Centre of Excellence
for Science and Innovation Studies

CESIS Electronic Working Paper Series

Paper No. 222

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February 2010

The Royal Institute of technology
Centre of Excellence for Science and Innovation Studies (CESIS)
http://www.cesis.se

Do External Technology Acquisitions Matter For Innovative Efficiency and Productivity?

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ABSTRACT

To quickly adapt to technological change and developments, and thus remain competitive, firms increasingly resort to the use of external technology. This paper investigates whether and to what extent the acquisition of external disembodied technology affects the efficiency and productivity *in* innovation of technology acquiring firms. Using the stochastic frontier analysis combined with a difference-in-difference matching approach and firm-level panel from the German Innovation Survey for the period 1992–2004, we find that manufacturing firms that acquire disembodied technology experience more growth in innovative productivity than non-acquiring firms do. Thus, this study provides evidence on complementarity between internal and external R&D in innovation production, which is attributed by increasing returns to R&D scale and increasing technical efficiency. Moreover, we find that firm size significantly contributes to innovative efficiency and productivity of external technology acquirers.

Keywords: Technology Acquisition, Innovative Efficiency, Innovative Productivity, SFA, Difference-in-Difference Matching

JEL Classifications: O30, L24, L25, L60

The authors would like to thank Friedel Bolle and Oleg Badunenko for their helpful comments. The usual disclaimer applies.

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1 Introduction

The recent rise of external technology acquisition is attributed to the growing complexity, speed, and uncertainty of technological developments, combined with greater codification of R&D processes that facilitate R&D contracting and segmentation of R&D activities (e.g., Grandstrand *et al.*, 1992; Narula, 2001). To create sustainable performance differentials with competitors, firms must constantly update their technological capabilities (Leonard-Barton, 1994). However, in many industries, accelerating own R&D efforts and developing internal innovative capabilities are no longer sufficient in light of the increasing cost, speed, and complexity of technological developments. Because of the high risk due to the low probability of innovation success and the length of required time for innovation to provide adequate returns, internal developments may be perceived as undesirable by firms (Hitt *et al*., 1991). Thus, firms prefer to invest fewer resources in internal R&D when faced with resource constraints or when there are attractive external sources of innovation. Compared to internal R&D, external sourcing allows a firm to obtain knowledge and technology beyond its current capability and routines (Mitchell and Singh, 1996). 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 the use of outside skills that can exploit in-house research more effectively.

The present paper examines the impact of external technology acquisition on a firm's innovation performance in transforming innovation resources into commercially successful output. We focus on the disembodied technology sourcing such as licensing-in and R&D contracting, which are similar in that neither requires a joint research effort. Both technology sources can be viewed as two, possibly substitutable, ways of acquiring innovative knowledge and entail very little financial risk but grant quick access to necessary technology that is beyond in-house capabilities. In contrast to previous studies, the innovation performance of firms is determined not only by their resources and innovation inputs, but more importantly by their productivity in innovation and the factors that affect this productivity. In particular, we separate the effects of technical efficiency, scale efficiency, and technological level in attaining innovative productivity.

With respect to *innovative productivity*, only a few examples in the literature discussed, independent from the issue of technology acquisition, *innovative efficiency* at the firm level by using quantitative approaches. Cosh *et al.* (2005) examine the impact of management characteristics and patterns of collaboration on a firm's innovative efficiency by comparing the Data Envelopment Analysis (DEA) and the Stochastic Frontier Analysis (SFA). Zhang *et al*. (2003) applied the SFA approach to the R&D efforts of Chinese firms to examine the difference in efficiency among various types of ownership. Hashimoto (2008) analyzed R&D efficiency change of Japanese pharmaceutical firms using DEA methodology. In addition, Korhonen *et al*. (2001) and Cherchye and Vanden (2005) applied the DEA technique to evaluate the efficiency of university R&D in Finland and the Netherlands, respectively. The few examples, however, use a two-stage approach when analyzing the inefficiency determinants[1] and are restricted to estimation of predicted inefficiency.

The main contribution of this paper to the existing literature is that, to the best of our knowledge, this study is the first attempt to empirically address the role of external technology acquisition in the achievement of innovative efficiency and productivity. More precisely, the present study quantifies to what extent technology acquirers are changing their innovative efficiency and productivity levels after acquiring external technology. The purpose of this study is twofold. First, we intend to measure the relative innovation performance of the firms within the German manufacturing sector. A stochastic output distance function is used to construct a generalized output Malmquist productivity index (Orea, 2002) for estimating the firm's innovative productivity. Second, we analyze the impact of external technology acquisition on the acquiring firms' innovative productivity growth. In particular, contribution of firm size to the growth of innovative productivity and its components – efficiency change, technical change and scale efficiency – following external technology activity is examined.

The paper proceeds as follows. Section 2 discusses the theoretical underpinnings of external technology sourcing and innovative productivity. Section 3 introduces empirical methodologies and specifications of the models estimated. The description of data that facilitate our empirical analysis and their descriptive analysis are provided in Section 4, while Section 5 presents estimation results of the empirical analysis. Section 6 concludes.

2 Theoretical Background

In developing new technological output, "dual sourcing" of R&D is imperative (Mitchell and Singh, 1996). Together, internal and external R&D create the absorptive capacity (Cohen and

[1] See Section 3.1.2 about drawbacks of this approach.

Levinthal, 1990) that underlies current and future technical output. Because external technology sourcing contributes to the development of absorptive capacity, it has implications for the ability of technological firms to generate and enhance new output. Expanding the scope of a firm's internal R&D may help mitigate the uncertainties associated with the emergence of a new technology. However, it is virtually impossible for a firm, regardless of its effort, to keep abreast of all the relevant technological advances solely through internal R&D. When a new technology emerges, the technological know-how required for its commercial application may well fall outside the firm's current area of expertise and the firm's internal stock of technical knowledge becomes less relevant (Teece, 1988). In this situation, firms must look to external technology sourcing to complement their in-house R&D. Access to technological complementarities is one of the most important reasons for firms to acquire technology externally since R&D and innovation projects usually require a larger amount and more specific assets than do the firm's other projects (Hagedoorn, 1993; Cassiman and Veugelers, 2006). In addition to acquiring the necessary knowledge and competencies, looking outside the firm for such also reduces the firm's own innovation costs and rectifies internal rigidities through cost sharing as well as through risk sharing.

The literature providing empirical evidence on the effect of external technology sourcing on a firm's innovation performance is growing recently (e.g., Cassiman and Veugelers, 2007; Narayanan and Bhat, 2009; Grimpe and Kaiser, 2008, Veugelers and Cassiman, 1999; Beneito, 2006). It has been argued that in order to absorb externally acquired knowledge, an effective 'absorptive capacity' to identify and effectively utilize this knowledge is essential (e.g., Cohen and Levinthal, 1989). In-house R&D activities are often required to create sufficient absorptive capacity, which suggests a complementarity between internal and external R&D. Empirically, the effective balance between internal R&D and external sourcing and interaction between these two strategies has however remained relatively unexplored.

Although the existing literature acknowledge that the efficient handling of organization costs might prove to be central for innovation success (Grimpe and Kaiser, 2008), they focus primarily on the success/failure of technology acquisition based on R&D efforts and R&D output. However, if R&D resources are not used effectively, additional investment may be of little support in stimulating innovation process. At the same time, if innovation outputs are not produced effectively, after a certain point, the R&D inefficiency may hinder the creation of innovation and eventually would lead to a technological exhaustion. Since external technology sourcing is aimed at securing access to new technology, which can make cost-cutting possible or allocate fixed costs over a broader R&D base, investigating efficiency and productivity in innovation is important for the effective allocation of external technology resources into internal R&D activities.

The literature discussing the effects of R&D investment on production productivity *in general* emphasizes the role of firm characteristics such as firm size and resource and capability constraints as important determinants of production efficiency and productivity (Henderson and Cockburn, 1996; Marriese and Hall, 1996; Danzon *et al*., 2003, Berghäll, 2006). Findings from the empirical literature on the relationship between firm size and efficiency are ambiguous, but there is indication that firm size could be a main source of the heterogeneity in *technical efficiency*. On the one hand, it is claimed that large firms could be more efficient in production because they use more specialized inputs and better coordinate their resources. On the other hand, it is emphasized that small firms could be more efficient because they have more flexible, non-hierarchical structures, and usually do not suffer from the so-called agency problem.

Moreover, size may have an indirect effect on productivity through other variables, such as resource and capability constraints, as variations in these will lead to different patterns of behavior between small and large firms (Geroski, 1998). From the evolutionary theory perspective, innovation is an accumulating learning process, irreversible with regard to the technological path (Malerba and Orsenigo, 1990; Pavitt *et al*., 1987). This implies that the level of accumulated resources and capabilities will significantly affect future innovative efficiency. These resources and capabilities vary among firms and are determined by a vast and complex number of both stimulating and restraining factors that appear to have a significant impact on the innovative process and thus on the innovative efficiency of firms (Freel, 2000; Vossen, 1998). According to Vossen (1998), large firms' strengths are predominantly material due to economies of scale and scope, and financial and technological resources, whereas small firms' strengths are mostly behavioral, that is, small firms are more dynamic, flexible, efficient, and often have closer proximity to the market. Hence, small firms will be more likely to face material resource and capability constraints to innovation than larger firms will, while larger firms will be more likely to experience behavioral constraints to innovation.

Scale efficiency is another major source of differences in productivity between small and large firms. Large firms are often argued to be more innovative as they enjoy greater economies of scale and scope than do smaller firms (Cohen and Klepper, 1996) and can capture the fruits of their innovation. They also have easier access to finance and greater capability to invest in R&D or acquire external innovation (Geroski *et al*., 2002). However, You (1995) suggests that efficient firm size is determined by the interaction between economies of scale stemming from increasing returns to production technology and diseconomies of scale stemming from decreasing returns to organizational technology. Thus, although large firms may have technological and learning economies of scale, these may be outweighed by organizational diseconomies of scale (Zenger, 1994). Indeed, there are various arguments as to the impact firm size has on innovation performance. When R&D expenditure is used as a proxy for innovation, there is evidence that innovation increases more than proportionately with firm size up to a threshold point. This is explained by the size advantages of large firms in terms of internal knowledge, financial resources for innovation, sales base, and market power (Cohen and Klepper, 1996). When patents and innovation counts are employed as indicators of innovative output, it emerges that R&D productivity tends to decline with firm size, either when measured as patents per R&D (Bound *et al*., 1984) or when measured by innovations per unit of R&D (Acs and Audretsch, 1990, 1991). When market structure is taken into account, the large firms' R&D advantage tends to disappear, innovative output (in terms of number of inventions) tends to fall as concentration grows, while the returns to R&D inputs decrease with firm size (Acs and Audretsch, 1988), which implies that industry specifics are key factors in innovative performance. These different findings suggest that the relationship between firm size and innovation performance depends on the choice of the performance indicator and the importance of technological regimes prevalent to a particular industry.

Finally, *technical change* could be an important factor in explaining innovative productivity dynamics because small and large firms use R&D inputs in different proportions. If technical change is neutral, then there will be a parallel shift in the production function. That is, all firms face the same rate of technical change. If technical change is biased, then firms operating at different scales will benefit from technical change at different rates. Based on the above considerations, we argue that firm size and technology regime may induce a significant effect on the differentials of firms' innovative productivity.

Various external sourcing modes are discussed in the technology management literature. The transaction cost perspective treats the external technology sourcing choice as an organization boundary choice among market, hierarchies, and networks/alliances with the aim of curbing opportunism (e.g., Hennart, 1991). According to the resource-based view, the choice of mode is driven by pursuit of competitive advantages and technological capability (e.g., Kogut and Zander, 1992; Nagarajan and Mitchell, 1998). Based on a comparison of different technology acquisition modes, the literature concludes that the effectiveness of any type of technology sourcing depends on the attributes of the technology being pursued, the extent of technical change, and uncertainty in the external environment (e.g., Arora and Gambardella, 1994; Steensma and Corley, 2000).

In the present paper, we investigate two major subcategories of disembodied technology acquisition: firstly, new technology disembodied through a licensing agreement and, secondly, outsourcing of technology development to an R&D contractor. According to Cassiman and Veugelers (2007), if a firm decides to acquire technology externally, it will find that licensing agreements or R&D contracts are the most flexible modes of external sourcing. The main advantage of licensing is the speed with which technologies can be acquired and applied to own production. To make licensing efficient, licensees must have the capability to screen, identify, process, and utilize the technological know-how licensed. Hoekman and Javorcik (2006) and Lopez (2008) argue that technology licensing generates productivity spillovers and increases productivity in upstream sectors. On the other side, Grimpe and Kaiser (2008) find positive and significant effects for both internal and contractual R&D expenditure on the innovation success measured in innovative product sales. R&D contracts help firms to acquire technologies without significant irreversible financial commitment and firms can selectively and flexibly acquire technology based on their needs and technological configuration. The contractor firm becomes a possibility to focus on particular areas of research, which provides substantial cost saving compared to full-fledged in-house research facilities. When appropriability is high, firms are willing to sell their technology to other firms to appropriate the benefits from innovating (Teece, 1986). However, licensing-in and contractual R&D might also lead to a reluctance of firms to rely heavily on external sourcing of technological knowledge due to the contractual uncertainty, information asymmetry, and a limited transferability of tacit knowledge (Teece, 1988).

3 Methodology

3.1 Measuring Innovative Efficiency and Productivity

Motivated by the knowledge production function set up in Pakes and Griliches (1984) and Griliches (1990), this paper considers R&D activity in manufacturing in the context of an innovative sales production function. The R&D production function applied to each firm is assumed to be well behaved and to exhibit variable returns to scale. It is presumed that all firms have the same underlying aggregate production function in terms of standardized quantities of outputs and inputs but that they may operate on a different part of it.

3.1.1 Estimation Approach

Total factor productivity (TFP) using a productivity index is theoretically defined as the ratio of an aggregate output index to an aggregate input index. The most widely used productivity index is the Malmquist TFP index presented in Färe *et al*. (1994). The Malmquist TFP index measures the TFP change between two data points by calculating the ratio of two associated distance functions. Distance functions are a convenient way of describing a well-behaved multi-input and multi-output production technology without the necessity of specifying behavioral assumptions such as cost minimization or profit maximization. Let a multi-input and multi-output production technology at time t be defined as:

$$S_t = \{x_t, y_t : x_t \text{ can produce } y_t\} \in \mathbb{R}_+^{M+N} \tag{1}$$

where $x_i = (x_{i1}, \ldots, x_{iN}) \in \mathbb{R}_+^N$ and $y_i = (y_{i1}, \ldots, y_{iM}) \in \mathbb{R}_+^M$ are input and output vectors for the i-th firm, $i = 1, \ldots, I$, respectively. With a specific time period t, the production technology S_t transforms inputs x_t into net outputs y_t for each time period t =1,..., T. Then, the distance function can be defined by rescaling the length of an input or output vector with the production frontier as a reference:

$$D_t^O(x_t, y_t) = \min\{\theta : (x_t, y_t / \theta) \in S_t\} \tag{2}$$

where $D_t^O(x_t, y_t) \le 1$ if and only if $(x_t, y_t) \in S_t$. Furthermore, $D_t^O(x_t, y_t) = 1$ if and only if (x_t, y_t) is located on the outer boundary of the feasible production set, which occurs only if production is technically efficient.

The output-oriented Malmquist TFP index as defined by Färe *et al*. (1994) measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. One main criticism of the Malmquist TFP index is that it is constructed under constant returns to scale assumption. Hence, the Malmquist TFP index does not provide an accurate measure of productivity change because it ignores the contribution of scale economies. Orea (2002) presents an approach to decompose the Malmquist TFP index into technical change, technical efficiency change, and scale efficiency change where the contribution of scale economies is taken into account without requiring the prior calculation of scale efficiency measures as presented by Balk (2001).[2]

The translog distance function for the case of N inputs ($x_1, x_2, \ldots, x_N$) and M outputs ($y_1, y_2, \ldots, y_M$) is quadratic in the variables $\ln y_t$, $\ln x_t$ and t[3]:

$$\begin{aligned}\ln D_t^O\left(y_t, x_t, t\right) = {} & \alpha_0 + \sum_{k=1}^{N}\alpha_k \ln x_{kt} + \sum_{j=1}^{M}\beta_j \ln y_{jt} + \frac{1}{2}\sum_{k=1}^{N}\sum_{h=1}^{N}\alpha_{kh}\ln x_{kt}\ln x_{ht} \\ & + \frac{1}{2}\sum_{j=1}^{M}\sum_{l=1}^{M}\beta_{jl}\ln y_{jt}\ln y_{lt} + \sum_{k=1}^{N}\sum_{j=1}^{M}\gamma_{kj}\ln x_{kt}\ln y_{jt} + \varphi_t t + \frac{1}{2}\varphi_{tt}t^2 \\ & + \sum_{k=1}^{N}\alpha_{kt} t \ln x_{kt} + \sum_{j=1}^{M}\beta_{jt} t \ln y_{jt}\end{aligned} \tag{3}$$

Applying Diewert's (1976) quadratic identity lemma to the translog distance function, Orea (2002) derives a generalized output-oriented Malmquist TFP index decomposition where the logarithmic form of the TFP change index between periods t and $t+1$ can be written as:

$$\begin{aligned}\ln G_{vrs}^O\left(x_{t+1}, y_{t+1}, x_t, y_t\right) = {} & \left[\frac{\ln D_{t+1}^O}{\ln D_t^O}\right] - \frac{1}{2}\left[\frac{\partial \ln D_{t+1}^O}{\partial t} + \frac{\partial \ln D_t^O}{\partial t}\right] \\ & + \frac{1}{2}\sum_{k=1}^{N}\left[\left(-\sum_{k=1}^{N}e_{kt+1} - 1\right)\cdot s_{kt+1} + \left(-\sum_{k=1}^{N}e_{kt} - 1\right)\cdot s_{kt}\right]\cdot \ln\left(\frac{x_{kt+1}}{x_{kt}}\right)\end{aligned} \tag{4}$$

where $e_{kt} = \partial \ln D_t^O / \partial \ln x_{kt}$ and $s_{kt} = e_{kt} / \sum_{k=1}^{N} e_{kt}$ represent the distance elasticity and distance elasticity share for the k-th input in period t, respectively. The negative of the sum of the input elasticities represents the scale elasticity, the inverse of which is the return to scale:

$$RTS = -\left[\sum_{k=1}^{N} e_{kt+1}\right]^{-1} \tag{5}$$

[2] Balk (2001) uses a parametric technique to decompose the Malmquist TFP index into technical change, technical efficiency change, scale efficiency change, and input- or output-mix effect. Although Balks's approach is appealing, it does require the prior calculation of scale efficiency measures in which the scale effects are measured using the most productive scale size as a reference. As Orea (2002) points out, the scale efficiency measures are not bounded for either globally increasing, decreasing, or constant returns to scale or for ray-homogenous technologies. More simply, in the case of a single output, a U-shaped average cost curve is required for the most productive scale size to exist.

[3] Including time as a variable in the production frontier allows for the shifts of the frontier over time, which are interpreted as technical change. Technical change is neutral if $\alpha_{kt} = 0,\ k = 1, \ldots, N$.

The scale term takes a positive value when there are increasing returns to scale, i.e. RTS < 1, and input expansion or decreasing returns to scale, i.e. RTS > 1, as well as when there is input contraction.

As a result, the components of the productivity index $\ln G_{vrs}^{O}$ present changes in output technical efficiency (*EFFCH*), technical change (*TECHCH*), and a scale term (*SCALE*) depending on RTS values and on changes in input quantities.[4]

3.1.2 Model Specification

In this study, we apply a translog functional form of an output distance function with two outputs and three inputs. Note that we employ a two-year time lag between inputs and outputs in the knowledge production function. Estimating the translog output distance function presented in equation (3) requires conditions of symmetry and linear homogeneity in outputs. Symmetry requires the restrictions $\beta_j = \beta_l, (j, l, ..., M)$ and $\alpha_{kh} = \alpha_{hk}, (k, h, ..., N)$. The linear homogeneity of degree +1 in outputs is given if $\sum_{j=1}^{M} \beta_j = 1, \sum_{l=1}^{M} \beta_{jl} = 0, \sum_{j=1}^{M} \gamma_{kj} = 0$ and $\sum_{j=1}^{M} \beta_{jt} = 0$ hold. The homogeneity restrictions can be imposed by estimating a model where the $M-1$ output quantities are normalized by the *M*-th output quantity.[5] The distance term, D^O, can be viewed as the error term as follows:

$$-\ln D^{O} = v_{it} - u_{it} \tag{6}$$

Then, the estimating form of the output distance function of our model is represented as:

$$\begin{aligned} -\ln y_{2it} = {} & \alpha_0 + \sum_{k=1}^{3} \alpha_k \ln x_{kit-2} + \beta_1 y_{1it}^{*} + \frac{1}{2} \sum_{k=1}^{3} \sum_{h=1}^{3} \alpha_{kh} \ln x_{kit-2} \ln x_{hit-2} + \beta_{11} \left(\ln y_{1it}^{*} \right)^2 \\ & + \sum_{k=1}^{3} \gamma_{k1} \ln x_{kit-2} y_{1it}^{*} + \varphi_t T + \frac{1}{2} \varphi_{tt} T^2 + \sum_{k=1}^{3} \alpha_{tk} T \ln x_{kit-2} + \beta_{t1} T \ln y_{1it}^{*} \\ & + \psi POST_{it} + \sum_{f=1}^{4} \phi r_{fit} + \eta WEST_{it} + v_{it} - u_{it} \end{aligned} \tag{7}$$

where $y_{1it}^{*} = y_{1it} / y_{2it}$; y_{1it}, y_{2it}, and x_{kit-2}, x_{hit-2} denote outputs and inputs of the *i*-th firm at the *t*-th and *t-2*-th time period, respectively; *T* is a linear time trend that is used as an index of

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4 The term $\ln G_{vrs}^{O}$ is viewed as the parametric counterpart of the generalized productivity index introduced by Griffel and Lovell (1999) when the distance function is translog.

5 The symmetry restrictions are imposed in the estimation.

technology; $POST_{it}$ is a post-acquisition binary variable; r_{fit} represents dummy variables for technology regimes that correspond to each firm in the sample; $WEST_{it}$ is a region-specific dummy variable; v_{it} is the random error, which is assumed to be *i.i.d.* and follows a $N\left(0,\sigma_v^2\right)$ distribution independent of the u_{it}, which is a non-negative random variable associated with technical inefficiency.

According to the Battese and Coelli (1995) model, u_{it} is specified as a function of firm-specific factors that might influence technical inefficiency. In particular, u_{it} is determined by the truncation (at zero) of the $N\left(\mu,\sigma_u^2\right)$ distribution where the general form of the firm-specific mean, μ_{it}, is specified as a function of variables explaining technical inefficiency of firms. In this study, we specify the model of technical inefficiency as follows:

$$\mu_{it} = \delta_0 + \delta_1 ACQ_{it} + \delta_2 T + \Phi_1 C_{it} + \Phi_2 S_{it} + \Phi_3 X_{it} + \varepsilon_{it} \tag{8}$$

where ACQ_{it} is the acquisition binary variable; T is a time trend; C_{it} is a set of dummy variables that indicate resource and capability constraints to innovation; S_{it} is a set of dummy variables for firm size categories; X_{it} is a set of firm-related characteristics; and ε_{it} is statistical noise. The unknown parameters of the stochastic frontier translog distance function (7) and the technical efficiency model (8) are estimated simultaneously using the method of maximum likelihood. This approach avoids the inconsistency problem of the two-stage approach used in previous empirical works when analyzing inefficiency determinants.[6]

Battesse and Corra (1977) suggest that the two variance parameters can be replaced by two new parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_v^2 / \sigma^2$. The γ-parameterization has advantages in obtaining maximum likelihood estimates because the parameter space for γ can be searched for a suitable starting value for the iterative maximization routine. If γ is close to one, the deterministic frontier is the result because all variation in the error term is attributed to inefficiency. Conversely, if γ is close to zero, there is no inefficiency in the disturbance, so the estimated function could be estimated by OLS method, for instance.

After simultaneous estimation of the output distance function (7) and the technical efficiency model (8), we can compute the components of the Malmquist TFP change index

[6] In a two-stage procedure, firstly, a stochastic frontier production function is estimated and the inefficiency scores are obtained under the assumption of independently and identically distributed inefficiency. However, in the second step, inefficiency effects are assumed to be a function of some firm-specific variables, which contradicts the assumption of identically distributed inefficiency.

presented in (4). First, the technical efficiency prediction for the *i*-th firm in the *t*-th time period can be calculated as follows:

$$TE_{it} = E\left[\exp\left(-u_{it}\right)\middle|e_{it}\right] \text{ where } e_{it} = v_{it} - u_{it}. \tag{9}$$

Thus, the technical efficiency change of the *i*-th firm between adjacent years t and $t+1$ yields:

$$\ln EFFCH_{i,tt+1} = \ln\left(\frac{TE_{it+1}}{TE_{it}}\right) = \ln\left(\frac{E\left(\exp\left(-u_{it+1}\right)\middle|\left(v_{it+1} - u_{it+1}\right)\right)}{E\left(\exp\left(-u_{it}\right)\middle|\left(v_{it} - u_{it}\right)\right)}\right) \tag{10}$$

The technical change and scale efficiency change can be calculated as follows:

$$\ln TECHCH_{i,tt+1} = -\frac{1}{2}\left[2\left(\varphi_t + \varphi_{tt}\left(t+1/2\right)\right) + \sum_{k=1}^{3}\alpha_{tk}\left(\ln x_{kit} + \ln x_{kit+1}\right) + \beta_{t1}\left(\ln y_{1it}^{*} + \ln y_{1it+1}^{*}\right)\right] \tag{11}$$

$$\ln SCALE_{i,tt+1} = \frac{1}{2}\sum_{k=1}^{N}\left[\left(-\sum_{k=1}^{N}e_{kit+1} - 1\right)\cdot s_{kit+1} + \left(-\sum_{k=1}^{N}e_{kit} - 1\right)\cdot s_{kit}\right]\cdot \ln\left(\frac{x_{kit+1}}{x_{kit}}\right) \tag{12}$$

where $e_{kit} = \partial \ln D_t^O / \partial \ln x_{kit} = \alpha_k + \alpha_{kk}\ln x_{kit} + \alpha_{kh}\ln x_{hit} + \gamma_{k1}\ln y_{1it}^{*} + \alpha_{tk}t$ and $s_{kit} = e_{kit} / \sum_{k=1}^{N} e_{kit}$.

3.2 Measuring the Effects of External Technology Acquisition

In this section, we present the econometric methodology that we apply for analyzing the effects of external technology acquisition on the innovative productivity of the acquirer firm. On the one hand, simply comparing the innovative productivity before and after the acquisition is not satisfactory because such a comparison would be beset with variation in outcome that is actually due to change in the market environment over time. On the other hand, solely comparing the innovative productivity between acquirer and non-acquirer firms in the post-acquisition period could be biased due to permanent differences between these groups of firms. To avoid these biases, we employ the difference-in-difference method (Ashenfelter and Card, 1985) which compares the difference in the outcome before and after the acquisition for acquiring firms to the difference in the outcome before and after the acquisition for a control group, *i.e*. non-acquiring firms.

However, it is doubtful whether the effects of external technology acquisition can be assessed properly if there are considerable differences in outcome between acquiring and non-acquiring firms. As discussed in Section 2, there are different patterns of innovative productivity among small and large firms, as well as between manufacturing sectors.

Moreover, recent empirical evidence indicates that since acquiring firms differ in some important aspects from other firms in the pre-acquisition period, it is important to take these differences into account in any performance study of acquisitions (Bertrand and Zitouna, 2008, Gantumur and Stephan, 2007). Choosing an appropriate control group will account for this selection bias. To this end, we integrate a propensity score method (Dehejia and Wahba, 2002) into the difference-in-difference approach, thereby controlling for endogeneity and ex-ante observable firm characteristics.

For each firm i in the sample, let ACQ_i be an acquisition indicator that equals one when the firm acquires technology externally and zero otherwise, Y_i^1 is the innovative productivity of acquiring and Y_i^0 is the innovative productivity of non-acquiring firms. Then, the effect of technology acquisition is defined by the difference between the expected innovative productivities as $E\left(Y_i^1 \middle| ACQ_i = 1\right) - E\left(Y_i^0 \middle| ACQ_i = 1\right)$. Since we do not have counterfactual evidence of what would have happened if a firm had not acquired external technology, $E\left(Y_i^0 \middle| ACQ_i = 1\right)$ is unobservable. However, it can be estimated by $E\left(Y_i^0 \middle| ACQ_i = 0\right)$ and the effect can be given by the difference in the average outcome between the acquiring and non-acquiring firms as $E\left(Y_i^1 \middle| ACQ_i = 1\right) - E\left(Y_i^0 \middle| ACQ_i = 0\right)$. The estimator will be unbiased only when the acquiring and the non-acquiring firms do not systematically differ in their firm characteristics. Rubin (1997) and Rosenbaum and Rubin (1983) show that a propensity score analysis of observational data can be used to create groups of treated and control units that have similar characteristics, whereby comparisons can be made within these matched groups.[7] The acquisition propensity score is then defined as the conditional probability of acquiring external technology given a set of firm's productivity characteristics Y_i and other firm-related characteristics X_i:

$$p\left(ACQ_{it}\right) = \Pr\left(ACQ_{it} = 1 \middle| Y_{it-2}, X_{it-2}\right) \tag{12}$$

Thus, we account for the lagged time structure of the technology acquisition decision problem.

[7] In these groups, there are firms that have been treated and firms that have not been treated; hence, the allocation of the treatment can be considered as random inside the groups of firms.

Based on the propensity score matched sample, the effects of acquisition on the acquirer's innovative productivity can be estimated using the following difference-in-difference estimator:

$$\left[E\left(Y_{it+2}^{1}\middle|ACQ_{it}=1\right)-E\left(Y_{it-2}^{1}\middle|ACQ_{it}=1\right)\right]-\left[E\left(Y_{it+2}^{0}\middle|ACQ_{it}=0\right)-E\left(Y_{it-2}^{0}\middle|ACQ_{it}=0\right)\right] \quad (12)$$

where $t-2$, $t+2$ denote the pre- and post-acquisition periods, respectively. The two-year time window surrounding the acquisition event in t allows us to account for the length of time required between acquisition of the technology and its adaptation for innovative sales production.

Finally, the above estimator is obtained by performing the following regression:

$$Y_{it}=\beta_0+\beta_1 ACQ_{it}+\beta_2 POST_{it}+\beta_3 ACQ_{it}\cdot POST_{it}+\Phi X_{it}+\varepsilon_{it} \quad (12)$$

where ACQ_{it} is a dummy variable that captures possible differences in outcome Y_{it} between acquiring and non-acquiring groups; $POST_{it}$ is a dummy variable for the post-acquisition time period, which controls for aggregate factors that would cause changes in outcome Y_{it} even in the absence of acquisition; the coefficient β_3 represents the difference-in-difference estimator of the effect of acquisition on the group of technology acquiring firms; and the vector X_{it} represents firm characteristics. Thus, controlling for the differences in the technology acquired and non-acquired firms' innovative productivity prior to acquisition, we estimate the firm's post-acquisition innovative productivity compared to what it would have been in the absence of the acquisition.

4 Data and Descriptive Analysis

4.1 Sample Description

The analysis makes use of data from the German Innovation Survey, which is the German contribution to the EU's Community Innovation Survey (CIS). This innovation survey fully complies with the methodological recommendations for CIS surveys and adopts the standard CIS questions (see Janz *et al.*, 2001 for a detailed discussion). The survey was conducted by the Centre for European Economic Research (ZEW) and covers a representative sample of the German manufacturing sector (as well as business-related services). It is designed as a panel survey and is conducted at the firm level on a yearly basis. The yearly data are updated with biannual survey data that include more comprehensive and detailed information and compensate for panel mortality. Each survey reports information on the innovation activity of firms in the previous three-year period. The panel design of the survey offers the possibility of analyzing seven waves, covering the periods 1990–1992 (1993), 1992–1994 (1995), 1994–1996 (1997), 1996–1998 (1999), 1998–2000 (2001), 2000–2002 (2003), and 2002–2004 (2005).

Combining the biannual surveys allows us to construct an unbalanced panel covering the period 1992–2004 (with lagged year 1992) in which firms appear in at least three subsequent survey waves, i.e. at least three times biannually which yields six years of observation so far. We use an unbalanced panel in order to account for developments in innovative efficiency and productivity growth caused by sector entrants and by market exits, which would not be possible using a balanced panel. In other words, a balanced panel containing only firms that were active over the whole observation period could bias our results. Next, we restrict our analysis to innovative firms that continuously employed internal R&D.[8] Furthermore, we choose firms with positive value on innovation outputs, such as innovative sales with new products to the firm and innovative sales with market novelties, and on at least one non-missing input, such as innovation expenditure, labor in R&D, and material expenditure at the end of each period. Our effective initial sample consists of 1,555 observations corresponding to 412 firms.

In the MIP questionnaire, firms are asked whether they engaged (i) in external R&D acquisition, (ii) in the acquisition of external knowledge such as licenses, patents, and non-patented inventions, and/or (iii) in R&D contracting during a certain year. Identification of external technology acquisition is based on whether one of these external sourcing activities has been undertaken. During the period 1994–2004, on average, 27 percent of the firms acquired disembodied technology externally. The frequency of the firms' technology acquisition over the years is shown in Table A4 in the Appendix.

[8] Each MIP survey wave contains a question as to whether a firm has engaged in continuous internal R&D for the last three years.

4.2 Variables of the Analysis

The description of the variables used in the analysis and their summary statistics are shown in Table 1. We use two outputs and three input variables in the production function specified in equation (7). In particular, the two output variables are defined as the innovative sales with significantly improved products or products new to the firm (Y_{INF}) and the innovative sales with market novelties (Y_{INM}). The outputs have been constructed as shares of total sales and they are mutually exclusive variables, depending on whether the product innovation is just new to the firm or new to the market.

The three input variables are innovation expenditure (X_{INEXP}), labor (X_{LRD}), and material (X_M). Innovation expenditures encompass, in addition to internal and external R&D, other costs incurred when innovating, such as training costs, market research, marketing activities, the purchase of licenses, capital expenditures for innovation, and design. We use the innovation expenditure intensity, which is measured as a share of total sales. Labor is defined by the number of R&D employees, and material comprises total material expenditure. The latter inputs are measured as shares of total employees and total sales, respectively.

Furthermore, in the distance function, we include a post-acquisition binary variable (POST) which is equal to one for all years subsequent to external technology sourcing and zero otherwise. POST allows shifting for the distance function in the post-acquisition period in relation to the pre-acquisition one.

In the inefficiency model (8), various variables are included to explain the technical inefficiency of firms. All surveyed firms were asked about the obstacles to innovation they have encountered and about the consequences of those obstacles on their innovation projects. Specifically, firms were asked to assess the importance of hampering factors. After rescaling[9] the values, we obtain a dummy variable that takes value zero, when a hampering factor does not constrain the innovation activity of a firm, and value one when a constraint to innovation is present. We include the factors that decrease the efficiency of innovative productivity such as high economic risk (*RISK*), high innovation cost (*COST*), lack of information about technologies (*TECH*), organizational rigidity (*RIG*), lack of suitably qualified personnel (*PERS*), and lack of market information (*MARKET*) as resource and capability constraints.

Moreover, we include in the inefficiency model specific firm-related variables, such as capital intensity (*CAP*), export intensity (*EXP*), and market share (*MS*). The expectations

[9] Different scaling was applied to the answers in different waves of the survey, that is, scaling from unimportant to important values is sometimes between 0 and 5, sometimes between 0 and 3, and sometimes between 0 and 1. Therefore, we have rescaled the values to obtain a binary variable.

regarding the effect of capital intensity on innovative efficiency are ambiguous. On the one hand, if a firm's production process is capital intensive, any changes or additions to that process required by a new product will have a substantial impact. Innovative efficiency could deteriorate due to substantial sunk investments made in R&D that cannot be exploited by existing production resources. On the other hand, dated fixed assets may often be designed to accommodate emerging shifts or variations in raw materials and market preferences. If this is the case, increasing capital intensity will enhance innovative efficiency. The market share, defined as firm sales over total sector[10] sales, captures the relevance of the firm's market power in its sector. There is mixed evidence implying a positive relationship between a firm's efficiency and its market share and increasing productivity due to the increased competition. We expect a positive relationship between export intensity of firms and their innovative efficiency.

An acquisition dummy variable (*ACQ*) which is equal to one for the technology acquiring firms and zero otherwise is included in the inefficiency model to assess the impact of technology sourcing on inefficiency. A linear time trend (*T*), which indicates how efficiency changes with time, is included in both the distance function and the inefficiency model.

A comparison of the means between the groups of technology acquiring (ACQ) and non-acquiring firms (NACQ) in Table 1 shows that there are significant differences not only with respect to the firm-related characteristics but also in the innovation-specific variables that determine the production distance function.

Table 1. Variables description and descriptive statistics,[a] 1992–2004

Variables	Description	SAMPLE[b]	NACQ[c]	ACQ[c]
OUTPUT				
Y_{INF}	Innovative sales with new products to the firm as a share in total assets	0.3691 (0.2467)	0.3110 (0.1245)	0.3929*** (0.1102)
Y_{INM}	Innovative sales with market novelties as a share in total sales	0.2392 (0.2164)	0.2053 (0.0087)	0.2305*** (0.0093)
INPUT				
X_{INEXP}	Innovation expenditure intensity as a share of innovation expenditure in total sales	0.0655 (0.0750)	0.0575 (0.0023)	0.0741*** (0.0033)
X_{LRD}	R&D labor intensity measured as a share of R&D employees in total employees	0.0755 (0.0503)	0.0713 (0.0022)	0.0827*** (0.0024)
X_M	Material expenditure intensity measured as a share of material expenditure in total sales	0.4834 (0.1899)	0.4815 (0.0067)	0.4967* (0.0088)
INNOVATION CONSTRAINTS				
RISK	High economic risk	0.4834 (0.4927)	0.5651 (0.0176)	0.5887 (0.2210)

[10] Sectors are defined according to NACE 2 industry classification.

COST	High innovation cost	0.6162	0.5939	0.6282
		(0.4864)	(0.0175)	(0.0217)
TECH	Lack of information on technologies	0.3745	0.3397	0.4314***
		(0.4846)	(0.0169)	(0.0224)
RIG	Organizational rigidity	0.3965	0.3651	0.4720***
		(0.4890)	(0.0172)	(0.0223)
PERS	Lack of suitably qualified personnel	0.3672	0.2984	0.3813**
		(0.4824)	(0.0285)	(0.0449)
MARKET	Lack of market information	0.3884	0.3470	0.4245***
		(0.4876)	(0.0189)	(0.0240)
FIRM-RELATED CHARACTERISTICS				
CAP	Capital intensity measured as a share of investment expenditure in total sales	0.0798 (0.1393)	0.0760 (0.0047)	0.0767 (0.0053)
EXP	Export intensity measured as a share of sales abroad of total sales	0.2701 (0.2555)	0.2215 (0.0081)	0.3575*** (0.0117)
MS	Market share measured as a share of firm's sales of total market sales	0.0903 (0.0870)	0.0464 (0.0036)	0.0671*** (0.0060)
SMALL	Dummy variable for firms with 10–49 employees	0.2836 (0.4508)	0.3402 (0.0156)	0.2053*** (0.0176)
MEDIUM	Dummy variable for firms with 50–249 employees	0.3852 (0.4868)	0.4076 (0.0162)	0.3403*** (0.0206)
LARGE	Dummy variable for firms with >250 employees	0.3311 (0.4707)	0.2521 (0.0143)	0.4543*** (0.0217)
SB	Dummy variable for "science-based" technological regime	0.2360 (0.4247)	0.1815 (0.0127)	0.3250*** (0.0204)
FP	Dummy variable for "fundamental process" technological regime	0.0848 (0.2788)	0.0891 (0.0093)	0.0836 (0.0120)
CS	Dummy variable for "complex (knowledge) systems" technological regime	0.2372 (0.4255)	0.1967 (0.0131)	0.2984*** (0.0199)
PE	Dummy variable for "production engineering" technological regime	0.1196 (0.3246)	0.1380 (0.0113)	0.0969*** (0.0129)
CP	Dummy variable for "continuous processes" technological regime	0.3221 (0.4674)	0.3945 (0.0161)	0.1958*** (0.0173)
WEST	Dummy variable for West region	0.6971	0.6663	0.7490***
		(0.4996)	(0.0155)	(0.0189)
Observations (firm-years)		1555	1129	426
% of total		-	73%	27%

Notes: [a] Comparison of means for acquiring (ACQ) and non-acquiring firms (NACQ).
[b] Standard deviations in parentheses.
[c] Standard errors of the test on the difference of means are parentheses.
** and *** significant at 5% and 1%, respectively.

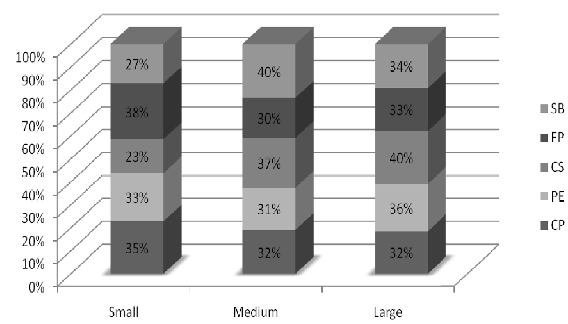
Furthermore, most factors hampering innovation are identified more frequently by acquiring firms than by non-acquiring firms. In addition, larger firms are more likely to supplement their internal R&D with externally acquired disembodied technology. Finally, external technology sourcing is predominant in all technological regimes expect for those involving continuous and fundamental processes.

4.3 Accounting for Firm Heterogeneity and Sector Specificity

In the inefficiency model, we include dummy variables for firm sizes in order to analyze the heterogeneity in innovative efficiency and productivity that is potentially induced by different size of firms. Firms are classified as small if they have 10–49 employees (*SMALL*), as medium if they have 50–250 employees (*MEDIUM*), and large if they have more than 250 employees (*LARGE*). A significant impact of firm sizes on the innovative inefficiency would show whether any significant differences with regard to innovative efficiency exist for different classes of firm size.

Moreover, in the distance function, we include dummy variables for technological regimes in order to control for differences in technological and market conditions between manufacturing sub-sectors. Empirical evidence confirms that patterns of innovation are technology specific and vary across industries (e.g., Nelson and Winters, 1982; Dosi, 1988). Hence, it is important to account for the technological regimes whose characteristics are common among firms belonging to different manufacturing sector, rather than controlling for the differences between industrial sectors without accounting for innovation characteristics. To this end, we apply Marsili's typology of technological regimes, which sorts regimes on the basis of technological opportunity conditions, appropriability conditions, cumulativeness of learning, and the nature of the knowledge base (for more details, see Marsili, 2001).

Figure 1. Distribution of product innovators across technological clusters by firm size



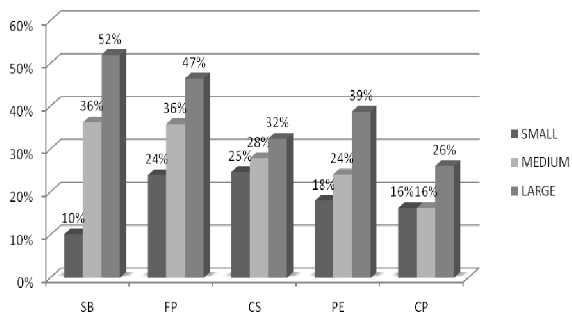
Using Marsili's typology, we classify the industrial sectors into five technological classes: science based (*SB*), fundamental processes (*FP*), complex (knowledge) systems (*CS*), production engineering (*PE*), and continuous processes (*CP*).[11] An overview of these technological regimes and their application to industry sectors is given in Table A1 in the Appendix. Figure 1 presents the percentage of innovators across technological regimes in our sample. The different size classes of firms in our sample are distributed quite evenly across

[11] The Marsili's classification has been applied to the Dutch and Norwegian manufacturing sector but has not yet been applied to the German manufacturing sector (e.g., Marsili and Verspagen, 2002).

technological regimes; there are slightly more medium-size firms in the science-based regime and more large firms in the process engineering regime.

Figure 2 shows that external technology acquisition was most prevalent for the science based firms, while the firms with continuous process technology were the least likely to use external technology for innovation. On average, 45 percent of total acquisitions were carried out by large firms, while small and medium-size firms conducted 19 and 36 percents of the acquisitions, respectively.

Figure 2. Distribution of external technology acquisitions by firm size and by technology regime



According to Table 2, small and medium-size firms, on average, are more innovative in both innovations new to the firm and new to the market than large firms are. As innovation is defined by innovative product sales, this implies that the firms with smaller firm size (expressed by the number of employees) are not hindered by potential constraints at the downstream value chain activities to bring an invention to the marketplace.

Table 2. Innovative product sales of manufacturing firms by size categories

	Observation	Innovation new to firm		Market novelties	
		Mean	Std.dev.	Mean	Std.dev.
SMALL	441	0.4401	0.2889	0.2889	0.2481
MEDIUM	599	0.3779	0.2414	0.2427	0.2109
LARGE	515	0.3084	0.2248	0.2008	0.1897
Total/Average	1,555	0.3691	0.2467	0.2392	0.2164

Since the time period of analysis covers the early years of the German Reunification as well, a dummy variable that distinguishes between the innovative productivity of East and West geographic regions is included in the production distance function. About 69 percent of the firms in our sample are located in the Western Germany.

5 Empirical Results

This section first reports the results for innovative efficiency based on stochastic frontier analysis. Using the parametric decomposition of a Generalized Malmquist Productivity Index as described in Section 3.1, we then present an analysis of the productivity effects regarding innovation of external technology acquisitions on efficiency change, technological change, and scale efficiency change of German manufacturing firms during the period 1994 through 2004.

5.1 Innovative Efficiency

In analyzing innovative efficiency in a year, it would not be appropriate to apply input and output data for the same year. Instead, we consider that variations in input do cause observed changes in output some years later. In this study, we apply a two-year time lag between input expenditure and realization of its outcome, e.g. innovative sales.

The results of the maximum likelihood estimation for the translog distance function (7) and the technical inefficiency model (8) are presented in Table A3 (in the Appendix) and Table 3, respectively.[12]

Table 3. Maximum-likelihood estimates for parameters of inefficiency effects model in stochastic frontier production function

Variable	Parameter	Estimated value	t-statistic
RISK	δ_1	0.2136	2.4591**
COST	δ_2	0.3628	2.9012**
TECH	δ_3	0.6731	5.1443***
RIG	δ_4	0.0294	1.0704
PERS	δ_5	0.0092	0.8573
MARKET	δ_6	0.8707	4.0739***
SMALL	δ_7	0.5892	2.5370**
LARGE	δ_8	0.2626	2.0732**
ACQ	δ_9	-0.4201	-5.3452***
CAP	δ_{10}	-0.8828	-4.2643***
EXP	δ_{11}	-0.1853	-0.4105
MS	δ_{12}	0.1127	0.0813
T	δ_{13}	0.0252	0.0524
Constant	δ_0	1.6532	7.0174***
Variance parameters of distance function			
SIGMA	$\sqrt{\sigma_u^2+\sigma_v^2}$	0.6129	5.7830***
LAMBDA	σ_u / σ_v	2.0468	9.1078***

[12] The model parameters are estimated using the FRONTIER 4.1 (Coelli, 1996).

GAMMA	$\sigma_u^2/\left(\sigma_u^2+\sigma_v^2\right)$	0.7841	8.0236***
Log likelihood	-1433.412		

Notes: The translog distance function and inefficiency effects model are estimated simultaneously.
The estimates for parameters of translog distance function are presented in Table A3 in the Appendix.
The group of medium-size firms is the base case used for the firm size comparison.
** and *** significant at 5% and 1%, respectively.

The estimates of λ and σ are large and significantly different from zero, indicating a good fit and confirms the specified distributional assumption. As λ is the ratio of the variances σ_u and σ_v, it becomes evident that the one-sided error term *u* dominates the symmetric error *v*, so that variation in innovative sales from production arises out of differences in the firms' R&D performance rather than being due to random variability. The estimate of γ suggests that 78 percent of random variation in innovative sales is explained by inefficiency. Therefore, the inefficiency effects are substantial in the stochastic frontier model analyzed.

Hypothesis tests regarding the structure of the production technology are conducted using likelihood ratio tests. Table 4 shows that the null hypothesis that all the δ - parameters and the intercept term are zero is rejected at the five percent significance level, confirming that the joint effect of these variables on technical inefficiency is statistically significant. Furthermore, we analyzed whether the chosen translog specification is appropriate by testing it against the simpler Cobb-Douglas functional form. The likelihood ratio test strongly rejects the hypothesis that the Cobb-Douglas function fits the data better, so we are confident that the translog specification is appropriate.

Table 4. Generalized likelihood ratio tests of hypotheses of the distance function and inefficiency effects model

Null hypothesis	Test statistic[a]	Critical value[b]	Decision
The inefficiency model is not appropriate H_o: $\gamma=\delta_0=\delta_1=...=\delta_{13}=0$	76.04	24.38(15)[c]	*Reject H_0*
Cobb-Douglas production function H_o: $\alpha_{11}+\alpha_{22}+\alpha_{33}+\alpha_{12}+\alpha_{13}+\alpha_{23}+\beta_{11}+\gamma_{11}+\gamma_{21}+\gamma_{31}=0$	37.98	17.67(10)	*Reject H_0*
No technical change H_o: $\varphi_t=\varphi_{tt}=\alpha_{t1}=\alpha_{t2}=\alpha_{t3}=\beta_{t1}=0$	48.84	12.59(6)	*Reject H_0*

Notes: [a] The test statistics have a χ^2 distribution with degrees of freedom equal to the difference between the parameters involved in the null and the alternative hypothesis.
[b] For a 95% significance level. Degrees of freedom are in parentheses.
[c] As γ takes values between 0 and 1, the statistic is distributed according to a mixed χ^2 whose critical value is obtained from Kodde and Palm (1986).

We further test whether the assumption of technical change is evident; the hypothesis of no technical change is rejected at the five percent significance level, so incorporation of a time trend is adequate. Thus, the likelihood ratio tests indicate the presence of inefficiency in production and that the determinants of inefficiency should be included in the efficiency effects model specification.

We now turn to the maximum likelihood estimates presented in Table A3 and Table 3. To interpret the estimated first-order parameters of the translog output distance function as elasticities of distance with respect to inputs and outputs evaluated at the sample means, all variables are scaled to have unit means. The share of turnover from market novelties is used as the normalizing output. All the first-order coefficients are statistically significant at the one percent level and they have the expected signs, implying that the output distance function is increasing in outputs and decreasing in inputs at the sample mean. Taking into account the homogeneity restriction presented in equation (7), the estimated output elasticities for the sales shares from market novelties and new products to the firm are found to be 0.385 and 0.614, respectively. Furthermore, since the sum of the input elasticities provides information on scale economies, the RTS is equal to 0.9496, indicating that the technology exhibits moderately increasing returns to scale at the sample mean.

The estimated coefficient of the post-acquisition dummy variable is statistically significant, indicating that the distance function is shifting in the post-acquisition period in relation to the pre-acquisition period. Furthermore, three of the four estimated coefficients of the dummy variables for technology regimes are statistically significant, indicating that the intercept of each estimated distance function is shifted by the technology regime factors vis-à-vis the intercept of an arbitrary base technology regime, i.e. the continuous processing regime. The shifting of the distance function is also apparent between West and East regions.

The parameter estimates for the inefficiency model suggest a number of factors which may explain technical inefficiency of innovative output. The results suggest that innovation constraining factors identified by the firms such as high economic risk, high innovation costs, and lack of technological and market information contribute significantly to R&D inefficiency. For an average firm, however, the inefficiency is not affected by internal organizational rigidities or the lack of qualified employees.

The estimated coefficients on the groups of small and large firms are both positive and statistically significant, indicating presence of significant size effect on the firm's innovative efficiency in the sample. This suggests that manufacturing firms of small and large sizes are less efficient than their counterparts of medium-size.

The estimate for the acquisition dummy variable indicates that innovative inefficiency is lower for an average acquirer of external technology than those for non-acquiring firms during the observed time period.

In addition, the estimated coefficient of the gross capital intensity has a significant negative coefficient, reflecting the fact that inefficiency and fixed assets intensity are negatively related. Thus, an average firm in the sample invests in rather flexible assets which are able to cope with market preferences, thereby increasing efficiency in R&D. The effects of market share and export intensity variables are insignificant. The insignificant coefficient for the time trend shows that inefficiency does not change over time.

The firm's technical efficiency is computed using the conditional expectation of the equation (9), conditioned on the composed error ($e_{it} = v_{it} - u_{it}$), and calculated using the estimated parameters presented in Tables A3 and 3. The summary statistics of the estimated technical efficiency scores are reported in Table 5.

Table 5. Summary statistics for technical efficiency scores

	SAMPLE	ACQ	NACQ
Mean	0.73	0.80	0.67
Standard deviation	0.21	0.19	0.21
Minimum	0.16	0.17	0.16
Median	0.70	0.78	0.68
Maximum	0.92	0.92	0.81
Observations	1,555	426	1,129

In total, the minimum estimated efficiency is 0.16 percent, the maximum is 0.92 percent. The mean efficiency value of 0.73 implies that, on average, the same inputs could have produced 19 percent more of the observed output if the inputs were deployed by firm using the frontier production technology. For the technology outsourcing firms, the mean efficiency is 13 percent larger than it is for non-acquiring firms.

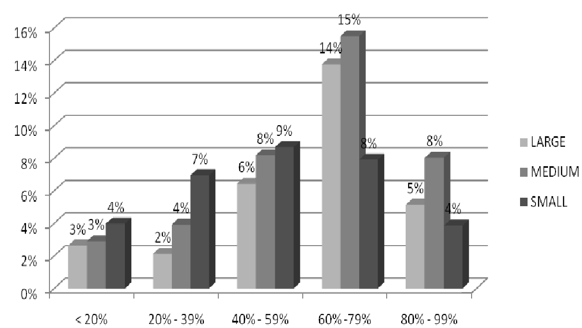
Table 6 shows the distribution of firms across the range of technical efficiencies. Note that the percentages of firms refer to each corresponding group of firms. Across the entire sample, 17 percent of the firms have a technical efficiency in the range above 80 percent, whereas the most technically efficient firms are those firms complementing externally technology to their in-house innovation activity. In contrast, 2 percent of the technology acquirers and 13 percent of the non-acquirers have a mean technical efficiency below 20 percent, and thus are considered technically inefficient.

Table 6. Acquiring and non-acquiring firms by technical efficiency

Technical efficiency (%)	SAMPLE	ACQ	NACQ
< 20	10%	2%	13%
20-39	13%	3%	18%
40-59	23%	10%	30%
60-79	37%	57%	27%
80-99	17%	28%	11%
Total	100%	100%	100%

In Figure 3, the distribution of firms of different sizes across technical efficiency ranges reveals that medium-size and large firms have the highest technical efficiency; 19 and 23 percents of the medium-size and large firms have a mean technical efficiency above 60 per cent, whereas only 12 percent of small firms fall within this range. Small firms are more frequently found in the technical efficiency range of 40 – 59 percent.

Figure 3. Distribution of firm size classes by technical efficiency



In sum, larger firms are more likely to acquire technology externally and firms engaging in external technology acquisitions present more innovative efficiency. However, the relationship between firm size and technical efficiency is curvilinear, implying that medium-size firms, on average, are the most efficient. Thus, smaller firms are, on average, more innovative in terms of innovation output (see Table 2), while medium-size firms are more technically efficient in innovation production.

5.2 Innovative Productivity and Post-Acquisition Changes

In this section we examine the effect of technology acquisition on productivity growth. Total factor productivity growth is computed from the estimated output distance function using equation (4). This allows us to disentangle the effects of technical change, technical efficiency changes and scale efficiency if inputs expand over time, which are evaluated according to the equations (10), (11), and (12), respectively. Table 7 presents summary statistics on the biannual growth of the measures of innovative productivity for technology acquiring and non-acquiring firms separately. Across the entire time period, technical change was strongly biased, accelerating from -3.6 percent to 9.2 percent. Thus, manufacturing firms were likely to render older technologies obsolete at a faster rate.

Table 7. Summary statistics on growth rates of efficiency change, technical change, scale change, and total factor productivity change

	EFFCH		TECHCH		SCALE		TFPCH	
	ACQ	NACQ	ACQ	NACQ	ACQ	NACQ	ACQ	NACQ
Mean	0.0163	0.0181	0.0414	0.0222	0.0203	0.0262	0.0780	0.0665
Std. Dev.	0.0093	0.0059	0.0382	0.0180	0.0177	0.0086	0.0684	0.0302
Min	-0.0267	-0.1920	-0.0360	-0.0161	-0.0051	-0.0210	-0.0678	-0.0229
Median	0.0155	0.0171	0.0451	0.0330	0.0228	0.0240	0.1112	0.0492
Max	0.0224	0.0291	0.0924	0.0617	0.0470	0.0423	0.1618	0.1331
Observation	406	928	406	928	406	928	406	928

Notes: The number of observations is smaller than that in Table 5 due to the inclusion of growth variables.

At the same time, the growth rates in efficiency change and scale efficiency were relatively moderate, ranging from -2.6 percent to 2.9 percent and from -0.5 percent to 4.7 percent, respectively. As a result, output-based TFP growth varies from -6.7 percent to 16.1 percent for technology acquirers, while for non-acquiring firms it ranges from -2.2 percent to 13.3 percent. The average TFP growth rate was 1.2 percent higher for acquiring firms than for non-acquiring firms during the sample period. Thereby, the highest growth rate for technology acquirers is in technical change, at 4.1 percent on average, whereas the highest growth for non-acquiring firms occurs in efficiency change and scale economies, at 1.8 percent and 2.6 percent, respectively.

After assessing the aggregate productivity of an average acquiring and non-acquiring firm, we now focus our analysis on the post-acquisition changes in innovative productivity. In particular, we estimate the effects of external technology acquisitions on innovative productivity, as described in Section 3.2.

First of all, we derive an appropriate counterfactual group for technology acquiring firms by estimating the propensity to outsource external technology using a probit model. The propensity to acquire is defined by the growth rates in innovative productivity and overall performance of firms. More specifically, the firms' growth rates in efficiency change, technical change, and scale efficiency change, as well as in market share, capital intensity, and export intensity, are included as determinants of acquisition probability. Moreover, we include factors indicative of resource and capability constraints to innovation. Note that the determinants are lagged by two years to avoid endogeneity problems in the input-output relationship. In addition, we include dummy variables for firm size classes.

The coefficient estimates of the probit model are shown in Table A4 in the Appendix.[13] Firms with lower technical efficiency change and scale efficiency have a significantly greater propensity to acquire technology externally. Hence, deterioration in innovative efficiency and diseconomies of R&D scale appear to be the driving forces behind the acquisition of disembodied technology. At the same time, firms experiencing greater technological change are more likely to employ external knowledge for their innovation production. Given the productivity determinants, we find that the likelihood of acquiring external knowledge is higher for larger firms. While acquisition of disembodied technology is attracted by the firms that have a scarcity of technological information, the firms identifying the high risk of innovation for marketplace and the firms facing problems with qualified personnel do not use external technology sourcing as a mean for overcoming their resource and capability constraints.

As the next step, we apply nearest-neighbor matching on the predicted propensity scores derived from the estimation described above. Thus, at each point in time, a technology acquiring firm is matched with a non-acquiring firm in the same technology cluster and size class, thereby reducing the possible bias related to unobservable changes. Table A5 in the Appendix displays the balancing outcome of our matching procedure. We include in the matching only variables on annual (e.g., biannual) changes. There are significant differences between the growth variables of acquiring and non-acquiring firms across the whole sample, while the differences of the same characteristics for acquiring and the matched control firms are insignificant. The matching method therefore provides a valid control group to which we compare changes in the productivity growth of technology acquirers.

We estimate for each of the outcome variables two model specifications: one analyzing overall effects on technology acquiring firms and another one accounting for firm size effects of acquirers. The former analysis reveals that medium-size and large firms have greater innovative efficiency and that they engage more in technology acquisition than do small

[13] Note, in this study, the primary aim of estimating the probability function is to find an appropriate control group of firms rather than to examine the determinants of the decision to pursue external technology acquisition, which is a question worthy of a separate investigation.

firms.[14] To study the heterogeneity of the technology acquisition effects for different size classes, we consider therefore the effects of technology acquisition by medium-size and large firms in a separate model by including the acquisition dummies for both size categories (ACQ_{MEDIUM} and ACQ_{LARGE}). Furthermore, the annual (e.g., biannual) changes in certain firm-related variables, such as capital intensity (CAPCH), export intensity (EXPCH), and market share (MSCH), are included as well. In addition, we account for unobserved constant heterogeneity across technological regimes, as well as potential external shocks, by including both technology regime and fixed year dummies. In this case, the OLS method with robust standard errors fits our estimation model well. Since the panel data sample has a cadence of two years, it allows accounting for technology adaptation and integration time after technology sourcing.

Table 8. Effects of external technology acquisition on efficiency change, technical change and scale change

	EFFCH		TECHCH		SCALE	
	(1)	(2)	(3)	(4)	(5)	(6)
ACQ	-0.0297**		0.0167		0.0390***	
	(0.0038)		(0.0289)		(0.0031)	
ACQ_{MEDIUM}		0.0038**		0.0344		0.0458**
		(0.0018)		(0.0401)		(0.0230)
ACQ_{LARGE}		0.0070**		0.0449		0.0419**
		(0.0032)		(0.0487)		(0.0183)
POST	-0.0840***	-0.0695***	0.0586**	0.0501***	-0.0643**	-0.0301***
	(0.0015)	(0.0049)	(0.0231)	(0.0029)	(0.0264)	(0.0019)
ACQ*POST	0.0071**		0.0014*		0.0091***	
	(0.0032)		(0.0008)		(0.0002)	
ACQ_{MEDIUM}*POST		0.0086***		0.0021**		0.0072**
		(0.0006)		(0.0010)		(0.0030)
ACQ_{LARGE}*POST		0.0052**		0.0019		0.0094**
		(0.0021)		(0.0021)		(0.0028)
CAPCH	0.0100	0.0835**	-0.0626**	-0.0290*	-0.0420***	-0.0602***
	(0.0151)	(0.0244)	(0.0217)	(0.0280)	(0.0032)	(0.0029)
EXPCH	0.0764**	0.0431*	-0.2807	-0.2451	0.0637***	0.0887***
	(0.0214)	(0.0270)	(0.3349)	(0.2996)	(0.00471)	(0.0036)
MSCH	0.0551**	0.0461*	- 0.0087	-0.0499	-0.1360	-0.0947
	(0.0201)	(0.0285)	(0.0137)	(0.0842)	(0.1765)	(0.1207)
Constant	0.0127***	0.0582***	0.0220**	0.0490***	0.0699***	0.0801***
	(0.0006)	(0.0008)	(0.0102)	(0.0030)	(0.0048)	(0.0030)
Observation	766	642	766	642	766	642
Adjusted R^2	0.58	0.68	0.62	0.64	0.52	0.62

Notes: The models (1), (3) and (5) include all firms. The models (2), (4) and (6) include medium-size and large firms only. Technological regime and year fixed effects are included.
Robust standard errors are in parentheses. *, **, *** significant at 10%, 5%; and 1%, respectively.

[14] In the last estimation sample (Table 8), we have 383 technology acquisitions in total, whereby 16, 40, and 44 percents of the acquisitions have been carried out by small, medium-size, and large firms, respectively.

A number of interesting insights emerge from the review of the estimates on the effects of technology acquisition in Table 8. The significant positive increase in efficiency change suggests that in the second year following technology acquisition, the efficiency change of the acquirers is 0.71 percent higher than that of non-acquiring firms with similar characteristics. The increase in the average efficiency change is mostly due to the 0.86 percent increase in efficiency change experienced by the medium-size acquirers. The medium-size acquirers show a low increase in technical change, while the large acquirers do not differ from their large non-acquiring counterparts with regard to growth of technical change. This causes a low technical change of 0.1 percent at a 10 percent significance level in the overall sample. Yet, the results is not surprising since the acquiring firms and control group have been matched within their corresponding technology regimes.

The positive and significant values in the scale effect regression imply the presence of increasing returns to scale and input expansion for technology acquirers after technology adaptation in their R&D production. Both medium-size and large acquiring firms have experienced a significantly positive impact on their R&D scale changes. After acquisition of disembodied technology, the medium-size firms have increased their returns to R&D scale by 0.72 percent, while the large firms had even higher returns to scale of 0.94 percent than large firms which rely solely on their internal R&D.

In Table 9, we summarize the growth rates after two years following external technology acquisition. Total productivity growth (TFPCH) is derived as the sum of the three growth components, i.e. EFFCH, TECHCH, and SCALE.

Table 9. Summary of post-acquisition growth rates of efficiency change, technical change, scale change, and total factor productivity change

	ACQ	ACQ_{MEDIUM}	ACQ_{LARGE}
EFFCH	0.0071	0.0086	0.0052
TECHCH	0.0014	0.0021	0.0000
SCALE	0.0091	0.0072	0.0094
TFPCH	0.0176	0.0179	0.0146
Observation/Acquisition	383	152	169

We find that acquisition of disembodied technology increases the innovative productivity of acquiring firms by 1.7 percent compared to the outcome that these firms would have experienced, on average, if they had not acquired external technology. The growth in innovative productivity is mostly driven by R&D scale efficiency change, whereas the contribution of the increase in technical change is only moderate. At the same time, the innovative productivity growth of the medium-size and large firms is higher than that of their non-acquiring counterparts; the differences between these two sizes of acquiring firms are very slight. The 1.7 percent increase in innovative productivity for the medium-size acquirers is due to the increase in efficiency change, while the increase in the large acquirers' innovative productivity of 1.4 percent is driven mostly by R&D scale effects.

To sum up, given the continuous internal R&D, the upgraded exploitation of resources, and capabilities of technology acquiring firms by combining internal and external R&D induce a significant higher innovative productivity growth attributed by increasing returns of R&D scale and innovative efficiency. Although no empirical evidence for this strong complementarity between internal and external R&D in the context of efficiency and productivity in innovation exists so far, our findings are with line to those of Beneito (2006) and Grimpe and Kaiser (2008). The former study finds that contracted R&D improves innovative output performance (measured by patent application) only when it is combined with internal R&D, and the latter study provides evidence that simultaneous use of contractual and internal R&D efforts contribute to innovation success (measured in innovative product sales).

6 Conclusions

The growing complexity, speed, and uncertainty of technological development is increasingly forcing manufacturing firms to make adequate adaptations to the technological changes and quickly respond to the essential technological development – often through external technology acquisition. In contrast to previous studies that investigate the effects of technology acquisition on innovation exclusively in the context of R&D success, in the present paper we investigate whether and to what extent an acquisition of external disembodied technology affects the efficiency and productivity *in* innovation of technology acquiring firms. The analysis in this paper, which is conducted at the most disaggregated level possible with respect to the interrelationship of innovative productivity, external technology sourcing, and firm size, finds that licensing-in and R&D contracting matter innovative efficiency and productivity.

Based on a stochastic frontier analysis approach, the empirical results reveal an R&D inefficiency of 27 percent, on average, for German manufacturing firms during the period from 1994 to 2004. This inefficiency is mostly driven by those firms that rely solely on internal R&D activity, while firms deploying external disembodied technology are, on average, 13 percent less inefficient than non-acquiring firms.

This study provides strong evidence of complementarity between internal and external R&D in innovation production, manifesting as increasing returns to R&D scale and increasing technical efficiency. The manufacturing firms that engaged in the acquisition of external disembodied technology experienced a 1.76 percent greater increase in innovative productivity than non-acquiring firms. In particular, the contribution of an increase in R&D scale efficiency change had considerable effects on the productivity growth increase of the technology acquirers. Overall, the increase in innovative productivity is driven more by medium-size firms engaged in the acquisition of external technology, highlighting that medium-size firms are more capable of adapting and then actually using external knowledge.

The analysis shows that with regard to firm size, firms are distributed quite evenly across different technological regimes, but that the technology regimes themselves show a great deal of diversity in their tendency to acquire external technology. The results also suggest that there are innovative efficiency differentials between manufacturing firms operating within different technological regimes. Although we emphasize the type of technology used by manufacturing firms by disaggregating the industry classification into technological regimes, it would be useful if future work on this topic could be based on a more refined analysis of different technological regimes, something we were not able to accomplish due to data limitations. Nevertheless, we believe the analysis presented in this paper provides a tractable contribution to the understanding of the impact external technology acquisition has on innovative efficiency and productivity, and the results provide encouraging step towards future studies.

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Appendix

Table A1. Sample size and distribution of external technology acquisitions over years

	1992	1994	1996	1998	2000	2002	2004	Total/ Average
Number of observations	109	221	201	272	329	249	174	1,555
Number of acquiring firms	-	43	77	96	123	44	43	426
Percent of acquiring firms	-	19%	38%	35%	37%	18%	25%	27%

Table A2. Application of Marsili's typology (2001) of technological regimes

Technological Regime	Characteristics	NACE Classification
Science based	High technological opportunity; high entry barriers; high cumulativeness of innovation; focus on product innovations.	30, 31, 32, 33
Fundamental process	Medium technological opportunity; high entry barriers, strong persistence on innovation; focus on process innovation.	10, 11, 12, 13, 14, 23, 24
Complex (knowledge) system	Medium to high levels of technological opportunity; entry barriers and persistence on innovation; high degree of differentiation.	29, 34, 35
Production engineering	Medium to high levels of technological opportunity, low entry barriers to innovation, medium persistence on innovation; high technological diversity, focus on product innovation.	25, 26, 27, 28
Continuous process	Low levels of technological opportunity, entry barriers and innovation persistence; heterogeneous technology; differentiated knowledge base.	15, 16, 17, 18, 19, 20, 22, 36, 37

Table A3. Maximum-likelihood estimates for parameters of translog distance function with inefficiency effects model

Variable	Parameter	Estimated value	*t*-statistic
Stochastic distance function			
Constant	α_0	0.4642	6.2170***
X_{INEXP}	α_1	-0.3384	-3.3881***
X_{LRD}	α_2	-0.2014	-5.6513***
X_M	α_3	-0.5132	-2.3881**
Y_{INM}/Y_{INF}	β_1	0.3850	3.3070**
$(X_{INEXP})^2$	α_{11}	0.1632	4.3661***
$(X_{LRD})^2$	α_{22}	0.1897	6.2009***
$(X_M)^2$	α_{33}	0.1123	8.126***
$X_{INEXP}\ X_{LRD}$	α_{12}	-0.0126	-4.6280***
$X_{EXPIN}\ X_M$	α_{13}	-0.0423	-0.9702

$X_{LRD}\,X_M$	α_{23}	-0.1230	-0.3751***
$(Y_{INM}/Y_{INF})^2$	β_{11}	-0.0304	-5.9727***
$X_{INEXP}\,(Y_{INM}/Y_{INF})$	γ_{11}	0.0704	2.7405***
$X_{LRD}(Y_{INM}/Y_{INF})$	γ_{12}	-0.1231	-3.1302***
$X_M(Y_{INM}/Y_{INF})$	γ_{13}	-0.0063	-1.3280
T	φ_t	0.0239	5.3092***
T^2	φ_{tt}	-0.1763	-0.8921
$X_{INEXP}T$	α_{t1}	-0.2326	-4.0726***
$X_{LRD}T$	α_{t2}	0.1945	0.1608
X_MT	α_{t3}	0.2380	4.4122***
$(Y_{INM}/Y_{INF})\,T$	β_{t1}	-0.0247	-0.1963**
POST	ψ	0.2348	2.4087**
SB	ϕ_1	0.4231	3.4521**
CS	ϕ_2	-0.3609	-6.7987***
PE	ϕ_3	0.5004	2.3880**
FP	ϕ_4	-0.4923	-1.5046
WEST	η	0.1930	4.1072***
Variance parameters of distance function			
SIGMA	$\sqrt{\sigma_u^2+\sigma_v^2}$	0.6129	5.7830***
LAMBDA	σ_u / σ_v	2.0468	9.1078***
GAMMA	$\sigma_u^2/\left(\sigma_u^2+\sigma_v^2\right)$	0.7841	8.0236***
Log likelihood	-1433.412		

Note: The translog distance function and inefficiency effects model are estimated simultaneously.
The estimation results of the inefficiency effects model are provided in Table 3.
All variables are in natural logarithm and are normalized by their sample median.
The technology regime of continuous process is the base case used for the comparison among technology regimes. ** and *** significant at 5% and 1%, respectively.

Table A4. Propensity of acquiring external technology

Dependent variable: ACQ

Variable	Estimated value
EFFCH	-0.7480***
	(0.0063)
TECHCH	0.8560**
	(0.3216)
SCALE	-1.0062*
	(0.5229)
CAPCH	-0.1323
	(0.1992)
EXPCH	0.0924***
	(0.0022)
MSCH	0.1495**
	(0.0419)
SMALL	-0.0692*
	(0.0466)
LARGE	0.3983**
	(0.1189)
RISK	-2.3926***
	(0.0613)
COST	0.3681
	(0.4051)
TECH	0.2200***
	(0.0042)
RIG	0.0157

	(0.0437)
PERS	-0.8613**
	(0.4037)
MARKET	0.0576
	(0.0488)
Constant	0.1041***
	(0.0008)
Observation	1,160
Log likelihood	-1,029.98
Prob > ChiSqd	0.00

Notes: The number of observations is smaller than in Table 5 due to the lagged structure of the treatment probability decision. The group of medium-size firms is the base case used for the firm size comparison. Standard errors are in parentheses.
*, **, *** significant at 10%, 5%, and 1%, respectively.

Table A5. Balancing effect of the matching approach

		NACQ	ACQ	CONTROL
EFFCH	Mean	0.0181	0.0161	0.0172
	t-statistic		4.2719***	-1.5225
TECHCH	Mean	0.0222	0.0414	0.0401
	t-statistic		-3.9781***	0.9632
SCALE	Mean	0.0262	0.0203	0.0212
	t-statistic		2.7812**	-1.2043
CAPCH	Mean	0.0141	0.0211	0.0173
	t-statistic		6.4539***	0.5742
EXPCH	Mean	0.0212	0.0309	0.0278
	t-statistic		-4.4878***	1.7592
MSCH	Mean	0.0197	0.0250	0.0212
	t-statistic		-2.5522**	1.1302
Observation		1160	383	383

Notes: ** and *** significant at 5% and 1%, respectively.