2005) is used. The Hausman test of random vs. fixed effects MLE is 33.4 (p<0.001) and 69.4 (p<0.001) for the linear and quadratic models, respectively. Estimation of GMM is carried out with the xtabond2 Stata 9.0 module by D. Roodman, Center for Global Development, Washington. Estimation of MLE is carried out with SAS/IML.

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