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The Nexus between Labor Diversity and Firm's Innovation*

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Abstract

This paper investigates the nexus between labor diversity and innovation in a population of Danish firms. Specifically, exploiting information retrieved from a comprehensive linked employer-employee database and implementing a proper instrumental variable strategy, we are able to identify the contribution of diversity in cultural background, skills and demographic characteristics to valuable firm's innovation activity. The latter is measured by: (1) the firm's propensity to apply for a patent, (2) the number of patent applications (intensive margin) and (3) the firm's ability to patent in different technological areas (extensive margin). We find that skill diversity plays a key role in propelling firm's innovation outcomes. The positive influence of heterogeneity in the ethnic dimension turns to be not negligible, too. Conversely, the effect of demographic diversity typically vanishes once detailed firm specific characteristics are included as control variables.

JEL Classification: C23, J24, L20.

Keywords: Labor diversity, patenting activity, extensive and intensive margins.

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1 Introduction

Similarly to other developed countries, Denmark has experienced many changes in the workforce composition which has lead to an increased heterogeneity of the labor force in terms of age, gender, skills and ethnicity. This is partly the result of policies adopted to counteract the problem of population aging, anti-discrimination measures, immigration and the worldwide globalization process (Pedersen et al., 2008). From the demand side, we observe increasing diversity across many workplaces and we hear often about the importance of further internationalization and demographic diversification. The promotion of diversity is often perceived as a chance to improve learning and knowledge management capabilities and then enhance the firm productivity (Parrotta et al., 2010) and innovation. In a relatively recent survey conducted by the European Commission, a large number of respondents identified innovation as a key benefit of having diversity policies and practices (European Commission, 2005).[1]

In the literature on the relationship between labor diversity and firm's innovation, a paradox has been recognized: whereas labor diversity can be a source of creativity and therefore foster innovation activity, a high degree of heterogeneity among workers may induce misunderstanding, conflicts and uncooperative behaviors within workplaces (Basset-Jones, 2005). There is no general agreement on which effect may prevail. However, the paradox weakens if we distinguish between non-cognitive and cognitive diversity. Specifically, differences in skills, education and more broadly in knowledge among employees seem to be beneficial rather than detrimental (Hong and Page, 2001 and 2004; Lazear, 1999). According to Lazear (1999), positive effects may prevail as long as workers'

[1]The study involves more than 1,200 small- and medium-sized enterprises (SMEs) from across 27 European countries and 70 SME intermediary organizations. The research shows that although the majority of SMEs recognises the business benefits coming from labor diversity, only a minority follows through and establishes formal human resource strategies to harness diversity.

information sets are not overlapping but relevant to one another. Ambiguity instead persists for diversity in ethnic and demographic characteristics of employees. On the one hand, differences in cultural background, age and gender may provide diverse perspectives, opinions and problem-solving abilities that could facilitate the achievement of optimal solutions and therefore stimulate innovations (Watson et. al. 1993; Drach-Zahavy, 2001; Hong and Page, 2001 and 2004). On the other hand, such heterogeneities might create communication barriers, reduce the workforce cohesion and prevent cooperative participation in research activities (Williams et al., 1998; Zajac et. al., 1991). Diversity in these dimensions generates high costs of "cross-cultural dealing" (Lazear, 1999). Thus, it is still unclear whether more ethnically and demographically heterogeneous firms outperform the relatively more homogeneous ones with respect to innovation.

The empirical literature exploring the relationship between labor diversity and firm's innovation is mainly composed of business case studies that often look at work team composition (Horwitz et. al., 2007; and Harrison and Klein, 2007) or even focus on diversity in top management teams only (Bantel and Jackson, 1989; Pitcher and Smith, 2001). That may be imputed to differences in research aims and approaches but also to the lack of more comprehensive employer-employee data, which provide a notable amount of information on the labor force composition at the firm level. To the best of our knowledge, the evidence using more comprehensive data is almost non-existent.[2]

[2]Since we began working on the paper, we became aware of two recent studies using linked employer-employee data (LEED) to analyze labor composition and innovation. The first work is Østergaard et. al. (2009), which merges the Danish LEED for the year 2002 with a survey that refers to the period 2003-2005 (Danish Innovation System: Comparative analyses, strength and bottlenecks, DISKO) and accounts of 1648 firms. Using the cross-section, the authors evaluate the effect of gender, age, ethnicity and education heterogeneity on firm's propensity to innovate. They find evidence of (a) positive effect of diversity in education and gender, (b) no significant effects of ethnic diversity and (c) negative effects of age diversity on firm's innovation. The second study by Söllner (2010) analyzes how occupational diversity, considered as a proxy of human capital heterogeneity, affects the firm's likelihood to introduce a product innovation. Controlling for age and tenure diversity among other covariates, he finds

In this paper, we investigate the nexus between labor diversity and innovation using a rich register-based linked employer-employee dataset (LEED) from Denmark for years 1995-2003. In addition to analyses of firm's propensity to apply for a patent, we focus on two other dimensions of innovation: the number of patents introduced each year and areas in which the firm has realized them. In this study, we deal with several problems that previous literature studying the impact of workforce diversity on innovation did not address properly. Firstly, it might be that firms are aware of the importance of labor diversity and leverage it to improve their performances then the relationship under investigation may be affected by simultaneity or endogeneity. To address these concerns, we implement an instrumental variable (IV) strategy based on levels of diversity in cultural background, skills and demographic characteristics computed for each commuting area. Secondly, as broadly documented by industrial and knowledge economics literatures, firms are characterized by different propensity to innovate. Thus, there exist unobserved and observed firm specific heterogeneities that should be taken into account to evaluate the effect of any labor diversity dimension on firm's innovation outcome. Moreover, since "success breeds success" firms may gain some locked-in advantage over other firms due to successful innovations (Simons, 1995). Following Blundell et al. (1995), we account for past firms' success in innovation and use pre-sample information as an observable proxy for unobservable permanent firm characteristics. Finally, we control for the potential role of the external knowledge in favoring firms' patenting activity. Both geographical and technological distances have been computed to build up knowledge spillovers indicators.

Implementing alternative estimation techniques, we find an evidence of the

that "occupational diversity is positively related to the propensity to innovate". However, both studies present some limitations, among others they neglect the problem of possible endogeneity of the relationship between diversity and innovation, which we properly address in the present article.

key role of the skill diversity in promoting firm's innovation. Diversity in cultural background has a positive and significant influence, too. Effects of diversity in demographics turn to be mostly insignificant when shares of male and differently aged employees are included as controls. We find evidence that diversity is an important driver for the creation of new ideas, since more diverse workforces are typically characterized by a broader spectrum of perspectives, which in turn facilitate innovations in different technological fields. Moreover, workforce diversity may stimulate innovation by providing useful information to firms about consumers' tastes and products' markets. In this regard, our findings are consistent with the theoretical framework proposed by Hong and Page (2001 and 2004), Berliant and Fujita (2008) and Osborne (2000). Several robustness checks corroborate our main findings and are consistent with our interpretation. Our results suggest firms to focus on recruitment strategies that explicitly account for skills and ethnic heterogeneity.

This article may also provide some suggestions to public authorities in terms of innovation policies. As shown in OECD (2009), looking at series of EPO patents, US Trademarks, industry R&D and annual GDP growth rates of the total of OECD countries for the period 1982-2006, it is possible to observe that patent filing and R&D expenditure have moved similarly to GDP dynamics. Thus, it clearly emerges a strong correlation between macroeconomic fluctuations and innovations. The interpretation of this empirical evidence assumes a specific (theoretical) causal relationship if we refer to models belonging to the New Growth Theory (NGT). Therefore, if the innovation is the engine of the economic growth then investigating the determinants of the innovation process may also lead to the identification of the sources of a sustainable growth. In this regard, public institutions and policy makers could invest resources to promote diversity within workplaces and in such a way increase the innovation, and ultimately an economic growth.

The structure of the paper is as follows: section 2 briefly describes the data, section 3 provides details on the empirical strategy, sections 4 and 5 explain all the results of our empirical analyses and Section 6 offers some concluding remarks.

2 Data

2.1 Data sources

The dataset we use for our analysis is obtained by merging three different data sources from Denmark. The first one is the 'Integrated Database for Labor Market Research' (IDA), which is a register based LEED managed by Statistics Denmark, a Danish governmental institute responsible for creating statistics on the Danish society and economy. IDA contains a broad set of information on individuals and firms, among them we are interested in gender, age, nationality, education, occupation and place of work, but also whether a firm is (partially or totally) foreign owned and multi-establishment. In IDA such variables are recorded for the period 1980-2006. The second data source is a register of firms' business accounts (REGNSKAB) that provides information on a number of financial items, which we need in order to construct values of firms' capital stock, information on whether a firm is an exporter and the 3-digit industry, in which the firm operates. This database is also maintained by Statistics Denmark and reports data for the period 1995-2006.[3] In REGNSKAB it is possible to identify partially and totally imputed values, which we do not include in our

[3]Part of the statistics in Regnskab refers to selected firms for direct surveying: all firms with more than 50 employees or profits higher than a given threshold. The rest is recorded in accordance with a stratified sample strategy. The surveyed firms can choose whether submit their annual accounts and other specifications or fill out a questionnaire. In order to facilitate responding, questions are formulated in the same way as required in the Danish annual accounts legislation.

final dataset in order to avoid any bias in the estimates. The last data source is a collection of patent application sent to the European Patent Office (EPO) by Danish firms.[4] It covers a period of 26 years (1978-2003) and allows us to account for 2822 applicants and 2244 granted firms.[5] We disregard those industries where there were no patenting firms during the period covered in our empirical analysis.[6] We also exclude from our sample enterprises with less than 10 employees to allow all investigated firms to potentially reach the highest degree of (ethnic) diversity at least when an aggregated specification is used. Thus, our final dataset contains information on approximately 14,000 firms per year over the period of 9 years (1995-2003).

2.2 Diversity measures

The workforce diversity (heterogeneity) measures used in this article are computed at the firm level and based on the Herfindahl index. The latter combines two important dimensions of diversity: the "richness", which refers to the number of defined categories within a firm, and the "evenness", which informs on how equally populated such categories are. Specifically, our diversity measures represent weighted averages of Herfindahl indexes computed at the workplace level:

$$Div\_h_{it} = \sum_{w=1}^{W} \frac{N_w}{N_i} \left(1 - \sum_{s=1}^{S} p_{wst}^2 \right) ,$$

where Div_h_{it} is the diversity index of firm i at time t for the dimension h, W

[4]The access to this data has been made possible thank to the Center for Economic and Business Research (CEBR), an independent research center affiliated with the Copenhagen Business School (CBS).

[5]More details concerning the construction and composition of the dataset can be found in Kaiser et al. (2005).

[6] Agriculture, fishing and quarrying; electricity, gas and water supply; sale and repair of motor vehicles; hotels and restaurants; transports; and public services.

is the total number of workplaces (w refers to a given workplace) constituting the firm, and therefore N_w and N_i denote the total number of workers at the workplace and firm level, respectively. Thus, the ratio between the last two variables corresponds to the weighting function, while p_{wst} is the proportion of workplace's employees falling into each category s at time t, with $s = 1, 2, ..., S$. The diversity index has a minimum value, which takes value on zero if there is only one category represented within the workplace, and a maximum value equal to $\left(1 - \frac{1}{S}\right)$ if all categories are equally represented. The index can be interpreted as the probability that two randomly drawn individuals in a workplace belong to different groups.

As we distinguish between cultural, educational (skill) and demographic diversity, a separate measure is computed along each of the three cited dimensions. Diversity in cultural background is associated with employees' country of origin[7] and is built by using the following eight categories: North America and Oceania, Central and South America, Africa, West and South Europe, Formerly Communist Countries, East Asia, Other Asia, Muslim Countries.[8] Diversity in education is based on six categories. In particular, tertiary education (PhD, Master and Bachelor) is divided into the following four groups: engineering, humanities, natural sciences and social sciences. The other two categories are represented by secondary and compulsory education. Eight categories instead refer to the demographic diversity, which is computed by combining gender and four age dichotomous indicators associated with quartiles of the overall age distribution.

However, given that the overall categorization might be somehow arbitrary, we decide to use a more disaggregated one, too. The alternative cultural background diversity is based on linguistic classification.[9] Specifically, we group for-

[7]Native Danes and the second generation of immigrants are excluded.
[8]See the Appendix for more details about the countries belonging to each ethnic category.
[9]Previous literature argues that linguistic distance serves as a good proxy for cultural

eign employees together by family of languages, to which the language spoken in their home country belongs to. Using the third linguistic tree level language classification drawn from Ethnologue, we end up having 40 linguistic groups.[10] Further, our disaggregate diversity indexes in education and demographics are based on eight and ten categories respectively. Differently from the former classification, the secondary education is split into 3 sub-groups: high school, business high school and vocational education. Demographic diversity is computed now by combining gender and five age dichotomous indicators associated with quintiles of the overall age distribution.

2.3 Descriptive statistics

Table 1 reports some descriptive statistics (median, mean and standard deviation) of the variables used in our empirical analysis. The firm population is divided into two groups based on whether a firm applied at least for a patent (patenting firm) or did not. Patenting firms are characterized by notably higher values of capital and labor inputs: the average capital stock is almost 9.5 times the value of the non patenting firms. The latter are more likely to be single-establishment companies and markedly less export oriented: on average the share of exporters halves among the never applicants. No significant differences are shown instead for the foreign ownership status: the foreign capital penetration is quite low among Danish firms. For the purposes of our analysis it appears extremely relevant to take into account the role of external sources of knowledge since they may facilitate firms' innovation activity. Although we already control (using the export dummy) whether firms compete in the international arena

distance (Guiso et al, 2009; Adsera and Pytlikova, 2010).

[10]The linguistic classification is more detailed than the grouping by nationality. Specifically, we group countries (their major official language spoken by the majority) by the third linguistic tree level, e.g. Germanic West vs. Germanic North vs. Romance languages. The information on languages is drawn from the encyclopedia of languages "Ethnologue: Languages of the World", see the Appendix section for more details about the list of countries and the linguistic groups included.

and then have access to foreign knowledge, more precise indexes of knowledge spillovers can be defined at the national level. Specifically, we construct two measures of knowledge spillovers, one based on the geographical distance and the other on the technological proximity, see Appendix 2 for a detailed description of the external knowledge indexes. Looking at these measures of knowledge spillovers, see Table 1, we find no evidence of diffused clustering behavior neither huge differences in technological distance between the two groups of firms. There are remarkable differences between patenting and non patenting firms with respect to firms' workforce composition. Not suprisingly, patenting firms are characterized by larger shares of highly educated employees, white-collar workers and managers, whereas the opposite holds true for middle managers. Interestingly, patenting firms also record a higher share of female and foreign employees. Workers in these knowledge based firms are a slightly older on average terms: presumably the share of the least aged is lower because patenting firms hire a wider proportion of well trained and experienced people. As matter of fact long tenure profiles are more common within patenting firms' environment. Diversity indexes register higher values for patenting firms. Particularly evident is the differential in the ethnic heterogeneity that is on average 3.5 times larger with respect to non-patenting firms. These report also substantial lower skill diversity, which is 16% poorer in mean values. Thus, the presented descriptives raise reasonable interest in evaluating the "nexus" between firms' patenting behavior and diversity in ethnicity, education and demographics.

3 Econometric methods

3.1 Propensity to innovate

To investigate the effect of labor diversity on firm's propensity to innovate we employ a standard binomial regression technique in our analyses. Specifically, we estimate the following probit model:

$$\begin{cases} z_{it} = 1 \quad if \quad z_{it}^{*} > 0 \\ z_{it} = 0 \quad otherwise \end{cases}$$

$$with \quad z_{it}^{*} = \gamma_c Div\_c_{it} + \gamma_s Div\_s_{it} + \gamma_d Div\_d_{it} + x_{it}^{'}\beta + \eta_i + v_{it}$$

where z_{it}^{*} denotes the unobservable variable inducing firm i to apply at least once for a patent at time t; z_{it} indicates whether firm i has concretely applied at time t; the first three terms at the right hand side are respectively diversity in cultural background, skills and demographics. The vector $x_{it}^{'}$ includes an extensive set of observable (time varying and time invariant) characteristics, like, among others, the external knowledge indexes and the firm specific characteristics described in section 2.3; η_i denotes the firm specific unobservable effect and the v_{it} is the error term. Similar to Blundell et al. (2002) we proxy for the unobserved heterogeneity η_i by arguing that the main source of unobserved permanent differences in firms' capabilities to innovate can be captured by the pre-sample history of innovative successes. In line with that, we assume that the firms' average number of patent applications provides a good approximation of the above unobservable heterogeneity component η_i. However, an overall increase in the number of patent applications is recorded during the pre-sample period. Thus, as in Kaiser et al. (2008) we deal with that by normalizing a firm's number of patents in a pre- sample year by the total number of patents applied for during that year:

$$\eta_i = \frac{1}{T} \sum_{t=\tau}^{T+\tau} \left(\frac{y_{it}}{\sum_{i=1}^{I} y_{it}} \right)$$

As firms can leverage labor diversity to improve their innovation performances, we also instrument our variables of interest in order to obtain a causal effect of workforce diversity on firm innovation activities. Specifically, we implement an instrumental variable (IV) strategy based on the levels of diversity in cultural background, skills and demographic characteristics computed at the commuting area where the firm is located.[11] The so-called functional economic regions or commuting areas are identified using a specific algorithm based on the following two criteria. Firstly a group of municipalities constitute a commuting area if the interaction within the group of municipalities is high compared to the interaction with other areas. Furthermore, at least one municipality in the area must be a centre, i.e. a certain share of the employees living in the municipality must work in the municipality, too (Andersen, 2000). In total, 51 commuting areas are identified as shown in Figure 1. This IV strategy seems to be well suited in our context because (except for the area around Copenhagen) commuting areas in Denmark are typically relatively small and therefore firms very likely recruit workers from a given local supply of labor, which is obviously characterized by a certain degree of heterogeneity. Moreover, the rather low Danish residential mobility (Deding et al., 2009) may reinforce the properness of our strategy. To reinforce the exogeneity of our instruments we exclude each firm workforce from the computation of labor diversity at the related commuting area. The same argument applies to the analyses of intensive and extensive margins too.

[11] Unfortunately in our dataset it is not possible to observe in which area each establishment of a multi-establishment firm is located. For the multi-establishments firms, the information about the location is only provided for the headquarter. However, we do not think this represents a serious problem as multi-establishments firms constitute only 26 % of our sample. This is reinforced by the fact that we always reject the hypothesis that our instrument is weak.

3.2 Extensive margins

The estimation approach used to evaluate the extensive margins of firms' patenting behavior is similar to that one adopted for the firms' propensity to patent. Although the count data models would be more suitable for the analyses of relationship between workforce diversity and the number of different technological areas of patent application, our data and concretely the lack of minimum observations required to run count data model do not allow us to use them. Instead, we evaluate whether more labor diversity increases the probability of a firm to (apply for a) patent in more than one technological area.

3.3 Intensive margins

As the number of patents is restricted by definition to non-negative integers, the econometric strategy used to analyze the relationship between intensive margins of patenting activity and labor diversity is grounded on the family of count models. As a starting point we assume that the data generating process follows a Poisson distribution. If the random variable Y_{it}, in our case number of patent applications filed by firm i at time t, is Poisson distributed, then the probability that exactly y applications are observed is as follows

$$P\left(Y_{it} = y \mid \lambda_{it}\right) = \frac{e^{-\lambda_{it}}\lambda^{y}}{y!} \ .$$

Covariates can be introduced by specifying the individual mean as

$$\lambda_{it} = exp\left(\beta_c Div\_c_{it} + \beta_s Div\_s_{it} + \beta_d Div\_d_{it} + w_{it}^{'}\beta_w + \eta_i\right) \ , \qquad (1)$$

where η_i stands for the unobserved time invariant firm specific heterogeneity term and w_{it} is a vector of patent production determinants, as specified in subsection 3.1. Following Blundell et al. (1995), we also include, among the covariates w_{it}, the discounted patent stock of firm i at period $t-1$ in order to account for potential state dependence in patenting activity. This is calculated as

$$disc\_stock_{it-1} = y_{it-1} + (1-\delta) disc\_stock_{it-2} \, ,$$

where y_{it-1} is the lagged number of patent applications and δ is the depreciation rate set equal to 30 per cent as in Blundell et al (1995).

We also add a dummy variable taking value on zero if the firm had never innovated prior to 1995, to capture persistent differences between patenting and non-patenting firms (Blundell et al. 1995; Blundell et al. 1999). In addition, this dummy variable represents a remedy for the so-called "zero-inflation problem" given that in our data many firms never applied for a single patent. The pre-sample information technique is feasible in a study like ours because we have a long series for the dependent variable (1977-1994) prior to the starting period (1995) of the final sample in use.

However, as the Poisson model imposes the equality of conditional mean and conditional variance of the dependent variable distribution, we also decide to implement a negative binomial model, which is more flexible. In fact, it allows the variance to exceed the mean and the dispersion parameter α to vary randomly between firms[12]:

$$P\left(Y_{it} = y \mid \alpha_i, \lambda_{it}\right) = \frac{\Gamma\left(y + \alpha^{-1}\right)}{y!\Gamma\left(\alpha^{-1}\right)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_{it}}\right)^{\alpha^{-1}} \left(\frac{\lambda_{it}}{\alpha^{-1} + \lambda_{it}}\right)^{y} \, ,$$

where Γ is the Gamma distribution.

[12]The Negative binomial model coincides to a Poisson distribution when $\alpha = 0$.

As we have already mentioned before, one may argue that the relationship between firm patenting activity and diversity could be affected by endogeneity. The latter issue might arise because there could be unobserved firm specific factors influencing both the number of patent applications and the degree of labor diversity. To address these concerns we apply a two-stage IV procedure to the Poisson model as suggested by Vuong (1984). In this case equation (1) is specified as follows:

$$\lambda_{it} = exp\left(\beta_c Div\_c_{it} + \beta_s Div\_s_{it} + \beta_d Div\_d_{it} + w_{it}^{'}\beta_w + \eta_i + u_{it}\right) \qquad (2)$$

where the term u_{it} can be interpreted as unobserved heterogeneity correlated with the diversity indexes but uncorrelated with the vector of patent production determinants w_{it}.[13] To model the correlation between the endogenous variables and u_{it}, we specify a system of linear reduced-form equations, one for each diversity index. This is

$$\begin{cases} Div\_c_{it} = w_{it}^{'}\gamma_w + z_{it}^{'}\gamma_z + \varepsilon_{cit} \\ Div\_s_{it} = w_{it}\gamma_w + z_{it}^{'}\gamma_z + \varepsilon_{sit} \\ Div\_d_{it} = w_{it}^{'}\gamma_w + z_{it}^{'}\gamma_z + \varepsilon_{dit} \end{cases}$$

where z_{it} is the vector of exogenous variables that affects firm level diversity but does not directly affect the number of patent applications. As in section 3.1, the excluded variables are the diversity indexes computed at the commuting area where the firm is located and the model is just-identified. The error terms ε are assumed to have zero mean and to be correlated across equations for a given firm i but uncorrelated across observations. Furthermore, we assume that

[13] The error term u_{it} is added to allow for endogeneity. It also induces overdispersion, so that the Poisson model and the Negative binomial model are empirically equivalent.

the errors u and ε are related via

$$u_{it} = \rho_c \varepsilon_{cit} + \rho_s \varepsilon_{sit} + \rho_d \varepsilon_{dit} + \zeta_{it} \tag{3}$$

where $\zeta_{it} \sim \left[0, \sigma^2_\zeta\right]$ is independent of ε_{cit}, ε_{sit} and ε_{cit}.[14] Substituting equation (3) in equation (2) for u_{it} and taking the expectation with respect to ζ yields

$$E_\zeta(\lambda) = exp(\beta_c Div\_c + \beta_s Div\_s + \beta_d Div\_d + w^{'}\beta + \eta + lnE(e^\zeta) + \rho_c\varepsilon_c + \rho_s\varepsilon_s + \rho_d\varepsilon_d).$$

The constant term $lnE(e^\zeta)$ can be absorbed in the coefficient of the intercept as an element of w. It follows that

$$\lambda_{it} = exp\left(\beta_c Div\_c_{it} + \beta_s Div\_s_{it} + \beta_d Div\_d_{it} + w^{'}_{it}\beta_w + \eta_i + \rho_c\varepsilon_{cit} + \rho_s\varepsilon_{sit} + \rho_d\varepsilon_{dit}\right) ,$$

where ε_{cit}, ε_{sit} and ε_{cit} are the new additional variables. Given that the former variables are unobservable, we follow a two-step estimation procedure where first we estimate and generate them and second we estimate parameters of the Poisson model after replacing ε_{cit}, ε_{sit} and ε_{cit} with $\hat{\varepsilon}_{cit}$, $\hat{\varepsilon}_{sit}$ and $\hat{\varepsilon}_{cit}$. Obviously, the variance and covariance matrix of the two-step estimator needs to be adjusted for the above replacement by bootstrapping the sequential two-step estimator.

4 Results

This section reports findings for each of the outcome dimensions we look at: propensity to innovate, intensive and extensive margins. Several specifications among the different econometric models here employed help in understanding

[14]This assumption means that ε is a common latent factor that affects both diversity and patent applications and is the only source of dependence between them, after controlling for the influence of the observable variables (Cameron and Trivedi, 2009).

the strength of our results. We also provide robustness checks, which focus on the measurement of our outcome variable, computation of diversity indexes and differences in diversity among occupations.

4.1 Results on labor diversity and propensity to innovate

Table 2 reports estimates concerning the propensity to patent. As explained in the previous section, we implement probit models having as dependent variable the dummy indicating whether a firm has applied for a patent in a given year. In column 1 we have the three diversity indexes as the only regressors, which can explain about the 15% of the overall variation in the dependent variable and are associated with sizable and significantly positive effects. Augmenting the specification by including industrial, time and size dummies reduces the size of our coefficients of interest and almost doubles the explanatory power of the model. Columns 3 and 4 show results from probit models with all other covariates; whether the former treats the diversity indexes as exogenous variables, the latter shows the IV specification. Results between the two full specification models are rather similar and imply that a standard deviation change in the ethnic and skill diversity increases the probability to apply for patent by 0.020 and 0.044 per cent respectively. The inclusion of the pre-sample fixed effects turns out to be extremely important to deal with time invariant unobserved heterogeneity among firms. The latter variable is associated with significant effects and corrects the estimates on labor diversity. Relevant contribution to patenting propensity is due to the shares of highly skilled and vocational workers. Instead, the two defined spillovers and the average firm tenure do not explain much of such a propensity. As expected, exporters are also more likely to apply for a patent. From column 5 to 8, the labor diversity is based on the more disaggregated categorization. Now the effect of a standard deviation change in the skill diversity produces an increase in the probability to apply for a patent by 0.059 per cent, whereas the effect of ethnic diversity appears negligible.

4.2 Results on labor diversity and intensive margins

Results on intensive margins are reported in Table 3 and 4, all represent elasticities. Table 3 and 4 illustrate the estimates when diversity in cultural background is based on countries of origin and families of languages, respectively. The first column in Table 3 shows the output of a Poisson regression having as regressors only the diversity measures: the coefficients on them are large, positive and significant. Once more, after including the industry, time and size dummies (column 2) and especially in the full model specification (column 3) their dimension and statistical significance largely decrease. Except for the demographic heterogeneity, all other indexes are significant also if we instrument them in the IV Poisson (column 4). Taking the last specification as the most reliable, we find that one per cent increase in the skill diversity leads to a 1.7 percentage increase in the number of patent applications. This effect is quite sizable given that the elasticity associated to a production input like human capital (proxied by the share of highly skilled workers) is just about 1.6 times larger. Important effects are also related to the shares of technicians, capital and labor stock, while spillovers do not show significant contributions to the overall number of patent applications. As in the case of patenting propensity, exporters benefit from the knowledge gained in the international markets. Fixed firm effects capture also in the count models the important portion of fixed unobserved heterogeneity. Except for the effect of ethnic diversity, which now turns to be insignificant, the economic interpretation of our findings remains almost unchanged after comparing such results with what obtained by implementing negative binomial models, which are more flexible since they allow the variance to be different from the mean.

Table 4 reports elasticities for Poisson and negative binomial for the more disaggregated classification of labor diversity dimensions. Although signs and significance levels of the estimates remain similar to Table 3, now some changes occur. Specifically, in the IV Poisson (column 4) the coefficient on the ethnic diversity turns to be quite insignificant; in addition a larger effect is also associated with heterogeneity in skills. According to this specification one percent increase in the educational heterogeneity implies a 2.23 per cent increases in the number of patent applications.[15]

4.3 Results on labor diversity and extensive margins

Table 5 reports the effects of labor diversity on the probability of applying in different technological areas in a given year. The structure of this table is similar to Table 2. The low number of annual patent applications does not allow us to use potentially more suited count models. The diversity indexes alone explain the 6.8 per cent of the overall variation in the dependent variable. As partially recorded in the propensity to apply for patents and intensive margins analyses, the significance of the heterogeneity in cultural background and demographics vanishes when all covariates are included. Interestingly and differently

[15] We have also investigated whether the effects of a particular dimension of diversity can be influenced by other forms of labor heterogeneity by inclusion of all possible interaction couples between the diversity indexes. Furthermore, driven by the hypothesis that there might be complementarities among different skills and demographic groups, in particular young and educated workers can together with a more diverse workforce stimulate innovation and creativity, we have augmented our models with interactions between diversity indexes and shares of highly skilled and younger workers. Nevertheless, neither of the interactions turned out to be statistically significant. Figures showing marginal effects of the interactions are available from the authors upon a request.

from the former cases, the coefficient on skill diversity increases its value. However, comparing estimates between more and less aggregated categories it drops substantially. No significant differences are registered in the more detailed specifications between the results from the full specification and those obtained with the instruments for labor heterogeneity dimensions. It seems that skill diversity is much more relevant for patenting in different technological areas than the patenting per se. Thus, in order to widen the patent technological spectrum it seems to be fundamental to increase the heterogeneity in the workers' competencies and knowledge orientation. Taking the lowest estimate between the full IV specifications, it turns out that a standard deviation increase in skill diversity may be associated to a raise of about 7.2 per cent in the probability to patent in different technological fields.

5 Sensitivity analysis

As mentioned above, as a part of the sensitivity analysis we evaluate eventual variations in the effects of labor diversity when it is differently computed or the outcome variable is measured in a stricter way. Referring to the computation of the labor diversity, we use both the Shannon-Weaver entropy and the richness indexes. The former is considered as one of the most profound and useful diversity indexes in biology,[16] whereas the latter is defined as a number of categories observed for each dimension of interest (it does not account for the "evenness"). We also decompose the labor diversity in accordance with the white or blue-collar occupations. This is driven by the idea that diversity could play a different role for distinct occupational groups and have consequently heterogeneous effects on firm innovation. It is in fact plausible communication

[16] See Maignan et al. (2003).

costs and benefits associated with diversity may vary by occupational groups.[17] Final checks come from the evaluation of the relationship between labor diversity and firms' granted patents rather than patent applications. The reason behind this sensitivity is based on the potential critique that applications may not result into granted patents afterward.

Table 6 reports marginal effects of the three dimensions of labor diversity on the firm probability to innovate. These findings do not substantially differ from the main results. Interestingly, the role of skill heterogeneity strengthens when the outcome variable is based on patent grants rather than applications. As expected, a significantly positive effect of ethnic diversity is recorded for the white-collar workers only. This result is confirmed also in Table 7, which illustrates the effects of labor diversity on the number of patents. Thus, both outcomes support the assumption that ethnic diversity is more effective among highly skilled employees. The rest of the robustness checks are in line with the main findings and hence their overall interpretation does not vary. That notably corroborates our main analyses and provides an evident support to the conclusions, which are outlined in the next section.

6 Discussion and conclusions

In this paper an overall assessment of the nexus between labor diversity and firms' patenting behavior has been provided. To the best of our knowledge, this study represents the first concrete attempt to formalize and generalize the relationship of labor diversity and innovation by using detailed information on

[17]Unfortunately, given the relatively low number of patenting firms (and the delay occurring between the application year and period in which the potential grant is received), it is not possible to evaluate how our main findings might have changed for the probability to patent in different technological areas in a given year. However, results regarding the use of the Shannon-Weaver entropy and the richness indexes are available from the authors upon a request.

firms' workforce composition.

Specifically, controlling for a large number of firm specific characteristics, proxying for time invariant unobservables, including reasonable measures of knowledge spillovers, adopting alternative categorizations for diversity and using proper instruments for the labor diversity dimensions of interest, we find robust evidence that diversity in labor force's education and skills is a fundamental source of innovation. That facilitates firms' patenting activity in several ways: (a) slightly increases their propensity to (apply for a) patent, (b) enlarges the breadth of patenting technological fields and (c) favors the raise in the overall number of patent applications. Our findings support the theoretical models developed by Hong and Page (2001 and 2004), Berliant and Fujita (2008) and Osborne (2000), according to which labor diversity is an important driver for the creation of new ideas or channel to provide useful information to firms about consumers' tastes and products' markets. Being prudent in the quantification of skill heterogeneity effect on all these aspects of patenting activities, we find that a percentage change in skill diversity increases the number of firms' patent applications by 1.7 per cent. Furthermore, a standard deviation change in its value could lead to a raise of about 7.2 per cent in the firms' probability to apply for a patent in different technological areas. Instead, the contribution of skill diversity in terms of general propensity to send at least one patent application in a given year is quite low and close to be negligible: a standard deviation change in its value turns to raise such a probability by 0.044 per cent. The influence of ethnic heterogeneity on the propensity to innovate and on the number of patent applications is important too, especially when we distinguish between occupations. Conversely, the effect of demographic diversity typically vanishes ones detailed firm specific characteristics are included as control variables.

The overall picture coming out from our empirical analysis seems to be particularly relevant not only for the design of firms' innovation strategies but also for public policies aimed at fostering innovation. Our results give an important insight into technological process, a driver of productivity growth and ultimately an economic growth. We find that increase in firm diversity in terms of skills and ethnicity has a positive effect on the firm innovation process, as measured by probability to apply for a patent, on the number of patents produced and on the number of different technological areas of patents applied. Thus governmental policies aimed to encourage the employment of different categories of skilled workers can be beneficial in terms of improvements in firms' patenting activities, increasing both private returns, directly, and social gains, through knowledge diffusion mechanisms. Nowadays, such policies might contribute to attract foreign and domestically less abundant skilled labor by supporting investments in human capital. That could be one of the determinants to invert the general decline in patenting activity recorded during the recent economic crisis among the OECD countries (2009).

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Appendix 1: Measurement of Ethnic Diversity

1) The citizens in the different nationality groups are: **Danish**, Danish native including second generation immigrants; **North America and Oceania**, United States, Canada, Australia, New Zealand; **Central and South America**, Guatemala, Belize, Costa Rica, Honduras, Panama, El Salvador, Nicaragua, Venezuela, Ecuador, Peru, Bolivia, Chile, Argentina, Brazil; **Formerly Communist Countries**, Armenia, Belarus, Estonia, Georgia, Latvia, Lithuania, Moldova, Russia, Tajikistan, Ukraine, Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Rep. of Macedonia, Montenegro, Serbia, and Slovenia; **Muslim Countries**, Afghanistan, Algeria, Arab Emirates, Azerbaijan, Bahrain, Bangladesh, Brunei Darussalem, Burkina Faso, Camoros, Chad, Djibouti, Egypt, Eritrea, Gambia, Guinea, Indonesia, Iran, Iraq, Jordan, Kazakstan, Kirgizstan, Kuwait, Lebanon, Libyan Arab Jamahiriya, Malaysia, Maldives, Mali, Mauritania, Morocco, Nigeria, Oman, Pakistan, Palestine, Qatar, Saudi Arabia, Senegal, Sierra Leone, Somalia, Sudan, Syria, Tadzhikstan, Tunisia, Turkey, Turkmenistan, Uzbekistan, Yemen; **East Asia**, China, Hong Kong, Japan, Korea, Korea Dem. People's Rep. Of, Macao, Mongolia, Taiwan; **Asia,** all the other Asian countries non included in both East Asia and Muslim Countries categories and **Africa,** all the other African countries not included in the Muslim Country; **West and South Europe**, all the other European countries not included in the Formerly Communist Countries category.

2) Using linguistic grouping: **Germanic West** (Antigua Barbuda, Aruba, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Botswana, Brunei, Cameroon, Canada, Cook Islands, Dominica, Eritrea, Gambia, Germany, Ghana, Grenada, Guyana, Haiti, Ireland, Jamaica, Liberia, Liechtenstein, Luxemburg, Mauritius, Namibia, Netherlands, Netherlands Antilles, New Zealand, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and Grenadines, Seychelles, Sierra Leone, Solomon Islands, South Africa, St. Helena, Suriname, Switzerland, Trinidad and Tobago, Uganda, United Kingdom, United States, Zambia, Zimbabwe), **Slavic West** (Czech Republic, Poland, Slovakia), **Germanic Nord** (Denmark, Iceland, Norway, Sweden), **Finno-Permic** (Finland, Estonia), **Romance** (Andorra, Angola, Argentina, Benin, Bolivia, Brazil, Burkina Faso, Cape Verde, Chile, Columbia, Costa Rica, Cote D'Ivoire, Cuba, Djibouti, Dominican Republic, Ecuador, El Salvador, Equatorial Guinea, France, French Guina, Gabon, Guadeloupe, Guatemala, Guinea, Guinea Bissau, Holy See, Honduras, Italy, Macau, Martinique, Mexico, Moldova, Mozambique, Nicaragua, Panama, Peru, Portugal, Puerto Rico, Reunion, Romania, San Marino, Sao Tome, Senegal, Spain, Uruguay, Venezuela), **Attic** (Cyprus, Greece)**, Ugric** (Hungary)**, Turkic South** (Azerbaijan, Turkey, Turkmenistan), **Gheg** (Albania, Kosovo, Republic of Macedonia, Montenegro), **Semitic Central** (Algeria, Bahrain, Comoros, Chad, Egypt, Irak, Israel, Jordan, Kuwait, Lebanon, Lybian Arab Jamahiria, Malta, Mauritiania, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, Tunisia, Yemen**,** United Arabs Emirates**), Indo-Aryan (**Bangladesh, Fiji, India, Maldives, Nepal, Pakistan, Sri Lanka**), Slavic South (**Bosnia and Herzegovina, Croatia, Serbia, Slovenia**), Mon-Khmer East** (Cambodia)**, Semitic South** (Ethiopia)**, Slavic East** (Belarus, Georgia, Mongolia, Russian Federation, Ukraine)**, Malayo-Polynesian West** (Indonesia, Philippines)**, Malayo-Polynesian Central East** (Kiribati, Marshall Islands, Nauru, Samoa, Tonga)**, Iranian** (Afghanistan, Iran, Tajikistan)**, Betai** (Laos, Thailand)**, Malayic** (Malasya)**, Cushitic East** (Somalia)**, Turkic East** (Uzbekistan)**, Viet-Muong** (Vietnam)**, Volta-Congo** (Burundi, Congo, Kenya, Lesotho, Malawi, Nigeria, Rwanda, Swaziland, Tanzania, Togo)**, Turkic West** (Kazakhstan, Kyrgystan)**, Baltic East** (Latvia, Lithuania)**, Barito** (Madagascar)**, Mande West** (Mali)**, Lolo-Burmese** (Burma)**, Chadic West**

(Niger), **Guarani** (Paraguay), **Himalayish** (Buthan), **Armenian** (Armenia), **Sino Tibetan** (China, Hong Kong, Singapore, Taiwan), **Japonic** (Japan, Republic of Korea, Korea D.P.R.O.).

Appendix 2: External knowledge indexes

The main literature on agglomeration economies emphasizes the importance of firm's local environment, which may reflect information advantages, labor or other inputs pooling and further beneficial network effects aimed at alleviating the burden represented by fixed costs. A seminal contribution in this field is due to Audretsch and Feldman (1996), who find that industries characterized by elevated R&D intensity or particularly skilled labor forces present a greater degree of geographic concentration of production. Other relevant studies, like Wallsten (2001), Adams and Jaffe (2002), and Adams (2002) provide evidence of the geographic extent of knowledge spillovers by computing the distance in miles between each firm-pair. However, the geography is not the only dimension of the external knowledge. In fact, there exists at least another approach which focuses on the concept of technological proximity (Jaffe, 1986; Adams, 1990; Inkmann and Pohlmeier, 1995). Specifically, the idea that the technology developed by a firm can affect other firms, even though they are not geographically close or no transactions of goods occur between them, has led to the definition of technological proximity as closeness between firm-pairs' technological profiles.

Following both the cited approaches we construct two indexes of knowledge spillovers. These are weighted sums of firms' codified knowledge proxied by the discounted stock of patent applications.[18] The weighting function for the first index refers to the geographical distance between pairs of workplaces' municipalities and is computed by using the firms' latitude and longitude coordinates (the address of their headquarters). Specifically, assuming a spherical earth of actual earth volume, this method allows us to measure the distance in kilome-

[18]See paragraph 4.2.

ters between any pair of firms i and j .[19] The first knowledge spillover index is then computed as follows:

$$K\_geo_{it} = \frac{1}{e^{dist_{ij}}} \sum_{j \neq i}^{I} disc\_stock_{jt} \ .$$

The second index is instead based on the technological proximity. Following Adams (1990), we use the shares of differently skilled workers to define our alternative weighting function ψ_{ij} that is the uncentered correlation:

$$\psi_{ij} = \frac{f_i f_j^{'}}{\left[\left(f_i f_i^{'}\right)\left(f_j f_j^{'}\right)\right]^{1/2}} \ .$$

The components of the generator vector f reflects firm's workforce composition in terms of skills using the disaggregated categorization as described in section 3.2. The second measure of knowledge spillover pool is therefore defined as

$$K\_tech_{it} = \psi_{ij} \sum_{j \neq i}^{I} disc\_stock_{jt} \ .$$

Thus, both K_geo_{it} and K_tech_{ij} contain weighting functions that might capture the so called firm's absorptive capacity, which is the ability to identify and exploit the knowledge externally produced (Cohen and Levinthal, 1990).

[19] We use the following formula $d_{ij} = 6378.7 * acos\{sin(lat_i/57.2958) * sin(lat_j/57.2958) + $ $+ cos(lat_i/57.2958) * cos(lat_j/57.2958) * cos(lon_j/57.2958 - lon_i/57.2958)\}$.

Table 1: Descriptive statistics

		All sample			Non-patenting firms			Patenting firms		
Variables	Definition	Median	Mean	Sd	Median	Mean	Sd	Median	Mean	Sd
IDA Variables:										
males	men as a proportion of all employees	0.786	0.709	0.243	0.786	0.706	0.247	0.174	0.674	0.199
foreigners	non-danish employees as a proportion of all employees	0	0.042	0.086	0	0.423	0.494	1	0.750	0.433
age1	employees aged 15-28 as a proportion of all employees	0.304	0.325	0.172	0.304	0.325	0.173	0.263	0.280	0.127
age2	employees aged 29-36 as a proportion of all employees	0.255	0.259	0.120	0.250	0.257	0.121	0.296	0.300	0.090
age3	employees aged 37-47 as a proportion of all employees	0.200	0.204	0.109	0.200	0.204	0.110	0.222	0.219	0.079
age4	employees aged 47-65 as a proportion of all employees	0.251	0.212	0.124	0.252	0.178	0.15	0.232	0.162	0.067
skill1	employees with compulsory education as a proportion of all employees	0.176	0.271	0.129	0.164	0.272	0.128	0.201	0.238	0.123
skill2	employees with a secondary/ post-secondary education as a proportion of all employees	0.714	0.689	0.189	0.714	0.690	0.189	0.658	0.662	0.147
skill3	employees with a tertiary education as a proportion of all employees	0	0.040	0.099	0	0.038	0.097	0.043	0.100	0.137
tenure	average tenure	4.473	4.622	1.867	4.466	4.616	1.871	5.038	5.025	1.596
manager	managers as a proportion of all employees	0.018	0.045	0.064	0.016	0.045	0.064	0.037	0.052	0.059
middle manager	middle managers as a proportion of all employees	0.837	0.762	0.241	0.842	0.764	0.240	0.658	0.599	0.240
blue collars	blue collars as a proportion of all employees	0.140	0.236	0.348	0.140	0.234	0.348	0	0.384	0.486
size1	1, if the firm has less than 50 employees	1	0.816	0.387	1	0.825	0.379	0	0.154	0.316
size2	1, if the firm has btw 50 and employees	0	0.096	0.295	0	0.093	0.291	0	0.416	0.498
size3	1, if the firm has more than 50 employees	0	0.087	0.281	0	0.080	0.272	0	0.056	0.324
Index Ethnic	Herfindahl diversity index based on employees' nationality	0	0.095	0.202	0	0.087	0.194	0.340	0.299	0.278
Index Skill	Herfindahl diversity index based on employees' skills	0.406	0.369	0.148	0.402	0.367	0.148	0.472	0.437	0.131
Index Demo	Herfindahl diversity index based on employees' demographic characteristics	0.762	0.748	0.082	0.760	0.746	0.081	0.804	0.795	0.055
Accounting Variables:										
Patent applications	annual number of patent applications	0	0.029	0.628	0	0	0	0	0.829	3.142
capital	(1000 kr.)	11334.29	73542.36	841303.4	10864	57015.39	781429.8	77714.73	541278.6	2071364
foreign-ownership	1, if the firm is foreign owned	0	0.004	0.066	0	0.005	0.066	0	0.004	0.061
multi	1, if the firm is multi-establishment	0	0.093	0.260	0	0.093	0.291	0	0.298	0.457
exp	1, if the firm is exporting	1	0.506	0.499	0	0.488	0.499	1	0.874	0.331
geo_spillover	spillover variable based on the technological distance	40.1925	226.697	456.646	40.19252	228.2731	228.2731	1130.534	1063.769	362.0997
tech_spillover	spillover variable based on the geographical distance	1091.168	1031.535	345.931	1090.384	1030.382	345.2853	50.08433	182.6429	340.2594
N			107536			103224			4312	

Notes: : All workforce composition and accounting variables are expressed as time averages from 1995 to 2003. The industrial sectors included in the empirical analysis are the following: food, beverages and tobacco (4.05 %); textiles (2.24 %), wood products (6.68 %), chemicals (3.49 %), other non-metallic mineral products (1.50 %), basic metals (19.13 %), furniture (3.79 %), construction (22.40 %), wholesale trade (14.67 %), retail trade (9.02 %), post and telecommunications (0.27 %), financial intermediation (1.19 %) and business activities (11.02 %).

Table 2: The effects of labor diversity on firm probability to innovate. Main results.

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
	Probit	**Probit**	**Probit**	**Probit (IV)**	**Probit**	**Probit**	**Probit**	**Probit (IV)**
Index Ethnic	0.020***	0.003***	0.001*	0.001**	0.008***	0.001***	0.000*	0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Index Skill	0.016***	0.006***	0.002**	0.003**	0.025***	0.011***	0.003***	0.004***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Index Demo	0.045***	0.008**	0.001	0.005*	0.028***	0.002	0.000	0.004
	(0.005)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)	(0.004)
Log(K)			0.001***	0.000***			0.000***	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Log(L)			0.000**	0.000*			0.000**	0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Log(fixed effects)			0.006***	0.006***			0.005***	0.005***
			(0.001)	(0.001)			(0.001)	(0.001)
age1			0.001	0.001*			0.000	0.001
			(0.001)	(0.001)			(0.001)	(0.001)
age2			0.002**	0.002**			0.002**	0.002**
			(0.001)	(0.001)			(0.001)	(0.001)
age3			0.002*	0.001			0.002*	0.002**
			(0.001)	(0.001)			(0.001)	(0.001)
males			-0.000	0.000			-0.000	-0.000
			(0.000)	(0.001)			(0.000)	(0.000)
foreigners			0.000	-0.000			-0.000	-0.000
			(0.001)	(0.001)			(0.001)	(0.001)
exp			0.001***	0.001***			0.001***	0.001***
			(0.000)	(0.000)			(0.000)	(0.000)
skill1			0.003**	0.004**			0.002***	0.002***
			(0.001)	(0.001)			(0.001)	(0.001)
skill2			0.006***	0.005***			0.005***	0.004***
			(0.001)	(0.001)			(0.001)	(0.001)
manager			0.001	0.001			0.001	0.001
			(0.001)	(0.001)			(0.001)	(0.001)
middle manager			-0.001*	-0.001			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)
tenure			-0.000***	-0.000***			-0.000**	-0.000**
			(0.000)	(0.000)			(0.000)	(0.000)
multi			-0.000	0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
$geo_s pillover$			-0.000	-0.000			-0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
$tech_s pillover$			-0.000***	-0.000***			-0.000***	-0.000***
			(0.000)	(0.000)			(0.000)	(0.000)
Industry/size/year dummies	no	yes	yes	yes	no	yes	yes	yes
N	105799	100704	100696	100696	105799	100704	100696	100696
pseudo R2	0.148	0.298	0.424	0.424	0.187	0.324	0.427	0.427

Notes: The dependent variable in all estimations is the probability to have at least one patent application. Marginal effects reported. Model1-Model4: diversity based on the aggregate specification. Model5-Model8: diversity based on the detailed specification. Model4 and Model8 report results from IV estimation. Wald tests on exogeneity, p-value (Model4)=0.453; p-value (Model8)=0,321. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level.

Table 3: The effects of labor diversity on firm patent applications. Diversity based on the aggregate specification.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	Poisson	**Poisson**	**Poisson**	**Poisson (IV)**	**Negbin**	**Negbin**	**Negbin**
Index Ethnic	0.382***	0.164***	0.044*	0.043*	0.308***	0.103***	0.027
	(0.033)	(0.033)	(0.023)	(0.024)	(0.017)	(0.018)	(0.020)
Index Skill	1.792***	1.502***	1.097**	1.701**	1.047***	0.850***	0.977**
	(0.356)	(0.364)	(0.459)	(0.700)	(0.210)	(0.215)	(0.345)
Index Demo	11.184***	4.282**	0.661	5.010	6.315***	2.212**	0.507
	(1.834)	(1.579)	(1.435)	(3.384)	(0.717)	(0.789)	(1.060)
Log(K)			4.901***	4.792***			4.222***
			(0.601)	(0.620)			(0.617)
Log(L)			0.837**	0.339			0.968**
			(0.340)	(0.485)			(0.350)
Discounted stock of applications			-0.000	-0.000			-0.000
			(0.000)	(0.000)			(0.000)
Log(fixed effects)			0.003	0.005*			0.003
			(0.002)	(0.003)			(0.002)
Fixed effect dummy			0.053***	0.052***			0.050***
			(0.006)	(0.006)			(0.005)
age1			0.154	0.452			0.140
			(0.262)	(0.327)			(0.212)
age2			0.212	0.195			0.326*
			(0.237)	(0.235)			(0.174)
age3			0.144	0.051			0.184
			(0.209)	(0.226)			(0.171)
males			0.266	0.717			0.023
			(0.524)	(0.641)			(0.368)
foreigners			0.032	0.029			0.017
			(0.033)	(0.033)			(0.027)
exp			0.496***	0.468***			0.462***
			(0.110)	(0.108)			(0.087)
skill1			2.079**	2.761**			1.858**
			(0.776)	(0.942)			(0.594)
skill2			0.162***	0.122**			0.150***
			(0.030)	(0.047)			(0.029)
manager			0.001	-0.007			0.037
			(0.038)	(0.039)			(0.034)
middle manager			-0.389	-0.309			-0.370
			(0.267)	(0.266)			(0.245)
tenure			-0.392	-0.425			-0.396**
			(0.290)	(0.286)			(0.200)
multi			-0.000	0.022			0.003
			(0.017)	(0.024)			(0.013)
$geo_spillover$			-0.392	-1.340			-0.446
			(0.580)	(0.991)			(0.484)
$tech_spillover$			-0.027	-0.009			-0.039
			(0.038)	(0.040)			(0.038)
Industry/size/year dummies	no	yes	yes	yes	no	yes	yes
N	105799	105799	105791	105787	105799	105799	105791
chi2	192.4	112434.3	50404.7	48668.4	606.2	69791.2	51064.6

Notes: The dependent variable in all estimations is the number of patent applications. Elasticities reported. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level. Poisson (IV): standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications. F-stats on excluded instruments: i) Index Ethnic at county level: 1299.68; ii) Index_skill at county level: 189.68; iii) Index_demo at county level: 221.79.

Table 4: The effects of labor diversity on firm patent applications. Diversity based on the detailed specification.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	Poisson	**Poisson**	**Poisson**	**Poisson (IV)**	**Negbin**	**Negbin**	**Negbin**
Index Ethnic	0.453***	0.232***	0.070**	0.045	0.323***	0.124***	0.043
	(0.041)	(0.039)	(0.032)	(0.044)	(0.021)	(0.024)	(0.028)
Index Skill	4.825***	5.426***	1.911***	2.234***	3.556***	3.987***	1.900***
	(0.476)	(0.615)	(0.503)	(0.627)	(0.250)	(0.376)	(0.392)
Index Demo	14.568***	3.864**	-0.027	4.612	7.711***	1.276	-0.161
	(2.503)	(1.869)	(1.568)	(4.997)	(0.885)	(0.885)	(1.159)
Log(K)			4.756***	4.821***			4.055***
			(0.601)	(0.599)			(0.604)
Log(L)			0.866**	0.932**			1.012**
			(0.339)	(0.343)			(0.346)
Discounted stock of applications			-0.000	-0.000			-0.000
			(0.000)	(0.000)			(0.000)
Log(fixed effects)			0.003	0.003			0.003
			(0.002)	(0.002)			(0.002)
Fixed effect dummy			0.052***	0.052***			0.049***
			(0.006)	(0.006)			(0.005)
age1			0.127	0.186			0.099
			(0.253)	(0.254)			(0.203)
age2			0.175	0.215			0.274*
			(0.234)	(0.229)			(0.171)
age3			0.183	0.233			0.204
			(0.200)	(0.194)			(0.166)
males			0.362	0.383			0.130
			(0.512)	(0.502)			(0.364)
foreigners			0.020	0.009			0.005
			(0.033)	(0.034)			(0.027)
exp			0.494***	0.486***			0.457***
			(0.110)	(0.107)			(0.087)
skill1			0.896**	0.844*			0.917**
			(0.448)	(0.433)			(0.355)
skill2			0.147***	0.144***			0.134***
			(0.028)	(0.028)			(0.028)
manager			0.021	0.023			0.058*
			(0.037)	(0.035)			(0.033)
middle manager			0.076	0.166			0.131
			(0.291)	(0.296)			(0.256)
tenure			-0.362	-0.323			-0.351*
			(0.291)	(0.294)			(0.199)
multi			0.004	0.005			0.007
			(0.017)	(0.016)			(0.013)
geo$_s$*pillover*			-0.635	-0.691			-0.838*
			(0.579)	(0.598)			(0.489)
tech$_s$*pillover*			-0.029	-0.047			-0.044
			(0.039)	(0.041)			(0.039)
Industry/size/year dummies	no	yes	yes	yes	no	yes	yes
N	105799	105799	105791	105787	105799	105799	105791
chi2	214.6	85033.9	44697.0	43060.7	687.2	56559.4	49796.4

*Notes:*The dependent variable in all estimations is the number of patent applications. Elasticities reported. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level. Poisson (IV): standard errors are bootstrapped using a sequential two step bootstrapping procedure with 200 replications. F-stats on excluded instruments: i) Index Ethnic at county level: 1585.02; ii) Index_skill at county level: 840.97; iii) Index_demo at county level: 483.28.

Table 5: The effects of labor diversity on the probability of applying in different technological areas.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	Probit	**Probit**	**Probit**	**Probit (IV)**	**Probit**	**Probit**	**Probit**	**Probit (IV)**
Index Ethnic	0.162**	0.109*	0.020	0.044	0.171***	0.142**	0.040	0.050
	(0.057)	(0.064)	(0.060)	(0.060)	(0.046)	(0.052)	(0.053)	(0.065)
Index Skill	0.572***	0.563***	0.988***	1.412***	0.821***	0.809***	0.488**	0.476**
	(0.129)	(0.156)	(0.299)	(0.392)	(0.143)	(0.193)	(0.209)	(0.203)
Index Demo	0.568*	0.217	0.433	1.070	0.525*	0.073	0.299	0.099
	(0.316)	(0.309)	(0.364)	(0.823)	(0.316)	(0.348)	(0.370)	(1.358)
Log(K)			0.030**	0.029**			0.030**	0.031**
			(0.012)	(0.012)			(0.012)	(0.012)
Log(L)			0.014	-0.009			0.014	0.016
			(0.023)	(0.029)			(0.024)	(0.024)
Log(fixed effects)			0.250***	0.278***			0.260***	0.258***
			(0.045)	(0.052)			(0.046)	(0.046)
age1			0.712***	0.800***			0.717***	0.758***
			(0.184)	(0.213)			(0.181)	(0.182)
age2			0.739***	0.695***			0.696***	0.713***
			(0.200)	(0.202)			(0.198)	(0.202)
age3			0.287	0.198			0.404	0.382
			(0.286)	(0.294)			(0.276)	(0.265)
males			0.143	0.195			0.125	0.125
			(0.099)	(0.127)			(0.099)	(0.098)
foreigners			0.231	0.175			0.189	0.062
			(0.258)	(0.257)			(0.274)	(0.275)
exp			0.004	0.001			0.016	0.016
			(0.041)	(0.040)			(0.042)	(0.041)
skill1			0.731**	1.031***			0.078	0.039
			(0.253)	(0.305)			(0.145)	(0.140)
skill2			0.151	-0.175			0.202	0.109
			(0.202)	(0.256)			(0.201)	(0.206)
manager			0.171	0.203			0.227	0.277
			(0.214)	(0.205)			(0.229)	(0.229)
middle manager			0.016	0.035			0.064	0.086
			(0.091)	(0.090)			(0.100)	(0.100)
tenure			-0.003	-0.004			-0.004	-0.003
			(0.010)	(0.010)			(0.010)	(0.010)
multi			0.006	0.044			0.005	0.009
			(0.035)	(0.047)			(0.037)	(0.037)
co-patent			0.024	0.030			0.009	0.000
			(0.032)	(0.032)			(0.021)	(0.000)
$geo_{s}pillover$			0.000	-0.000			0.000	-0.000
			(0.000)	(0.000)			(0.000)	(0.000)
$tech_{s}pillover$			-0.000	-0.000			-0.000	0.013
			(0.000)	(0.000)			(0.000)	(0.021)
Industry/size/year dummies	no	yes	yes	yes	no	yes	yes	yes
N	1146	1116	1116	1116	1146	1116	1116	1116
pseudo R2	0.068	0.146	0.378	0.332	0.100	0.159	0.371	0.324

Notes: The dependent variable in all estimations is the probability of applying a patent in different technological areas. Marginal effects reported. Model1-Model4: diversity based on the aggregate specification. Model5-Model8: diversity based on the detailed specification. Model4 and Model8 report results from IV estimation. Wald tests on exogeneity, p-value (Model4)=0.657; p-value (Model8)=0.823. Significance levels: ***1%, **5%, 10*%. Standard errors clustered at the firm level.

Table 6: The effects of labor diversity on firm probability to innovate. Robustness checks.

	(1)	(2)	(3)	(4)	(5)
	Occupation specific diversity		**Shannon entropy index**	**Richness index**	**Grants-based definition of innovation**
	White collar	*Blue collar*			
Index Ethnic Aggr	0.001**	-0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Index Skill Aggr	0.001**	0.001	0.001**	0.001***	0.003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Index Demo Aggr	0.000	-0.000	0.000	0.000	0.002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
N	100696		100696	105791	100696
pseudo R2	0.424		0.425	0.368	0.646
Index Ethnic Disaggr	0.000*	0.000	0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Index Skill Disaggr	0.001**	0.001**	0.003***	0.001***	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Index Demo Disaggr	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
N	100696		100696	105791	100696
pseudo R2	0.425		0.425	0.371	0.427

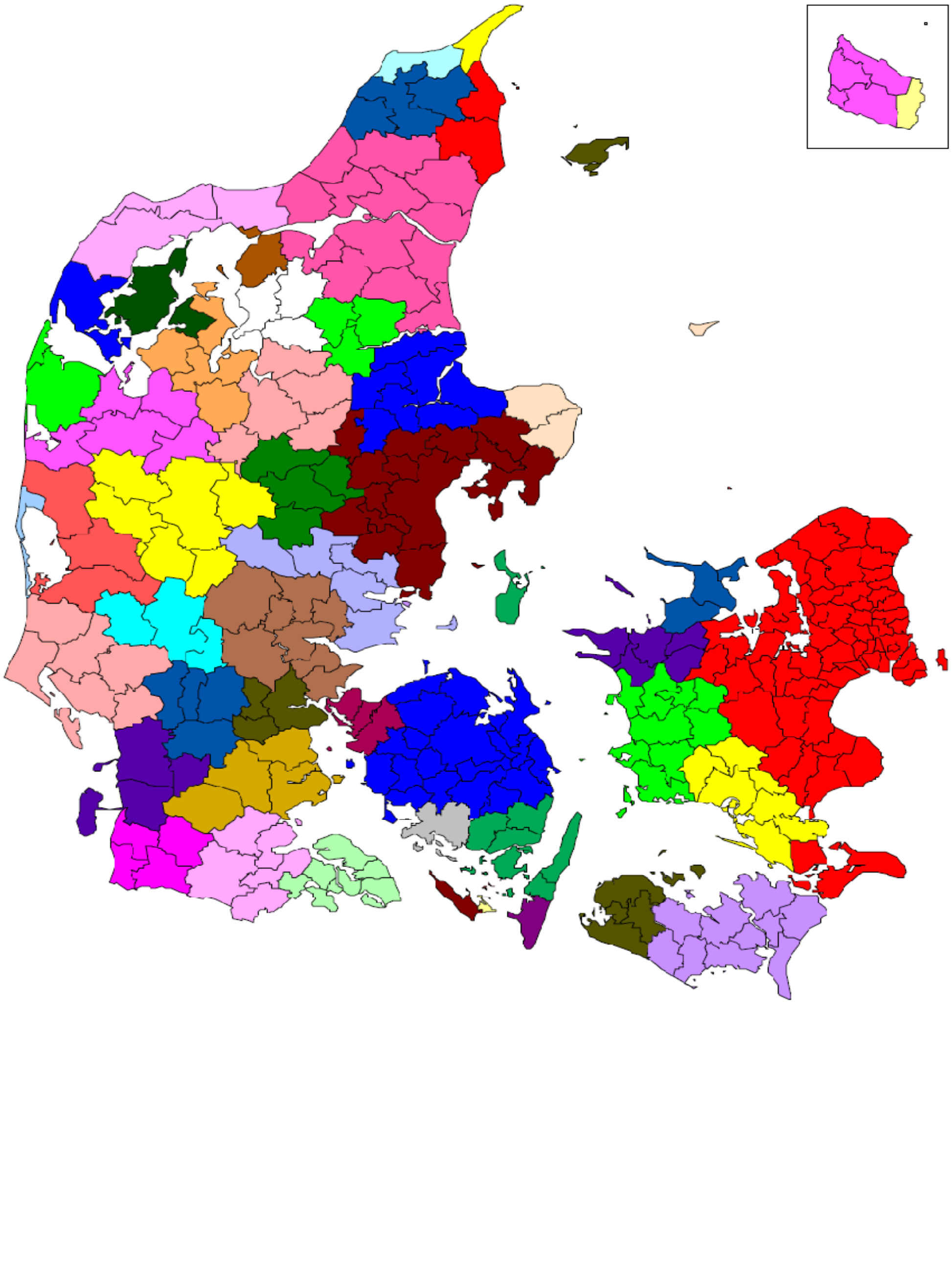
Notes: The dependent variable in all estimations is the probability to have at least one patent application. Marginal effects reported. All regressions include all the firm specific characteristics, year and three-digit industry dummies. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level.

Table 7: The effects of labor diversity on firm patents. Robustness checks.

	(1)	(2)	(3)	(4)	(5)
	Occupation specific diversity		**Shannon entropy index**	**Richness index**	**Grants-based definition of innovation**
	White collar	*Blue collar*			
Index Ethnic Aggr	0.033*	0.007	0.099	0.034	0.044*
	(0.019)	(0.004)	(0.080)	(0.022)	(0.023)
Index Skill Aggr	0.422**	0.065	0.811*	0.191**	1.097**
	(0.173)	(0.057)	(0.445)	(0.082)	(0.459)
Index Demo Aggr	-0.465	0.131	0.195	0.334	0.661
	(0.427)	(0.114)	(0.527)	(0.321)	(1.435)
N	105791		105791	105791	105791
chi2	60480.9		53127.0	3147.2	50404.7
Index Ethnic Disaggr	0.051**	0.014*	0.090**	0.015***	0.027
	(0.026)	(0.008)	(0.041)	(0.003)	(0.020)
Index Skill Disaggr	0.739***	0.197	0.672**	1.282***	0.977**
	(0.193)	(0.133)	(0.257)	(0.186)	(0.345)
Index Demo Disaggr	-0.691*	0.074	-0.058	0.325	0.507
	(0.355)	(0.165)	(0.461)	(0.325)	(1.060)
N	105791		105791	105791	105791
chi2	61299.9		56458.7	3509.1	51064.6

Notes: The dependent variable in all estimations is the probability to have at least one patent application. Elasticities reported. All regressions include all the firm specific characteristics, year and three-digit industry dummies. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level.

Figure 1: Commuting areas,1995, Denmark.



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