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# KOF Working Papers

Technological Diversification and Innovation Performance

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# Technological Diversification and Innovation Performance

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## Abstract

This paper analyzes the impact of technological diversity on innovation inputs and success using Swiss firm-level panel data. While we do not find any impact of diversity on R&D intensity, we confirm a positive impact of diversity on patent applications as suggested by the literature. However, since patent applications reflect an intermediate innovation input rather than output, we extend the analysis to the share of sales generated by new products. We find a significant negative effect of diversity on the sales share of new products. Hence, technologically more specialized firms have a lower propensity to patent and greater shares of new products. We find neither a direct nor indirect effect of diversity on the sales share generated by improved products. These results suggest that specialization pays-off through more drastic innovations that yield greater market success through a passing monopoly status.

JEL Classification: O3

Key words: patent applications, innovative sales share, new products, improved products, technological diversity,

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## 1. Introduction

Evolution means solving current problems (Nelson 1995) and the problem solving capacity of a society strongly depends on the innovativeness of private firms. With the paper at hand we will investigate whether the role of technological diversity differs for the patent success of a firm and for the innovation performance (output) of a firm measured through the sales share of innovative products.

The existing empirical literature mainly consists of two different strands of investigations. On the one hand there are broad empirical studies that investigate the relationship between technological diversification (diversity) and the number of patent applications (innovation input), but they do not provide empirical evidence about how diversity relates to innovation performance in the product market. Such studies proclaim a positive impact of diversity on the number of patent applications (see, e.g., Leten et al., 2007, Garcia-Vega, 2006).

On the other hand there are a few industry specific studies that analyse the relevance of diversity in various stages of the innovation process in the pharmaceutical and biotech sector. They find that the probability of technological success and the probability of market success follow different processes but provide mixed results in terms of how technological diversity affects the various stages (see, e.g., Danzon et al., 2005, Arora et al. 2009, Plotnikova, 2010).

Since the first strand of literature only looks at the patent level, which can be seen as a measure of intermediate innovation input (see, e.g., Griliches, 1998, Brouwer and Kleinknecht, 1999), and the second strand of literature only looks at one very specific industry, we extend the existing literature in the following way. We go beyond a particular industry and beyond the level of patent applications. Furthermore, we provide estimates of quantitative product market success rather than the probability of successful market introduction. This way we detect the two different faces of technological diversity in terms of technological success and market success, which clearly poses a great challenge for policy makers.

Concretely, our study contributes to the existing literature by combining firm-level panel data stemming from the Swiss innovation survey (equivalent to the European “Community Innovation Survey”) with information about patent applications and the corresponding International Patent Classification (IPC) inscriptions for the panel firms. The resulting data set allows us to compare the impact of technological diversity on alternative measures of innovation performance. We contrast the traditional measures “research and development (R&D) intensity” and “number of patent applications” to the widely applied innovation

measure “share of innovative sales” (see, e.g., Miotti and Sachwald, 2003, Belderbos et al. 2004).

Our results confirm the established findings that technological diversification increases the number of patent applications. However, based on a comprehensive control vector we do not find any significant relationship between diversity and R&D intensity. Hence we conclude that diversity is (partly) positively related to innovation input. This confirms existing evidence.

However, we also show that the findings at the technological level (patents) do not necessarily apply at the level of markets. Our analysis of innovation output, for which there exists no broader empirical evidence, suggests a negative impact of diversity on the sales share of new products. This result contradicts the findings for innovation inputs (patents). We argue that the different effects of diversity arise because drastic innovations reduce patent propensity but increase market success. Concretely, since Mansfield and Wagner (1975) we know that technologically more ambitious projects have a greater risk to fail in technological terms but promise a greater degree of novelty and market potential once they pass technological completeness. Hence, in this view, factors driving intermediate innovation input (patents) may hinder innovation output, since different levels of completion might require different skills or different types of strategies. That view is consistent with what we observe in terms of diversity. Technological diversification increases patent propensity but decreases the sales share of new products. We strengthen our explanation of this contradiction by showing that diversity has no impact on the share of improved products, implying that diversity decreases the propensity of more advanced (radical) innovation output but not incremental innovation output. However, the relationship between diversity, innovation output, degree of novelty and market success requires further empirical investigations.

The results of the study at hand further point at some policy issues. Risk-averse firms and managers (Miller 2006) prefer technologically less ambitious projects with larger probability of project completion and patenting. However, such projects promise lower benefits in the market and smaller spillovers to the larger economy. Hence, encouraging firms to take up a more risky project appears to provide a promising route for policy makers to take, thereby improving both the market success of firms and the generated spillovers.

The paper is organized as follows. Section 2 discusses the relationship between technological diversification and innovation based on the existing literature and develops our research

hypotheses. Section 3 presents the employed data set and econometric specification. Section 4 discusses the results and section 5 concludes the paper.

## **2. Literature Review and Hypothesis**

The paper at hand focuses on the relationship between technological diversification and the innovation output of a firm, where innovation output is measured in two different ways, i.e. sales share of essentially modified products and sales share of new products.

Existing empirical investigations look at the role of technological diversification for innovation input (R&D intensity), intermediate innovation input (patents) and firm performance (profitability or financial performance of firms (e.g. Kim et al. 2009, Miller 2006, Chiu et al. 2008)). However, they disregard the meaning of technological diversification for innovation output. Hence, in investigating the level of innovation success, the study at hand fills a research gap.

### *Benefits of technological diversification*

There is extensive evidence that technological diversification increases patent propensity. Garcia-Vega (2006), Gambardella and Torrisi (1998), Gemba and Kodama (2001), and Nesta and Saviotti (2005) found a positive relationship, while Leten et al. (2007) found an inverted-U relationship between technological diversification and number of patent application. Moreover Leten et al. (2007) showed that a higher level of coherence in the technology portfolio increases the positive relationship between technological diversification and the number of patent applications.

One reasoning for the observed relationship suggests that a diverse knowledge structure increases the absorptive capacity of firms (Cohen and Levinthal 1989, 1990). The absorptive capacity enables a firm to keep track of the technological developments outside its core capabilities. This way, it can lower the risk of technological lock-in effects, since it is unlikely that the economic potential and competence destroying character of alternative technologies are overseen. Furthermore, a diverse knowledge base makes it more likely to benefit from spillovers from other (related) technological fields (Garcia-Vega 2006) and it opens a broader field of potential technological opportunities, where research fields do cross-fertilize each

other and help to develop new technologies (Leten et al. 2007). It is also more likely that diverse firms are collaborating with science institutions or other firms in order to transfer knowledge, since links are more easily created.

Moreover firms benefit from diversification, since it creates further investment incentives. Such incentives are generated at least for two reasons. Firstly, diversification reduces the risk of technological investments (provided that the projects are negatively correlated), since R&D investments are distributed over diverging projects and therefore the probability of technological success increases. Secondly, there is evidence that technologically diversified firms patent close to related fields (Breschi et al. 2003). This is true in particular for very large diversifiers. By filling up technological gaps in their portfolio, they increase the density of their knowledge and further protect the firm's knowledge base. This way, they increase their number of patents.

A further reason put forward by Leten et al. (2007) is the fixed cost nature of R&D capabilities implying that excess resources might be used to diversify into new technological fields (see e.g. Schumpeter, 1942).

#### *Costs of technological diversification*

However, technological diversification is a costly exercise (Danneels 2002). Researchers have to tap into new research fields with considerable uncertainty about technological possibilities until positive learning effects occur. Learning comes along with a sufficiently large knowledge stock in a single technology, which is costly to build. Costs of equipment and salaries of researchers might be particularly high in respect to the creation of drastic innovations.

Furthermore, diversity creates additional communication requirements and coordination duties (Leten et al. 2007). This increases costs not only on the level of the R&D activities but also on value chain steps following technological development. Argyres (1996) found that interdivisional coordination costs are lower for more specialized R&D. However, firms accept to some extent increasing costs of diversification, since they want to reduce risks. Consequently, risk averse managers tend to diversify too much in order to lower the risk of technological development (Miller 2006).

Several studies suggest that beyond a certain point, the benefits of diversity are outweighed by increasing coordination costs (Holmström 1989, Zenger 1994). Similarly, Leten et al. (2007)



combine costs and benefits arguments by suggesting that the costs of diversification increase more than proportionally while the benefits have a decreasing marginal return. They support this view by empirically showing an inverted U-shaped relationship between technological diversification and patent activities. Similar evidence has already been brought forward by Henderson and Cockburn (1996) investigating the pharmaceutical industry. They detected synergies in conducting two or more related, comprehensive research projects. However, a further increase in the number of comprehensive projects has a negative effect on patent applications, suggesting an inverted U-shaped relationship between the number of large scale research projects and patent applications. Similarly, Alonso-Borrego and Forcadell (2010) found an inverted U-shaped relationship between related diversity and R&D intensity.

Given the arguments about benefits and costs of technological diversifications and the empirical findings so far, we suggest the following two hypotheses:

*Hypothesis 1: Technological diversification is positively related with patent activities/R&D intensity.*

*Hypothesis 2: Technological diversification is negatively related with patent activities/R&D intensity if diversification goes beyond certain limits.*

#### *Technological diversification at the expense of market success*

The findings at the technological level do not necessarily apply at the level of markets. It is plausible that factors supporting the technological development in terms of patent applications are hindering the market success of innovative products measured through sales share of new or improved products. Hence, this section argues that technological diversification is negatively correlated with the sales share of new products.

Following Mansfield and Wagner (1975) it is reasonable to separate technological success (e.g. patent application) from market success (e.g. sales share of innovative products). They found that the rate of technological completion goes down if firms invest a larger share of R&D expenditures in technological advanced projects selected by the R&D department. Technological completion can be indicated by a prototype or a patent application. However, once the technological difficulties of such technologically advanced projects are solved and the project leads to a market product, such products are likely to exert an above average

market success. On the contrary, if we would observe a strong intervention of other than R&D departments (e.g. marketing) in R&D project decisions, it is likely that the probability of technological success increases, since marketing is expected to be less ambitious in terms of technology. However, less demanding technological goals lower the magnitude of market success, since the degree of novelty is lower. Similarly, Atuahene-Gima and Evangelista (2000) found that the influence of marketing people (as reported by R&D people) significantly lowers new product performance.

Arguing that spillover effects of research projects are more important for technological success than for market success, a small literature studies the probability of completing the various stages of the innovation process in the pharmaceutical and biotech industries. They show that the probability of technological success and the probability of market success represent different processes, but find mixed results in terms of how technological diversity affects the different innovation stages (Danzon et al. 2005, Arora et al. 2009, Plotnikova 2010).

Furthermore, the following paragraphs develop two additional reasons, why the impact of diversity differs between patent applications and market success.

First, it is plausible to assume that technological specialization is necessary for drastic innovations (see Woerter 2009), because a large, specialized knowledge stock is required to produce the desired learning effects to further the progress in scientific disciplines, and to develop new technologies or to file far-ranging patents. This view is supported by the anecdotal evidence in respect to the great technological breakthroughs during the last decades, in which specialized knowledge at universities broke the ground for new innovative products. Biotechnology clearly has its origins at very specialized university institutes and also the discovery of the nanoscale goes back to specialized research groups at universities. Subsequently, this knowledge has been transferred to the private sector and essentially contributed to new products (Zucker et al. 2002, Arvanitis et al. 2008). Secondly, this relationship between drastic innovations, their market performance and patenting activity is further strengthened by the fact that patents of drastic innovations enjoy broader protection with longer effective patent live than incremental patents, since it is more difficult for the patent examiner to object broader protection claims from applicants if the invention opens up a new field (European Patent Office 2000)<sup>1</sup>. A similar argument is that very advanced firms

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<sup>1</sup> Usually it is left to the courts to limit patent protection (Merges and Nelson 1990). However, broader patents are likely to be challenged by infringement or patent validity trials induced by competitors. If such trials are successful, effective protection time could be shortened (Yiannaka and Fulton 2006).

might have a lower patent propensity because they do not want to disclose the necessary information for the patent application. They prefer other protection mechanisms (e.g. secrecy). These arguments suggest that frequency of patents and the market success of new products are negatively correlated.

Given that drastic innovations are likely to be triggered by very specialized knowledge and that drastic innovations are granted broader patent protection that is difficult to challenge by competitors, we would formulate the following hypotheses:

*Hypotheses 3: Technological diversification decreases the sales share of new products.*

Since incremental innovations do not require the same degree of learning, the relevance of cross-fertilization and coordination costs dominate learning effects in respect to the market success obtained from improved products. Hence, we hypothesize that

*Hypotheses 4: Technological diversification increases the sales share of improved products.*

While hypotheses 1 to hypotheses 4 represent our main fields of investigation, our econometric setting allows for testing of less controversial hypotheses. Griliches (1998) and Brouwer and Kleinknecht (1999) suggest that patents are an intermediate innovation input. Hence, we formulate the following hypothesis:

*Hypothesis 5: Patent stock increases innovation output, i.e. sales share generated by new and improved products.*

### **3. Data and Methodology**

The employed panel data stems from 5 waves of the Swiss innovation survey<sup>2</sup> conducted by the KOF in the years  $t=\{1996, 1999, 2002, 2005, \text{ and } 2008\}$ , where  $t$  denotes the time period. The surveys are based on a disproportionately stratified random sample of firms with more than 5 employees (full time equivalent) covering the most important industries of the

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<sup>2</sup> Questionnaires of the survey, which resembles closely the “Community Innovation Survey”, are available at [www.kof.ethz.ch](http://www.kof.ethz.ch) in German, Italian, and French language.

manufacturing, construction and service sector. Stratification takes place on industry and within each industry on three firm size classes. Responses were received from 1748 (32.5%), 2172 firms (33.8%), 2583 firms (39.6%), 2555 firms (38.7%), and 2141 (36.1%) for the years 1996, 1999, 2002, 2005 and 2008 respectively. However, the investigation at hand only uses data from R&D active manufacturing firms. Dropping observations with missing values yields a highly unbalanced firm-panel with 1457 observations.

We enrich the innovation survey with information about patent applications from the European Patent Office (EPO). Patents and the corresponding technological fields have been collected in cooperation with a specialized firm, NetBreeze<sup>3</sup>, using the patent information available on “esp@cenet” (patent applications and granted patents around the world - [www.espacenet.com](http://www.espacenet.com)). This allows us to construct the existing patent stock of a firm and the number of new patent applications in a period. Given the three-year periodicity of the innovation survey, we define the number of new patent applications ( $Patents_{it}$ ) of firm  $i$  in period  $t$  as the sum of patent applications over the corresponding three years. Following the perpetual inventory method (Cockburn and Griliches, 1988), the patent stock ( $Patent\ Stock_{it}$ ) of firm  $i$  in period  $t$  refers to the discounted sum of patent applications in the six years before the period, where we follow the literature in assuming a geometric discounting process with depreciation rate of 15% (see, e.g., Keller 2002, Aghion et al. 2011).

The patent data also entails information about patent section inscriptions (IPC code). Following Garcia-Vega (2006), we define diversity ( $Div_{it}$ ) as one minus the Herfindahl index, which is calculated as the sum of squared patent section inscription shares:

$$Div_{it} = 1 - \left( \sum_j (N_{jit} / N_{it})^2 \right)$$

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<sup>3</sup> [www.netbreeze.ch](http://www.netbreeze.ch)

$N_{jit}$  denotes the discounted number of patent section inscriptions of firm  $i$ 's patent stock in section  $j$  in period  $t$ . The discounted patent stock in period  $t$ ,  $N_{it}$ , refers to the discounted sum of patent applications in the six years before the period.

This paper employs two types of dependent variables (see Table 1). Following the existing literature (see, e.g., Garcia-Vega 2006, Leten et al. 2007), the first type refers to innovation inputs. We differentiate two innovation inputs, namely R&D intensity ( $R\&D\ Intensity_{it}$ ) and the intermediate input, patent applications in the current three-year period,  $t$  ( $Patents_{it}$ ).

Insert Table 1 about here

Following Leten et al. (2007) and Garcia-Vega (2006), we control for R&D intensity ( $R\&D\ Intensity_{it}$ ), firm size ( $Size_{it}$ ) and the existing patent stock ( $Patent\ Stock_{it}$ ). Since our measure for diversity can take the value 0 either because a firm has no patents or because all patents fall into a single patent section, we further include a dummy variable indicating whether the patent stock of a firm is empty ( $Patdummy_{it}$ ). In order to capture the differences in the ability of patents in protecting innovations, we further include a dummy variable that indicates whether protection measures (e.g. patents, copyrights, secrecy) are effective ( $Protection_{it}$ ). In addition, we include the share of personnel with tertiary education ( $Qualification_{it}$ ) to account for the firm's absorptive capacity. Year dummies ( $\alpha_t$ ) capture unobserved heterogeneity across time (for the summary statistics see Table 2).

Insert Table 2 about here

Building the diversity index based on the lagged patent stock in  $(t-1)$  and  $(t-2)$  accounts for reverse causality. In order to address the problem of unobserved heterogeneity (e.g. management abilities), we include individual intercepts ( $\alpha_i$ ), i.e. present fixed effects estimates.

Hence, we write our econometric estimations for R&D intensity as

$$\ln R \& D_{it} = \alpha_1 + \alpha_{1t} + \alpha_{1i} + \beta_1 \ln Diversity_{it-1} + \gamma_{11} Patdummy_{it-1} + \gamma_{12} \ln PatentStock_{it-1} + \delta_{11} Protection_{it} + \delta_{12} \ln Size_{it} + \delta_{13} \ln Size_{it}^2 + \delta_{14} \ln Qualification_{it} + \varepsilon_{1it} \quad (1)$$

The estimation strategy for new patent applications is essentially the same as for the R&D intensity. However, we use the fixed effect zero-inflated negative binomial regression (Hausman et al., 1984, Cameron and Trivedi, 1986) to account for both overdispersion and count data nature of new patent applications.

In addition, we include R&D intensity in the patent application equation, i.e. assume that current R&D intensity serves as an input in the production process of the intermediate innovation input, patent applications. In order to account for the potential endogeneity of the R&D intensity, we use the industry average to instrument R&D intensity.<sup>4</sup> We bootstrap the standard errors to account for the non-simultaneity of our instrumental variable approach. Hence the equation for new patent applications is given by

$$\begin{aligned} Patnew_{it} = & \alpha_2 + \alpha_{2t} + \alpha_{2i} + \beta_2 \ln Diversity_{it-1} + \delta_{11} \ln \hat{R} \& DIntensity_{it} \\ & + \gamma_{21} Patdummy_{it-1} + \gamma_{22} \ln PatentStock_{it-1} + \delta_{21} Protection_{it} \\ & + \delta_{22} \ln Size_{it} + \delta_{23} \ln Size_{it}^2 + \delta_{24} \ln Qualification_{it} + \varepsilon_{2it} \end{aligned} \quad (2)$$

The second type of dependent variable measures the sales share of innovative sales, a widely applied measure of innovation output (see, e.g., Miotti and Sachwald, 2003, Belderbos et al. 2004). The paper differentiates between innovative sales due to new products (New) and innovative sales due to improved products (Imp). Hence we can distinguish between more advanced (drastic) and incremental innovations. The OLS estimations for sales generated by new and improved products entail the same set of control variables as the equation for patent applications:

$$\begin{aligned} \ln Salesshare_{it} = & \alpha_3 + \alpha_{3t} + \alpha_{3i} + \beta_3 \ln Diversity_{it-1} + \delta_{31} \ln \hat{R} \& DIntensity_{it} \\ & + \gamma_{31} Patdummy_{it-1} + \gamma_{32} \ln Patstock_{it-1} + \delta_{31} Protection_{it} \\ & + \delta_{32} \ln Size_{it} + \delta_{33} \ln Size_{it}^2 + \delta_{34} \ln Qualification_{it} + \varepsilon_{3it} \end{aligned} \quad (3)$$

#### 4. Results

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<sup>4</sup> To ensure that our instrument is not driven by the correlation of the firms R&D intensity and the industry average, we calculate the average excluding the R&D intensity of the firm.

Table 3 presents crosscorrelations of the variables. As expected we see – on the one hand – a strong positive correlation between ‘diversity’, ‘patent stock’, and ‘patents’ respectively. Also ‘patents’ and ‘size’ as well as ‘R&D intensity’ and ‘qualification’ are clearly positively correlated. On the other hand we see a slightly negative correlation between ‘new sales’ and ‘diversity’. These results point already at different effects of ‘diversity’ on ‘patents’ and on ‘new sales’, respectively.

Insert Table 3 about here

Table 4 displays our main results for the innovation input variables, R&D intensity and patent applications. The left-hand panel, i.e. the first three columns, report regressions on R&D intensity using alternative functional forms for diversity. Columns one and two entail simple linear (Diversity) and quadratic specifications (Diversity<sup>2</sup>). In order to account for the large number of firms with zero diversification, column three further shows the results of a linear specification that additionally includes a dummy variable indicating whether diversity takes the value zero (Diversity=0). Thereby, we control for the large number of firms with a single patent. These firms necessarily have a diversity of 0 though this might not necessarily reflect a specialization choice. The right hand panel, i.e. columns four through six, show the same set of specifications for the regressions using the number of new patent applications as dependent variable.

The left-hand panel of Table 4 analyzing R&D intensity supports neither hypothesis 1 nor hypothesis 2, as we do not find any significant impact of technological diversification on R&D intensity. Because we estimate a model with firm fixed effects, we do not find any impact of the dummy measuring past patenting, the patent stock, protection effectiveness or firm size on R&D intensity. However, the results provide mild evidence for a positive impact of the share of workers holding a tertiary education, though only at a 10% significance level. Moreover, we see a significant positive impact of the industry average of R&D expenditures (excluding the single firm) on the R&D expenditures of the firm (see Table 6). Hence, the technological regime under which a firm operates is very important for its R&D expenditures (see Peneder 2010, Peneder and Woerter 2013).

*Insert Table 4 about here*

The right hand-panel of Table 4 supports hypothesis 1, stating that diversity increases patenting activity as proposed by Gambardella and Torrisi (1998), Gemba and Kodama (2001), Nesta and Saviotti (2005) and Garcia-Vega (2006).<sup>5</sup> Concretely, the log of diversity is significantly positive in both models allowing for non-linearity in the impact of diversity. Remarkably, we also see a positive sign of the quadratic diversity term, although the coefficient is rather small. However, this result contradicts the findings of Leten et al. (2007) suggesting an inverse U-relationship between technological diversification and patent propensity.<sup>6</sup>

In respect to the other control variables, we see an insignificant coefficient for the patent dummy. Since patenting activity is highly persistent, this might indicate that our fixed effect estimator has too little variation to identify the effect. If we look at the patent stock, we see the expected positive relationship between the knowledge base of a firm and its patent affinity. Rather surprisingly, we find no significant impact of protection effectiveness on new patent applications, though the effect has the expected positive sign. Furthermore, R&D intensity, size and the share of qualified workers have a negative sign, though only the coefficient of size is significant.<sup>7</sup>

Table 5 displays the results of our analysis of innovation output measured as the sales share of new products or, alternatively as the sales share of improved products. As for innovation inputs, we show three models for each of the dependent variables, namely one including the log of diversity, one additionally including the square of it and one including a dummy variable indicating zero diversity. The results for the sales share of new and improved products appear in the left and right-hand panels, respectively.

Hypotheses 3 suggests that diversity is negatively related with the sales share of new products, since technological specialization is necessary for a more drastic type of innovation and only drastic innovations are likely to yield considerable sales shares of new products. In fact, we find that diversity decreases the sales share of new products as the coefficient of the

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<sup>5</sup> The lower number of observations arises because the number of patent applications does not differ over time in about 50% of the sample.

<sup>6</sup> Those differences might be due to the fact that Leten et al. (2007) have a relatively small sample of 187 firms and focus on high-tech industries, i.e. pharmaceuticals and biotechnology; chemicals; engineering and general machinery; information technology (IT) hardware (i.e., computers and communication equipment); and electronics and electrical machinery.

<sup>7</sup> Preliminary analysis suggests a multicollinearity problem with the patent stock. Concretely, dropping patent stock from the estimation renders size insignificant, though still negative. The results in respect to diversity remain qualitatively the same. These results are available upon request from the authors. As our model focuses on the impact of diversity, we have chosen to include all of the control variables in the estimation.



log of diversity is negative in all three models. Given the technological success, more specialized firms reap greater sales shares from new products compared to more diverse firms. Hence, our findings support hypothesis 3.

Taking together the results from the patent equation in Table 4 and the results for sales share of new products we find a similar phenomenon like Mansfield and Wagner (1975), i.e. diversity is positively related with the number of patent application and negatively related with the sales share of new products. As suggested by hypothesis 3, this might be because learning processes are more important for drastic innovations. Alternatively, it might reflect the lower patenting propensity of firms pursuing drastic innovations due to broader patent protection or higher relevance of other means of protecting their intellectual property (e.g. secrecy).

This reasoning is also in line with the empirical results supporting hypothesis 4, i.e. that diversity is unrelated with the sales share of improved products (see Table 5; last three columns). Improved products have a lower degree of innovativeness and they are more similar to already existing products. Specialized firms do not have any particular advantages in modifying existing products, since learning effects are less relevant. Following the results from Cantner and Plotnikova (2009) technologically more diversified firms have a more diversified product portfolio. Since product diversification quite often goes along with product modification, technologically diversified firms are more likely to modify products.

*Insert Table 5 about here*

Hypothesis 5 suggests that the stock of patents increases innovation output measured by the share of sales generated by both new and improved products. Our findings support this hypothesis, partly. Concretely, differentiating between the share of new and improved products reveals a positive influence of the patent stock on the share of new, but not of improved products. This finding suggests that the patent stock improves the ability of firms to produce drastic innovations. However, the coefficient turns negative in the estimations analyzing the process of improving existing products, though only marginally significant. This supports the idea that innovating (exploring) and exploiting the existing product base create conflicting interests (Arrow, 1962, March 1991).

Furthermore, we find that protection effectiveness has a significantly negative effect on the sales share of new products, but no impact on sales share of improved products. This finding supports the theoretical argument that if patents protect innovations ineffectively, firms are forced to conduct radical innovations, thereby protecting innovation rents by gaining a substantial head-start from competitors.

In respect to the control variables, we find a positive impact of R&D intensity on the sales share of new products and a negative, though only marginally significant impact on sales shares of improved products. The negative sign of R&D intensity points to a clash between exploration of new knowledge and exploitation of existing knowledge (March 1991). Size remains insignificant in all models. Qualification enters the new share equation marginally negative and the improved share equation insignificantly positive.

*Insert Table 6 about here*

## **5. Conclusions**

Based on comprehensive firm-level panel data across 12 years we investigate, on the one hand, the relationship between technological diversification (diversity) and patent propensity of firms and on the other hand, the relationship between technological diversification and sales share of innovative products. Our empirical results show that the impact of diversity differs between intermediate innovation input and innovation output, thereby questioning the existing literature that collapses the innovation process into a single stage. Concretely, we do not find any impact of patent stock or diversity on R&D intensity, while both significantly increase patent applications. We also find a negative direct impact of diversity on sales share of new products and no effect of diversity on sales share of improved products.

Our results confirm the results from other investigations, i.e. that diversity is positively related with patent application. Moreover, and most interestingly, we see that diversity is negatively related with the sales share of new products. This is the first evidence for such a connection in the related empirical literature.

This result is somehow puzzling. However, if we think along the lines of Mansfield and Wagner (1975) or the step-by-step approach in the pharmaceutical industry (Danzon et al. 2005, Plotnikova 2010, Arora et al. 2009), the results appear in a different light, namely that

technological success (patents) and market success (sales share of new products) are driven by different factors. In particular, drastic innovation projects have a lower probability of technological completion and hence of resulting in a patent. However, the market potential of drastic innovations exceeds the market potential of incremental innovations. Hence, assuming that learning effects are very important for drastic innovations explains why diversity increases patent applications but reduces market success.

Furthermore, we argue that technologically specialized firms have a lower patent propensity, since their patents receive a broader protection status. Hence there is less need to patent strategically in order to avoid imitation. In addition it is likely that technologically very advanced firms might not patent at all, since they even do not want to disclose the necessary information for the patent application. They prefer other protection mechanisms (e.g. secrecy). However, once they have successfully passed the technological step and a new product has been developed, the expected market competition is low and the market potential of the new product considerable.

From a policy point of view we see that more drastic innovations based on specialized knowledge have greater market potential, hence, providing greater consumer benefits. Since specialization and very advanced technological goals involve greater risk of technological completion, the majority of firms would pursue more moderate technological goals. Hence, public innovation policy should aim at promoting more advanced technological projects.

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## Tables

Table 1: Variable Description

Variable	Description
R&D Intensity	Research and Development (R&D) expenditures divided by sales
Patents	Number of patent applications in t*
Innovative Sales	Share of sales generated by innovative products in %
New Sales	Share of sales generated by new products in %
Improved Sales	Share of sales generated by improved products in %
Diversity	One minus the Herfindahl index based on patent section inscriptions in (t-1) and (t-2)*
Patdummy	Dummy variable that takes the value 1 if the Patent stock is nonzero and 0 otherwise
Patent Stock	Number of patent applications in (t-1) and (t-2)*
Protection	Dummy variable that takes the value 1 if the effectiveness of product innovation protection, e.g. through patents, copyrights, secrecy, is high (4 or 5 on a 5 point Likert scale) and 0 otherwise
Qualification	Share of personnel with tertiary education in %
Size	Number of employees (full-time equivalents) in 1000

\* t refers to a 3 year period

Table 2: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
R&D Intensity	1457	3.58	4.88	0	49.83
Patents	1457	10.84	56.34	0	1102
New Sales	1457	18.95	19.30	0	100
Improved Sales	1457	21.02	18.91	0	100
Diversity	1457	0.35	0.61	0	3.25
Patdummy	1457	0.45	0.50	0	1
Patent Stock	1457	11.28	37.67	0	616
Protection	1457	0.48	0.50	0	1
Size	1457	372.95	1055.45	1	15170
Qualification	1457	22.41	16.75	0	100

Table 3: Crosscorrelations

	R&D Intensity	Patents	New Sales	Improved Sales	Diversity	Patdummy	Patent Stock	Protection	Size
R&D Intensity	1								
Patents	0.0357	1							
New Sales	0.1674	0.0229	1						
Improved Sales	0.0704	0.0068	-0.0496	1					
Diversity	0.0966	0.3218	-0.0064	0.0223	1				
Patdummy	0.079	0.1896	0.018	0.0197	0.633	1			
Patent Stock	0.0344	0.4641	0.0442	0.0347	0.5711	0.3338	1		
Protection	0.0322	0.0327	-0.0077	-0.0215	0.0045	-0.0054	0.0305	1	
Size	0.115	0.3528	0.0386	0.0033	0.1426	0.0518	0.1751	0.0945	1
Qualification	0.3487	0.0849	0.0808	0.0992	0.085	0.0658	0.078	-0.0071	0.1349

Table 4: Estimation Results of R&amp;D Intensity and Patent Applications

Dep Var	lnR&D Intensity	lnR&D Intensity	lnR&D Intensity	Patents	Patents	Patents
Diversity=0			0.364 (0.396)			1.823** (0.796)
lnDiversity	-0.000 (0.024)	0.106 (0.169)	0.090 (0.103)	-0.027 (0.057)	0.583** (0.288)	0.415** (0.194)
lnDiversity^2		0.021 (0.032)			0.120** (0.056)	
ln $\hat{R}$ & $D$ Intensity				-1.349 (0.869)	-1.392 (0.891)	-1.438* (0.829)
Patdummy	-0.013 (0.077)	-0.009 (0.079)	-0.009 (0.078)	-0.070 (0.252)	0.009 (0.257)	0.004 (0.270)
lnPatent Stock	-0.025 (0.050)	-0.027 (0.050)	-0.026 (0.049)	0.484*** (0.081)	0.474*** (0.079)	0.480*** (0.084)
Protection	0.040 (0.041)	0.039 (0.041)	0.038 (0.041)	0.085 (0.109)	0.071 (0.116)	0.069 (0.107)
lnSize	0.009 (0.121)	0.005 (0.122)	0.003 (0.122)	-0.320** (0.158)	-0.339** (0.165)	-0.344** (0.158)
lnSize^2	0.003 (0.023)	0.003 (0.023)	0.003 (0.023)	-0.068 (0.043)	-0.073* (0.043)	-0.073* (0.043)
lnQualification	0.041* (0.025)	0.042* (0.025)	0.042* (0.025)	-0.015 (0.094)	-0.007 (0.076)	-0.005 (0.082)
1999	-0.304*** (0.063)	-0.303*** (0.063)	-0.304*** (0.063)	-0.665** (0.316)	-0.650** (0.307)	-0.665** (0.314)
2002	0.072 (0.060)	0.073 (0.060)	0.073 (0.060)	-0.197 (0.190)	-0.163 (0.192)	-0.165 (0.189)
2005	0.087 (0.054)	0.088 (0.054)	0.087 (0.054)	0.055 (0.174)	0.078 (0.162)	0.077 (0.145)
2008	0.050 (0.049)	0.050 (0.049)	0.049 (0.049)	-0.148 (0.135)	-0.120 (0.131)	-0.120 (0.129)
Constant	1.076*** (0.195)	1.123*** (0.201)	1.118*** (0.194)	0.203 (1.036)	0.470 (1.059)	0.468 (1.053)
N	1457	1457	1457	729	729	729

The left-hand panel shows OLS fixed effect coefficient estimates and the right-hand panel displays marginal effects of zero-inflated negative binomial fixed effect regressions. Standard errors appear in parentheses, which are robust in the R&D equations and bootstrapped in the patent equations. \*, \*\* and \*\*\* denote significance on the levels 10%, 5% and 1%, respectively.  $\hat{R}$  &  $D$  Intensity refers to predicted values based on the corresponding R&D equation in table 6.



Table 5: Estimation Results of Sales Share of New and Improved Products

Dep Var	lnNew Sales	lnNew Sales	lnNew Sales	lnImproved Sales	lnImproved Sales	lnImproved Sales
Diversity=0			-1.330*			-0.377
			(0.789)			(1.008)
lnDiversity	-0.102**	-0.595*	-0.433**	0.045	-0.030	-0.049
	(0.040)	(0.305)	(0.202)	(0.046)	(0.344)	(0.243)
lnDiversity^2		-0.095			-0.014	
		(0.058)			(0.067)	
ln $\hat{R}$ & D Intensity	1.363**	1.394**	1.414**	-1.354	-1.349*	-1.340
	(0.588)	(0.618)	(0.621)	(0.853)	(0.812)	(0.834)
Patdummy	-0.086	-0.107	-0.100	0.085	0.082	0.081
	(0.140)	(0.149)	(0.138)	(0.156)	(0.149)	(0.168)
lnPatent Stock	0.148*	0.156**	0.150*	-0.183*	-0.181*	-0.182*
	(0.076)	(0.079)	(0.079)	(0.094)	(0.098)	(0.099)
Protection	-0.151**	-0.149**	-0.148**	0.039	0.040	0.040
	(0.073)	(0.064)	(0.072)	(0.081)	(0.095)	(0.086)
lnSize	-0.080	-0.062	-0.059	0.273	0.276	0.280
	(0.264)	(0.249)	(0.265)	(0.326)	(0.333)	(0.331)
lnSize^2	-0.055	-0.055	-0.054	-0.003	-0.003	-0.003
	(0.055)	(0.056)	(0.055)	(0.077)	(0.084)	(0.083)
lnQualification	-0.105**	-0.109**	-0.110**	0.070	0.069	0.069
	(0.052)	(0.054)	(0.051)	(0.066)	(0.073)	(0.067)
1999	0.656***	0.663***	0.670***	-0.275	-0.273	-0.270
	(0.210)	(0.225)	(0.237)	(0.269)	(0.281)	(0.286)
2002	0.061	0.051	0.052	0.190	0.188	0.187
	(0.110)	(0.109)	(0.104)	(0.139)	(0.131)	(0.132)
2005	-0.150	-0.155	-0.155	-0.034	-0.035	-0.035
	(0.109)	(0.112)	(0.108)	(0.144)	(0.136)	(0.137)
2008	-0.208**	-0.209**	-0.209**	-0.051	-0.051	-0.051
	(0.095)	(0.100)	(0.085)	(0.116)	(0.109)	(0.118)
Constant	0.932	0.683	0.726	4.829***	4.791***	4.770***
	(0.729)	(0.784)	(0.849)	(1.061)	(1.048)	(1.035)
N	1457	1457	1457	1457	1457	1457

The table shows OLS fixed effect coefficient estimates and bootstrapped standard errors in parentheses. \*, \*\* and \*\*\* denote significance on the levels 10%, 5% and 1%, respectively.  $\hat{R}$  & D Intensity refers to predicted values based on the corresponding R&D equation in table 6.

Table 6: Instrumental Variable Regressions for R&amp;D intensity

Dep Var	lnR&D Intensity	lnR&D Intensity	lnR&D Intensity
Diversity=0			0.321 (0.389)
lnDiversity	0.000 (0.024)	0.096 (0.167)	0.080 (0.101)
lnDiversity^2		0.018 (0.031)	
lnR&D Average	0.240** (0.105)	0.239** (0.105)	0.237** (0.105)
Patdummy	-0.013 (0.077)	-0.009 (0.079)	-0.010 (0.078)
lnPatent Stock	-0.031 (0.050)	-0.033 (0.050)	-0.031 (0.050)
Protection	0.035 (0.041)	0.035 (0.041)	0.034 (0.041)
lnSize	0.022 (0.120)	0.018 (0.121)	0.016 (0.121)
lnSize^2	0.006 (0.023)	0.006 (0.023)	0.005 (0.023)
lnQualification	0.044* (0.026)	0.044* (0.026)	0.044* (0.026)
1999	-0.259*** (0.064)	-0.259*** (0.064)	-0.259*** (0.064)
2002	0.050 (0.062)	0.051 (0.062)	0.051 (0.062)
2005	0.069 (0.055)	0.070 (0.055)	0.069 (0.055)
2008	0.032 (0.049)	0.032 (0.049)	0.032 (0.049)
Constant	0.813*** (0.236)	0.856*** (0.238)	0.853*** (0.233)
N	1457	1457	1457

The table shows OLS fixed effect coefficient estimates. Robust standard errors appear in parentheses. \*,\*\* and \*\*\* denote significance on the levels 10%, 5% and 1%, respectively. The instrument, R&D Average, refers to the industry average of R&D Intensity excluding the individual firm.