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IZA DP No. 6972

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October 2012

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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IZA Discussion Paper No. 6972
October 2012

ABSTRACT

The Nexus between Labor Diversity and Firm's Innovation*

In this paper we investigate the nexus between firm labor diversity and innovation using a linked employer-employee data from Denmark. Specifically, exploiting information retrieved from this comprehensive database and implementing proper instrumental variable strategies, we are able to identify the contribution of workers' diversity in cultural background, education 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 ethnic diversity plays an important role in propelling firm's innovation outcomes.

JEL Classification: J15, J16, J24, J61, J82, O32

Keywords: labor diversity, ethnic diversity, patenting activity, extensive and intensive margins

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* We thank Guglielmo Barone, Tor Eriksson, Hideo Owan, Pekka Ilmakunnas, Michael Rosholm, Chad Syverson and Måns Soderbom (alphabetical order) for helpful suggestions. In addition, we appreciate comments from participants at seminars organized by the Copenhagen Business School, University of Bergamo, Aarhus School of Business, University of Lausanne, and from participants at the following conferences: ESPE 2010, The 5th Nordic Summer Institute in Labor Economics, The 2010 Ratio Young Scientist Colloquium, ESEM 2010, CAED/COST 2010 in London, the 2010 International Symposium on Contemporary Labor Economics at WISE, Xiamen, and EALE 2011 in Paphos. We also thank Ulrich Kaiser and Cedric Schneider for graciously providing us the data on patent applications. Pierpaolo Parrotta acknowledges the financial support from the Swiss National Centre of Competence in Research LIVES and Graduate School for Integration, Production and Welfare. Mariola Pytlikova gratefully acknowledges funding from the NORFACE Migration Programme "Migration: Integration, Impact and Interaction". The usual disclaimer applies.

1 Introduction

Many developed and developing countries have experienced several changes in the workforce composition which has led 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 often hear 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 firm productivity (Parrotta et al. 2011). Besides, workforce diversity is believed to be an important source of innovation. For instance, 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). If this is the case, firms could benefit from the growing diverse cultural backgrounds, demographic, and knowledge bases of the workforces. Moreover, since there is a widespread consensus that innovation is crucial for sustainable growth and economic development (as suggested in the new growth theories), understanding the link between workforce diversity and innovation seems to be essential for policy makers.

From a theoretical point of view, a paradox has been recognized: whereas a high degree of heterogeneity among workers can be a source of creativity and therefore foster innovation activity, it can also induce misunderstanding, conflicts and uncooperative behaviors within workplaces and in this way hinder innovation (Basset-Jones, 2005). There is no general agreement on which effect prevails. Specifically, differences in skills, education and more broadly in knowledge among employees seem to be beneficial rather than detrimental. According to Lazear (1999), positive effects may prevail as long as workers' information sets are not overlapping but relevant to one another. Ambiguity instead persists for diversity in ethnic and demographic characteristics of employees. On one hand, people of different cultural backgrounds may provide diverse perspectives, valuable ideas, problem-solving abilities, and in this way facilitate the achievement of optimal creative solutions and therefore stimulate innovations (Watson et al. 1993; Drach-Zahavy and Somech, 2001; Hong and Page, 2001 and 2004). As people of different ethnic backgrounds also possess knowledge about global markets and customers tastes, they may stimulate firm to improve or develop products sold abroad (Osborne, 2000; Berliant and Fujita, 2008). On the other hand, such heterogeneities might create communication barriers, reduce the workforce cohesion and prevent cooperative participation in research activities, bringing high costs of "cross-cultural dealing" (Williams and O'Reilly, 1998; Zajac et al., 1991; Lazear, 1999). Effects of diversity in demographics are two-faced, too. For instance, age heterogeneity may facilitate innovation because there are complementarities between the human capital of younger and older workers: younger employees have knowledge of new technologies and IT and older employees have a better understanding and experience with the intra-firm structures and the operating process (Lazear, 1998). But, demographic heterogeneity among workers may create communication frictions if workers are prejudiced, and therefore bring some cost connected to the frictions (Becker, 1957).

The empirical literature exploring the relationship between labor diversity and firm's innovation consists mainly of business case studies that often look at work-team compositions (Horwitz and Horwitz, 2007; and Harrison and Klein, 2007) or even focus on diversity in top management teams only (Bantel and Jackson, 1989; Knight et al. 1999; Pitcher and Smith, 2001).[1] 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 virtually non-existent.

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 the years 1995-2003. Regarding measures of innovation, we follow previous literature and make use of information on patents to proxy for innovation (Griliches, 1990; Bloom and Van Reenen,

[1] There exists also some literature on the effects of diversity - typically ethnic labor diversity - on innovation using aggregate regional or industry data, for instance Kelley and Helper (1999), Feldman and Audretsch (1999), Anderson et al. (2005), Niebuhr (2010); Kerr and Lincoln (2010).

2002). Specifically, we use the following three measures: (1) firm's propensity to apply for a patent, (2) the number of patents introduced each year and (3) firm's propensity to apply in more than one technological area, conditional on patenting. We investigate the effect of labor diversity on firm innovation by looking at three dimensions of employee diversity: cultural background, skills/education and demographics. The comprehensive data allows us to dig deeper into the mechanisms by which diverse workforces may affect innovation. In particular we test two hypotheses. First, we test the creativity hypothesis proposed by the theoretical frameworks by Hong and Page (2001 and 2004) and Berliant and Fujita (2008). Specifically, we expect that the beneficial effects of diverse problem-solving abilities and creativity would materialize more in terms of innovation for white-collar occupations compared to blue-collar occupations. Second, we exclude certain groups of foreigners from calculation of ethnic diversity measures to test whether the costs of "cross-cultural dealing" play a role. In particular, we expect that communication costs associated with ethnic diversity may increase after subtracting out foreigners who are likely to speak Danish or English.

In addition, we deal with several problems that previous literature studying the impact of workforce diversity on innovation did not properly address. Most importantly, if firms are aware of the importance of labor diversity and leverage it to improve their performance, then the relationship under investigation is very likely to be affected by endogeneity. To address these concerns, we implement an instrumental variable (IV) strategy à la Card (2001) based on measures of historical workforce diversity patterns at the commuting area level (where a firm is located) as instruments for the current firm labor diversity. In addition, we use an alternative instrument for the workplace ethnic diversity based on foreign population shares at the commuting areas predicted from a model of migration determinants. Furthermore, firms are characterized by a different propensity to innovate. Thus, there exist unobserved and observed firm-specific heterogeneity that should be taken into account to evaluate the effect of any labor diversity dimension on firm's innovation outcome. 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 and compute knowledge spillovers indicators based on geographical and technological distances between firms.

Implementing alternative estimation techniques, we find evidence of the key role of ethnic diversity in promoting firm's innovation as measured by the number of patent applications, the probability to apply for a patent or to patent in more than one technological field, conditional on patenting. Specifically, we find that a 10 percentage change in ethnic diversity increases the number of firms' patent applications by approximately 4.4 (2.3) percent, in the aggregate (disaggregate) diversity specification. Whereas the contribution of ethnic diversity to start patenting is economically meaningful, the effect of ethnic diversity on extensive margins is very large: conditional on patent application, a standard deviation increase in ethnic diversity duplicates the probability to patent in different technological fields, according to the most conservative estimates. Effects of diversity in education and demographics turn out to be mostly insignificant when either the full set of controls is included or endogenity is taken care of.

These results support the hypothesis that ethnically diverse workers tend to have a wider pool of different experiences, knowledge bases and heuristics boosting their problem-solving capacities and creativity, which in turn facilitate innovations. In this regard, our findings are consistent with the theoretical frameworks proposed by Hong and Page (2001 and 2004) and Berliant and Fujita (2008). These positive effects of workforce diversity on innovation clearly outweigh any costs of "cross-cultural dealing". Hence, our results suggest firms aiming to promote innovation to focus on recruitment strategies that explicitly account for heterogeneity in ethnicity. This article may also provide some suggestions to public authorities in terms of innovation policies. Given that innovation is considered as one of the most important components for the long-term economic growth, 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 ethnic diversity within workplaces and in such a way increase the innovation, and ultimately the economic growth.

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

2 Data

2.1 Data sources

The data set 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 in charge for creating statistics on the Danish society and economy. IDA contains a broad set of information on individuals and firms for years 1980-2006. In particular, we are interested in gender, age, nationality, education, occupation, tenure, place of work, whether a company is (partially or totally) foreign-owned and a multi-establishment firm. 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 the Statistics Denmark and reports data for the period 1995-2006.[2] In REGNSKAB it is possible to identify partially and totally imputed values, which we exclude from our final data set in order to avoid any bias in the estimates. The last data source is a collection of patent applications sent to the European Patent Office (EPO) by Danish firms.[3] It covers a period of 26 years (1978-2003) and allows us to account for 2822 applicants and 2244 granted firms.[4] We

[2]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 to submit their annual accounts and other specifications or to fill out a questionnaire. In order to facilitate responding, questions are formulated in the same way as required in the Danish annual accounts legislation.

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

[4]More details concerning the construction and composition of the data set can be found in Kaiser, Kongsted and Rønde (2008).

disregard industries[5] with no patenting firms during the period covered in our empirical analysis. We also exclude enterprises with less than 10 employees from our sample to allow all investigated firms to reach (potentially) the highest degree of (ethnic) diversity at least when an aggregate specification is used, as outlined in the next section. Finally we leave out firms that were founded during the estimation period (1995-2003), given that we use a "pre-sample" estimator that requires information on firms' patenting behavior prior to 1995. Thus, our final data set contains information on approximately 12,000 firms per year over a period of 9 years (1995-2003).

2.2 Diversity measures

The workforce diversity (heterogeneity) measures used in this article are computed at the workplace level and then aggregated at the firm level and are 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 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 levels, respectively. Thus, the ratio between the last two variables corresponds to the weighting function, while p_{wst} is the proportion of the 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

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

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[6] and is built by using the following eight categories: North America and Oceania, Central and South America, Africa, Western and Southern Europe, Formerly Communist Countries, East Asia, Other Asia, Muslim Countries.[7] 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.

Given that the overall categorization might be somehow arbitrary, we decide to use a more disaggregate one, too. The alternative cultural background diversity is based on linguistic classification.[8] Specifically, we group foreign employees together by family of languages, to which the language spoken in their home country belongs.[9] Using the third linguistic tree level language classification drawn from Ethnologue, we end up having 40 linguistic groups.[10] Further, our disaggregated 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: general high school, business high school and vocational education. Demographic diversity is computed by combining gender and five age dichotomous indicators associated with quintiles of the overall age dis-

[6]Native Danes are excluded.

[7]See Appendix1 for more details about the countries belonging to each ethnic category.

[8]Previous literature argues that linguistic distance serves also as a proxy for cultural distance (Guiso et al., 2009; Adsera and Pytlikova, 2012).

[9]Specifically, we use the official language spoken by majority in a given country of origin to link the country into groups by family of languages.

[10]The linguistic classification is more detailed than the grouping by nationality categories. Specifically, we group countries (their major official language spoken by the majority in a particular country) 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. Furthermore, we adjust the index to take account of the firm size. Specifically, we standardize the index for a maximum value equal to $\left(1-\frac{1}{N}\right)$ when the total number of employees (N) is lower than the number of linguistic groups (S).

tribution.

2.3 Descriptive statistics

Table 1 reports some descriptive statistics of the variables used in our empirical analysis. Besides showing means and standard deviations for the full sample of firms, we also split the firm population into two groups based on whether a firm applied for at least one patent (patenting firm) or did not, and we show the descriptive statistics for patenting and non-patenting firms. As we can observe from the Table 1, there are remarkable differences between patenting and non-patenting firms with respect to firms' workforce composition. Not surprisingly, patenting firms are characterized by larger shares of highly educated employees, white-collar workers, middle managers and managers. Interestingly, patenting firms also record a higher share of female and foreign employees. Workers in these knowledge-based firms are slightly older on average terms: presumably the share of young employees is lower because patenting firms hire a wider proportion of well trained and experienced people. As a matter of fact long tenure profiles are more common within patenting firms' environment. Regarding the workforce diversity variables central for the main hypotheses in this paper, there is a number of interesting facts arising from the Table 1. First, it is obvious that patenting firms in Denmark have more diverse workforces. In particular there is a clear difference between patenting and non-patenting firms with respect to the ethnic heterogeneity, which is more than 3 times larger on average in patenting firms. Patenting firms have also larger educational and demographic diversity compared to non-patenting firms.

Further, patenting firms are characterized by notably higher values of capital and labor inputs: the average capital stock is about 9.7 times the value of the non-patenting firms. Patenting firms are also more likely to be multi-establishment companies and markedly (82 percent) more export-oriented. Regarding the foreign owership status, in general we can observe that the foreign capital penetration is quite low among firms in Denmark, and there is no difference with respect to foreign ownership status between patenting and non-patenting firms.

For the purposes of our analyses it appears relevant to take into account the role of external sources of knowledge since they may facilitate firms' innovation activity. Therefore 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 or huge differences in technological distance between the two groups of firms.

Overall, the presented descriptives raise a reasonable interest in evaluating the "nexus" between workforce diversity in ethnicity, education and demographics and firms' patenting behavior, which is something we are going to investigate in depth in the next sections.

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. Specifically, we estimate the following probit model:

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

$$with \quad z^*_{it} = \gamma_c Div\_c_{it} + \gamma_s Div\_s_{it} + \gamma_d Div\_d_{it} + x^{'}_{it}\beta + v_{it}$$

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 concretely has applied at time t; the first three terms at the right-hand side are diversity in cultural background, skills and demographics respectively and v_{it} is the error term. The vector $x^{'}_{it}$ includes an extensive set of observable characteristics that might affect firms' innovation outcomes. More specifically, we include detailed workforce composition characteristics such as shares of foreigners coming from a given group of countries under the aggregate diversity specification (e.g. shares of foreigners from North America and Oceania, Central and South America, Africa, Western and Southern Europe, Formerly Communist Countries, East Asia, Other Asia, and Muslim Countries), shares of managers, middle managers, males, shares of workers with either tertiary or secondary education, and shares of differently aged workers belonging to the employees' age distribution quartiles, the average firm tenure, whether the firm is an exporter and controls for partial/total foreign ownership and multi-establishment dummy. Further, we control for possible knowledge spillover effects, and we include two external knowledge indexes, which we constructed ourselves and which are described in detail in Appendix 2. Whereas controls on workforce composition improve the precision of estimates on diversity indexes (as the latter are based on such shares), the inclusion of spillover measures and foreign ownership status may capture effects related to external knowledge production. Finally, we include a set of year, regional and 3-digit industry classification dummies in order to capture any business cycle influences, regional- or industry-specific effects.

3.2 Identification

If firms aim at labor diversity to improve their innovation performances, then the relationship under investigation is very likely to be affected by endogeneity. To address the potential endogeneity issues, we follow an instrumental variable (IV) strategy in order to obtain a causal effect of workforce diversity on firm innovation activities. More specifically, we instrument our diversity variables with indexes of workforce diversity in cultural background, skills and demographic characteristics, computed at the commuting area, where the firm is located.[11] Given that the current geographical location of firms may not be random, we predict the current composition of the labor supply at the commuting area level by using

[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; secondly, at least one municipality in the area must be a center, i.e. a certain share of the employees living in the municipality must work in the municipality, too (Andersen, 2000). In total 104 commuting areas are identified.

its historical composition and the current population stocks (Card, 2001).[12] Pre-existing workforce diversity at the commuting area level is unlikely to be correlated with a current firm' s innovation, if measured with a sufficient time lag. In particular we use workforce composition at the commuting areas from year 1990.[13] In this approach, for example, the predicted share of immigrants from country c and living in a commuting area l at time t, $\hat{m}_{clt}$, is computed using the early 90's stock of immigrants from country c living in l and its current population of immigrants:

$$\hat{m}_{clt} = \frac{stock_{cl1990}}{\sum_{c=1}^{C} stock_{clt}}$$

We believe that diversity at the commuting area level presents a suitable supply driven instrument for workplace level diversity because commuting areas in Denmark (except for the area around Copenhagen) are typically relatively small and therefore firms very likely recruit workers from a given local supply of labor, which is characterized by a certain degree of heterogeneity. This argument is further reinforced by the role of networks in the employment process (Montgomery, 1991, Munshi, 2003). Thus firms placed in areas with high labor diversity are also more likely to employ a more diverse workforce. It is important to emphasize that although the commuting areas are not closed economies in the sense that workers are free to move out, there is a clear evidence of low residential mobility for Denmark (Deding et al. 2009), which seems to support the properness of our IV strategy. This IV approach represents a plausible solution also to the selective settlement of immigrants,

[12]See also research by Card and Di Nardo (2000), Dustmann et al. (2005) and Cortes (2008) for similarly computed instruments.

[13]We chose year 1990 as a historical base for our predictions because we believe that the lag of 5-13 years should be a sufficient lag for the purposes of our IV construction. In addition, the development in immigration to Denmark also supports the choice. The eighties and nineties were characterized by rather restrictive immigration policy with respect to economic migrants from countries outside the European Union (EU), which made it rather difficult for firms in Denmark to hire applicants from the international pool of applicants (due to consequences of the Oil Crisis). Immigration to Denmark from those countries during the eighties til mid-nineties was rather characterized by immigration on the basis of humanitarian reasons and family-reunion. However, since then Denmark has further tightened its immigration policy (even laws concerning family reunification and asylum). In particular since the 2001 election, in which the right-wing Danish People's Party (DF) with its anti-immigration agenda acquired a significant political power, the immigration policy in Denmark became one of the strictest in the world. For firms it meant almost no possibilities to hire international workers from countries outside the EU, which has often been criticized by the Confederation of Danish Industry (DI). Given those historical developments, we decided to use shares of immigrants from 1990 as a base for our predictions.

because (i) immigrants are likely to settle where there are existing migrants' networks and the presence of individuals with the same cultural and linguistic background as themselves (Damm, 2009; Pedersen at al. 2008)[14], and (ii) pre-existing (from 5 to 13 years earlier) immigrant concentrations are unlikely to be correlated with current firm innovation. Our identification strategy is further strengthened by the fact that the firm location decisions are shown not to be specifically driven by the degree of workforce diversity but rather by the size of the local demand, the proximity to customers and suppliers, the quality of local physical infrastructure, the access to firms' knowledge spillovers (Krugman, 1991; Audretsch and Feldman, 1996; Adams and Jaffe, 1996; Alcacer and Chung, 2010; Delgado et al. 2010). And in relation to the last aspect, our measures of firms' knowledge spillovers, described in the previous section, should be able to partly control for the endogeneity of firm location decisions. We use the described IV strategy for analyses of all three dimensions of innovation: propensity to innovate, intensive and extensive margins.

As a part of the robustness analyses, we use an additional instrument for the workplace ethnic diversity, in which we compute our ethnic diversity levels at commuting areas on predicted shares of foreign population based on coefficients obtained from an empirical model of determinants of migration. Specifically we run the following empirical specification, which is based on time variant push and pull factors, and costs of migration (Pedersen et al. 2008; Ortega and Peri, 2009):

$$m_{clt} = \alpha + \theta_t + (\gamma_l * \theta_t) + (\sigma_c * \theta_t) + \lambda_{cl} + \epsilon$$

where m_{clt} is a share of foreigners from source country c and living in a commuting area l at time t, $\theta_t$are year dummies, γ_l and σ_c are country of origin and commuting areas fixed effects, respectively, and λ_{cl} are time invariant pair of country and commuting areas

[14]In the case of Denmark, there was also a special dispersal policy implemented for refugees between years 1986 and 1998 by the Danish authorities. The dispersal policy implied that new refugees were randomly distributed across locations in Denmark, see e.g. Damm (2009). This fact as well supports the validity of our instrument because the refugees, as a part of international migrants to Denmark, were not driven by the firm innovation outcomes when settling, but by those dispersal policies or by the migrant networks. In addition, the inflows of economic migrants are driven by push and pull factors of destination and origin countries, costs of migration and other bilateral relationships between the origins and destinations (Pedersen et al. 2008; Ortega and Peri, 2009). We believe that those migration determinants are unlikely to be correlated with a firm' s innovation outcomes.

fixed effects, which represent controls for costs of migration and other bilateral historical relationship between the country of origin and commuting areas. We then predict the share of immigrants from country c and living in a commuting area l at time t, $\hat{m}_{clt}$, based on the obtained coefficients from the empirical model of determinants of migration. Further, we use those predicted shares to compute an ethnic diversity index at the commuting area level and use it as an instrument for the workplace ethnic diversity. We believe that the determinants of migration are likely to be orthogonal with respect to innovation outcomes at the workplace levels.

3.3 Intensive margins

Our point of departure for the analysis of the intensive margins, is the patent production function. Following a standard procedure within the literature (Blundell et al., 1995, Kaiser et al., 2008), we assume a Cobb-Douglas functional form. Moreover, as our dependent variable is the number of patents, which is by definition restricted 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 (firm) mean as

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

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.[15] Similar to Blundell, Griffith and Van Reenen (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 Kaiser et al. (2008) suggest, 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:

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

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.

[15]Unfortunately our dataset lacks a very important input which is not included in our specification: R&D expenditures or R&D workers. However, the inclusion of capital stock and of the share of highly skilled workers partly attenuate this omitted variable bias.

As described in the identification subsection above, 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:

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

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}.[16] 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 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 $\zeta_{it} \sim \left[0, \sigma_{\zeta}^2\right]$ is independent of ε_{cit}, ε_{sit} and ε_{cit}.[17] Substituting equation (3) in

[16] 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.

[17] 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 observed variables.

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 we first 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.

3.4 Extensive margins

The estimation approach used to evaluate the extensive margins of firms' patenting behavior is similar to the 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 models 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, conditional on patenting.

4 Results

This section reports findings for each of the outcome dimensions we look at: propensity to innovate, intensive and extensive margins. Further, we dig deeper into the analyses and we test three main hypotheses, which help us to uncover the role of the mechanisms by which diverse workforces affect firms' innovation outcomes. First, we test the creativity hypothesis proposed by the theoretical frameworks in Hong and Page (2001 and 2004) and Berliant and Fujita (2008) by distinguishing between diversity among white- and blue-collar workers. Second, we exclude certain groups of foreigners from calculation of ethnic diversity measures to investigate the role of the costs of "cross-cultural dealing" as suggested by Williams and O'Reilly (1998), Zajac et al. (1991) and Lazear (1999). Finally, in the sensitivity analyses subsection we examine whether the results differ across alternative diversity measures and samples.

4.1 Results on labor diversity and propensity to innovate

Table 2 reports estimates concerning the propensity to apply for a patent in a given year. In column 1, we show a model with the three workforce diversity indexes as the only regressors. The workforce diversity can explain about 14% of the overall variation in the dependent variable and is associated with sizable and significantly positive effects. Columns 2 and 3 show results from probit models with all other covariates; while the former treats the diversity indexes as exogenous variables, the latter shows the IV specification with predicted workforce diversity levels at commuting areas as instruments for the firm workforce diversity. The results obtained from the IV estimator imply that a standard deviation change in the ethnic diversity increases the probability to apply for patent by 0.16 percentage points. This corresponds to a rise in the probability to innovate by about 5 percent.[18] On the contrary, the significance of the effects related to education and demographic diversity vanish. Note that the first stage of our IV approach clearly shows that our instruments are strongly correlated with the firm level diversity. Their statistical validity is also confirmed by the F-statistics, as the latter are always above 70, which allows us to dismiss the null hypothesis of weak instrument (Stock and Yogo, 2005).[19]

[18]These figures are obtained using the average probability of innovating. From the estimates in Table 2, the average probability of innovating is around 0.03. Therefore, the changes in the probability of innovating, in percentage terms, are $(0.16/0.03) = 5.33$.

[19]The first stage results are available on request from the authors.

Columns 4 to 6 report models with single diversity dimensions to check whether one dimension of diversity captures the effects associated with other indexes. Ethnic diversity, for example, may pick up some of the skill diversity effects as individuals with the same education but coming from different countries may present degrees of educational heterogeneity as well. Both educational and demographic diversity remains insignificant even when they enter the probit model separately while the coefficient of ethnic diversity remains stable. We cannot, however, rule out that the ethnic diversity is still capturing heterogeneity in a specific educational level (employees with same degree but coming from different universitary systems may still present some degree of heterogeneity).

Turning to the other control variables, firms with higher shares of highly skilled and vocational workers, and exporting firms have higher propensity to patent. Instead, the knowledge spillovers and the average firm tenure do not explain much of such a propensity.

As mentioned in section 2.2, we additionally estimate probit models using diversity indexes based on a more detailed category specification; the results are shown in the Table 2, columns 7 and 8. Now the effect of a standard deviation change in the ethnic diversity produces an increase in the probability to apply for a patent by 0.08 percentage points which correspond to a rise in the probability to innovate by 2.5 percent, whereas the effects of education and demographic diversity appear negligible.[20]

4.2 Results on labor diversity and intensive margins

In the next step, we analyze how firm workforce diversity contribute to the number of patent application. Tables 3 reports the results of the intensive margins analyses, here the estimated coefficients represent elasticities. The first column in Table 3 shows the output of a Poisson regression[21] having only the diversity measures as regressors: the coefficients to all diversity indexes are large, positive and significant. Once more, after including all the other control variables (column 2) their dimension and statistical significance decreases. Nonetheless, except for the ethnic heterogeneity, the diversity indexes don't retain their

[20]Results obtained from the specifications with single diversity dimensions are very similar to the ones reported in columns 4, 5 and 6 and are available on request from the authors.

[21]Negative binomial models provide very similar results which are available on request from the authors.

statistical significance. Taking the IV Poisson specifications as the most reliable, we find that ten percent increase in the ethnic diversity leads to 4.4 percent increase in the number of patent applications for the aggregated diversity measures. This effect is quite sizable given that the elasticity associated with a production input like human capital (proxied by the share of highly skilled workers) is actually slightly smaller. Similar conclusions are drawn when all the diversity indexes enter separately the Poisson equation. As in the previous section, our first stage results confirm that our instruments are very good predictors of the firm level diversity.[22]

In line with previous literature, we find important effects of the shares of highly skilled workers, capital and labor stock on the number of patent applications, whereas knowledge spillovers do not seem to have significant contributions to the overall number of patent applications. As in the case of patenting propensity, exporters benefit from the knowledge gained on the international markets.

Columns 7 and 8 in Table 3 report results for models using the labor diversity indexes based on disaggregate groupings. The results are similar to those using aggregate diversity specifications, although the coefficients to our diversity variables are slightly smaller in size. Specifically, in the IV Poisson (column 3) a ten percent increase in ethnic diversity implies a 2.3 percent increase in the number of patent applications.[23]

4.3 Results on labor diversity and extensive margins

Table 4 reports the effects of labor diversity on the probability of patenting in different technological areas in a given year, conditional on patent application. The structure of this table is similar to the previous ones. Regarding the variables of interest, we find that the diversity indexes alone explain 7 percent of the overall variation in the dependent variable and

[22] The results from the first stage are available on request from the authors.

[23] 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 together with a more diverse workforce can stimulate innovation and creativity, we have augmented our models with interactions between diversity indexes and shares of highly skilled and younger workers. Nevertheless, none of the interactions turned out to be statistically significant. Figures showing marginal effects of the interactions are available from the authors upon request.

that the coefficients to diversity indexes are positive and statistically significant. However, the significance of the diversity in education and demographic characteristics vanishes when endogeneity is taken care of. Overall, we find that ethnic diversity is important for patenting in different technological areas. Taking the estimates from the full IV specification, it turns out that a standard deviation increase in ethnic diversity is associated with a raise of about 19 (29) percent points in the probability to patent in different technological fields for the aggregate (disaggregate) diversity, conditional on patent application. Or alternatively, a standard deviation increase in ethnic diversity duplicates the probability to patent in different technological fields, according to the most conservative estimates.[24] Thus it seems as the ethnic diversity is much more relevant for patenting in different technological areas rather than for the patenting per se.

Turning to the other control variables, firms with higher shares of highly skilled and young workers, and larger capital stock have higher probability of patenting in different technological areas.

4.4 Results - mechanisms involved

Our rich dataset allows us to uncover the role of different mechanisms by which diverse workforces affect firms' innovation outcomes as proposed by the theory and thus we test a number of hypotheses. Firstly, we calculate our diversity indexes for white- and blue-collar occupations separately. This is driven by the idea that diversity could play a different role for distinct occupational groups and consequently have diverse effects on firm innovation. In particular, we expect that the beneficial effects of diverse problem-solving abilities and creativity would materialize more in terms of innovation for white-collar occupations compared to blue-collar occupations. Second, we exclude certain groups of foreigners from calculation of ethnic diversity measures to test how important are the communication costs and costs of "cross-cultural dealing". In these analysis and those reported in the next section, we use disaggregate indexes only, as we think that the indexes based on a detailed categorization

[24]From the estimates in Table 4, the average probability of patenting in different technological areas is around 0.18. Therefore, the changes in the corresponding probability, in percentage terms, are (19/0.18) = 105.

may be more adequate to represent workforce diversity.[25]

The results of the effect of diversity indexes calculated separately for the two occupational groups on firm probability to innovate, number of patent applications and firm probability of applying for a patent in different technological areas are presented in the first two columns of Table 5. Our results show that that workforce diversity is indeed much more important for white-collar than for blue-collar occupations. The effect of ethnic diversity on both the intensive and extensive margins of innovation is positive and statistically significant for the group of white-collar workers only. Conversely, the effect of education and demographic diversity is insignificant for both white- and blue-collar occupations except for the demographic diversity, which turns out to have statistically significant positive effect on the probability to innovate among blue-collar workers. Thus, our results support the creativity hypothesis proposed by the theoretical frameworks by Hong and Page (2001 and 2004) and Berliant and Fujita (2008).

To test the role of "cross-cultural dealing" we exclude from the calculation of ethnic diversity alternative groups of foreigners: (1) the second generation immigrants, who are very likely fluent in Danish and who are almost perfectly integrated into the Danish society and culture; (2) foreigners with tertiary education and (3) foreigners speaking one of the language belonging to the germanic group. The last two groups are likely to absorb Danish or English (which is the communication language in many businesses in Denmark) more quickly. It is plausible to expect that communication costs associated with ethnic diversity may increase after subtracting out foreigners who are likely to speak Danish or English. The results are shown in Table 5, columns 3, 4 and 5 for measures treating the second generation of immigrants, foreigners with a language belonging to the Germanic group of languages and foreingers with university education as natives, respectively. Interestingly, the role of ethnic heterogeneity on innovation weakens once we exclude foreigners who probably speak English or Danish, confirming the idea that the communication costs and costs of "cross-cultural dealing" are likely to be more important when foreigners don't speak the same language. This is shown by results of analyses from all innovation outcomes under

[25] The results using the aggregate indexes are qualitatively similar to the detailed categorization, and they are available from the authors upon request.

consideration. Furthermore, the fact that the effect of ethnic diversity on the number of patent applications remains positive and significant even when we exclude university graduates may also indicate that the latter effects are not merely driven by the recruitment of talented high skilled workers from abroad.

4.5 Sensitivity analyses

In this section, we examine whether the effects of labor diversity on patenting activity of firms hold across alternative diversity measures and samples. All results are again based on the full IV specifications described in the previous section and they are shown in Table 6.

First, as a part of the sensitivity analysis we evaluate eventual variations in the effects of labor diversity when the diversity measure is differently computed. In particular, we use two alternative diversity indexes: the Shannon-Weaver entropy and the richness indexes. The entropy index is considered as one of the most profound and useful diversity indexes in biology (Maignan et al., 2003), whereas the richness index is defined as a number of categories observed for each dimension of interest (it does not account for the "evenness" dimension). The results are shown in Table 6, columns 1 and 2, respectively, and both measures support the results from our main analyses using our preferred Herfindhal index and show that ethnic diversity has significant positive effect on all considered innovation outcomes.

Next, we include an Herfindhal index for the type of tertiary education (this index has now only 4 categories: engineering, natural sciences, social sciences and humanities) and the standard deviation for the years of education and age. This allows us, on one hand, to treat age as a cardinal variable and, on the other, to disantangle the effects associated with the amount of education from those related to the type of tertiary education. The results from Table 6, column 3, show that the effects of both education and demographic diversity are never significant.

As big cities have usually a lot of immigrants and at the same time a high percentage of innovative firms, in the next robustness check we drop Copenhagen (the only real agglomeration area in Denmark) and environs from the analysis. Results from this robustness check are reported in column 4, Table 6, and do not qualitatively differ from the main results.

As labor diversity has been computed at the firm level (weighting average of Herfindahl indexes computed at the workplace level), we evaluate how results change if multi-establishment enterprises are excluded from the sample. Restricting our attention to single workplaces, we check whether the relationship between workforce diversity and innovation is sensitive to the level of analysis or whether it is mainly driven by big companies. Column 5 of Table 6 reports infomation on such a check: the interpretation of these findings does not significantly differ from that related to the main results.

Next, we run our analyses using an alternative instrument for the workplace ethnic diversity based on shares of immigrants at the commuting areas predicted from a model of migration determinants. Specifically, we use the model of migration determinants to predict shares of immigrants from a particular source country living in a particular commuting area. We then use the predicted shares of immigrants to construct ethnic diversity levels at commuting areas, which we then use as an instrument for ethnic diversity on the workplace level. More details on how the alternative instrument is calculated, is given in section 3.2. above. The results using the alternative IV shown in column 6, Table 6, confirm our main findings. For all three studied innovation outcomes we observe that the ethnic diversity has a significantly positive effect, whereas the effects of educational and demographic diversity are statistically insignificant.

Finally, we look at whether there is any difference in the effect of diversity on innovation for firms with or without pre-sample patents. Not surprisingly, the last two columns of Table 6 show that the impact of ethnic diversity is stronger for firms with pre-sample patents.

5 Discussion and conclusions

In this paper we provide an overall assessment of the nexus between labor diversity and firms' patenting behavior. To the best of our knowledge, this study represents the first concrete attempt to formalize and generalize the relationship between labor diversity and innovation by using detailed information on 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 a robust evidence that ethnic diversity of the labor force is an important source of innovation. That facilitates firms' patenting activity in several ways: (a) it increases their propensity to (apply for a) patent, (b) it increases the overall number of patent applications and (c) it enlarges the breadth of patenting technological fields. Being prudent in the quantification of ethnic heterogeneity effects on all these aspects of patenting activities, we find that a 10 percentage change in ethnic diversity increases the number of firms' patent applications by approximately 2.3 percent, according to the most conservative estimates. The contribution of ethnic diversity in terms of general propensity to send at least one patent application in a given year is economically sound: a standard deviation change in its value turns to raise such a probability by 2.5-5 percent. Conditional on patenting, the effect of ethnic diversity on extensive margins is very large, a standard deviation change in skill diversity duplicates the firms' probability to apply for a patent in different technological areas. Thus, in order to widen the patent technological spectrum it seems to be fundamental to increase the heterogeneity in the workers' perspectives stemming from different cultural background. Regarding the results of education and demographic diversity on innovation, their effects typically vanish when we include the full set of controls or once we instrument the diversity measures. Finally, we find that the beneficial effect of ethnic diversity on innovation materializes for white-collar occupations only, whereas the effect for the group of blue-collar workers is negligible. These results support the hypothesis that more educated workers tend to have a wider pool of different experiences, knowledge bases and heuristics boosting their problem-solving capacities and creativity, which in turn facilitate innovations. In this regard, our findings are consistent with the theoretical frameworks proposed by Hong and Page (2001 and 2004) and Berliant and Fujita (2008).

The overall picture coming out from our empirical analyses seems to be particularly relevant not only for the design of firms' innovation and hiring strategies but also for public policies aimed at fostering innovation. Our results give an important insight into the technological process, a driver of productivity growth and hence of the economic growth. We find that an increase in firm labor diversity in terms of ethnicity has a positive effect on the firm innovation process. Thus, governmental policies aimed to promote an employment of workers with different cultural backgrounds can be beneficial in terms of improvements in firms' patenting activities, increasing both private returns, directly, and social gains, through knowledge diffusion mechanisms. Such policies might help to invert the general decline in patenting activity recorded during the recent economic crisis among the OECD countries (OECD, 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; **Western and Southern 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), **Germanic Nord** (Denmark, Iceland, Norway, Sweden), **Slavic West** (Czech Republic, Poland, Slovakia), **Slavic South (**Bosnia and Herzegovina, Croatia, Serbia, Slovenia)**, Slavic East** (Belarus, Georgia, Mongolia, Russian Federation, Ukraine)**, Baltic East** (Latvia, Lithuania)**, Finno-Permic** (Finland, Estonia), **Ugric** (Hungary)**, 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)**, Turkic South** (Azerbaijan, Turkey, Turkmenistan), **Turkic West** (Kazakhstan, Kyrgystan)**, Turkic East** (Uzbekistan)**, 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**), Mon-Khmer East** (Cambodia)**, Semitic South** (Ethiopia)**, 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)**, Viet-Muong** (Vietnam), **Volta-Congo** (Burundi, Congo, Kenya, Lesotho, Malawi, Nigeria, Rwanda, Swaziland, Tanzania, Togo)**, 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) and Adams and Jaffe (1996) 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). 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.[26] 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 kilometers between any pair of firms i and j .[27] 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

[26] See paragraph 4.2.

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

(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).

Table 1: Descriptive statistics

		All sample		Firms without patents		Firms with at least one patent	
Variables	Definition	Mean	Sd	Mean	Sd	Mean	Sd
IDA Variables:							
males	men as a proportion of all employees	0.716	0.232	0.716	0.233	0.696	0.180
foreigners	non-danish employees as a proportion of all employees	0.046	0.085	0.045	0.085	0.058	0.062
age1	employees aged 15-28 as a proportion of all employees	0.276	0.174	0.279	0.174	0.196	0.107
age2	employees aged 29-36 as a proportion of all employees	0.298	0.130	0.295	0.130	0.352	0.103
age3	employees aged 37-47 as a proportion of all employees	0.226	0.111	0.225	0.111	0.255	0.079
age4	employees aged 47-65 as a proportion of all employees	0.201	0.101	0.201	0.101	0.197	0.099
skill1	employees with compulsory education as a proportion of all employees	0.332	0.121	0.332	0.121	0.281	0.087
skill2	employees with a secondary/ post-secondary education as a proportion of all employees	0.632	0.173	0.632	0.174	0.636	0.138
skill3	employees with a tertiary education as a proportion of all employees	0.038	0.092	0.036	0.090	0.084	0.120
tenure	average tenure	4.890	1.973	4.876	1.979	5.265	1.741
manager	managers as a proportion of all employees	0.040	0.056	0.039	0.056	0.045	0.046
middle manager	middle managers as a proportion of all employees	0.167	0.202	0.162	0.199	0.289	0.208
blue collars	blue collars as a proportion of all employees	0.799	0.276	0.799	0.276	0.666	0.234
size1	1, if firm size is less than 50 employees	0.768	0.422	0.785	0.410	0.323	0.467
size2	1, if firm size is between 51 and 100 employees	0.123	0.328	0.120	0.325	0.386	0.183
size3	1, if firm size is less than 100 employees	0.109	0.312	0.094	0.292	0.493	0.500
Index ethnic aggr	diversity index based on employees' country of origin	0.122	0.224	0.113	0.216	0.352	0.279
Index edu aggr	diversity index based on employees' education	0.418	0.112	0.416	0.111	0.457	0.108
Index demo aggr	diversity index based on employees' demographic characteristics	0.754	0.072	0.752	0.072	0.793	0.051
Index ethnic disaggr	diversity index based on employees' spoken language	0.155	0.265	0.144	0.256	0.514	0.428
Index edu disaggr	diversity index based on employees' education	0.579	0.133	0.574	0.131	0.686	0.105
Index demo disaggr	diversity index based on employees' demographic characteristics	0.880	0.072	0.878	0.072	0.922	0.053
Accounting Variables:							
Patent applications	annual number of patent applications	0.032	0.656	-	-	0.854	3.306
capital	(1000 kr.)	76713.070	885217.900	58087.59	795076.7	561131.8	2116710
foreign-ownership	1, if the firm is foreign owned	0.004	0.060	0.004	0.060	0.004	0.064
multi	1, if the firm is multi-establishment	0.111	0.314	0.103	0.305	0.285	0.451
exp	1, if the firm is exporting	0.527	0.499	0.511	0.499	0.931	0.252
geo_spillover	spillover variable based on the technological distance	1027.412	347.979	1025.982	347.3635	1064.611	361.694
tech_spillover	spillover variable based on the geographical distance	93.109	133.614	93.398	134.263	85.589	115.199
N		96636		93058		3578	

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 (IV)**	**Probit (IV)**	**Probit (IV)**	**Probit (IV)**	**Probit**	**Probit (IV)**
Index ethnic	0.023***	0.001**	0.007**	0.008***			0.0001**	0.003**
	(0.002)	(0.000)	(0.002)	(0.002)			(0.000)	(0.002)
Index Edu	0.018***	0.001	0.001		0.004		0.004***	0.002
	(0.004)	(0.001)	(0.005)		(0.004)		(0.001)	(0.002)
Index Demo	0.046***	0.000	0.007			0.008	0.0001	0.011
	(0.006)	(0.001)	(0.005)			(0.005)	(0.001)	(0.006)
Log(K)		0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(L)		0.001***	0.001***	0.001***	0.001***	0.0001**	0.0001***	0.0001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age1		0.0001	0.001	0.0001	-0.0001	0.001	-0.000	0.001*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2		0.001*	0.002**	0.001*	0.001	0.001**	0.001	0.001*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age3		0.001*	0.001*	0.002**	0.001*	0.001	0.001*	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
males		-0.001*	0.0001	-0.001	-0.001**	0.000	-0.000	0.001
		(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
exp		0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
skill1		0.002**	0.002	0.002**	0.003*	0.002**	0.002**	0.002**
		(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
skill2		0.005***	0.005	0.005***	0.004	0.006***	0.003**	0.004**
		(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)
manager		0.001*	0.001*	0.002*	0.001*	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
middle manager		0.001**	0.001*	0.001**	0.001**	0.001**	0.0001	0.0001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tenure		-0.0001*	-0.0001	-0.0001	-0.0001*	-0.0001**	-0.0001	-0.0001*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
multi		-0.0001	0.001*	0.001	-0.0001	-0.0001	-0.0001	0.001
		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
geo_spillover		0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tech_spillover		0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry/size/year dummies	no	yes	yes	yes	yes	yes	yes	yes
Share of foreigners by group of country	no	yes	yes	yes	yes	yes	yes	yes
N	96636	96636	96636	96636	96636	96636	96636	96636
pseudo R-sq	0.136	0.384	0.386	0.386	0.383	0.384	0.387	0.389

Notes: The dependent variable in all estimations is the probability to have at least one patent application. Marginal effects are reported. Model1-Model6: diversity based on the aggregate specification. Model7-Model8: diversity based on the disaggregate specification. Model3-Model6 and Model8 report results from IV estimation. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level.

Table 3: The effects of labor diversity on firm patent applications. Main results.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	Poisson	**Poisson**	**Poisson (IV)**	**Poisson (IV)**	**Poisson (IV)**	**Poisson (IV)**	**Poisson**	**Poisson (IV)**
Index ethnic	0.530***	0.088**	0.444**	0.431**			0.065*	0.234**
	(0.048)	(0.032)	(0.211)	(0.211)			(0.036)	(0.115)
Index edu	2.323***	0.945*	3.448		3.003		2.361***	1.089
	(0.492)	(0.574)	(3.235)		(2.936)		(0.663)	(1.133)
Index demo	9.319***	0.248	1.563			0.133	-0.110	1.148
	(1.522)	(1.606)	(3.849)			(3.187)	(1.790)	(4.013)
Log(K)		5.015***	5.125***	5.066***	5.079***	5.011***	4.839***	5.155***
		(0.659)	(0.657)	(0.665)	(0.644)	(0.664)	(0.654)	(0.637)
Log(L)		0.956**	0.139	0.155	1.413***	1.274**	1.038**	0.035
		(0.388)	(0.703)	(0.661)	(0.411)	(0.439)	(0.375)	(0.799)
Discounted stock of applications		0.00001	0.00001	0.00001	0.001	0.00001	0.00001	0.00001
		(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Log(fixed effects)		0.003	0.003	0.003	0.004*	0.004	0.003	0.004
		(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed effect dummy		0.057***	0.052***	0.053***	0.056***	0.057***	0.056***	0.058***
		(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
age1		0.182	0.421	0.242	0.310	0.201	0.149	0.582**
		(0.253)	(0.360)	(0.251)	(0.280)	(0.279)	(0.256)	(0.284)
age2		0.142	0.209	0.165	0.145	0.134	0.115	0.265
		(0.301)	(0.309)	(0.297)	(0.289)	(0.303)	(0.295)	(0.299)
age3		0.237	0.298	0.278	0.276	0.246	0.242	0.250
		(0.246)	(0.233)	(0.244)	(0.234)	(0.237)	(0.243)	(0.236)
males		0.047	0.094	0.040	-0.113	-0.033	0.238	0.450
		(0.555)	(0.601)	(0.434)	(0.378)	(0.560)	(0.556)	(0.533)
exp		0.550***	0.555***	0.544***	0.570***	0.556***	0.531***	0.548***
		(0.125)	(0.124)	(0.123)	(0.125)	(0.126)	(0.119)	(0.119)
skill1		1.754**	-1.221	1.213**	-0.999	1.135**	0.869**	0.447
		(0.679)	(2.346)	(0.454)	(2.154)	(0.451)	(0.426)	(0.440)
skill2		0.128***	0.367**	0.182***	0.353**	0.191***	0.104**	0.227***
		(0.034)	(0.178)	(0.035)	(0.164)	(0.035)	(0.032)	(0.048)
manager		0.020	0.008	0.019	0.008	0.016	0.008	0.012
		(0.041)	(0.042)	(0.041)	(0.042)	(0.040)	(0.040)	(0.040)
middle manager		0.139**	0.047	0.105	0.070	0.118*	0.021	0.186**
		(0.067)	(0.070)	(0.069)	(0.067)	(0.068)	(0.075)	(0.095)
tenure		-0.342	-0.235	-0.279	-0.271	-0.323	-0.320	-0.462
		(0.286)	(0.313)	(0.293)	(0.305)	(0.298)	(0.287)	(0.321)
multi		-0.005	0.014	0.024	-0.036	-0.021	0.001	0.023
		(0.020)	(0.029)	(0.025)	(0.023)	(0.023)	(0.020)	(0.029)
geo_spillover		0.538	3.062	0.296	2.949	0.465	0.972*	1.506
		(0.591)	(2.663)	(0.532)	(2.530)	(0.560)	(0.590)	(1.026)
tech_spillover		0.061*	0.077*	0.086**	0.047	0.053	0.065*	0.040
		(0.037)	(0.044)	(0.043)	(0.038)	(0.038)	(0.037)	(0.044)
Industry/size/year dummies	no	yes	yes	yes	yes	yes	yes	yes
Share of foreigners by groups of country	no	yes	yes	yes	yes	yes	yes	yes
N	96636	96636	96636	96636	96636	96636	96636	96636
chi2	162.0	25624.3	29912.4	28261.9	25077.9	25359.1	22785.7	25848.2

Notes: The dependent variable in all estimations is the number of patent applications. Elasticities are reported. Model1-Model6: diversity based on the aggregate specification. Model7-Model8: diversity based on the disaggregate specification. Model3-Model6 and Model8 report results from IV estimation. 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.

Table 4: The effects of labor diversity on the probability of applying in different technological areas. Main results.

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
	Probit	**Probit**	**Probit (IV)**	**Probit (IV)**	**Probit (IV)**	**Probit (IV)**	**Probit**	**Probit (IV)**
Index ethnic	0.190**	0.051**	1.063**	1.041**			0.011**	0.455**
	(0.061)	(0.025)	(0.384)	(0.380)			(0.042)	(0.190)
Index edu	0.615***	1.377***	-0.910		-0.782		0.563**	-0.085
	(0.157)	(0.331)	(0.925)		(0.928)		(0.240)	(0.408)
Index demo	0.572*	-0.085	-0.020			-0.015	0.430	1.232
	(0.353)	(0.348)	(0.918)			(0.904)	(0.358)	(1.051)
Log(K)		0.051***	0.054***	0.053***	0.052***	0.051***	0.048***	0.050***
		(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
Log(L)		0.042*	-0.043	-0.045	0.056**	0.052*	0.048**	-0.021
		(0.022)	(0.041)	(0.038)	(0.023)	(0.027)	(0.023)	(0.050)
age1		0.402**	0.553**	0.505**	0.526**	0.483**	0.406**	0.595**
		(0.195)	(0.220)	(0.186)	(0.204)	(0.203)	(0.206)	(0.232)
age2		0.402**	0.448**	0.452**	0.418**	0.421**	0.395**	0.459**
		(0.187)	(0.186)	(0.176)	(0.178)	(0.192)	(0.185)	(0.187)
age3		0.138	0.261	0.239	0.184	0.168	0.107	0.145
		(0.253)	(0.257)	(0.247)	(0.248)	(0.255)	(0.256)	(0.267)
males		-0.002	-0.010	0.009	-0.033	-0.021	0.063	0.107
		(0.092)	(0.130)	(0.075)	(0.078)	(0.128)	(0.098)	(0.141)
exp		0.010	0.010	0.007	0.015	0.012	0.030	0.032
		(0.045)	(0.044)	(0.044)	(0.044)	(0.045)	(0.042)	(0.041)
skill1		0.937***	-0.068	0.370**	-0.062	0.316**	0.065	0.007
		(0.233)	(0.444)	(0.146)	(0.445)	(0.146)	(0.142)	(0.145)
skill2		-0.074	1.178**	0.665**	1.210**	0.767***	0.197	0.493*
		(0.231)	(0.580)	(0.205)	(0.588)	(0.206)	(0.226)	(0.281)
manager		0.274	0.235	0.257	0.195	0.217	0.257	0.248
		(0.228)	(0.232)	(0.226)	(0.228)	(0.232)	(0.245)	(0.252)
middle manager		0.069	-0.052	-0.016	-0.025	0.005	-0.009	0.094
		(0.095)	(0.100)	(0.093)	(0.102)	(0.095)	(0.099)	(0.117)
tenure		0.006	0.012	0.011	0.009	0.008	0.006	0.006
		(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
multi		0.002	0.079	0.098*	-0.041	-0.028	0.001	0.072
		(0.029)	(0.066)	(0.060)	(0.028)	(0.035)	(0.031)	(0.071)
copatent		-0.026	-0.024	-0.025	-0.022	-0.023	-0.021	-0.023
		(0.024)	(0.024)	(0.024)	(0.025)	(0.024)	(0.026)	(0.026)
geo_spillover		0.0001	0.001**	0.001***	0.001**	0.001***	0.0001	0.0001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tech_spillover		0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry/size/year dummies	no	yes	yes	yes	yes	yes	yes	yes
Share of foreigners by group of country	no	yes	yes	yes	yes	yes	yes	yes
N	1086	1086	1086	1086	1086	1086	1086	1086
pseudo R2	0.067	0.304	0.318	0.317	0.309	0.309	0.292	0.297

Notes: The dependent variable in all estimations is the probability of applying a patent in different technological areas. Marginal effects are reported. Model1-Model6: diversity based on the aggregate specification. Model7-Model8: diversity based on the disaggregate specification. Model3-Model6 and Model8 report results from IV estimation. Significance levels: ***1%, **5%, 10*%. Standard errors clustered at the firm level.

Table 5: The effects of labor diversity on firm innovation, the mechanisms involved.

	Probability to innovate				
	Occupation specific diversity		**2nd gen. Imm. as natives**	**Germanic group as natives**	**University graduates as natives**
	White collar	*Blue collar*			
index ethnic disaggr	0.017**	0.003	0.001**	0.0001*	0.000
	(0.006)	(0.002)	(0.000)	(0.000)	(0.000)
index edu disaggr	-0.002	0.001	0.003	0.003*	0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
index demo disaggr	0.007	0.012*	0.011	0.011	0.011
	(0.004)	(0.006)	(0.006)	(0.006)	(0.006)
N	96636	96636	96636	96636	96636
pseudo R2	0.384	0.385	0.389	0.389	0.389
	Number of firm patents				
	Occupation specific diversity		**2nd gen. Imm. as natives**	**Germanic group as natives**	**University graduates as natives**
	White collar	*Blue collar*			
index ethnic disaggr	0.165**	-0.223	0.015**	0.039	0.180**
	(0.079)	(0.335)	(0.004)	(0.025)	(0.075)
index edu disaggr	1.254	-3.109	0.986	1.078	0.953
	(1.799)	(1.159)	(1.141)	(1.148)	(1.125)
index demo disaggr	1.860	2.109	1.004	2.712	2.561
	(3.538)	(4.274)	(3.792)	(3.816)	(3.781)
N	96636	96636	96636	96636	96636
pseudo R2	33730.0	27768.3	26982.2	27186.8	24934.8
	Probability of applying in different technological areas				
	Occupation specific diversity		**2nd gen. Imm. as natives**	**Germanic group as natives**	**University graduates as natives**
	White collar	*Blue collar*			
index ethnic disaggr	0.792**	0.028	0.022	0.100	0.054
	(0.320)	(0.480)	(0.020)	(0.066)	(0.047)
index edu disaggr	-1.019	-0.032	-0.024	-0.058	-0.007
	(0.783)	(0.445)	(0.404)	(0.393)	(0.395)
index demo disaggr	0.978	1.712	1.319	1.180	1.210
	(1.197)	(1.158)	(0.984)	(0.987)	(0.960)
N	1086	1086	1086	1086	1086
pseudo R2	0.292	0.289	0.296	0.298	0.297

Notes: In the first and last panel marginal effects are reported. In the middle panel elasticities are reported. All regressions are estimated with the same IV approach used in the previous tables and 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 6: The effects of labor diversity on firm innovation, robustness checks.

	Shannon entropy index	Richness	Edu and demo diversity as sd	Copehagen is excluded	Mono-establishment firms	IV migration determinants	Firms without pre-sample patents	Firms with pre-sample patents
Probability to innovate								
index ethnic disaggr	0.011**	0.003***	0.006**	0.004*	0.004**	0.002***	0.018***	0.258***
	(0.005)	(0.000)	(0.002)	(0.002)	(0.002)	(0.000)	(0.003)	(0.108)
index edu disaggr	0.002	0.0001	0.019	0.001	0.003	0.003	0.004	-0.226
	(0.002)	(0.000)	(0.013)	(0.002)	(0.002)	(0.002)	(0.003)	(0.261)
Sd(years of education)			-0.007			0.010		
			(0.007)			(0.007)		
index demo disaggr	0.007	0.0001	0.0001	0.010	0.008		0.012	-0.564
	(0.004)	(0.000)	(0.001)	(0.004)	(0.005)		(0.007)	(0.717)
Sd(age)			0.000					
			(0.001)					
Male								
N	96636	96636	96636	85555	78964	96636	93268	3368
pseudo R2	0.388	0.337	0.426	0.388	0.348	0.390	657.6	329.7
Number of firm patents								
	Shannon entropy index	Richness	Edu and demo diversity as sd	Copehagen is excluded	Mono-establishment firms	IV migration determinants	Firms without pre-sample patents	Firms with pre-sample patents
index ethnic disaggr	1.513**	0.101**	0.255***	0.233***	0.305***	0.170*	0.220	0.652**
	(0.727)	(0.040)	(0.122)	(0.115)	(0.052)	(0.083)	(0.313)	(0.332)
index edu disaggr	2.364	0.659	0.557	1.028	1.030	-0.098	1.071	1.700
	(1.860)	(0.597)	(1.834)	(0.706)	(0.699)	(0.597)	(1.430)	(1.657)
Sd(years of education)			2.274					
			(2.356)					
index demo disaggr	0.521	0.750		0.913	1.907	1.304	1.301	1.992
	(0.458)	(1.545)		(2.228)	(2.150)	(1.070)	(1.948)	(2.065)
Sd(age)			0.105					
			(1.004)					
Male			0.225					
			(0.369)					
N	96636	96636	96636	89480	85943	96636	93268	3368
pseudo R2	42368.8	5932.8	6035.7	31969.8	5346.5	55405.0	1007.1	3000.5
Probability of applying in different technological areas								
	Shannon entropy index	Richness	Edu and demo diversity as sd	Copehagen is excluded	Mono-establishment firms	IV migration determinants	Firms without pre-sample patents	Firms with pre-sample patents
index ethnic disaggr	1.921*	0.031	0.627	0.386*	0.180	0.460*	0.114	-
	(1.134)	(0.044)	(0.460)	(0.206)	(0.419)	(0.209)	(0.294)	-
index edu disaggr	-0.705	-0.063	-1.169	-0.261	-0.052	-0.111	0.128	-
	(0.504)	(0.055)	(3.832)	(0.409)	(0.422)	(0.402)	(0.371)	-
Sd(years of education)			0.783					
			(1.938)					
index demo disaggr	0.559	0.056		1.024	0.373	0.941	0.956	-
	(0.558)	(0.078)		(1.056)	(0.999)	(1.007)	(1.028)	-
Sd(age)			0.100					
			(0.121)					
Male			0.014					
			(0.120)					
N	1086	1086	1086	1014	691	1086	935	-
pseudo R2	0.297	0.273	0.301	0.300	0.255	0.290	0.298	-

Notes: In the first and last panel marginal effects are reported. In the middle panel elasticities are reported. Probability of applying in different technological areas: convergence is not achieved for the sub-sample of mono-establishment firms and of firms with pre-sample patents. All regressions are estimated with the IV approach and include all the firm specific characteristics, year and three-digit industry dummies. Significance levels: ***1%, **5%, *10%. Standard errors clustered at the firm level.