Centre of Excellence for Science and Innovation Studies

CESIS Electronic Working Paper Series

Paper No. 360

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April, 2014

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

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ABSTRACT

This paper tests the importance of firm level knowledge and neighborhood diversity, as a source for localized knowledge spillovers, on firms propensity to innovate. Diversity is measured in terms of industries as well as employee education and occupation, of which the results show a positive neighborhood effect from diversity in education. In addition, an added positive effect from neighborhood diversity in education is found for firms with a larger share of highly educated employees, which points to the importance of absorptive capacity. However, firm characteristics, such as the knowledge of the own employees, provide to be the strongest determinants for the innovativeness of firms.

Keywords: Knowledge; neighborhood diversity; education; skills; innovation.

JEL Classification: J21, J24, O31, R32

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Acknowledgement: The author gratefully acknowledges financial support from the Swedish Research Council Formas (grant 2009-1192), the European Union/European Regional Development Fund (grant 162 888), the Regional Development Council of Jönköping County and the County Administrative Board in Jönköping.

1. Introduction

In the seminal work of Jane Jacobs (1969) the economic and social diversity of cities is highlighted as the driving force of urban growth and innovation. Firms benefit from being located in diverse environments due to the creation of new ideas that spill over between people, firms and industries, which spur the innovative and imitative potential of firms. Benefits from diversity are hence commonly denoted as Jacobs externalities. In recent research there is an argument that for diversity to give rise to knowledge spillovers some sort of cognitive proximity or complementarity between firms is required. Noteboom (2000) argues that "…information is useless if it is not new, but it is also useless if it is so new that it cannot be understood" (p.153). This implies that diversity in related areas, i.e. cognitively not too far apart, should stimulate knowledge flows and thus innovation and growth. Frenken et al. (2007) denote this type of diversity as 'related variety', which is commonly measured as within-industry diversity[1].

Cognitive proximity in terms of industries captures one dimension of relatedness. However, Desrochers and Leppälä (2011), Brachert et al. (2011), and Wixe and Andersson (2013), among others, argue that diversity in terms of individuals and relatedness in terms of human capital may be even more important to consider in order to capture Jacobs externalities. This is due to that knowledge is embedded in individuals, rather than being "in the air", and flows between individuals, rather than firms per se. The present paper tests this line of thinking by exploring the relationship between related diversity in terms of employee education and occupation, and the innovative performance of firms. Due to that recent research show that knowledge spillovers are bounded in space (see e.g. Arzaghi and Henderson (2008) and Andersson et al. (2012)) diversity is measured on the neighborhood level. To the knowledge of the present author, there is no previous study connecting neighborhood diversity to firm innovativeness.

Although knowledge externalities may be present in the surrounding milieu, firms do not automatically benefit from them. Being there may not be enough. The ability to absorb knowledge spillovers depends on the absorptive capacity of the firm (Cohen and Levinthal 1990), which is determined by the pre-existing knowledge within the firm, which in turn is determined by the skills and abilities of the employees. Absorptive capacity allows a firm to use external knowledge in order to create something new, i.e. the innovative capacity is

[1] For consistency, in the present paper the term related diversity will be used instead of related variety. In the mind of the present author, there is no difference between within variety and within diversity. For a discussion on diversity versus variety, see Harrison and Klein (2007).

enhanced. This differs from internal learning-by-doing, which instead enhances the efficiency of already existing activities (Cohen and Levinthal 1989). The argument that firm knowledge is necessary in order to exploit external knowledge is now well established. However, it is still mostly a theoretical argument and there are few studies that test this empirically. The present paper attempts to fill this gap.

The knowledge and skills of the employees in a firm are not only important in order to absorb potential knowledge spillovers. There is also a direct link between firm knowledge, or human capital, and firm performance (c.f. Blundell et al. (1999)). By the end of the day, the employees are very much responsible for the innovation output generated by the firm. In the present paper firm level knowledge is measured in terms of employee education and occupation. This is possible due to access to micro-level data, which connect all employees in Sweden to the firm at which they work. Sweden provides a good case to study even besides the unique data availability. In 2010, Sweden had the fastest growing economy, the highest level of innovation and was the most competitive economy in the European Union (World Economic Forum 2010).

Hence, the purpose of the paper is to empirically test the importance of firm level knowledge and neighborhood diversity, as well as the combination of them, on firms propensity to innovate. Following Jacobs (1969), diversity in the surrounding milieu is introduced as a source for knowledge spillovers. In the present paper, a firm is classified as being innovative if it has introduced a new or substantially improved product (good or service) on the market during the last three years. This follows from the Community Innovation Survey (CIS), carried out every two years in the European Union (EU). The CIS defines an innovation as new to the firm, but not necessarily new to the market. The analysis is performed both for the complete CIS sample and for industrial and service industries separately, since these types of industries differ from each other in many respects. In particular, previous research have found that the service sector benefits from diversity while the manufacturing sector[2] does not (Combes 2000; Van Stel and Nieuwenhuijsen 2004; Bishop 2008).

The results show that even though neighborhood related diversity plays a role, the main determinants for firm innovativeness are firm-specific. Having highly educated and cognitively skilled employees have significant positive effects throughout, with larger effects found for the industrial sector than the service sector. Positive effects on firm innovativeness

[2] A large part of the industrial sector, analyzed in the present paper, consists of manufacturing industries.

from neighborhood related diversity is found for education only, which may indicate that educational background represent cognitive proximity to a larger extent than occupation and industrial belonging. To directly test the hypothesis of absorptive capacity interaction terms between firm knowledge and neighborhood diversity are introduced. The added effect from the combination of highly educated employees in the firm and neighborhood diversity in education is positive while the added effect from the combination of highly educated employees and diversity in occupation is negative. This points to that the hypothesis of absorptive capacity is valid also empirically, but only for similar types of knowledge.

The remainder of the paper is organized as follows. Section 2 provides further background and motivation for the paper, while section 3 describes the data and method used in the empirical application. An overview of the variables and the measurement of these, both concerning firm characteristics and regional characteristics, are given in Section 4. Section 5 presents and discusses the empirical results and section 6 concludes.

2. Background and motivation

2.1. Agglomeration economies and the role of diversity

The present paper builds on the theory of agglomeration economies, and especially the effect of potential knowledge spillovers on the innovative performance of firms. The concept of agglomeration economies dates back to Marshall (1890), who argues that firms benefit from agglomeration due to the reduction of transport costs, access to labor, and knowledge spillovers. In Marshall's view these benefits arise due to industrial specialization. However, the opposing view is that diversity is what gives rise to agglomeration economies, as advocated by Jacobs (1969). There has been a long academic debate as to whether specialization or diversity promotes innovation and growth, or in other words, whether Marshall or Jacobs is right (see e.g. Beaudry and Schiffauerova (2009) for an overview). The present paper does not contribute to this debate but focus solely on the diversity side of it.

Diversity has for quite some time been recognized as an important phenomenon for regional economic performance. Quigley (1998), in a major theoretical and empirical review of the field so far, concludes that diversity in firms and industries is beneficial for regional economies, due to external scale economies. Theoretical models show that the diversity of large, modern cities enhances economic growth, which is confirmed by empirical studies. Glaeser et al. (1992) provide a seminal example of this when explaining subsequent employment growth by initial conditions. The results show that industrial diversity is enhancing the economic performance of large city-industries. Florida and Gates (2001) find that diversity is a strong indicator for growth in urban high-tech industries. The uniqueness of the studies by Florida (and colleagues) is that diversity is measured based on e.g. gays, bohemians and foreign-born individuals, i.e. characteristics of individuals rather than firms. More theoretically, Desrochers (2001) argues that diversified cities increase the probabilities of the creation of new combinations, due to large and diverse knowledge pools.

Based on the ideas by Marshall (1890), Duranton and Puga (2004) distinguish between three types of mechanisms behind agglomeration economies; *sharing* of e.g. indivisible goods and facilities as well as input sources, *matching* on the labor market, and *learning* due to knowledge spillovers and human capital accumulation. In the present paper, the main interest is in the third mechanism, which according to Duranton and Puga (2004) and Puga (2010) is the least modeled and hence the least understood. This warrants further studies on the micro-foundations of learning and knowledge spillovers. Duranton and Puga (2004) conclude that heterogeneity of workers and firms is the foundation of the three mechanisms behind agglomeration economies, thus supporting the view of Jacobs (1969).

As discussed in the introduction, more recent research take the issue of diversity one step further and argue that Jacobs externalities result from related diversity rather than diversity in general. This is due to the need of some sort of relatedness, or cognitive proximity, for knowledge spillovers to be effective. Without cognitive proximity, that is some sort of common knowledge base, economic agents may not have the absorptive capacity to benefit from new types of knowledge. Desrochers and Leppälä (2011), Brachert et al. (2011) and Wixe and Andersson (2013), among others, argue that relatedness should be analyzed in terms of individuals and their knowledge, skills and experiences, rather than in terms of firms, products or industries. Learning and knowledge spillovers occur mostly at the level of individuals and due to e.g. division of labor and functional specialization (Duranton and Puga 2005), relatedness based on education and occupation reflect cognitive proximity to a larger extent than industrial belonging. This is due to that educational background and current occupation capture the formal knowledge base and the learning and knowledge gained from the daily work, respectively[3]. Hence, in the present paper measures of relatedness in terms of education and occupation are applied. These measures of related diversity directly follows Wixe and Andersson (2013), with the difference that they are calculated for smaller geographical units. In addition, the present paper analyzes firm innovation, rather than regional growth. Since most empirical research still focus on the industrial dimension (see e.g.

[3] See Wixe and Andersson (2013) for a longer conceptual discussion on relatedness based on education and occupation versus industrial belonging.

Frenken et al. (2007), Boschma and Iammarino (2009) and Hartog et al. (2012)), relatedness in terms of industrial belonging is also included in the empirical application.

The potential for agglomeration economies are commonly explored by measuring e.g. diversity and/or specialization at the level of urban areas or labor market regions. These areas may be suitable when considering agglomeration economies in terms of sharing and matching (c.f. Duranton and Puga (2004)), since these effects can be argued to extend over relatively large distances. However, regarding learning already Marshall (1890) acknowledged the importance of direct contact between economic agents for knowledge transfers to take place. Due to the exponential increase in information- and communication technology as well as enormous reductions in transport costs, the possibilities for longer distance travel and communication are obviously much greater in the 21st century than in Marshall's 19th century. Despite this, face-to-face contact is still highlighted as an important source for knowledge spillovers, since direct contacts ease the formation of relationships, networks and trust (see e.g. Storper and Venables (2004)).

The potential for personal interaction and knowledge sharing between economic agents is naturally greater the smaller and denser the area is. Recent empirical research confirm that agglomeration economies, with knowledge spillovers in particular, are very much bounded in space. Arzaghi and Henderson (2008), by use of a detailed geographical level, which locates firms within a 250 meter radius, show that there is an extremely rapid distance decay in information externalities. Also Andersson et al. (2012) find a sharp attenuation of agglomeration effects, by exploring squares of 1 and 0.0625 square kilometers. Neighborhood effects are argued to capture non-market effects of agglomeration economies, such as knowledge spillovers. Koster et al. (2014) find that the willingness-to-pay for office space is higher for high-rise buildings, which is explained by within-building agglomeration economies, a landmark effect and a view effect. In addition, the results of Van Soest et al. (2006), Baldwin et al. (2008) and Rosenthal and Strange (2008) point in the same direction, even though the geographical scale is not quite as small as in the above-mentioned studies.

Hence, there are both theoretical arguments and empirical evidence for that knowledge spillovers are neighborhood effects, rather than regional effects. As a consequence, in the present paper the potential sources for agglomeration economies are measured on the neighborhood level. The neighborhoods are defined according to the approximately 9,200 small areas for market statistics (SAMS), which cover the whole of Sweden. SAMS represent actual neighborhoods, which are based on municipality sub-areas in larger municipalities and voting districts in smaller municipalities.

2.2. The role of knowledge

Knowledge has long been regarded as a crucial input factor for productivity, growth and innovation, for individual firms as well as for regions and nations. One of the first adaptions to early growth models was the inclusion of human capital, which implies that the importance of skilled and educated labor and not just labor as such was acknowledged (c.f. Lucas (1988), Romer (1990) and Mankiw et al. (1992)). Also knowledge in terms of research and development (R&D) is emphasized in early theoretical models, such as the knowledge production function, formalized by Grilliches (1979). However, the more disaggregated the unit of observation is the weaker is the relationship between R&D and innovation output, especially when smaller firms are considered (Audretsch 1998). Hence, when conducting firm-level studies it may be more relevant to account for the potential knowledge of the employees (c.f. Audretsch (1995)). This approach is followed in the present paper where the firm knowledge is measured in terms of highly educated employees as well as cognitively skilled employees.

The above-mentioned theories of innovation and growth treat the firm as an isolated island and consider only the direct link between knowledge inputs and output. However, if firms are completely self-contained and if knowledge is bounded within them there is no reason why firms and people would cluster geographically, which is what is observed in the real world. Clustering can be explained by agglomeration economies, such as knowledge spillovers. As discussed in the introduction, the ability to exploit these potential knowledge spillovers is dependent on the knowledge of the employees in the firm, since the employees play a central role for the absorptive capacity. Hence, the employees are important both as direct resources and as channels of external knowledge.

There is a large, mostly theoretical, literature on the importance of external knowledge, interactions, networks and other R&D collaborations for innovation (see e.g. Håkansson (1987), Lundvall (1992), Asheim and Isaksen (1997), Edquist (1997), Baptista and Swann (1998), and Cooke and Morgan (1998)). Cohen and Levinthal (1990) argue that the ability to exploit external knowledge is a crucial innovative capability of firms. In addition, Chesbrough (2003), with the model of open innovation, stresses the importance of external knowledge in innovation activities. In a closed innovation model a firm generates, develops and commercializes its own ideas, and all R&D activities are thus internal. For this model to work the firm needs to be in total control of its intellectual property, e.g. the employees. The increase in labor mobility, together with a larger share of highly educated employees, makes the closed innovation model less sustainable. A firm that incorporates the open innovation model is broadening its view and uses knowledge of its own employees as well as knowledge external to the firm. The importance of external knowledge for the innovative performance of firms and industries have been shown by Feldman (1994), Caloghirou et al. (2004), and Laursen and Salter (2006), among others.

In recent times a majority of firms make use of external sources in their innovative activities, that is they apply a more or less open innovation strategy. Usually there is a combination of external and internal sources and how well this combination works depends on the quality of both types of sources. In addition, Johansson and Quigley (2004) emphasize that well-functioning links and networks facilitate the transfer of knowledge. A majority of studies find that internal knowledge, commonly measured as R&D efforts, and external knowledge complement each other (c.f. Arora and Gambardella (1990; 1994), Lowe and Taylor, Veugelers (1997), Becker and Dietz (2004), Cassiman and Veugelers (2006)). However, other studies point in the opposite direction (c.f. Laursen and Salter (2006)), why no general conclusion can be drawn regarding this issue.

The above mentioned studies concern specific sources for external knowledge as well as actual acquisitions of external knowledge. Other studies measure external knowledge in more indirect terms, such as the sources for potential knowledge in the region. This approach is followed in the present paper. Johansson et al. (2013) provide another example of this. They find that the conjunction of internal knowledge, measured as schooling, and external knowledge, measured as access to employees in the Knowledge Intensive Business Service (KIBS) sector, enhances innovative performance. However, the analysis is conducted at the level of local industries, which does not allow for inferences about individual firms, an issue referred to as ecological fallacy. Oerlemans et al. (1998) and Freel (2003) show that, even though external networks matter, internal resources are the main determinants for the innovative performance of firms. Hence, in order to retain firm level variation the present paper takes the firm as the unit of analysis.

3. Data and method

In the present paper an employer-employee matched data set, collected by Statistics Sweden, is applied. In addition, some of the replies from the Community Innovation Survey (CIS) for Sweden have been added to the firm data. The CIS is a survey of innovation activities in firms, conducted every two years in the EU member states. The survey collects information about different types of innovations that the firms may have introduced during a three year period. For the present case an issue with the CIS data is that innovation is reported on the firm level while the geographic location is given only at the establishment level. This poses a problem since a firm can comprise many different establishments located in different regions, which is the case for about 29 percent of the firms in the CIS from 2010. To deal with this issue the geographic location of the firm is determined based on the location of the establishment with the largest share of employees. A similar procedure is used in Martin et al. (2011) and Wixe (2014). To distinguish these firms from single-establishment firms a dummy variable is introduced.

In the present case, the CIS is applied in order to classify firms as being innovative or not. The CIS questions that are relevant for the present study concern product innovations, which are defined as new or substantially improved goods and/or services. A downside of using CIS is that it covers only a sample of firms, with at least ten employees. The latest survey available is from 2010, which covers the innovation activities between 2008 and 2010. During this period 60 percent of the firms responded to have engaged in innovation activities, of which 61 percent introduced product innovations. In general, larger firms are more innovative than smaller firms. 5,422 firms were sampled for CIS 2010, of which 4,552[4] responded, resulting in a response rate of 84 percent. The total population consisted of 16,743 firms, which implies that the final sample constitute around 27 percent of all firms (with at least ten employees). The CIS is directed to firms in industries 05 to 72[5], which includes both the industrial sector and the service sector. Table A1 provides a description of the included industries. In 2010, the sampling frame was divided into subgroups based on industries, size[6] and regions[7]. (Statistics Sweden 2012)

3.1. Method

The dependent variable, y_i, is binary and takes the value 0 or 1 depending on the outcome.

$$y_i = \begin{cases} 1, & Firm\ i\ has\ introduced\ an\ innovation. \\ 0, & Firm\ i\ has\ not\ introduced\ an\ innovation. \end{cases}$$

[4] The number of observations in the estimations is 4,477, which is due to missing information on either firm-, establishment, or individual level.
[5] Standard Industrial Classifications, SNI2007, which is equivalent to NACE at the two-digit level.
[6] 10-49 employees, 50-249 employees, 250 or more employees.
[7] NUTS2.

The probability that y_i takes the value 1 is given by some function of the variables $\boldsymbol{x}$, which are presented in section 4. In the present case logit estimation is applied, which implies that the cumulative density function of the logistic distribution, here denoted Λ, is applied.

$$Pr\{\, y_i = 1\} = \Lambda(\boldsymbol{x}_i'\boldsymbol{\beta}) = \frac{e^{\boldsymbol{x}_i'\boldsymbol{\beta}}}{1 + e^{\boldsymbol{x}_i'\boldsymbol{\beta}}} \tag{1}$$

The log of the odds-ratio is a linear function of the parameters:

$$\ln \frac{Pr(y_i = 1)}{Pr(y_i = 0)} = \ln \frac{\Lambda(\boldsymbol{x}_i'\boldsymbol{\beta})}{1 - \Lambda(\boldsymbol{x}_i'\boldsymbol{\beta})} = \boldsymbol{x}_i'\boldsymbol{\beta} \tag{2}$$

In the present paper the results are presented in terms of odds-ratios, which are simply the antilog of Equation 2. The odds-ratio provides a straightforward interpretation, if it is greater than one, the effect is positive, while the effect is negative if the odds-ratio is smaller than one. Throughout the estimations, robust standard errors clustered on 93 labor market regions are applied. This provides an attempt to control for spatial autocorrelation within these regions.

4. Variables

The dependent variable in the present study is thus binary and states whether or not the firm has introduced a product innovation in the years 2008 to 2010. Since the dependent variable is based on a period of three years, the independent variables are constructed for the same three years. In the estimations, the average values are applied[8].

4.1. Firm characteristics

In order to explain the innovative performance of firms, it is crucial to include variables that describe firm-specific characteristics. These variables include both independent variables of main interest and control variables, where the former concern the abilities of the employees. These abilities are measured using two different approaches. First, as is commonly done, the percentage of employees with three or more years of higher education is applied. This captures the formal educational background among the employees. The expectation is that the greater the share of highly educated employees is, the higher is the probability that the firm is innovative.

[8] Due to especially the regional variables changing slowly over time, choosing either year for the independent variables does not change the results.

In more recent years researchers have highlighted individual skills and abilities beyond measures of education. Florida (2002) introduced the creative class, Autor et al. (2003) focus on routine and non-routine tasks, and Bacolod et al. (2009) distinguish between cognitive skills, people skills and motor skills. The common denominator is that these measures of skills are based on occupational rather than educational classifications. In the present paper the skill level of the firm is measured as the percentage of employees with occupations that require cognitive skills.[9] Again, the expectation is that the greater the share of cognitively skilled employees is, the higher is the probability that the firm is innovative.

To find the cognitive occupations, the categorization of the Swedish occupational codes by Johansson and Klaesson (2011) is followed. This categorization is based on Bacolod et al. (2009) and distinguishes between occupations that require cognitive skills, management and administration skills, social skills, and motoric and other skills. Typical cognitive skills occupations are engineers and natural scientists, which are commonly hired for the purpose of research and development. However, also occupations such as specialists in healthcare and teaching, social scientists, and arts and crafts workers are categorized as being cognitive, which implies that the concept of cognitive skills is broader than what may be expected. This also implies that cognitive skills occupations are found in both the industrial sector and the service sector.

Control variables at the firm-level are the size as in number of employees, the age of the firm, the average age of the employees, the share of females, the ownership structure, and whether the firm is engaged in international trade. The latter is introduced to control for the possibility of import- and export-led learning. In addition, industry dummies are included, which indicate which type of industry the firm belongs to, e.g. high-tech or low-tech manufacturing, knowledge-intensive business services (KIBS) or wholesale and retail. Lastly, a dummy variable denoting whether the firm has multiple establishments is introduced.

4.2. Neighborhood and regional characteristics

The neighborhood characteristics concern diversity, where diversity is measured as related diversity. This follows from the ideas of the importance of cognitive proximity (Noteboom 2000; Frenken et al. 2007), as discussed earlier. The entropy (or the Shannon index) approach

[9] There is a strong relationship between the cognitive skills occupations à la Bacolod et al. (2009) and the occupations with a high share of non-routine tasks à la Autor et al. (2003). Both approaches have been tested in the present case and the results are robust to the inclusion of whichever of these two measures. The choice fell on the cognitive skills classification since for the share of non-routine tasks a rather arbitrary choice needs to be done when deciding how high the share of non-routine tasks needs to be in order for the occupation to be regarded as “high-skilled”.

is commonly applied to measure diversity, see e.g. Jacquemin and Berry (1979), Attaran (1986) and Frenken et al. (2007). An advantage of the entropy measure is that it takes the relative abundance of groups into account, and not only the absolute presence of them.

In the present case, all entropies are calculated using employment in each group. The data is limited to employed individuals between 20 and 64[10] years of age with a positive income. Regarding industries the 2-digit and the 5-digit SIC codes are used where each 5-digit industry belongs to a specific 2-digit industry. Following Attaran (1986), let S_g denote the 2-digit sets where $g = 1,\dots,$ G. E_g denotes the share of employees working in the 2-digit industry g, where E_g is measured as the share of total regional employment. Furthermore, let E_{ig} denote the share of employees working in the 5-digit industry i, where $i = 1,\dots,$ I, where E_{ig} is measured as the share of employment in the respective 2-digit industry g. The distribution of employees across 5-digit industries within each 2-digit industry is calculated as follows:

$$H_g = -\sum_{i=1}^{I} E_{ig} \ln E_{ig}. \tag{3}$$

The range of H_g is from 0 to $\ln I$, where zero diversity is reached when all employees in the 2-digit industry g are working in the same 5-digit industry i, where $i \in S_g$. Accordingly, maximum diversity for industry g, $\ln \mathrm{I}$, is achieved when there is an equal distribution of employees over all 5-digit industries i, where $i \in S_g$.

The information about the degree of within diversity for each 2-digit industry g, i.e. H_g, is weighted by the relative size of industry g. Summing over all g gives the entropy measure for related diversity in industries (RD), regarding the region as a whole. These two steps are formally shown by Equation 4.

$$\mathrm{RD} = \sum_{g=1}^{G} E_g H_g \tag{4}$$

This measure of related diversity makes sense when conducting the analysis at the regional level (as in Frenken et al. (2007)). However, when analyzing firm performance, what matters is the diversity within the specific 2-digit industry the firm belongs to, as discussed by Bishop and Gripaios (2010). Hence, regarding industries, Equation 3 is applied in order to calculate related diversity for each 2-digit industry. On the other hand, when measuring related

[10] 64 is the actual average year of retirement in Sweden.

diversity in education and occupation, Equation 4 is used, in order to allow knowledge spillovers to transcend industry boundaries.

Related diversity for the educational and the occupational dimension are hence calculated as demonstrated above, with the difference that the educational and the occupational codes are used instead of the SIC codes. When constructing the measures for educational diversity a combination of education length and specialization is used. Employees are first categorized as either having three or more years of higher education or not. After this categorization education specialization is used at the 2- and 4-digit levels. This implies that employees that have the same 2-digit educational code *and* have three or more years of higher education are seen as related. Regarding the occupational dimension occupational codes at the 1- and 3-digit levels are used instead of the educational codes. Tables A2 and A3 provide overviews of the 2-digit educational groups and the 1-digit occupational groups, respectively.

The expectations for the effects of the various measures of related diversity differ. Previous research on the effect of related diversity in industries on regional productivity growth (Frenken et al. 2007; Wixe and Andersson 2013) and plant productivity (Wixe 2014) show a negative effect of related diversity in industries, which suggests that cognitive proximity in terms of industrial belonging is not enough to give rise to productivity-enhancing Jacobs externalities. This, in combination with the close connection between productivity and innovation, leads to the expectation that the relationship between related diversity in industries and the innovative performance of firms is non-positive. On the other hand, related diversity in terms of education and occupation are expected to positively influence firm innovativeness, due to the potential of education and occupation to better capture cognitive proximity.

The above measures of related diversity are calculated for the approximately 9,200 small areas for market statistics (SAMS), which represent actual neighborhoods. However, there are interactions between neighborhoods and between municipalities, especially within labor market regions. To capture these interactions a measure of accessibility is introduced as a control variable. Andersson and Gråsjö (2009) find that the inclusion of accessibility as a representation of spatial interaction captures the spatial dependence between locations, both when applying actual data[11] and when running simulations. In the present case, this provides a further control for spatial autocorrelation, besides the already mentioned cluster-robust standard errors.

[11] The actual data is for Sweden and the hierarchical structure is the same as applied in the present paper.

In the present case, accessibility is measured as access to market potential, in terms of wage sums (WS). Johansson et al. (2002) divide the accessible market into a local, an intra-regional and an extra-regional part. The local market consists of the municipality in question and the intra-regional market is the functional economic region (or labor market region), which typically comprises four to five municipalities. The extra-regional market consists of the municipalities outside the functional region. The different accessibility measures are calculated as follows (Andersson and Klaesson, 2009):

$$A_r^l = WS_r \exp\{-\lambda_r t_{rr}\}, \tag{5}$$

$$A_r^{ir} = \sum_{R-r} WS_k \exp\{-\lambda_{ir} t_{rk}\}, \tag{6}$$

$$A_r^{er} = \sum_{W-R} WS_k \exp\{-\lambda_{er} t_{rk}\}, \tag{7}$$

in which A_r^l denotes the local, A_r^{ir} the intra-regional and A_r^{er} the extra-regional market accessibility for municipality r. R constitutes all the municipalities within a functional economic region and W is the set of all Swedish municipalities; t_{rk} is the travel time distance between municipality r and municipality k, where $r \neq k$. The market potential is thus adjusted for travel times between locations. Finally, the λ's are measures of time-distance sensitivity. Using Swedish commuting data for 1998, Johansson *et al.* (2003) estimated λ_r to 0.02, λ_{ir} to 0.1 and λ_{er} to 0.05. Equations 5 to 7 are summed up in order to find the total market potential for firms located in municipality r. Hence, besides controlling for spatial autocorrelation, total accessibility measures the economic size of the municipality the firm is located in. This implies a control for agglomeration economies that extend over urban areas, such as input sharing and labor pooling.

4.3. Interaction terms

To assess whether the combination of firm knowledge and neighborhood diversity enhances the probability that firms are innovative, interaction terms between the percentage of employees with higher education as well as with cognitive skills, and neighborhood related diversity, are introduced. This results in a total of six interaction terms. These terms are introduced to test the hypothesis of absorptive capacity, that is whether firms with more internal knowledge are better at incorporating potential knowledge spillovers, which in the present case result from neighborhood related diversity. The expectation is that firm knowledge in conjunction with related diversity, that is where there is some sort of cognitive proximity among employees, increases the innovative performance of firms. Following Wixe and Andersson (2013) cognitive proximity in terms of education and occupation are expected to give rise to positive interaction effects, while the expectation regarding cognitive proximity in terms of industrial belonging is unclear. Due to issues of multicollinearity the relevant variables are centered before the creation of the interaction terms. Table A5 shows that the correlations between interaction terms and original values are low. Correlations between interaction terms are higher but the variance inflation factors (VIF), which are all below 2.5, do not indicate problems with multicollinearity.

4.4. Summary of variables

Table 1 provides a summary of all variables, besides the interaction terms. Descriptive statistics can be found in Table A6.

Table 1. Summary of variables.

Variable	Definition
Innovative	Dummy=1 if the firm has introduced a new or substantially improved product (good and/or service). Dependent variable.
Firm characteristics	
Education	Percentage of employees with three or more years of higher education.
Skills	Percentage of employees with cognitive skills occupations.
Average age	Average age of the employees.
Female	Percentage of females
Size (ln)	Number of employees, log transformed.
Firm age	Years since establishment[12].
Ownership	Dummies for: - Public (base) - Private part of a group - Private not part of a group - Foreign
International	Dummy=1 if the firm is an exporter or importer
Multi-establishment	Dummy=1 if the firm has multiple establishments
Industry	Dummies for[13]: - Agriculture, mining etc. (base) - Low-tech manufacturing - High-tech manufacturing - Knowledge Intensive Business Services (KIBS) - Wholesale and retail - Other services - Public services - Gas, electricity etc.
Neighborhood characteristics	
RD Industry	Related diversity in industries.
RD Education	Related diversity in educational background.
RD Occupation	Related diversity in occupations.
Regional characteristics	
Market potential (ln)	Total access to wage sums, log transformed.

5. Empirical results

Table 2 provides the results for the CIS sample as a whole, which implies that firms from all industries are included in the estimations. The results are presented in three specifications, first including the firm level characteristics, then including the neighborhood and regional characteristics, and last including characteristics at all three levels.

[12] The year of establishment is given by the Swedish FAD-definition, which implies that firms started before 1986 are assigned the year 1986 in the dataset.
[13] Low-tech and high-tech manufacturing, KIBS, wholesale and retail, and other services are based on OECD categorization.

Table 2. Estimated odds-ratios for firm, neighborhood and regional characteristics. All industries. Dependent variable: Product innovation.

	(1) All industries	(2) All industries	(3) All industries
Firm characteristics			
Education	1.0085***		1.0091***
	(.0027)		(.0031)
Skills	1.0080***		1.0078***
	(.0023)		(.0022)
Average age	.9743***		.9741***
	(.0065)		(.0066)
Female	1.0060***		1.0066***
	(.0021)		(.0023)
Size (ln)	1.3440***		1.3402***
	(.0453)		(.0461)
Firm age	1.0032		1.0029
	(.0053)		(.0054)
International	1.5555***		1.5530***
	(.1462)		(.1452)
Multi-establishment	1.0321		1.0351
	(.0658)		(.0673)
Ownership dummies	*Yes*		*Yes*
Industry dummies	*Yes*		*Yes*
Neighborhood and regional characteristics			
RD Industry		.9837	1.0741
		(.0691)	(.0996)
RD Education		2.4547***	1.1621
		(.3437)	(.1736)
RD Occupation		.6643***	.7778*
		(.0748)	(.1086)
Market potential (ln)		1.0903***	.9632
		(.0284)	(.0333)
Constant	.0679***	.0332***	.1757
	(.0393)	(.0201)	(.1946)
Chi-square	675.13***	80.76***	763.82***
% cases correctly predicted	66.74	60.87	66.81
Observations	4,477	4,477	4,477

Notes: Cluster-robust standard errors are reported in parenthesis. *** denote significance at 1 percent level, ** denote significance at 5 percent level, and * denotes significance at 10 percent level.

From Table 2 it is evident that firm characteristics provide stronger determinants for firm innovativeness than neighborhood characteristics, which shows the importance of controlling for firm level heterogeneity. The results for the firm characteristics are robust to the inclusion of the neighborhood and regional variables while the opposite does not hold. This is in line with previous studies on firm innovativeness (c.f. Oerlemans et al. (1998) and Freel (2003)), and strengthens the issue of ecological fallacy in regional level studies of agglomeration economies.

The results imply that firm knowledge, measured as highly educated and cognitively skilled employees, is more important than potential knowledge sources in the neighborhood, measured in terms of related diversity. A higher share of highly educated employees and a higher share of cognitively skilled employees have a positive influence on the probability that a firm has introduced a product innovation. Increasing the percentage of educated employees by ten percentage units is associated with an increase in the odds of being innovative by approximately nine percent. The corresponding figure for increasing the percentage of cognitively skilled employees by ten percentage units is approximately eight percent. The odds-ratios are not statistically different from each other, which implies that no conclusion can be drawn regarding the relative importance of highly educated versus cognitively skilled employees.

Among the three measures of related diversity, a positive effect is found for related diversity in education. This effect is significant when including only the regional characteristics but turns insignificant when adding all firm level characteristics. However, when excluding the industry dummies (not shown in Table 2), which proves to be strong determinants for innovativeness, related diversity in education is still significant, although the magnitude of the effect is very much decreased. Overall, the results regarding related diversity in education may be interpreted as if educational background is a stronger indicator of cognitive proximity than industry belonging and occupation. This points in the same direction as the findings by Wixe and Andersson (2013), who show that related diversity in education is an especially strong determinant for regional productivity growth. Considering that the level of analysis and the geographic area for the calculation of related diversity, as well as the output variable, differ in the present study, related diversity in education seems to be an important determinant for economic performance in general terms.

On the other hand, the effect of related diversity in occupation is negative and significant, also when introducing the firm level variables. Hence, no evidence is found that neighborhood relatedness in terms of occupation results in knowledge spillovers that increase the innovativeness of local firms. This even implies that firms that are located in neighborhoods with more related diversity in occupation have a reduced probability of being innovative, which goes against the expectation. A potential explanation for the opposite results for education and occupation may be that relatedness in terms of education results in higher-quality knowledge flows. This is due to that a great majority of the educational codes implies some sort of education beyond compulsory school (see Table A2), which implies that higher values of related variety in education is a result of relatedness between employees who have, at least theoretically, achieved a certain level of knowledge. Regarding occupations, all occupations are included (see Table A3), which implies that a higher degree of related diversity in occupation may result from relatedness in low-skilled occupations.

Table 3 presents the corresponding results for the industrial sector and the service sector.

Table 3 shows differences between the industrial sector and the service sector, both regarding firm knowledge and neighborhood diversity. Having highly educated employees within the firm proves to be a stronger determinant in the industrial sector than in the service sector, since both the significance and the magnitude of the effect is greater. This may be due to that firms in the industrial sector are more technology-oriented and hence depend relatively more on firm knowledge (c.f. Bishop (2008)), such as highly educated employees. On the other hand, firms in the service sector may benefit relatively more from a diverse economic milieu, due to being more diverse in themselves in terms of e.g. inputs and the industries they supply (c.f. Combes (2000) and Bishop (2008)). This latter argument is supported in the present case since regarding related diversity in education the results show a robust positive effect for the service sector only, even though the magnitude and significance of the effect decrease with the inclusion of the firm characteristics. For the industrial sector, there are no significant effects from neighborhood diversity when controlling for firm characteristics.

Regarding the control variables, the results show that firms with older employees are less innovative. On the other hand, firms with a higher share of female employees, larger firms and firms that engage in international trade, are more innovative. There are no significant effects from the age of the firm, nor from having more than one establishment. In addition, there is no significant effect from the size of the whole urban area when controlling for the firm characteristics. This may be a result of self-selection of innovative firms, especially with highly educated and skilled employees, to urbanized regions, which washes away the positive effect from urbanization.

To further explore the difference in the results regarding related diversity in education and related diversity in occupation, the distribution of these across the neighborhoods (SAMS) in the southern half of Sweden are shown by Figure 1 and 2, respectively. Figure 2 gives the location of the three metropolitan areas; Stockholm, Gothenburg and Malmö.

Table 3. Estimated odds-ratios for firm, neighborhood and regional characteristics. Dependent variable: Product innovation.

	(4) Industrial sector	(5) Industrial sector	(6) Industrial sector	(7) Service sector	(8) Service sector	(9) Service sector
Firm characteristics						
Education	1.0159***		1.0176***	1.0043*		1.0043*
	(.0043)		(.0047)	(.0025)		(.0026)
Skills	1.0094**		1.0097**	1.0070***		1.0063***
	(.0040)		(.0039)	(.0022)		(.0023)
Average age	.9651***		.9647***	.9760***		.9760***
	(.0120)		(.0121)	(.0061)		(.0060)
Female	1.0055**		1.0058**	1.0061**		1.0064***
	(.0028)		(.0029)	(.0025)		(.0027)
Size (ln)	1.4847***		1.4874***	1.1355**		1.1301***
	(.0702)		(.0717)	(.0569)		(.0535)
Firm age	1.0072		1.0070	1.0028		1.0031
	(.0092)		(.0092)	(.0053)		(.0053)
International	1.6878***		1.6729***	1.7231***		1.7033***
	(.2706)		(.2653)	(.1874)		(.1889)
Multi-establishment	1.0248		1.0281	1.0309		1.0331
	(.1063)		(.1082)	(.0899)		(.0937)
Ownership dummies	*Yes*		*Yes*	*Yes*		*Yes*
Industry dummies	*Yes*		*Yes*	*Yes*		*Yes*
Neighborhood and regional characteristics						
RD Industry		.8308	1.1023		1.1119	1.0747
		(.1029)	(.1536)		(.0833)	(.1215)
RD Education		2.3118***	.8743		3.3183***	1.5627**
		(.4636)	(.2019)		(.7698)	(.2891)
RD Occupation		.6125**	.9670		.7510*	.7012*
		(.1225)	(.1976)		(.1161)	(.1305)
Market potential (ln)		1.0730**	.9524		1.1609	1.0043
		(.0314)	(.0333)		(.0441)	(.0501)
Constant	.0443***	.0669***	.1735	.5670	.0031***	.3863
	(.0334)	(.0469)	(.2179)	(.2460)	(.0023)	(.5097)
Chi-square	275.27***	37.46***	294.13***	415.48***	114.73***	440.63***
% cases correctly predicted	67.82	59.65	68.13	65.84	62.32	65.84
Observations	2,545	2,545	2,545	1,932	1,932	1,932

Notes: Cluster-robust standard errors are reported in parenthesis. *** denote significance at 1 percent level, ** denote significance at 5 percent level, and * denotes significance at 10 percent level.

Figure 1. Quantile map of related diversity in education in southern Swedish SAMS (darker color implies greater diversity).

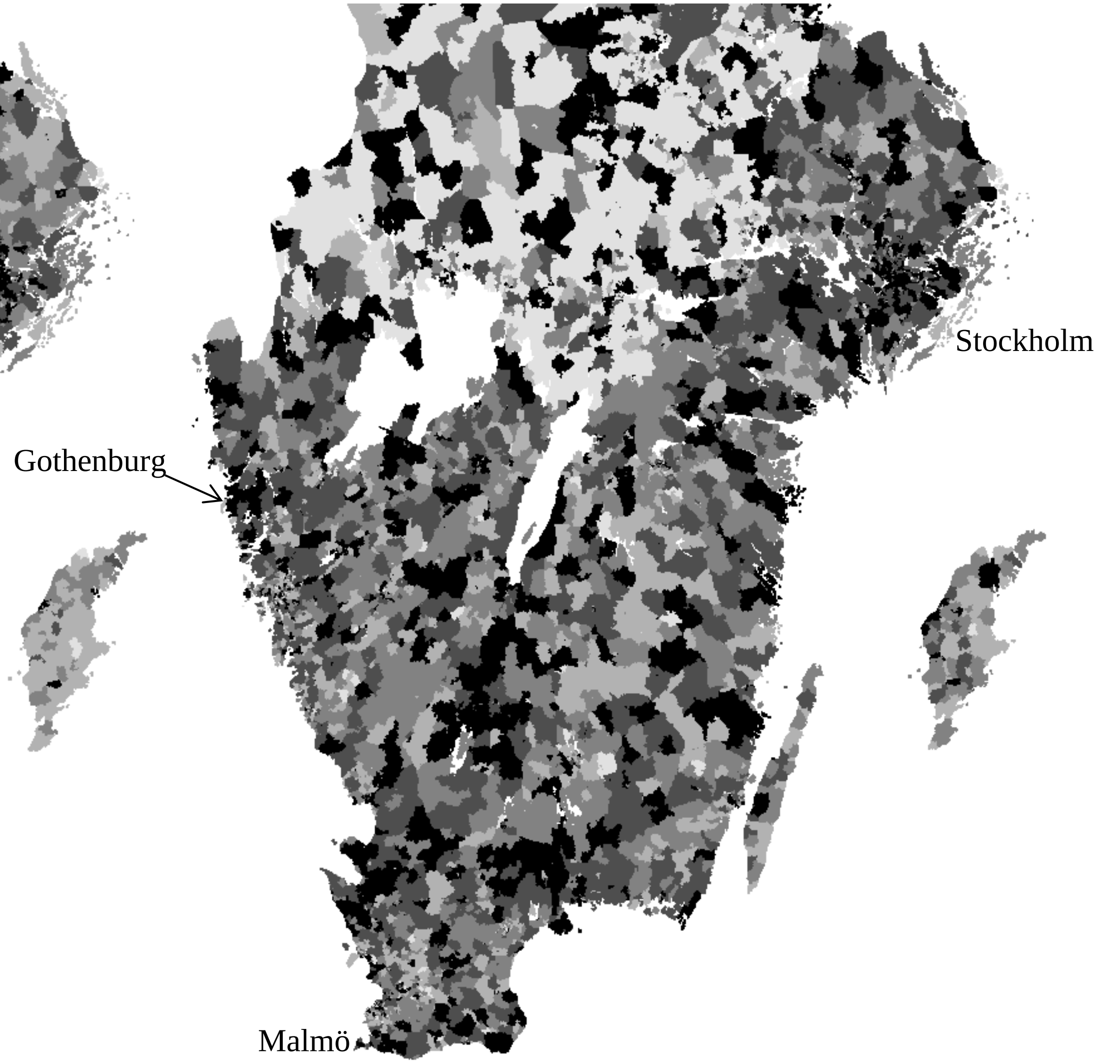

Figure 2. Quantile map of related diversity in occupation in southern Swedish SAMS (darker color implies greater diversity).

The sparsely populated northern half of Sweden is not shown in the maps, due to not exhibiting any obvious differences between related diversity in education and occupation. In this part of the country, neighborhoods with a higher (lower) degree of related diversity in education have to a large extent also a higher (lower) degree of related diversity in occupation. The story for the southern half of Sweden, which is more urbanized, is different. It may seem as if the map of related diversity in occupation (Figure 2) contains more darker colored areas but since both maps are quantile maps the number of neighborhoods in each of the (five) categories is the same. The difference is that regarding related variety in education the high value neighborhoods are mostly concentrated to the core of the cities, where the neighborhoods are geographically smaller. On the other hand, related diversity in occupation is more evenly spread across the southern part of the country. Since highly educated and skilled individuals are in general attracted to urban areas, the pattern shown by Figure 1 implies that high values of related diversity in education are associated with high degrees of knowledge. Regarding related diversity in occupation, the pattern in Figure 2 imply that high values of related diversity in occupation may be a result of relatedness in lower skilled occupations, which comprise a larger share of the occupations in less urban areas. This strengthens the argument above that relatedness in terms of education results in more high-quality knowledge spillovers, at least when measured as in the present study.

The last issue dealt with concerns absorptive capacity, or more specifically, whether firms with more internal knowledge are better at incorporating the potential knowledge flows from neighborhood related diversity. Table 4 presents the results from the estimations with interaction effects.

As expected, there are no significant effects from the interactions between firm level knowledge and related diversity in industries. However, the interactions with related diversity in education and occupation provide interesting results. The odds-ratios for these four interaction terms are, at least weakly, significant for the sample as a whole, while the interaction terms with related diversity in occupation are significant for the service sector. Regarding the industrial sector there are no added effects from the combination of firm knowledge and neighborhood diversity. This reinforces the conclusion above, that firms in the industrial sector is less dependent on the neighborhood than firms in the service sector.

Table 4. Estimated odds-ratios for regressions with interaction terms.

	(10) **All sectors**	**(11)** **Industrial sector**	**(12)** **Service sector**
Firm characteristics			
Education	1.0103***	1.0154***	1.0060***
	(.0022)	(.0042)	(.0021)
Skills	1.0073***	1.0115***	1.0050**
	(.0019)	(.0038)	(.0020)
Average age	.9741***	.9645***	.9762***
	(.0067)	(.0121)	(.0058)
Female	1.0064***	1.0059**	1.0058**
	(.0024)	(.0030)	(.0030)
Size (ln)	1.3488***	1.4894***	1.1369***
	(.0465)	(.0737)	(.0560)
Firm age	1.0034	1.0071	1.0046
	(.0055)	(.0093)	(.0055)
International	1.5466***	1.6634***	1.7063***
	(.1443)	(.2634)	(.1874)
Multi-establishment	1.0252	1.0252	1.0254
	(.0697)	(.1075)	(.0962)
Ownership dummies	*Yes*	*Yes*	*Yes*
Industry dummies	*Yes*	*Yes*	*Yes*
Neighborhood and regional characteristics			
RD Industry	1.1127	1.0684	1.0824
	(.0955)	(.1505)	(.1215)
RD Education	1.1459	.9728	1.6107*
	(.1604)	(.2494)	(.3949)
RD Occupation	.7441**	.9585	.6951
	(.1059)	(.1996)	(.1578)
Market potential (ln)	.9661	.9479	1.0082
	(.0342)	(.0349)	(.0514)
Interaction terms			
Education # RD Industry	.9979	.9889	1.0022
	(.0021)	(.0088)	(.0024)
Education # RD Education	1.0171*	1.0210	1.0124
	(.0102)	(.0190)	(.0099)
Education # RD Occupation	.9820*	1.0014	.9770**
	(.0104)	(.0159)	(.0107)
Skills # RD Industry	1.0010	1.0106	1.0001
	(.0026)	(.0072)	(.0046)
Skills # RD Education	.9793**	.9861	.9801
	(.0096)	(.0148)	(.0124)
Skills # RD Occupation	1.0147*	.9993	1.0199***
	(.0080)	(.0129)	(.0076)
Constant	.1708	.1604	.3261
	(.1842)	(.2072)	(.4259)
Chi-square	982.26***	358.48***	557.57***
% cases correctly predicted	67.21	68.02	66.56
Observations	4,477	2,545	1,932

Notes: Cluster-robust standard errors are reported in parenthesis. *** denote significance at 1 percent level, ** denote significance at 5 percent level, and * denotes significance at 10 percent level.

The results for the interaction terms indicate that for firms in general to capture positive effects from related diversity in education, they need to have highly educated employees. In addition, for firms in general to gain positively from related diversity in occupation, they need to have cognitively skilled employees. Hence, firm- and neighborhood level potential knowledge based on education are complementary, while firm- and neighborhood level potential knowledge based on occupation are complementary. On the other hand, the results show that firms with a higher share of educated employees are less innovative in neighborhoods with more related diversity in occupation. This may be interpreted as if firms gain less in innovative potential from their educated employees when located in these types of environments. At the same time firms gain less from their cognitively skilled employees when located in neighborhoods with more related diversity in education.[14] The hypothesis of absorptive capacity is thus partly confirmed. However, the results show that it is not as simple as if firm knowledge and neighborhood knowledge sources are complementary in all situations.

5.1. Robustness check

As a robustness check an equivalent data set is constructed for the 2008 Community Innovation Survey (CIS), which covers innovation activities between 2006 and 2008. The number of observations in the 2008 sample is 4,505, of which 2,644 belong to the industrial sector and 1,861 are service firms. The same estimations as above are run using this data set. Regarding the firm characteristics the results are robust between 2008 and 2010, with two exceptions. For the 2008 sample the multi-establishment dummy is significant and positive for the sample as a whole as well as for firms in the service sector. In addition, the positive effect from having a larger share of female employees is insignificant for firms in the service sector.

Regarding the neighborhood characteristics, the results for related diversity in education are robust between 2008 and 2010. However, the negative effect from related diversity in occupation, which was found for the 2010 sample, is not significant using the 2008 data. On the other hand, related diversity in industries is negative and significant for the sample as a whole as well as for service firms, also when including firm characteristics. This again points

[14] To further test the appeared substitutability between knowledge based on education and knowledge based on occupation estimations with an interaction effect between percentage of highly educated employees and percentage of cognitively skilled employees are run. The added effect is negative and significant, which confirms the results from the interaction terms between firm knowledge and neighborhood related diversity in education and occupation.

to that among the three measures of relatedness, educational background is the strongest determinant for cognitive proximity. It is thus (related) diversity in the educational dimension that is positively related to the innovativeness of firms, which may be due to knowledge spillovers. Regarding related diversity in occupation and industries, no results point to positive effects. Besides this, no general conclusions can be drawn regarding these types of diversity.

For the sample as a whole, the results for the interaction terms with firm knowledge in terms of highly educated employees are robust, while they are not robust for firm knowledge in terms of cognitively skilled employees. Instead, a negative added effect is found for the interaction between the share of cognitively skilled employees and related diversity in industries. On the other hand, this effect is found for also the industrial sector, as well as the service sector. Besides this, the only significant result for the service sector concerns the interaction between highly educated employees and related diversity in education, which again points to the importance of education.[15]

6. Conclusions

The present paper has tested the importance of firm knowledge, measured as highly educated and cognitively skilled employees, and neighborhood related diversity, on firms propensity to innovate. Neighborhood related diversity is introduced as a source for localized knowledge spillovers. Related implies that there is some sort of relatedness, or cognitive proximity, in the diversity, which results from employees sharing a common knowledge base. In the present case relatedness between employees is measured in terms of industrial belonging, educational background and current occupation. Since both theoretical arguments and empirical research point to that knowledge spillovers are heavily bounded in space, related diversity is measured at the neighborhood level rather than the regional level, which is commonly the case in previous studies. The results show that even though there are significant effects from related diversity, firm knowledge is a much stronger determinant for firm innovativeness, especially for firms in the industrial sector. Firms in the service sector do benefit from relatedness among the employees in the neighborhood, but only in terms of educational background. This may be interpreted as if cognitive proximity is better captured by education than by occupation or industry belonging. The effect from related diversity in occupation is even negative, although this result is not found to be robust.

[15] The full regression results for the 2008 data set can be obtained from the author upon request.

In addition, the hypothesis of absorptive capacity was tested, that is whether there are any added effects from the combination of the firm knowledge sources and the neighborhood knowledge sources. The main result in regard to this show that for firms in general, being located in a neighborhood with relatively more related diversity in employee education is positive for firms with higher shares of educated employees. This indicates that firms with more absorptive capacity, measured in terms of educated employees, are better at implementing the potential knowledge spillovers from having more educational diversity in the neighborhood.

It was argued that the opposite effects from related diversity in education and occupation may be due to the construction of the measures. Educational codes largely imply some sort of higher education, while occupational codes include all occupations, ranging from elementary ones to advanced. This implies that high values of related diversity in education in general reflect high-quality knowledge flows, which may not be the case for high values of related diversity in occupation. The untangling of what lies behind related diversity in education and occupation is a potential area for further research, which may include a focus on “high-skill” occupations for related diversity in occupation. Lastly, what should be emphasized is that even though the results show positive effects on innovativeness from related diversity in education, this should not be seen as evidence for the existence of knowledge spillovers. Whether these effects spring from flows of knowledge, matching, sharing or simply because of a more diverse consumer base, can only be speculated in. However, taking the firm as the unit of analysis and bringing the analysis of diversity down to the neighborhood level is one step closer to the core of the issue.

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Appendix

Table A1. Industries included in CIS 2010.

SNI2007/NACE	Description	No of firms
	Industries in the industrial sector	
05-09	Mining and quarrying	48
10-33	Manufacturing	2,232
35-39	Electricity, gas, steam, air conditioning and water supply; sewerage, waste management and remediation activities	272
	Industries in the service sector	
46	Wholesale trade, except of motor vehicles	338
49-53	Transport and warehousing	514
58+61-63	Information and communication, except film, radio and TV	463
64-66	Financial and insurance activities	302
71-72	Architectural and engineering activities; technical testing and analysis, as well as scientific research and development	295

Source: Statistics Sweden (2012).

Table A2. Educational groups.

Educational code (Sun2000Inr)	Education focus
01	General education
08	Reading and writing for adults
09	Personal development
14	Pedagogics and teaching
21	Arts and media
22	The humanities
31	Social and behavioral science
32	Journalism and information
34	Business
38	Law and legal science
42	Biology and environmental science
44	Physics, chemistry and geoscience
46	Mathematics and natural science
48	Computer science
52	Engineering: Technical, mechanical, chemical and electronics
54	Engineering: Manufacturing
58	Engineering: Construction
62	Agriculture
64	Animal healthcare
72	Healthcare
76	Social work
81	Personal services
84	Transport services
85	Environmental care
86	Security

Table A3. Occupational groups.

ISCO/SSYK code	Occupation
0	Militaries
1	Managers, legislators and senior officials
21 & 31	Physical, mathematical and engineering science professionals and associate professionals
22 & 32	Life science and health professionals and associate professionals
23 & 33	Teaching professionals and associate professionals
24 & 34	Other professionals and associate professionals
4	Office and customer services clerks
5	Salespersons, demonstrators, personal and protective services workers
6	Market-oriented skilled agricultural and fishery workers
7	Extraction, building, metal, machinery, handicraft and related trades workers
8	Stationary-plant, machine, mobile-plant and related operators
9	Sales and services elementary occupations, agricultural, mining, transport and related laborers

Table A4. Correlation matrix over dependent and independent variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	VIF
1. Innovative	1													
2. Education	.17	1												2.08
3. Skills	.18	.61	1											1.70
4. Average age	-.08	-.15	-.08	1										1.13
5. Female	.09	.24	.03	-.02	1									1.13
6. Size (ln)	.21	.04	.08	.02	.07	1								1.45
7. Firm age	.02	-.28	-.17	.31	-.02	.25	1							1.31
8. Trade	.16	.01	.03	.00	-.02	.28	.18	1						1.13
9. Multi-establishment	.09	.07	.09	.05	.11	.41	.06	.09	1					1.23
10. RV Industry	.02	.18	.08	-.09	.05	-.09	-.10	.00	.03	1				1.21
11. RV Education	.08	.27	.28	-.06	.09	.12	-.10	.00	.12	.25	1			1.53
12. RV Occupation	.01	.22	.15	-.05	.16	-.07	-.11	-.09	.04	.32	.52	1		1.51
13. Market potential (ln)	.07	.47	.28	-.13	.18	.04	-.21	-.00	.07	.27	.26	.18	1	1.39

Table A5. Correlation matrix for interaction variables.

	1	2	3	4	5	6	7	8	9	10	11	VIF
1. Education	1											2.05
2. Skills	.61	1										1.93
3. RV Industry	.18	.08	1									1.21
4. RV Education	.27	.28	.25	1								1.60
5. RV Occupation	.22	.15	.32	.52	1							1.53
6. Education # RV Industry	.25	.09	.12	-.02	.10	1						1.86
7. Education # RV Education	.31	.23	-.02	-.15	-.16	.22	1					2.23
8. Education # RV Occupation	.25	.07	.11	-.15	.03	.42	.32	1				2.32
9. Skills # RV Industry	.10	.17	-.11	-.02	.04	.53	.19	.22	1			1.82
10. Skills # RV Education	.22	.34	-.02	-.08	-.14	.13	.67	.17	.28	1		2.34
11. Skills # RV Occupation	.06	.18	.03	-.13	.03	.18	.20	.58	.39	.36	1	2.28

Table A6. Descriptive statistics.

Variable	Mean	Median	Min	Max
Education	18.35	9.00	0	100
Skills	24.72	15.06	0	100
Average age	42.36	42.83	20	65
Female	28.39	24.07	0	100
Size	96.27	29.67	1	10,755
Firm age	18.77	23	1	25
RD Industry	0.42	0.19	0	3.01
RD Education	1.63	1.67	0.41	2.32
RD Occupation	1.31	1.33	0.21	1.84
Market potential	5.22e+10	1.68e+10	3.76e+08	1.88e+11

Notes: The number of observations is 4,477.