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Human Capital Diversity and Product Innovation: A Micro-Level Analysis

René Söllner*

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Abstract

The paper investigates the relationship between human capital diversity measured in terms of occupational diversity and a firm's likelihood to innovate. The empirical analysis is based on a linked employer-employee panel dataset of German firms over the period 1998 to 2007. Despite notable differences between service and manufacturing firms, our results clearly indicate a positive relationship between occupational diversity and the propensity to innovate.

JEL classification: J24, L20, O31
Keywords: Human Capital, Diversity, Innovation

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1 Introduction

Since the pioneering work of Edith Penrose (1959), it has been known that performance differentials between firms can be attributed to differences in resources and capabilities (see Wernerfelt, 1984; Rumelt, 1984; Barney, 1986). According to Hitt et al. (2001), these resources can be classified into two broad categories: intangible and tangible. Tangible resources mainly refer to the physical and financial assets that a firm possesses. Intangible resources can be associated with internal human capital assets in terms of skills, knowledge, and technological capabilities. Since intangible resources are socially complex and can hardly be imitated by competitors, they constitute strategically the most crucial resources (see Barney, 1991; Peteraf, 1993; among others). The economic literature has long been recognized that human capital endowments (including education, experience, and skills) provide the basis for a firm's competitiveness (Bartel, 1989; Senker and Brady, 1989; Howell and Wolff, 1991; Prais, 1995; Pennings et al., 1998; Black and Lynch, 1996; Hitt et al., 2001). The conventional wisdom is that a firm's stock of knowledge embodied in its human capital resources affects economic performance through productivity increases and the creation of innovation. This line of reasoning can be found in Welch (1970), who argues that better educated workers have an enhanced ability to acquire and to decode information about costs and productive characteristics of inputs. Further, increases in human capital facilitate the adaptation to technological change (Nelson and Phelps, 1966; Bartel and Sicherman, 1998), and lead to a faster accumulation and transfer of knowledge (Grant, 1996).

While it is well accepted in the literature that a firm's stock of human capital exerts a positive influence on economic performance and innovation, surprisingly, only little is known about the way in which the composition of human capital may affect innovative performance. The basic claim we have is that a diverse human capital pool becomes increasingly important in a business environment which is shaped by competitive advantages arising from innovative activities. Studies show that diversity among team members is related to greater knowledge, creativity and innovation (Watson et al., 1993; Maimunah and Lawrence, 2008). In the empirical analysis of this paper, we take a closer look at this issue. The goal is to assess a potential relationship between the diversity of a firm's human capital measured in terms of occupational diversity and the propensity to innovate. In order to do so, we employ a rich dataset of German manufacturing and service firms over time period 1998 to

2007. The contribution of this section is substantive. To the best of our knowledge, there is no previous study that investigates the impact of occupational diversity on a firms' propensity to innovate using such a rich dataset. Another novel aspect of the section is to bring together two so far rather parallel existing research streams. Arguments for a positive relationship between workforce diversity and firm performance in terms of innovative output can be found in the economics of innovation but also in the human resource management literature. We are not aware of any other study that takes arguments of both research strands explicitly into account.

The results of the current paper can briefly be summarized. The empirical analysis shows that there is positive relationship between a firm's human capital diversity (measured in terms of occupational diversity) and the probability of innovation. Further, by using different innovative performance measures, we can detect differences between service and manufacturing firms. The remainder of this paper is as follows. After this introductory section (section 1), we will give a short overview about the theoretical background and related literature on that topic (section 2). A description of the dataset and of the underlying estimation strategy is presented in section 3. Section 4 reports the results of the empirical analysis. Section 5 concludes.

2 Literature Review

In the evolutionary economics literature, diversity is often considered to be among the central factors explaining economic performance. According to Giuri et al. (2002), due to increases in the complexity of products, the last few decades have been characterized by a growing technological diversification of firms and industries. Evolutionary theory suggests that maintaining positions in a diverse range of technologies is essential for long-run economic success (Dosi, 1982; Nelson and Winter, 1982). More recently, Breschi et al. (2003) has observed that firms need to span their innovative activities over more than one technology. In particular, technology-based firms need to diversify in order to attain sustained economic growth (Suzuki and Kodama, 2004). Since innovations are often designed to solve unrelated problems, firms that are more technologically diversified are better able to capture technological opportunities (Nelson, 1959), and to obtain higher cross-fertilization between different, although related technologies (Granstrand, 1996). Based on organizational learning research, Quintana-Garcia and Benavides-Velasco (2008) test how technological

diversification enables organizations to improve their innovative capacity. Their results show that a diversified technology portfolio positively and significantly affects a firm's competence to innovate. Implementing new technologies into the firm's knowledge system seems to facilitate the search for complementarities and novel solutions, the generation of new ideas, and the avoidance of learning traps. This general finding can be linked to the concept of 'absorptive capacity' (Cohen and Levinthal, 1989, 1990), suggesting that prior knowledge confers an ability to recognize the value of new information and to incorporate and apply it for commercial uses. Cohen and Levinthal (1990) argue that the absorptive capacity of a firm is likely to increase with the broadness of the internal knowledge structure as reflected by the diversity of skills and capabilities of the workforce. Firms exhibiting a diverse human capital structure among their employees are more likely to innovate, since different points of view, educational backgrounds, and experiences facilitate complex problem solving, the generation of new ideas and novel combinations (Quintana-Garcia and Benavides-Velasco, 2008). In an empirical study on creativity and innovation, Van der Vegt and Janssen (2003) show that an individual's innovative behavior is the complex product of his relationships with fellow team members and the team context. This finding is consistent with the theoretical framework developed by Woodman et al. (1993) explaining organizational creativity by complex interactions of persons in a social setting. The authors highlight that diversity rather than homogeneity among group member is important in fostering creative group outcomes.

The relation between the diversity of human capital being manifested in the variety of knowledge, experiences and skills among employees and a firm's economic performance has been the subject of a considerable amount of research. In particular, the human resource management literature is replete with discussion of the impact of workforce heterogeneity. Most of the existing literature has been focused on the effects of diversity in the top management teams. For instance, Hambrick et al. (1996), examining 32 U.S. airlines over eight years, find that top management teams being diverse in terms of functional backgrounds, education, and company tenure, exhibit strikingly positive effects on corporate outcomes. Using a sample of 84 Fortune 500 food and oil companies, observed over the period 1967 to 1981, Murray (1989) tests how occupational heterogeneity of top management groups impinges on the short-term and on the long-term performance of firms. Along with Hambrick and Mason (1984), Murray shows that there is a potential trade-off. In the short-run, heterogeneity in management groups reduces performance due to an increase in the likelihood of misunderstandings and mistrust (Tuckman, 1965). In the long-run,

however, heterogeneous management groups do have an advantage of greater creativity and enhanced adaptability which positively affects performance (Katz, 1982). In a study by Smith et al. (1994), top management team heterogeneity with respect to educational levels was found to be positively associated with a firm's return on investment and growth in sales. Kilduff et al. (2000) differentiate between demographic diversity in top management teams (measured by variables such as age, gender, and race) and cognitive diversity, which is obtained through direct questionnaire measures of attitudinal and normative differences between individuals. Concerning the effects of demographic and cognitive diversity on performance, Kilduff et al. (2000) find mixed results. Only one demographic diversity measure (age heterogeneity) and one of the cognitive diversity measures (interpretative ambiguity) significantly positively affect overall firm performance.

In his literature review of research analyzing the general impact of team diversity on performance, Horwitz (2005) states that the relationship is not yet clearly understood. While some studies allude towards a positive effect of diversity (e.g., Cox and Blake, 1991; Nemeth, 1986; Iranzo et al., 2008), others stress the negative effects on performance (e.g., O'Reilly et al., 1989; Wiersema and Bantel, 1992; Wagner et al., 1984). Studies suggesting a positive impact of team and workforce diversity put forward the argument that groups consisting of heterogeneous members enhance creativity, innovation, and problem solving, thus generating more informed decisions. Nemeth (1986) finds that heterogeneous teams incorporating minority members more carefully think about an issue, and generate more creative ideas than homogeneous teams. Pelled et al. (1999) observe that team diversity in terms of education and company tenure influence the quality of debates and thus positively affect the decision-making process. Examining the relationship between a culturally diverse workforce and organizational performance, Richard (2000) demonstrates that cultural diversity does in fact add to firm value, and contributes to a firm's competitive advantage. Using a dataset of Italian manufacturing firms, Iranzo et al. (2008) show that a firm's productivity is positively related to the dispersion of skills within the firm. Though many studies seem to support the conclusion that diversity is beneficial for performance, organization theorists recently emphasize the potential costs associated with heterogeneity. As noted by Horwitz (2005), workforce diversity can be a double-edged sword. The greater the amount of diversity in a group, the less integrated the group is likely to be (O'Reilly et al., 1989), and the higher the level of dissatisfaction and tensions (e.g., Wagner et al., 1984). Intragroup conflict, miscommunication, and lack of trust lead to increased transaction costs. Accordingly,

homogeneous groups may likely to be more productive than heterogeneous groups because of mutual attraction of group members with similar characteristics. An empirical study by Wiersema and Bantel (1992) finds that homogeneity with respect to demographic traits leads to a shared language among individuals that enhances the communication frequency and integration. The researchers note that homogeneous teams, in general, perform better than their heterogeneous counterparts on tasks requiring coordinated activities among team members.

As pointed out by Williams and O'Reilly (1998), the conflicting empirical findings of studies analyzing a relation between diversity and firm performance might stem from differences in defining performance measures. While most of the previous studies rely on performance measures such as productivity, return on investment, or sales, the current study takes a closer look at the relationship between diversity and innovative performance. Studies focusing on the effect of diversity on innovative outcomes of firms are scarce. In a study of the top management groups of banks, Bantel and Jackson (1989) find that the more diverse the group was in terms of functional background, the larger the amount of administrative innovation. However, they do not find any relationship between functional heterogeneity of the top management team and the number of technical innovations the bank made. A field study of top management teams in financial service corporations by Pitcher and Smith (2001) supports the idea that diversity exerts a positive influence on innovation. The effect of task interdependence and group diversity on the innovative behavior of individual team members in a Dutch multinational financial service firm is analyzed by Van der Vegt and Janssen (2003). Their results do not indicate a relationship between group diversity and innovative behavior. A study of 45 product teams by Ancona and Caldwell (1992) reveals that functional diversity has a negative direct effect on innovation and team-rated performance, but it has a positive indirect effect on innovation through its association with an increased rate of communication with those outside the project group. Zajac et al. (1991) investigate how diversity affects the innovativeness of internal corporate joint ventures. Their empirical findings suggest that less age diversity is significantly positively related to innovation.

A shortcoming of a number of previous studies that try to explore a relationship between diversity and innovation is the restricted focus on the diversity of the top management team (e.g., Bantel and Jackson, 1989; Pitcher and Smith, 2001). Although organizational leaders may be of importance, we would rather suggest that a firm's propensity to innovate is determined by the diversity of skills and capabilities

of the entire workforce. The broadness of the knowledge base constitutes a firm's absorptive capacity (Cohen and Levinthal, 1989, 1990) and, hence, its ability to generate innovation. Since the broadness of the internal knowledge structure is reflected by the collective skills and abilities of all employees, it is not sufficient to just analyze the diversity of a particular organizational group. In contrast to other studies, we will therefore focus on the diversity of entire workforce rather than on the diversity of the top management team.

Employees differ with respect to a large set of dimensions. Consequently, different types of diversity exist. As described by Kilduff et al. (2000), the different types of diversity can be classified into two broad categories: i) diversity on observable attributes, such as age, gender, race, or organizational tenure, and ii) diversity with respect to relatively unobservable attributes, such as attitudes, values, and beliefs. In order to measure the extent of diversity among employees, we rely on measurable characteristics.[1] As previously mentioned, a type of diversity that is of particular relevance for the generation of innovation is the diversity of skills and knowledge (Milliken and Martins, 1996). Knowledge allows individuals to recognize the value of new information, to incorporate and to use it (Cohen and Levinthal, 1990). Bantel and Jackson (1989) point out that knowledge facilitates the identification of problems, as well as the detection and evaluation of feasible solutions. Regarding differences in knowledge, the presence of individuals with differing points of view, diverse abilities and perspectives guarantees the consideration of a larger set of problems and a larger set of potential solutions. Since innovation is an interactive process (Lundvall, 1988), which requires diverse knowledge bases among those who interact, knowledge (or human capital) diversity among employee should generally positively affect the generation of innovation in a firm. The question is, however, how to obtain an appropriate measure of human capital diversity? According to Bantel and Jackson (1989) and Merton et al. (1957), the functional or occupational background shapes a person's cognitive and attitudinal perspectives. It also affects how problems are formulated, and what types of solutions are generated. In this line of reasoning, we claim that occupational diversity acts as an appropriate measure for the heterogeneity of perspectives, skills, and abilities within a firm's workforce. As cross-functional communication is considered to be a precursor to innovation (Shrivastava and Souder, 1985), and groups composed of individuals having a variety of skills, knowledge, and perspectives are in general more effective when solving complex, non-routine

[1] Hambrick and Mason (1984) consider observable attributes to be convenient proxies for unobservable attributes.

problems (Shaw, 1976; Wanous and Youtz, 1986), we expect occupational diversity to be positively related to a firm's propensity to innovate.

Diversity of employees in terms of their occupational background has already been acknowledged to be a factor influencing a firm's likelihood to innovate (Bantel and Jackson, 1989; Pitcher and Smith, 2001). A general drawback of these studies is, however, that they merely consider the occupational diversity of the top management team. Related studies take a broader perspective by focusing on the entire workforce, but they predominantly concentrate on diversity types such as age, gender, ethnicity, or educational diversity that affect innovation (Van der Vegt and Janssen, 2003; Zajac et al., 1991; Ostergaard et al., 2009; Laursen et al., 2005; Drach-Zahavy and Somech, 2001; Watson et al., 1993).

3 Data and Methodology

The empirical analysis is based on the linked employer-employee dataset (LIAB) provided by the Institute for Employment Research (IAB) of the German Federal Employment Agency.[2] The dataset contains both establishment-level data of an annual panel survey of about 16,000 German businesses, and linked individual data of employees. The information of individuals includes all employees covered by the social security system. From the available cross-sections of the dataset, we utilize the period 1998 to 2007. Since the data are based on official employment statistics derived from social security, they can be regarded as highly reliable. For the purpose of the current study, the LIAB dataset is well suited. Besides establishment information about innovative activities and other relevant characteristics (e.g., size, exports, profitability), the data contain rich information on the occupational background[3], education, work experience, age etc. of employees in the establishment. Consequently, the question how human capital diversity impinges on the innovative behavior of businesses can adequately be addressed.

Dependent Variable. We employ two different innovative performance measures. First, we construct a binary variable indicating whether a business introduced an

[2] A detail description of the dataset can be found in Alda et al. (2005).

[3] In fact, the data allow a distinction between 336 different occupations at a three-digit classification level.

innovation during the two preceding years.[4] A value of 1 is assigned if a success in one of the following innovation categories was reported: i) an improvement of an existing product; ii) the introduction of product that was new to the business but known to the market; iii) the creation of a completely new product (i.e., new to the business and new to the market). If one of these criteria is fulfilled, we denote this as a *general product innovation* being implemented. In a second model specification, a value of 1 for the dependent variable is assigned if and only if a business successfully introduced a completely new product (i.e., product improvements and the introduction of products already known to the market are not considered). In the latter case, we speak of *fundamental product innovation* or the generation of market novelties.

Independent Variables. We are basically interested in a relation between occupational diversity (presumably reflecting the diversity of human capital) and the propensity to innovate. In our analysis, we calculate a Shannon (1948) entropy index to account for the occupational diversity of a business. The entropy index for establishment i is defined as

$$occ_div_i = \sum_j s_{ij} \cdot \ln\left(1/s_{ij}\right) \tag{1}$$

where s_{ij} denotes the employment share of occupation j, $j=1,...,J$, in total employment.[5]

In the previous section, we pointed out that other types of diversity are likely to affect the innovative behavior of firms. Zajac et al. (1991), for instance, find that diversity in age exerts a negative effect on innovative performance. The opposite result is detected by Ostergaard et al. (2009). In order to account for the age diversity in the workforce, we calculate a coefficient of variation. Referring back to Allison (1978),

[4] Note that questions about product innovations are subject of the LIAB panel survey only every three years. The questions regarding innovative activities correspond to the two preceding years. Thus, although the corresponding panel consist of data collected for the time period 1998 to 2007, the data structure only allows the application of 3 periods. The dependent variable refers to innovative output for the years 1999 to 2001, 2002 to 2004, and 2005 to 2007, and the independent variables refer to the years 1998, 2001, and 2004 respectively.

[5] Employment shares of occupations are obtained at a three-digit classification level. In order to rule out that the results depend the level of aggregation, human capital diversity was also calculated at a two-digit occupational level. Further, a Herfindahl-based diversification index was computed, which takes the form $1 - \sum s_{ij}^2$, where s_{ij} denotes the employment share of occupation j in business i. It turned out that none of this alternative specifications lead to qualitative changes of the results.

Harrison and Sin (2006) argue that a coefficient of variation provides the most direct workforce diversity measure for non-negative variables with interval-level properties such as age, tenure and wage. The coefficient of variation for age (age_div_i) is given by

$$age_div_i = \frac{\sigma_{age,i}}{\mu_{age,i}} \tag{2}$$

where $\sigma_{age,i}$ stands for standard deviation of employee ages, and $\mu_{age,i}$ is the mean age.

Further, since Ancona and Caldwell (1992) and Chi et al. (2009) stress that the diversity of employees in terms of their organizational tenure might also be crucial for innovation, we compute a coefficient of variation ($tenure_div_i$) that is based on the work experience of employees (measured in years) within a business. The coefficient is obtained in the same way as for age diversity.

In order to investigate a systematic relation between human capital diversity (as reflected by occupational diversity) and the propensity to innovate, we employ binomial regression techniques. In fact, we estimate a random-effects probit model.[6] The respective econometric model to be estimated has the following form:

$$y^*_{it} = \beta_0 + \beta_1 occ_div_{it-3} + \beta_2 age_div_{it-3} + \beta_2 tenure_div_{it-3} + \gamma' X_{it-3} + \alpha_i + \varepsilon_{it} \tag{3}$$

$i = 1, ..., n \qquad t = 1, ..., T$

with

$$\begin{aligned} y_{it} &= 1 \;\; if \;\; y^*_{it} > 0 \\ y_{it} &= 0 \;\; if \;\; y^*_{it} \leq 0 \end{aligned}$$

[6] Note that the estimation of a random-effects logit model did not reveal systematic differences. We do not employ an unconditional fixed-effects probit model as it can be severely biased (see Heckman, 1981; among others).

where y_{it} denotes the binary outcome variable, which takes the value of 1 if business i has introduced a product innovation, y_{it}^* is an unobserved latent variable. The occupational diversity measure is occ_div_{it-3}; age_div_{it-3} and $tenure_div_{it-3}$ denote the other diversity measures for age and tenure, respectively. The term X_{it-3} stands for a vector of control variables that are incorporated in the empirical analysis, a_i is an i.i.d. random effect with $\alpha_i \sim N\left(0, \sigma_\alpha^2\right)$, and ϵ_{it} is the error term. All explanatory variables enter the regression equation with a lag of three years.[7] The estimation of random-effects probit models is appropriate for large N and small T since the underlying quadrature technique becomes less accurate as panel size increases. Although this requirement is true for the current dataset by hand, a check for different numbers of quadrature points is conducted. We find that changes in the number of quadrature points do not affect the results. Hence, the use of a random effects probit model is suitable.

Control Variables. In the introductory section of this paper, it was argued that a firm's stock of knowledge, embodied in its human capital resources, determines the creation of innovation. In order to account for the human capital stock, we incorporate a variable that measures the share of high qualified people (i.e., those with tertiary education) in total employment.

A number of studies suggest that, in addition to age heterogeneity, the average age of the workforce influences economic performance (e.g., Hambrick et al., 1996; among others). With respect to innovation, it can be assumed that young employees received their education more recently than older employees. Accordingly, their technical knowledge might be more contemporary, which presumably enhances innovative activity. Moreover, innovation is always associated with risk taking behavior. Jianakoplos and Bernasek (2006) show that individuals exhibit a decreasing risk taking behavior with increasing age. For that reason, we expect a lower propensity to innovate for businesses that have a higher average age in their workforce.

In the literature, general firm-specific experience among employees (measured by the average time spent in a respective firm) is also considered to determine innovation. As pointed out by Bantel and Jackson (1989), employees who work a considerable time within an organization create a commitment to the group status quo.[8] Since innovation distorts this status quo, they could be tempted to reject innovative activities.

[7] It was mentioned above that this is due to the survey design of the LIAB.
[8] See also Staw and Ross (1980) and Stevens et al. (1978).

Hence, a negative relation between innovation and average tenure across employees is expected.

Further, we suspect that firm size (measured by the logarithm of number of employees) enhances innovation. The assumption of a positive relation between size and innovation dates back to Schumpeter (1942). A majority of works confirm the hypothesis of an increase of innovative activity with firm size, although there are arguments that support the opposite hypothesis (Holmstrom, 1989). More favorable conditions to finance innovations, better access to human capital resource, or the exploitation of scale effects can be reasons for the expected positive relationship between size and innovation.

Since the pioneering work of Pakes and Grilliches (1980), it has been argued in the literature that there is a positive connection between innovative input and innovative output (see also Hausman et al., 1984). We assume that businesses are particularly innovative if they devote resources to the development of new products. In order to account for this, we include a binary variable in our analysis that has the value 1 if an establishment reported to be explicitly engaged in R&D activities (e.g., due to the existence of a R&D division). Of course, R&D intensity measured by the ratio of R&D expenditures (or R&D employees) to sales would better reflect innovative activity on the firm-level. However, the LIAB dataset of the Institute for Employment Research (IAB) does not contain information on the amount of R&D expenditures or the number of R&D employees. Thus, R&D activity has to be implemented as a binary variable.

Nowadays, exporting plays an increasing role in company strategies, as markets become more globalized. Firms involved in international trade are exposed to international competition forces. In this context, we expect innovation to be a critical source for the competitive advantage and long-run economic success. Hence, a positive relation between export intensity and the propensity to innovate is assumed. We measure an establishment's export intensity by the share of sales exported in total sales and include this variable in our econometric model.

Also financial endowments might influence innovative activities. To a certain extent, the outcome of innovative activities is uncertain. Since potential capital investors such as banks could be deterred by the risk of innovative projects, businesses often have to rely on their own financial resources. Consequently, more profitable firms

should be more inclined to conduct innovative ventures as they have the required monetary resources. In order to control for that, we construct a binary variable capturing the profitability of a business. A value of 1 is assigned when a business has assessed its profitability to be better than 3 on a scale from 1 to 5. A value of 1 for the respective binary variable means that that profitability was rated as 'good' or 'very good'. Unfortunately, the dataset does not enable us to construct a continuous profitability measure, since the required information on intermediate inputs is lacking.

In addition, we incorporate a dummy variable in our regression equation that accounts for differences between East- and West German firms. The variable has the binary outcome 1 when an establishment is located in East-Germany and 0 otherwise. A summary of variable definitions is reported in Table 1.

Table 1: Summary of variable definitions

Name	Definition
General Product Innovation	Binary variable indicating the improvement of an existing product, the introduction of a product new to the company, or the introduction of a product new to the market (1 = successful innovation).
Fundamental Product Innovation	Binary variable indicating the introduction of a product new to the market (1 = successful innovation).
Occupational Diversity	Entropy index based on the employment shares of occupations.
Age Diversity	Diversity of employment structure with respect to the age of workers (standard deviation relative to mean age).
Tenure Diversity	Diversity of employment structure with respect to the duration of membership in an establishment (standard deviation relative to mean tenure).
Share of High-qualified	Share of workers with tertiary education.
Average Age	Average age of workers (in years).
Average Tenure	Average establishment tenure of workers (in years).
Size	Logarithm of total number of employees.
R&D	Binary variable indicating that an establishment allocates resources to R&D activities.
Export Intensity	Share of sales exported in total sales.
Profitability	Binary variable indicating good or very good profitability (self-reported).
East	Dummy variable indicating that an establishment is located in the East Germany.

4 Empirical Results

Table A.1 in the Appendix displays descriptive statistics for all variables of interest. Most remarkably in this table is the difference between the two innovative performance measures. Whereas on average 49% of the establishments stated having developed a general product innovation during the last two years, only about 10% were able to bring a fundamental product innovation to market. Table A.2 in the Appendix presents pairwise correlation coefficients. In general, the correlations among the independent variables indicate that we should not expect problems arising from multicollinearity. The highest correlation that we observe is between establishment

size and occupational diversity, with a coefficient of 0.68.[9] Table 2 displays the composition of the dataset with respect to firm size. We can see that approximately 55% of all firms have less than 50 employees. Large firms with more than 250 employees account for about 17%. A distinction between service and manufacturing reveals the fact that the service sector is overrepresented: 62,93% of all firms in the sample can be assigned to service industries, while only 37.07% belong to manufacturing.

Table 2: The composition of the dataset with regard to firm size

Size category	**Service**	**Manufacturing**	**Total**
Less than 10 employees	27.86	18.04	24.22
10 - 50 employees	30.71	32.73	31.45
51 - 100 employees	12.20	13.28	12.60
101 - 250 employees	13.40	16.45	14.53
251 - 500 employees	8.06	9.22	8.49
More than 500 employees	7.77	10.28	8.70
Total	62.93%	37.07%	100%

The estimation results for the random effects probit regression of equation (3) is reported in Table 3. The regression table is split up into two parts. The first part (Model 1 and Model 2) shows the regression results for the binary outcome variable *general product innovation*.

Model 1 is the baseline model that does not include the estimates for our alternative diversity measures. The results we obtain are consistent with our expectation. In fact, we find support for the hypothesis that occupational diversity exerts positive influence on the probability to innovate. The coefficient for *occupational diversity* is positive and highly significant. In Model 2, we further include the alternative diversity measures for age (*age diversity*) and company tenure (*tenure diversity*). Both coefficients turn out to be negative but insignificant. Note that the estimate for *occupational diversity* is not affected by the inclusion of additional diversity measures – it remains positive and significant. In the second part of Table 3 (Model 3 and Model 4), we change the measure of the dependent variable. In fact, we consider only those businesses as being innovative that launched a product which was new to the market (*fundamental product innovation*). The estimates for *occupational diversity*

[9] A positive relationship between size and diversity is a frequent finding in various research areas. This includes the typical positive relation between firm size and product diversification (e.g., Amey, 1964; Utton, 1977; Gollop and Monahan, 1991; Sutton, 1998), technological diversification (e.g., Breschi et al., 2003), and board diversification (Carter et al., 2003).

Table 3: Occupational diversity and the propensity to innovate

	General Product Innovation		Fundamental Product Innovation	
Variables	Model 1	Model 2	Model 3	Model 4
Occupational Diversity	0.1374***	0.1379***	0.1177***	0.1157***
	(0.0368)	(0.0369)	(0.0436)	(0.0437)
	(0.0548)	*(0.0550)*	*(0.0462)*	*(0.0455)*
Age Diversity		-0.3464		0.1538
		(0.2820)		(0.3780)
		(-0.1381)		*(0.0613)*
Tenure Diversity		-0.0110		0.1372
		(0.0791)		(0.1004)
		(-0.0044)		*(0.0545)*
Share of High-qualified	0.5773***	0.5817***	0.9539***	0.9838***
	(0.1901)	(0.1935)	(0.1933)	(0.1959)
	(0.2303)	*(0.23209*	*(0.3798)*	*(0.3917)*
Average Age	-0.0204***	-0.0228***	-0.0186***	-0.0162***
	(0.0041)	(0.0045)	(0.0053)	(0.0058)
	(-0.0081)	*(-0.0091)*	*(-0.0056)*	*(-0.0052)*
Average Tenure	-0.0115*	-.0112*	-0.0277***	-0.0276***
	(0.0063)	(0.0064)	(0.0075)	(0.0075)
	(-0.0046)	*(-0.0045)*	*(-0.0109)*	*(-0.0108)*
Size	0.2010***	0.2010***	0.0831***	0.0831***
	(0.0183)	(0.0184)	(0.02094)	(0.0075)
	(0.0802)	*(0.0802)*	*(0.0316)*	*(0.0316)*
R&D	1.0146***	1.0130***	0.5015***	0.5036***
	(0.0647)	(0.0648)	(0.0609)	(0.0609)
	(0.3690)	*(0.3681)*	*(0.1991)*	*(0.1999)*
Export Intensity	0.0080***	0.0079***	0.0033***	0.0035***
	(0.0014)	(0.0014)	(0.0012)	(0.0012)
	(0.0032)	*(0.0032)*	*(0.0013)*	*(0.0014)*
Profitability	0.0843**	0.08260**	0.0326	0.0308
	(0.0384)	(0.0385)	(0.0454)	(0.0455)
	(0.0336)	*(0.0329)*	*(0.0130)*	*(0.0123)*
East	-0.0765*	-0.0788*	-0.0001	0.0212
	(0.0424)	(0.0448)	(0.0511)	(0.0534)
	(-0.0305)	*(-0.0314)*	*(-0.0000)*	*(0.0085)*
Constant	-1.1986***	1.007***	-2.3665***	-2.5958***
	(0.2089)	(0.2558)	(0.3162)	(0.3769)
Industry Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	10683	10653	10723	10693
Wald chi2	1075.40	1068.97	510.52	510.03
Log Likelihood	-5807.02	-5793.19	-2990.45	-2988.30
rho	0.423	0.430	0.291	0.291
LR-test	233.39	235.54	41.36	41.05
Prob > chi2	0.000	0.000	0.000	0.000

*Notes: The estimation method is random effects probit. Standard errors are reported in parentheses.Values in italic parentheses denote the marginal effect of the respective coefficient. *** 1% level of significance, ** 5% level of significance, * 10% level of significance.*

are in line with the previous regressions. We obtain highly significant and positive coefficients.[10] Compared to Model 2, the coefficients for *age* and *tenure diversity* in Model 4 change their signs, but still remain insignificant. In addition to parameter estimates, Table 3 displays a number of regression diagnostics. In this respect, the estimates of *rho* are of particular interest, since they show the proportion of the total variance contributed by the panel-level variance component. All estimates of *rho* are well above zero. This indicates that the panel-level variance component is of importance and that a random effects probit model provides much more precise estimates than just a simple cross-sectional probit analysis.

With respect to the control variables, we see that most of the estimated coefficients do only slightly change across the model specifications (Model 1 to Model 4). The estimates are fully in line with our expectation. We identify a positive and significant effect for the *share of high-qualified* on the likelihood to innovate. Indeed, a marginal effect of about 0.23 in Model 1 and Model 2 suggests that, on average, a 1% increase in the share of high-qualified workers increases the probability to innovate by 23%. With a value of 0.38 and 0.39, the marginal effect in Model 3 and Model 4 is even larger. This finding confirms the results of a number of other studies (see Rammer et al., 2005; Dakhli and De Clercq, 2003; among others), and indicates that human capital is a critical source for innovation. An increasing age of the workforce tends to slow down innovative activities. The respective coefficients for *average age* are negative and highly significant, which could be interpreted as a sign for the importance of young professionals with contemporary technical knowledge, and who are more favorable towards risk-taking than their older counterparts (Bantel and Jackson, 1989). However, the marginal effects for the estimated coefficients suggest that the impact of *average age* on the likelihood to innovate is rather small.

Average tenure turns out to be negative and significant which could mean that an older workforce might be more reluctant to changes accompanied by innovative activities. Alternatively, this finding could hint to a technological 'lock-in' of the older workforce to incumbent technologies, preventing the adoption of potentially superior alternatives. The coefficients for *size* are positive and statistically highly significant across all four models. This result is in accordance with a number of empirical studies

[10] We also performed tests for a curvilinear relationship between occupational diversity and innovation by incorporating squared terms in the estimations. The insignificant coefficients we obtained do not support the existence of a non-linear (e.g., inverted U-shaped) relationship. We further included interaction effects between occupational diversity and the share of high-qualified workers, and between occupational diversity and firm size in the regressions. Again, none of the estimated coefficients turned out to be significant.

(Dosi, 1988; Acs and Audretsch, 1988, 1991), and could suggest that large firms have better capital resources to finance innovation, and/or a higher potential to acquire qualified labor necessary to facilitate the generation of new ideas. Not surprisingly, R&D activities (*R&D*) increase the likelihood of product innovation substantially. The respective coefficients are all positive and significant, confirming the finding of studies, which state that R&D activity is a catalyst for innovation (Audretsch, 1995; Kleinknecht, 1996; Freeman and Soete, 1997).

Also, involvement in international trade (*export intensity*) seems to be beneficial for product innovation. There are, at least, two possible explanations for this result. Either innovation becomes more and more a necessary element to resist competitive forces in international markets or, due to learning effects from foreign competitors, exporting businesses are more successful in bringing novel products to the market. There are slight differences with respect to the coefficients for *profitability* between the regressions with *general product innovation* as outcome variable (Model 1 and Model 2) and the models with *fundamental product innovation* as the dependent variable (Model 3 and Model 4). For Model 1 and Model 2, we obtain positive and significant estimates. The significance, however, vanishes for Model 3 and Model 4. One interpretation is that economic success and respective financial resources are, in general, useful for innovation, but in order to 'keep with the pace' of competitors regarding the creation of market novelties, profitability does not matter. The coefficients for our variable indicating East German establishments (*east*) are negative, but only weakly significant in Model 1 and Model 2. This could indicate that businesses in East-Germany exhibit a slightly lower tendency to produce product innovation.

Next, we want to present a robustness check for our main result that occupational diversity is strongly related to the likelihood to innovate. In order to do so, we split up the dataset into service and manufacturing industries and run separate regressions for both groups. The separation is considered to be important since research has uncovered crucial differences between service and manufacturing with respect to innovation and product development (Griffin, 1997; Sirilli and Evangelista, 1998; Evangelista, 2000; Miles, 2004; Tether, 2003). Detailed results of the analysis are shown in Table 4.

Table 4: Occupational diversity and the propensity to innovate in services and manufacturing

	General Product Innovation		**Fundamental Product Innovation**	
	Service	Manufacturing	Service	Manufacturing
Variables	Model 5	Model 6	Model 7	Model 8
Occupational Diversity	0.2279***	0.0496	0.0907	0.1411**
	(0.0542)	(0.0646)	(0.0696)	(0.0621)
	(0.0879)	*(0.0166)*	*(0.0359)*	*(0.0207)*
Age Diversity	0.0654	-0.7698	-0.3944	0.5077
	(0.3933)	(0.5410)	(0.5476)	(0.6205)
	(0.0250)	*(-0.2578)*	*(-0.1564)*	*(0.0747)*
Tenure Diversity	-0.1492	0.3334**	0.0970	0.3751**
	(0.1090)	(0.1496)	(0.1498)	(0.1538)
	(-0.0571)	*(0.1117)*	*(0.0386)*	*(0.0552)*
Share of High-qualified	0.4808**	0.8103*	0.5803***	1.4984***
	(0.2279)	(0.4569)	(0.2573)	(0.3474)
	(0.1841)	*(0.2714)*	*(0.2313)*	*(0.22031)*
Average Age	-0.0248***	-.01896**	-0.02925***	-0.0043
	(0.0060)	(0.0087)	(0.0084)	(0.0098)
	(-0.0095)	*(-0.0063)*	*(-0.0058)*	*(-0.0006)*
Average Tenure	-0.0054	-.01848*	0.0018	-0.0380***
	(0.0099)	(0.0110)	(0.0134)	(0.0103)
	(-0.0021)	*(-0.0062)*	*(0.0007)*	*(-0.0056)*
Size	0.1497***	0.3073***	0.0896***	0.0918***
	(0.0241)	(0.0369)	(0.0311)	(0.0318)
	(0.0573)	*(0.1029)*	*(0.0348)*	*(0.0135)*
R&D	0.6984***	1.1407***	0.5287***	0.4809***
	(0.1254)	(0.0878)	(0.1315)	(0.0723)
	(0.2731)	*(0.3382)*	*(0.2108)*	*(0.0776)*
Export Intensity	0.0052**	0.0078***	0.0038	0.0029*
	(0.0026)	(0.0019)	(0.0028)	(0.0015)
	(0.0020)	*(0.0026)*	*(0.0015)*	*(0.0004)*
Profitability	0.0780	0.1072	0.0267	-0.0034
	(0.0571)	(0.0659)	(0.0770)	(0.0613)
	(0.0310)	*(0.0355)*	*(0.0107)*	*(-0.0005)*
East	-0.1297**	0.0963	-0.1335	0.1223
	(0.0646)	(0.0813)	(0.0862)	(0.0781)
	(-0.0494)	*(0.0322)*	*(-0.0532)*	*(0.0180)*
Constant	-0.1565	0.6685	-1.1046*	-2.3132***
	(0.3165)	(0.4663)	(0.4304)	(0.5343)
Industry Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	4290	4520	4203	4541
Wald chi2	299.40	477.94	138.40	276.53
Log Likelihood	-2587.76	-2109.65	-1037.48	-1663.71
rho	0.429	0.465	0.274	0.275
LR-test	92.89	108.11	24.71	24.76
Prob > chi2	0.000	0.000	0.000	0.000

*Notes: The estimation method is random effects probit. Standard errors are reported in parentheses.Values in italic parentheses denote the marginal effect of the respective coefficient. *** 1% level of significance, ** 5% level of significance, * 10% level of significance.*

In general, Table 4 confirms the findings of the previous regressions. Model 5 just mirrors the results of Table 3. For businesses in the service sector, we find a positive and significant effect of *occupational diversity* on the propensity to innovate. Other types of diversity seem to be of minor importance. All other control variables keep their signs, but some such as *profitability* and *average tenure* lose in statistical significance. If we have a look at manufacturing (Model 6), we see that *occupational diversity* in not longer significant. This result is puzzling and certainly deserves further investigation. Actually, we expected to find a positive relationship between human capital diversity and innovation in manufacturing. Instead, a positive and significant coefficient for the heterogeneity of employees in terms of their company tenure (*tenure diversity*) is observed. High tenure diversity suggests that employees entered an establishment at different points in time. As a consequence, people may not share the same social network within the organization (Chi et al., 2009). As knowledge, experiences, and perspectives in the same social network are often similar and redundant (Granovetter, 1973), a workforce with high levels of tenure diversity is more likely to possess distinct and non-redundant perspectives. This can lead to more innovative ideas and solutions (De Dreu and West, 2001), which facilitate the generation of innovation. We now shift the attention towards the effects of workforce heterogeneity on the likelihood of generating market novelties (Model 7 and Model 8). Regarding service businesses (Model 7), we do not observe any significant impact of diversity: neither *occupational* nor *age* or *tenure diversity* seem to facilitate the creation of fundamental product innovation. The picture is changing if we pay attention to businesses in manufacturing industries (Model 8). The positive and significant estimates for *occupational diversity* and *tenure diversity* imply a positive effect of workforce diversity on new product development. The absence of a significant effect of human capital diversity (*occupational diversity*) on fundamental product innovation (Model 7) might be partly due to peculiarities of innovative processes in service industries. In contrast to manufacturing, innovation in services less often results from internal knowledge generating activities (Sheehan, 2006), and has an incremental nature (Djellal and Gallouj, 2001). Furthermore, innovation in service industries is largely dependent upon adopting externally developed technologies that enhance efficiency (Tether, 2003). The minor importance of fundamental product innovation and the reliance on external sources for innovation support the insignificant effect of our human capital diversity measure in Model 7. This does not mean that human capital diversity does not matter in services at all. A certain amount of innovative activities in service firms are oriented to the adaptation of services to the wide range of users' needs (Hipp and Grupp, 2005). Diverse human

capital resources certainly constitute a crucial asset for this interactive and complex activity, and would explain why a positive and significant impact of *occupational diversity* on general product innovation in Model 5 is observed.

In Table A.3 of the Appendix, we offer a further robustness check. So far, the econometric model was estimated for the entire sample of establishments and separately for sub-samples of businesses in service and manufacturing industries. In Table A.3 of the Appendix, the random effects probit estimation is performed after the exclusion of subsidiaries and establishments with fewer than 10 employees. The remaining sample now encompasses only larger businesses, which can be regarded as legally independent entities. Regression Table A.3 does not reveal systematic differences compared to Table 3. The estimated coefficients for *occupational diversity* are positive and significant across all model specifications (Model 9 to Model 12). Interestingly, we obtain a negative and significant coefficient for *age diversity* with regard to the binary outcome variable *general product innovation* (Model 10). According to Zajac et al. (1991), this finding might be due to a greater conflict potential and less social cohesion in an age diverse workforce that negatively impinges on innovation. Note, however, that a negative relation between age diversity and innovation is not present in Model 12, where the interest is set to the generation of *fundamental product innovation*. With respect to *tenure diversity,* we do not find any significant effect on innovation. The coefficient in both Model 10 and Model 12 is positive but insignificant. Compared to regression Table 3, the estimates of the control variables yield only minor changes. Most notably is the positive but insignificant coefficient for *size* (Model 13 and Model 14) which was highly significant before (see Table 3). Also *average tenure* partly turns out to be insignificant (Model 11 and Model 12). This, however, is not too surprising, since the respective estimates were only weakly significant in the regressions based on the entire sample of establishments. In a nutshell, the results of the robustness checks are consistent with the previous findings, suggesting that links between occupational diversity and product innovation found above are well-grounded.

5 Conclusions

The aim of the study was to analyze the relationship between occupational diversity and the propensity to innovate. As innovation is an interactive process, which

requires the combination of diverse knowledge bases and different points of views, occupational diversity (human capital diversity) among employees should positively affect the generation of innovation in a firm. The empirical analysis of this paper has indeed shown that occupational diversity is positively related to the propensity to innovate. Besides occupational diversity, we also incorporated other types of diversity measures in our framework. It turned out that a greater heterogeneity of the workforce with regard to work experience can also be beneficial for innovation. Note that this result could only be observed for businesses in manufacturing industries. On the basis of our findings, we can derive an important implication for firms. Our results suggest that companies implementing workforce diversity policies may gain a long-term competitive advantage, which arises from an increased likelihood to innovate.

However, at the present stage of analysis, the findings of this paper should cautiously be interpreted. One open question for discussion is whether a positive association between occupational diversity and innovation can be identified as a causal effect. We cannot *per se* exclude reverse causality, since successful innovation may enable firms to acquire a more diverse workforce. One of the major tasks on the research agenda will therefore be to reveal a causal relationship between occupational diversity and innovation.

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A Appendix

A.1 Summary statistics of employed variables

	Mean	**Std. Dev.**	**Min**	**Max**
General Product Innovation	0.488	0.500	0	1
Fundamental Product Innovation	0.105	0.307	0	1
Occupational Diversity	1.507	0.803	0	3.905
Age Diversity	0.279	0.075	0	0.736
Tenure Diversity	0.646	0.263	0	2.831
Share of High-qualified	0.064	0.119	0	1
Average Age	40.310	5.081	19.5	63
Average Tenure	6.521	3.653	0.211	22.158
(Log) Firm Size	3.747	1.574	0.693	10.827
R&D	0.197	0.398	0	1
Export Intensity (in percent)	8.548	19.173	0	100
Profitability	0.326	0.469	0	1
East	0.451	0.498	0	1

A.2 Pairwise correlation coefficients

	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)	12)	13)
1) General Product Inn.	1												
2) Fundamental Product Inn.	-	1											
3) Occupational Diversity	0.300	0.173	1										
4) Age Diversity	-0.040	-0.017	-0.105	1									
5) Tenure Diversity	-0.016	-0.003	-0.111	0.297	1								
6) Share of High-qualified	0.150	0.149	0.260	-0.184	-0.133	1							
7) Average Age	0.004	0.000	0.179	-0.431	-0.193	0.132	1						
8) Average Tenure	0.100	0.027	0.309	-0.116	-0.042	0.006	0.317	1					
9) (Log) Firm Size	0.315	0.154	0.678	-0.073	-0.053	0.153	0.043	0.305	1				
10) R&D	0.390	0.265	0.440	-0.095	-0.079	0.242	0.062	0.165	0.400	1			
11) Export Intensity	0.297	0.200	0.412	-0.105	-0.052	0.180	0.081	0.220	0.377	0.505	1		
12) Profitability	0.063	0.044	0.051	-0.026	0.009	0.064	-0.042	-0.061	0.051	0.063	0.093	1	
13) East	-0.076	-0.014	-0.081	-0.065	-0.344	0.106	0.028	0.320	-0.159	-0.069	-0.161	0.027	1

A.3 Occupational diversity and the propensity to innovate

	General Product Innovation		Fundamental Product Innovation	
Variables	Model 9	Model 10	Model 11	Model 12
Occupational Diversity	0.143***	0.151***	0.154***	0.155***
	(0.447)	(0.045)	(0.053)	(0.053)
	(0.056)	*(0.059)*	*(0.059)*	*(0.060)*
Age Diversity		-1.439***		0.440
		(0.451)		(0.554)
		(-0.567)		*(0.174)*
Tenure Diversity		0.091		0.164
		(0.106)		(0.129)
		(0.036)		*(0.065)*
Share of High-qualified	0.663**	0.603***	1.079***	1.114***
	(0.257)	(0.253)	(0.248)	(0.250)
	(0.261)	*(0.238)*	*(0.429)*	*(0.443)*
Average Age	-0.025***	-0.034***	-0.023***	-0.018**
	(0.006)	(0.007)	(0.007)	(0.008)
	(-0.001)	*(-0.013)*	*(-0.006)*	*(-0.006)*
Average Tenure	-0.010	-0.009	-0.024***	-0.024***
	(0.008)	(0.008)	(0.009)	(0.009)
	(-0.004)	*(-0.003)*	*(-0.009)*	*(-0.009)*
Firm Size	0.165***	0.162***	0.024	0.026
	(0.024)	(0.025)	(0.027)	(0.027)
	(0.065)	*(0.064)*	*(0.010)*	*(0.010)*
R&D	1.016***	1.016***	0.525***	0.525***
	(0.074)	(0.075)	(0.070)	(0.070)
	(0.357)	*(0.357)*	*(0.208)*	*(0.208)*
Export Intensity	0.008***	0.008***	0.003**	0.003**
	(0.002)	(0.002)	(0.001)	(0.001)
	(0.003)	*(0.003)*	*(0.001)*	*(0.001)*
Profitability	0.043	0.037	-0.013	-0.016
	(0.047)	(0.047)	(0.054)	(0.054)
	(0.017)	*(0.015)*	*(-0.005)*	*(-0.006)*
East	-0.074	-0.067	0.001	0.030
	(0.053)	(0.057)	(0.062)	(0.066)
	(-0.029)	*(-0.029)*	*(-0.027)*	*(0.000)*
Constant	-0.931***	-0.238	-2.125***	-2.569***
	(0.276)	(0.371)	(0.398)	(0.511)
Industry Dummies	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Observations	6937	6937	6960	6960
Wald chi2	714.28	713.30	349.17	349.48
Log Likelihood	-3784.49	-3779.32	-2062.48	-2061.02
rho	0.415	0.417	0.274	0.274
LR-test	143.04	144.93	23.81	23.68
Prob > chi2	0.000	0.000	0.000	0.000

*Notes: The table reports the regressions for legally independent businesses with more than 10 employees. The estimation method is random effects probit. Standard errors are reported in parentheses. Values in italic parentheses denote the marginal effect of the respective coefficient. *** 1% level of significance, ** 5% level of significance, * 10% level of significance.*