Work Force Composition and Innovation:
How Diversity in Employees' Ethnical and Disciplinary Backgrounds Facilitates Knowledge Re-combination

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Abstract: In this paper, we study how workforce composition is related to firm's radical innovation. Previous studies have argued that teams composed by individuals with diverse background are able to perform more information processing and make a deeper use of the information, which is important to accomplish complex tasks. We suggest that this argument can be extended to the level of the aggregate workforce of high technology firms. Our theoretical interest is focused on the extent to which insights from the literatures on science and invention can be applied to firms' abilities to achieve radical innovation. In particular, we argue that having a set of employees with greater ethnical and higher education diversity is associated with superior radical innovation performance. Using a sample of 3,888 Swedish firms, we find that greater workforce ethnic diversity is positively correlated to the share of a firm's turnover generated by radical innovation, while it is neutral to incremental innovation. Greater diversity in terms of higher educational disciplinary background of the workforce is positively correlated to the share of turnover generated by both radical and incremental innovation. Contrary to our hypothesis, we also find that having more external collaborations reduces the importance of a workforce with a diverse disciplinary background, while the importance of ethnic diversity is hold unchanged. Our findings hold after using alternatives measures of dependent and independent variables, alternative sample sizes, and alternative estimation techniques including panel data, and structural equation modeling for simultaneous estimation of diversity, R&D intensity and external search.

Keywords: Ethnic diversity; Education diversity; External search; Radical innovation
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"*The more diversity you have around the table, the more likely you are to ask all the questions that need asking. If you are too harmonized or the same type of people, the risk is that there would be fewer questions asked and fewer new initiatives. That's why I think diversity is so crucial*." Michael Treschow, former chairman of Ericsson and current chairman of Unilever[4].

INTRODUCTION

The question of what capabilities allow firms to successfully launch radically new innovations has received substantial attention from scholars. One important element of the scholarly debate in this area concerns the diversity of the knowledge input available to the firm, within and beyond firm boundaries. For example, in March's (1991) model of exploration and exploitation, socialization processes reduce the diversity of knowledge within an organization, which reduces exploration. Similarly, Huber (1991) argues that diversity provides an organization with a broader set of cognitive maps, which is associated with original and creative problem-solving.

However, the literature on firm innovation has paid limited attention to workforce diversity perspectives, focusing instead on investment decisions, innovation strategies and external networks. The human factor contribution has been difficult to analyze because of the lack of data on single individuals or because the information about employees are crudely aggregated, making rare or dramatic events especially difficult to monitor.

By contrast, a long-established corpus of scholarly studies of science has devoted attention to the performance of individual scientists and engineers (Antonelli et al., 2011, Diamond, 1996, Stephan, 1996). These studies typically adopt a fine-grained level of investigation and look at scientists and inventors working individually or in relatively small teams, in which each member can be characterized in terms of his or her individual attributes. The choice of a small unit of analysis has always been important in the studies of science, because of the typical skewness of the achievements in science and innovation, which makes

[4] http://m.thelocal.se/20150318/michael-treschow-sweden-cant-be-welcoming-enough-in-a-global-world-connect-sweden-tlccu

the investigator interested in events that do not represent the average outcome and rather happen at the tail of the distribution.

In this paper we take inspiration from the studies of science by looking at the human resources that work in companies at a more fine-grained level of analysis. We take advantage of the availability of individual data on employees to build fine-grained measures of human capital composition and study the relationship between employees' composition and diversity and the firm's innovation performance.

A large body of works on science and technology has investigated the degree to which innovation is related to the knowledge endowment that individuals possess. This literature has a notion of individuals as repositories of unique knowledge sets with limited capacity to spread, due to tacitness and embeddedness (Allen, 1997, Breschi and Lissoni, 2001, Feldmann and Kogler, 2010, Jaffe et al., 1993) and has emphasized the importance of knowledge heterogeneity, knowledge flows and recombination to sustain innovation processes (Fleming, 2001, Jones, 2008, Katz and Martin, 1997).

The studies of science have built on these insights by studying individual mobility (Agrawal et al., 2008, Stephan, 2006) and individual disciplinary background (Adams and Clemmons, 2011) as factors potentially affecting scientific performance.

In this paper we move from these findings to test the extent to which the innovation performance of companies correlates to the characteristics of the company's human capital composition with respect to diversity in ethnic origin and in higher education (disciplinary) background. Guided by the view that the most ambitious projects of industrial R&D resemble those conducted by scholars in basic science in terms of novelty and uncertainty, we focus our theoretical interest on the extent to which insights from the literatures on science and invention can be applied to firms' abilities to achieve *radical* innovation. We use individual data about all employees in positions requiring advanced skills to build fine-grained human capital composition attributes. The dataset is obtained by combining multiple rounds of the Swedish Community Innovation Survey (CIS) with employer-employee information. Using the CIS data, we are able to account separately for radical and incremental innovation. Using the employer-employee databases, we create suitable measures of firms' employees diversity concerning international mobility and higher education background and investigate how these correlate to innovation outcomes. We find that greater diversity in workforce international background is positively correlated to the share of turnover generated by radical innovation, but is neutral to incremental innovation. Greater diversity in terms of educational disciplinary background of the human capital is positively correlated to both radical and incremental innovation.

We also find there is a substitution effect between external collaboration and disciplinary background for both radical and incremental innovation. However we do not find such an effect between ethnic diversity and external collaboration.

In order to allay concerns about alternative explanations and robustness of our results, we use an extensive list of controls, alternatives measures of dependent and independent variables, alternative sample sizes, and alternative estimation techniques, including panel data and structural equation modeling.

The structure of this article is set out as follows. In the following section we review the literature and develop our hypotheses. In the third section we introduce our dataset, methodology and analysis. Finally we conclude with a discussion of the findings, contributions, and limitations.

THEORY AND HYPOTHESES

Background

The management and organization literature has studied individual diversity and its impact on performance extensively (for a review see Williams and O'Reilly (1998), Stewart

(2006), van Knippenberg and Schippers (2007), Milliken and Martins (1996)). A stylized fact of this literature is that the benefits of diversity increase with the level of complexity and innovativeness of task (Page, 2007). The majority of studies have focused on diversity in small groups and teams such as the top management (Bantel and Jackson, 1989, Certo et al., 2006, Richard et al., 2004), the board of directors (Campbell and Minguez-Vera, 2008, Miller and Triana, 2009), inventors or product teams (Ancona and Caldwell, 1992, Fleming et al., 2007). These studies usually measure diversity in terms of organizational tenure, functional and educational background, age, gender and ethnicity. The team level analysis of diversity uses three primary theories of diversity: social categorization, homophily and informational diversity and decision making (Williams and O'Reilly, 1998). The theoretical argument is in essence that individuals with diverse background in comparison with homogenous individuals together have access to a broader range of knowledge, perspectives and experience. This potentially creates more conflict and less cohesion (which reduces the efficiency of work related to routine tasks), but also brings to the discussion more perspectives and more information, ideally spurring problem solving and creativity (van Knippenberg and Schippers, 2007). Lazear (1999), for example, argues that immigrants' knowledge and information is different than that of the domestic workforce and that multi-cultural teams therefore often are better positioned to contribute to firms' innovation performance.

The view of diversity as potentially relevant for firms' innovation processes has spurred significant scholarly interest in diversity and informational diversity, often guided by decision making theory. This interest, however, has been strongly focused on interaction within functional teams and smaller groups of individuals. Recent studies provide compelling arguments, suggesting that diversity plays a significant role also at the level of a firm's total workforce. Ostergaard et al. (2011) uses employer-employee data on 1,648 Danish companies and shows that innovation outcome, measured as probability to introduce a new product or service, are positively correlated to heterogeneity of employees with regard to education and gender. Parrotta et al. (2014), who also use a sample of Danish firms, find a positive relationship between workforce diversity and the probability to apply for a patent as well as the technological breadth of firms' patents. Aggarwal et al. (2015), using a sample of biotechnology firms show that across-team diversity lead to greater firm-level innovation compared to within-team diversity. This finding suggests that important inherent benefits of diversity could be understood as firm-level processes of knowledge search and recombination. The impact of aggregate workforce innovation could thereby be argued to be greater than the sum of team-level effects.

Human capital, knowledge search and innovation

A substantial body of literature has looked at the way in which companies access knowledge internally and externally to their boundaries and at how this knowledge sustains firms' innovation processes (Cohen et al., 2002, Mansfield, 1991). In recent years considerable attention has been devoted to the importance of external knowledge sources, especially as drivers of radical innovation. The Open Innovation literature, for example, has convincingly documented the importance of external sources of ideas and knowledge in supporting a company's innovation processes (Chesbrough, 2003, Katila and Ahuja, 2002). This literature suggests that, whereas internal search – typically conducted by the R&D department of a company – is path-dependent and biased in favor of existing technologies (Almeida and Kogut, 1999, Song et al., 2003), external search facilitates access to ideas and technical solutions that would not lie within the perimeter of the company's know-how. External knowledge potentially provided by partners and users is therefore seen as especially important for conducting 'distant search' (as opposed to 'local search'), thus potentially leading to more radically-new solutions (Laursen and Salter, 2006, Rosenkopf and Almeida, 2003). External knowledge, it is concluded, is therefore a primary ingredient for sustaining the strategic innovation processes of companies, especially where such processes are of an exploratory nature.

While firms' involvement in formal alliances as well as in informal networks, firms' organizational design and corporate culture have been identified as important factors explaining firms shifting 'openness' and their ability to capitalize on external knowledge flows, human capital aspects of these problems have received considerably less attention. For example, the literature on external knowledge sources maintains that employees should act both as brokers of external knowledge in search processes (Almeida and Kogut, 1999, Audia and Goncalo, 2007) and as facilitators of knowledge assimilation, by ensuring enough absorptive capacity of the ideas and solutions coming from outside (Cohen and Levinthal, 1990). Other studies have looked at intra-firm networks and at employees' ideas management, highlighting the importance of social capital and internal connectivity (Bjork and Magnusson, 2009, Colombo et al., 2011). Where studies have speculated on the importance of employees as facilitators of external search, they have typically not gone further to connect directly workforce composition factors and innovation performance.

The relevance of heterogeneous individual background has conversely been largely emphasized in the studies of science, where the small scale of the typical unit of analysis – the research team – has permitted investigating the human capital composition at a finer grain of observation. The distinctive contribution of this paper is to borrow from the insights of these contributions and apply the approach at the firm's workforce level. We look at the correlation of two individual characteristics – ethnic composition and higher educational (disciplinary) background – with innovation performance expressed in terms of share of turnover and innovation events.

In the next two subsections, we review the contributions of the science studies on ethnic composition and education discipline respectively.

Ethnic composition and innovation

In the latest years a growing corpus of works has looked at the geographic mobility of scientists. These studies move from the premises that knowledge usually entails a tacit component that makes ideas prone to be locally-developed and difficult to transfer beyond the circles of individuals who work in close proximity (Almeida and Kogut, 1999, Feldmann and Kogler, 2010). Although the output of scientific investigation is in part codified into published articles, a large part of the knowledge produced by scientists is known to remain bound within individual brains (Stephan, 1996). This also means that, when scientists relocate, they bring with them the unique sets of knowledge and skills that they have acquired during prior training (Stephan, 2006) and while working in partly separated scientific communities (Borjas and Doran, 2012, Ganguli, Forthcoming, Scellato et al., 2015). Consequently, mobile individuals are assumed to be holding knowledge that is relatively unique in the location of destination. A question of considerable importance that has only recently begun to be analyzed is if the holding of unique knowledge sets translates into more innovation and greater achievements in the person's new location. In this respect, the empirical tests are complicated by the known circumstance that mobile individuals tend to be pre-selected among the best performing, prior to mobility (Borjas, 1994, Grogger and Hanson, 2011). Ganguli (Forthcoming) and Borjas and Doran (2012) attempt to overcome this problem by looking at migration pushed for political reasons, instead of career concerns. The former finds evidence of a productivity growth after migration. The latter finds a small positive effect, although not statistically significant. Franzoni et al. (2014) instrument migration for work or study with migration in childhood (that is presumably not caused by skills) and find that the work of foreign born academics is of higher impact than that of non-mobile natives. They speculate that the post-mobility boost in performance may happen because the individuals move to locations that provide a special match or complementarity for their knowledge

(Jones, 2008) or that the performance boost may happen because heterogeneity unlocks creativity and problem solving (Fleming, 2001). Recent work by Freeman and Huang (2014) provides evidence in support of the latter, showing that the teams of coauthors who are ethnically diverse outperform the teams of coauthors of the same ethnicity, including those entirely comprised of foreign scientists. This appears to indicate that the premium is associated to settings in which the knowledge of the foreign-born is somehow recombined with domestic knowledge. Hence it is knowledge heterogeneity at the final location that appears to spur innovative performance, not the 'knowledge arbitrage' ensured by geographic mobility in itself.

Interestingly, the evidence produced by the studies of inventors may be consistent to this view. A study on historical data by Moser et al. (2014) finds that US inventors became more productive after the inflow of German Jewish inventors in the US post-1933 and that this effect seems associated to the attraction of more inventors in the fields where migrants were more active, rather than to a greater productivity of American inventors. Hunt (2011) finds that the migrants that come to the US for training or employment are on average more likely than natives to file or commercialize a patent and to publish articles in scientific outlets, but the differential is almost entirely explained by choices of education and area of work, rather than to productivity. Similarly, Kerr and Lincoln (2010) analyze the ethnicity of recent US inventors and find that Anglo-Saxon and non-Anglo-Saxon inventors perform at comparable levels. Overall, these results are not conclusive, but would be compatible with the view that foreign born are not necessarily a value added in themselves, but they become so when their knowledge is used in combination with that of the natives.

We use the insights of this literature to formulate our first research proposition. We are interested at understanding whether the capacity for successful innovation of a radical nature is higher in companies whose employees are relatively more heterogeneous in terms of their prior knowledge background, presumably because these companies are more likely to have internal access to distant knowledge. Although the causality link between ethnic heterogeneity and radical innovation is hard to prove (as will be discussed later), if this is true, we should observe at least a positive correlation between the two. We therefore formulate the first hypothesis as follows:

Hp.1 All else equal, firms with ethnically diverse workforces are more successful in introducing radical innovations

Education disciplines composition and innovation

A second possible source of background knowledge diversity relates to the field in which an individual has been trained. In science, where specialization is important (Jones, 2008), most of the research teams are composed of scientists who have been trained in the same or very similar field. Nonetheless, collaboration between scientists from different disciplines has been known to facilitate major breakthroughs. For example, biotechnology has emerged at the interdisciplinary convergence of molecular biology and medical engineering. A question that has always sparked considerable debate related to whether or not an interdisciplinary framework may systematically spur greater productivity and/or more radical advances (Schunn et al., 2006). To the best of our knowledge the implications of interdisciplinarity for innovativeness have been rarely tasted in empirical analyses. An exception is a recent paper of Lee et al. (2015) who study a large sample of US scientific teams whose team-members were coded into 29 different scientific fields. They find that greater field variety of team members is associated to more novel scientific outcomes. Haussler and Sauermann (2014) find that novel fields in science have more division of labor and more interdisciplinary contributions. Adams and Clemmons (2011) show that interdisciplinary knowledge flows enhance scientific productivity but they do so to a less extent compared to the same-field flows and suggests that the costs of sourcing from a distant knowledge domain are greater than those of sourcing from ones' own domain. Millar (2013) finds that US PhD recipients who graduated with an interdisciplinary dissertation are moderately more productive in the first 1-4 years after graduation.

We use the insights of this literature to formulate our second research proposition. We are interested to understand whether firms whose employees have a more heterogeneous disciplinary background are more innovative, under the assumption that a broader knowledge background enables more distant search being accomplished within the company's boundaries. Again, establish a clear direction of causality between heterogeneous background and radical innovation may be quite difficult. However, we expect to find a positive correlation between the two. Consequently, this is our second hypothesis:

Hp.2 All else equal, companies with a more diverse disciplinary background in their workforce are more successful in introducing radical innovations

External Search Breadth and Workforce diversity

We have argued that workforce diversity facilitates knowledge search and knowledge recombination within a firm. While external search may to a large degree be performed through informal channels and networks, we expect that the knowledge-oriented benefits of workforce diversity increases the benefits also of formalized external collaboration. Similar results of complementarity between internal resources and activities relevant for innovation and external linkages have been reported by Lee et al. (2001), Caloghirou et al. (2004) and Cassiman and Veugelers (2006). In this particular case, our expectation of a positive relationship is also strengthened by the stylized view of the negative impact of diversity in terms of cognitive distance on the transfer of complex information and tacit knowledge (e.g. Boschma, 2005). In other words: it should be easier for a firm with a diversified workforce to scan outside knowledge and find a match with an external partner which minimises friction caused by cognitive differences between individuals. Therefore we hypothesise that workforce diversity moderates the correlation between the breadth of external search and the innovation performance. We formulate the following hypothesis:

Hp.3 All else equal, the relationship between search breadth in terms of active external collaboration and the successful introduction of radical innovations is stronger for companies whose employees are more (ethnically and disciplinary) heterogeneous.

DATA AND METHODS

Sample

We test our three hypotheses using data from Sweden. While investment in innovation and education as well as ethnic diversity are all expected to continue to increase in most countries, Sweden has a forerunner position in at least two of these three dimensions. First, Sweden is among the most innovative countries in the world. Sweden is one of the top five countries worldwide for research and development spending. In 2012, Swedish R&D expenditure was 3.41 percent of GDP (European Union average is 1.97% of GDP)[5]. Sweden also has been ranked among the top three countries in The Global Innovation Index[6], in 2008-2014. Second, Sweden has a very diverse multiethnic demography, with over 15 percent of inhabitants being foreign born[7]. The percentage of foreign born in Sweden is larger than in the US (12%)[8] and above the average of the European Union countries (6.5%)[9]. Both these characteristics make the Swedish setting very suitable for testing our hypotheses. In particular, it provides sufficient variation in key variables of interest (radical innovation,

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5 http://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?order=wbapi_data_value_2012+wbapi_data_value+wbapi_data_value-last&sort=asc

6 https://www.globalinnovationindex.org/content.aspx?page=data-analysis

7 Figures are from 2012. In 2014, the share of foreign born inhabitants in Sweden had further raised over 16 percent. Since 2008 Sweden adopted one of the most liberal labor immigration policies in OECD countries which expect to increase workforce diversity. This demand driven model gives Swedish employers the right to unilaterally decide whether or not labor immigrants are needed, provided that pay and working conditions are in accordance with the collective agreements. As a member of the EU, Sweden is also open for migration from other member states.

8 http://www.census.gov/population/foreign/data/cps.html

9 http://www.migrationpolicy.org/article/assessing-immigrant-integration-sweden-after-may-2013-riots

ethnic diversity), the lack of which have been identified as problematic in previous studies. For example, Williams and O'Reilly (1998) argue that there is a lack of research on ethnic diversity and top management team because top management teams are usually ethnically homogeneous.

For the purpose of the study we wish to build a sample of employer-employee-innovation data. In order to do so, we took data from the Swedish Community Innovation survey (CIS).[10]. The CIS is administered to firms biannually. Firms are asked about the innovative activities that they have conducted in the two years prior to responding. We use five rounds of the CIS: 2004, 2006, 2008, 2010 and 2012. We restrict our sample to respondent firms which: (1) have more than 10 employees and (2) are in high technology industries, which we coded as all firms in NACE (Rev 1.1) classified as high-technology, medium high-technology and knowledge intensive services.[11]

We match our CIS sample with two sources of data provided by Statistics Sweden (SCB).[12] The first source includes information from annual reports of all registered firms in Sweden. The second source includes individual information on all of Swedish workforce, including age, gender, place of birth, education level and type, place of work, position and wage. Although the firms and the individuals in the datasets are anonymous, an identification code associated with each entry makes it possible to link employers and employees, having a unique database comprising firms' innovation and balance-sheet data and individual information on their employees.

Our final sample comprises 7,389 firm-year observations from 3,888 firms. The sample will be used first as a cross-section and in additional analysis as a panel. Table 1 provides a summary of the number of observation per year.

[10] The CIS has been used extensively in studying innovation in European firms, a simple search on Google Scholar return over 7,000 articles that used CIS in their analysis (e.g. Laursen and Salter (2006), Leiponen and Helfat (2010))

[11] http://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an2.pdf

[12] http://www.scb.se/en_/

[Table 1 about here]

Variables

Explanatory variables: We focus on diversity with respect to two characteristics: ethnicity and higher education background. Ethnic diversity (*EthnDiv*) is based on coding individuals by seven areas of birth. The seven areas are: 1-Sweden (natives), 2-other Nordic countries (Norway, Denmark, Finland and Iceland), 3-Western Europe (EU15 except Finland and Denmark), 4-other European countries (excluding 1, 2 and 3), 5-North America, 6-Asia, and 7-Others. Higher education background diversity (*EduDiv*) is based on coding individuals by five disciplinary area of university degree. The disciplinary areas are: 1-engineering, 2-humanities, 3-health sciences, 4-natural sciences, 5- social science, and 5-others.[13]

Following Harrison and Klein (2007), we chose a measure of diversity that emphasizes the *variety* of the background of employees. This is well captured by the Teachman's EntropyIndex,[14] also known as the Shannon-Weaver index (Teachman, 1980). The index is calculated as follows:

$-\sum p_i . \ln(p_i)$, where p_i are the shares of employees in the *i*th category.

Because we are primarily interested in innovation processes, we exclude production workers and employees in standardized administrative support functions, who are presumably not involved in decision making relative to new products and services (Page, 2007; Parrotta et al., 2014) and focus only on the employees in knowledge-intensive positions.

The identification of high-skilled workers is based on the Swedish Standard Classification of Occupations (SSYK). We include all individuals in employment position of

[13] We alternatively used a measure proposed by Ostergaard et al. (2011) which take into consideration both field and level of education. Results are similar to the main analysis.

[14] Alternatively we used Blau's (1977) index of heterogeneity. The results are similar and available upon request. The correlation between both measures is around 95%.

managers (SSYK 100-21, 131,111, 122, and 123) or professionals[15] (SSYK 200-399) and exclude production workers, clerks and other supporting staff (SSYK 400-999).

Because in the CIS the respondents are asked information about the innovation activities of the firm in the last two years, we measure our exploratory variables with two years lag. For example, data from the CIS 2004 are combined with employees diversity measured in 2002. Concerning our measure of External Collaboration, we chose to build a variable capturing External *Search Breadth*, counting the number of different external collaboration that the firm undertakes, as in prior studies by Laursen and Salter (2006), Leiponen and Helfat (2010) and Mol and Birkinshaw (2009). We code five different external entities: 1-suppliers, 2-competitors, 3-customers, 4-external subsidiaries of the same company, and 4-knowledge institutes, which in turn comprises universities, consultants, governmental research institutes and commercial R & D labs. Our final measure of *Search Breadth* is a count from 0 to 5 of the number of external sources of knowledge that the firm is actively using.

Dependent variables: We employ three dependent variables, all coming from the CIS. The first dependent variable (*Turnino*) is a self-reported estimate of what proportion of the firm's sales is derived from new products and services (irrespective of whether these were new to the market or not). The Second dependent variable (*Turnradical*) is a self-reported estimate of what proportion of the firm's sales comes from products and services that are *new to market* and can therefore be considered radical innovations. The third variable (*Turnincremental*) is a self-reported estimate of what proportion of the firm's sales comes from products and services that are *new to the firm* and can therefore be considered incremental innovations.

Control variables: We control for variables concerning other characteristics of the workforce composition, such as the share of women employees (*Share Women*) and the share of employees with a PhD degree (*PhD share)*. We further included all standard control

[15] The definition of this category is that the position requires advanced tertiary education and training.

variables included in previous studies that modeled the share of sales from innovative products and services (e.g. Laursen & Salter, 2006). These are: *R&D intensity*, captured by R&D expenditures divided by sales (Chen and Miller, 2007), firm age, measured by a dummy variable with a value of one if the firm is younger than 10 years old (*young firm).* Size is captured by a set of dummies based on classes of total number of employees as follows: 10-50 (small; omitted category), 50-250 (medium), 250-1000 (large) and over 1000 (very large). Our industry categorization is intended to reflect variations in firm-level innovativeness across industries and is based on six categories: Manufacturing, Transport, Communication, Financial services, Business services and others (omitted category).[16] We include a set of controls related to the ownership structure of the firm, which could potentially affect the firm's strategy and resources (Dachs et al., 2008). We code four kinds of ownership structure by means of dummy variables: *independent*, *domestic group*, *domestic multinationals* and *foreign multinationals* (omitted category). We code firm location, which can potentially affect the access to resources, networks or markets, by means of separate dummy variables for each main metropolitan area: *Stockholm, Gothenburg, Malmo*[17] or other non-metropolitan locations (omitted category). Finally, we control for firm performance, by means of return on assets (*ROA* = net profit divided by the average assets value) and economy-wide time trends, by means of year fixed effects. Table 2 reports all variables and their definition.

[Table 2 about here]

RESULTS

Summary statistics and univariate analysis

Table 3 reports descriptive statistics including mean and standard deviation in addition to correlation of variables.

[16] Alternatively we used two-digit level of NACE industry codes (Leiponen and Helfat, 2010). Results are similar

[17] These are the most densely populated areas in Sweden in which more than 60 percent of population lives in, while it occupies only 5 percent of land (SCB, 2014, Folkmängd i riket, län och kommuner).

[Table 3 about here]

On average, 11.2% of firms' turnover is related to new products (*Turnino*), while 6.1% of the sales are generated from radical innovations (products new to market) and 5.1% of the sales are generated from incremental innovations (products new to firm). The entropy measure of diversity grows with the relative diversity of the workforce. The average firm ethnic diversity is 0.27 and the average firm education diversity is 0.51. On average firms have relationships with 1 external partner (*Search Breadth*).

Women represent 25.3% of firms (qualified) workers and 2.4% of the workers have a PhD degree. On average firms spend the equivalent of 6.2% of their sales on R&D (*research intensity*) and yield a return on assets (*ROA*) of 3.8%. About 46.5% of firms are *young*. The share of *independent*, *domestic group* and *domestic* multinationals is respectively 20.0%, 27.4% and 27.2%.

Multivariate analysis

Across the entire sample, the mean Variance Inflated Factor (VIF) is under 2 for all our main variables of observation (Average VIF=2.45), showing that our model does not have multi-collinearity problems.

In this paper we are interested to study the correlation of workforce diversity with firm radical innovation and the moderation effect of ethnic and higher education diversity on the effect of external search on radical innovation. Our general estimation model can be specified as follows:

$Y_{it}=\beta_0+ \beta_1 X_{it}+ \beta_3 \textit{Search Breadth}_{it}+ \beta_3 \textit{Search Breadth}_{it}* X_{it} +\beta_2 Z_{it}+ \beta_5 Y_t+ \varepsilon_{it,}$

Where the subscript *i* refers to firms, the subscript *t* refers to time.

Y_{it} is the dependent variable, expressed as the share of the turnover generated by all innovations (*Turnino*), by radical innovation only (*Turnradical*) and by incremental innovations only (*Turnincremental*). X_{it} is a vector of independent variables concerning employee diversity. In order to test hypothesis 3 we include two interaction terms of *Search Breadth* and each of the two diversity measures. Z_{it} is a vector of control variables and Y_t includes dummies of year fixed effect.

Since our dependent variable is a censored variable, we use a Tobit model estimator. Furthermore since we have more than one observation for some firms, potentially generating serial correlation of the error term, we use clustered robust standard errors.

Table 4 shows the result of multivariate analysis. In model 1-9 we use Tobit model. In all models we control for firm size, industry, location and year fixed effect.

[Table 4 about here]

As explained in our theoretical section, we are primarily interested to investigate the relationship between ethnic diversity, higher education diversity and search breadth with radical innovation (*Turnradical*). When presenting the estimates, we first (Models 1-3 of Table 4) show the correlation of our variables of observation with general firm innovativeness, regardless of the kind (*Turnino*) and then show how this average effect decomposes when we code separately performance in radical innovation (Models 4-6 of Table 4) (*Turnradical*) and incremental innovation (Models 7-9 of Table 4) (*Turnincremental*). Models 1, 4 and 7 include only the three main variables of observation: ethnic diversity (*EthnDiv*), higher education diversity (*EduDiv*) and external search (*Search breadth*). In Models 2, 5 and 8 and 3, 6, 9 of Table 4 we add the interaction terms between search breadth and education diversity and search breadth and higher education diversity respectively.

The results of model 1 show that ethnic diversity is positively correlated to the dependent variable ($b= 0.05$, $p<0.05$) and so is higher education diversity ($b= 0.11$, $p<0.01$). In model 2 we include the interaction between *Search Breadth and* education diversity (*EduDiv).* The coefficient is negative and statistically significant ($b= -0.04$, $p<0.01$). In model

3 we include the interaction term between *Search Breadth* and ethnic diversity (*EthnDiv*). The coefficient is negative but it is not statistically significant (b= -0.01, n.s).

In model 4, 5 and 6 we focus on radical innovation (*Turnradical*). Model 4 confirms that that ethnic diversity (*EthnDiv*) is positively correlated to the dependent variable (b= 0.05, p<0. 05), supporting our hypothesis 1. Model 5 further confirms that higher education diversity (*EduDiv*) has a positive and statistically significant correlation with radical innovation (b= 0.11, p<0. 01), in line with hypothesis 2. Quite interestingly, education diversity is also relevant for incremental innovation, while ethnic diversity is not (Model 7). Overall, this indicates that the positive association of workforce composition and innovation observed in Model 1 can be decomposed into a positive association of ethnic diversity to radical innovation (Model 4) and by a positive association of educational diversity to both radical (Model 4) and incremental (Model 7) innovation.

When we focus on the interaction of ethnic and education diversity with search breadth, we see that the coefficient of the interaction between *Search Breadth* and *EduDiv* is always negative and statistically significant in all models, (Model 2, 5 and 8) and the interaction between *Search Breadth* and *EthnDiv* is negative but not statistically significant in any of the models.

Overall, the result support H1 and H2 indicating that workforce ethnic and education diversity are positively correlated to firms' radical innovation. Our results also shows that while education diversity is also positively correlated to incremental innovation (albeit with a weaker relationship), ethnic diversity is positively correlated to radical innovation, but is not correlated by incremental innovation. We also find evidence supporting a substitution effect for *EduDiv* but do not observe any complementary or substitution effect for *EthnDiv*. These results are similar across both types of innovation.

Robustness test: alternative outcome variable

In the main analysis, our dependent variable is the percentage of turnover generated from any new product/services (*Turnino)*, new product/services new to market (Turnradical) and new product/services new to firm (*Turnincremental*). We check the robustness of our estimates by looking at a set of alternative dependent variables that comprise only dummy variables, instead of the turnover form innovation. We do so by looking at other questions in the CIS. We use the dummy variable *innovation* taking value one if a firm was involved in any kind of innovations, radical or incremental. The first variable (*innovation*) is whether firm introduced any new product/process. We code a second dependent variable (*radical innovation*) as a dummy is equal to one if the firm introduced any new product/services new to market, regardless of whether it also introduced incremental innovation in the time period or not. We finally coded a third dummy variable (*incremental innovation*) set to one if the firm introduced at least one new product/process to the firm, but none which was also new to the market. Table 5 shows the result of multivariate analysis using alternative dummy dependent variables in a Probit model analysis.

[Table 5 about here]

The results regarding *EthnDiv* are very similar to table 4. As before, *EthDiv* is positively and significantly correlated with *radical innovation* (b= 0.16, p<0.0 5), and it is not significantly correlated to *incremental innovation* (b= -0.06, n.s). *EduDiv* is positively related to both *radical innovation* (b= 0.36, p<0.0 1) and *incremental innovation* (b= 0.18, p<0.0 1). Regarding hypothesis 3 we find results consistent with Table 4 in which we observed a substitution effect for *EduDiv* but not for *EthnDiv* for both radical and incremental innovation.

Additional analysis

In this study of workforce diversity and innovation, we grounded our hypotheses of an association between workforce composition and radical innovation on the impact of knowledge search and knowledge recombination on innovative performance. We are nonetheless aware that the correlations observed between diversity and radical innovation in the empirical analysis could not let us claim causality. Alternative explanations to the empirical findings reported above are clearly conceivable. For example, firms with higher ambitions in R&D may be more likely to recruit individuals with a foreign background as a result of a more active international search for specialized technical competence in their recruitment processes. An ethnically and educationally diverse workforce could also be the result of a recruitment policy that intentionally aims to ensure knowledge input diversity, as the quote reported at the beginning of our paper appears to suggest. These possibilities suggest that greater workforce diversity could be a consequence – rather than a cause – of the firm's strategic dedication to innovation.

Our finding of a complementary relationship between external search and workforce diversity goes some way towards helping us interpret the results as suggesting that diversity influences innovation, as it seems unlikely that alternative explanations for the association between diversity and innovation (such as differences in recruitment preferences) would simultaneously provide an explanation for the complementary relationship. Nonetheless, in the remainder of this section, we report additional effort to investigate this relationship using empirical analysis that allow further investigation on the knowledge-related advantages of diversity for innovation processes.

A first step in this direction is to relax the assumption of our two diversity variables being independent of firm's R&D investment and external search. We therefore model these linkages in a structural equation modelling (SEM) framework, where we also explicitly model firms' decisions about R&D investment and formal external interactions following the standard of the literature on R&D and innovation (Crepon et al., 1998; Lööf and Broström, 2008). The results of Tobit model estimates, which are not showed in detail here for the sake of brevity, show that also when explicitly controlling for the (relatively strong and highly significant) correlations between R&D, external search and workforce diversity, the relationship between both types of workforce diversity and radical innovation remain very close to the estimates reported in Table 4.

As a further step, we exploit the longitudinal nature of the data and employ panel model estimates. In order to obtain a balanced sample, we limit this analysis to firms that answered at least three waves of the CIS, using 4,025 observations on 1,239 firms. Table 6 shows the result of Tobit panel analysis. Once again, the results are very similar to those showed in Table 4. As before, we observe that *EthnDiv* is positively and significantly correlated to *Turnradical* (b= 0.06, p<0. 05) but not to *Turnincremental* (b= 0.02, n.s). *EduDiv* is positively related to both *Turnradical* (b= 0.12, p<0.0 1) and *Turnincremental* (b= 0.05, p<0.0 1). Regarding hypothesis 3 we find results consistent with Table 4 in which we observe a substitution effect for *EduDiv* but not for *EthnDiv* for both radical and incremental innovation.

[Table 6 about here]

Finally, we use a method proposed by Blundell et al. (1995), who recommends using pre-sample history in order to take into account unobserved firm heterogeneity. We have pre-sample data on firms' patent application activities in 1997-2002.[18] We include in our model a dummy variable equal to one if the firm has any patent application in the pre-sample period. Alternatively we use the average number of patent application per year in the pre-sample

[18] We do not have data on patent citation to identify the quality and importance of patents.

period (Blundell et al., 1995). Also in this case the results, omitted for brevity, are very similar to those shown in Table 4. All omitted output is available upon request to the authors.

DISCUSSION

In this paper we study the relationship between employees' composition and innovation outcomes. We focus on two dimensions of ethnic and higher education (disciplinary) diversity as two alternative sources of knowledge input. We focus on radical innovation and further investigate if the two types of diversity stand in different relationships with radical and incremental innovation.

The theoretical basis of this paper is built on a view of diversity as facilitating knowledge search and knowledge recombination. Seeking guidance from the studies of science, which point at a positive link between ethnic and disciplinary diversity and performance, we construct the hypotheses that firms whose employees have a more heterogeneous ethnic and disciplinary background are more likely to be innovative obtain more benefits when conducting distant search.

We build our sample based on matching several waves of CIS with employer-employee data in Sweden. One primary result of our analysis is that having an ethnically diverse employee composition is positively correlated to greater turnover generated by radical innovation and to more instances of radical innovation in general. At the same time, ethnic diversity does not seem to be correlated to incremental innovation. A second result of our analysis is that also having employees with diverse disciplinary background (expressed by the subject of their higher education diploma) is positively correlated with the turnover generated by radical innovation and with more instances of radical innovation. However, higher education diversity is positively correlated to more incremental innovation as well. We also find that the positive effect of education diversity reduces as the level of collaboration with other partners outside of the firm boundaries increases, suggesting that educational diversity can be replaced by a broader set of external links. We did not observe any interaction effect between external collaboration and ethnic diversity.

This study contributes to two important streams of literature. First we contribute to the literature on the consequences of diversity for the innovative performance of organizations. While previous studies focused extensively on team composition, very few studies have studied diversity across the entire company's workforce. We contribute to this stream of literature in two ways. First we provide additional evidence about the relationship between human capital diversity and innovative performance of the firms. Second, we empirically explore to what extent the hypothesized influence of diversity on radical innovation extends to successful innovation of an incremental type, recognizing that these outcomes are related to markedly different types of knowledge and search strategies.

By investigating two dimensions of diversity -ethnic diversity and educational diversity- we also contribute to the literature that studied specifically ethnicity and multisciplinarity and corroborate prior findings of a positive linkage between diversity and firm performance (Herring, 2009, Parrotta et al., 2014, Richard, 2000).

Second, we contribute to the innovation literature that studied the role of different types of knowledge on the innovative performance of firms. By studying diversity as a source of knowledge and information input we have shown that internal knowledge plays an important role for radical innovation. We further showed that internal diversity can only in part be replaced by external knowledge search. More specifically, while educational diversity can be replaced if the company is active in keeping external connections (e.g. nurturing an Open Innovation strategy), ethnic diversity appears to offer a distinctive source of innovation advantage that cannot be replaced by external links.

While prior literature focused on how employee skill levels and R&D activities create the absorptive capacity to assimilate and use external knowledge, we argue that workforce diversity –especially ethnic diversity- enhances these capabilities and expands distant search.

The paper has some limitations that could be addressed in future research. First, while we focus on diversity among skilled employees which might be involved in innovation process we do not have any information if these employees are directly involved in innovation process. Second, our empirical setting does not allow us to make strong causal inference since the workforce compositions may be non-randomly assigned. To cope with this known problem, we used a broad set of control variables (time variant and time invariants), and performed two additional analyses, one using a structural equation model that estimates simultaneously diversity and R&D intensity, and one that controls for pre-sample history (Blundell, et al., 1995). Both analyses are consistent to the main findings and suggest that diversity positively impacts innovation. However causal interpretation should be interpreted with caution here. Repeating the test on other samples, as well as employing instrumental variables and natural experiments could definitely be helpful to shed definitive light on this issue.

If confirmed by further analyses, the finding that ethnic and educational diversity increase the success of radical innovation would bring immediate and important practical implications. It would suggest that companies may pursue recruitment policies inspired by greater ethnic and disciplinary diversity as a measure to boost the innovativeness of the organization. It would further imply that disciplinary diversity could be potentially replaced by more external links, while ethnic diversity would not. Our research has also other important implication for managers and organizations. Ambidexterity is known to be an important determinant of organizational survival and success (Raisch and Birkinshaw, 2008). Ambidexterity is achieved when firms pursue both exploitation and exploration activities (March, 1991, Tushman and O'Reilly, 1997). In this research we have shown that ethnic diversity and education diversity have different implication for radical and incremental innovation. Radical and incremental innovations are resonant respectively with exploration and exploitation (Tushman and Smith, 2002). The ambidexterity in organizational structure can be achieved by creating separate units that pursue either exploitation or exploration (Raisch and Birkinshaw, 2008). Our result shows while education diversity is helpful in both units, ethnic diversity can be more important in units pursuing exploration.

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TABLES:

Table 1- CIS sample size

Time period	Sample
CIS 2004	1,212
CIS 2006	1,211
CIS 2008	1,489
CIS 2010	1,510
CIS 2012	1,967
All	7,389

Table 2- Variables definitions

Variables	Definition
	Explanatory Variable
EthnDiv	Entropy index considering place of birth in Sweden, Nordic, Western Europe, Other Europe, North America, Asia and others
EduDiv	Entropy index of education among educated employees considering 6 different subjects of engineering, social science, humanities, health science, natural science and other fields.
	Dependent Variable
Turnino	Turnover from any new product/process
Turnradical	Turnover from any new product/services new to market
Turnincremental	Turnover from any new product/process new to firm
Search Breadth	Number of external sources of knowledge a value between 0-5
	Control Variables
Women share	Share of female professionals
PhD share	Share of professionals with PhD degree
R&D intensity	R &D investment divided by sales
ROA	Net profit divided by total assets
Young firm	A dummy=1 if firm is than 10 years old
Ownership	Four dummies showing firm is independent, domestic group, domestic multinational or Foreign multinational
Firm Size	Four dummies showing firm is small, medium, large or extra large
Location fixed effect	Four dummies showing firm is located in Stockholm, Gothenburg, Malmo or others

Table 3- Summary statistics and correlation matrix (N=7,389)

	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1- Turnino	0.112	0.210	1.00												
2- Turnradical	0.061	0.155	0.79	1.00											
3- Turnincremental	0.051	0.128	0.68	0.09	1.00										
4- EthnDiv	0.275	0.269	0.09	0.08	0.05	1.00									
5- EduDiv	0.512	0.464	0.11	0.10	0.06	0.33	1.00								
6- Search breadth	0.938	1.574	0.30	0.24	0.19	0.12	0.18	1.00							
7- Women share	0.253	0.204	-0.04	-0.04	-0.03	0.17	0.27	0.02	1.00						
8- PhD share	0.024	0.074	0.15	0.15	0.07	0.21	0.20	0.21	0.18	1.00					
9- Research intensity	0.062	0.254	0.25	0.24	0.11	0.08	0.10	0.16	0.06	0.29	1.00				
10- ROA	0.038	0.339	-0.13	-0.13	-0.07	-0.04	-0.06	-0.04	-0.01	-0.17	-0.20	1.00			
11- Young firm	0.465	0.499	0.09	0.07	0.06	0.02	0.00	-0.06	0.07	0.02	0.07	-0.06	1.00		
12- Independent	0.200	0.400	-0.02	-0.02	-0.01	-0.12	-0.25	-0.12	-0.07	-0.03	-0.01	0.00	0.08	1.00	
13- Domestic group	0.274	0.446	-0.06	-0.05	-0.03	-0.12	-0.17	-0.09	-0.02	-0.01	-0.02	0.02	0.00	-0.31	1.00
14- Domestic Multinationals	0.272	0.445	0.07	0.07	0.02	0.03	0.16	0.11	0.02	0.05	0.04	-0.02	-0.04	-0.31	-0.37

Table 4- Cross sectional Tobit analysis of effect of ethnical and education diversity on type of innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Turnino			**Turnradical**			**Turnincremental**	
EthnDiv	0.05**	0.05**	0.06**	0.05**	0.05**	0.05**	0.01	0.01	0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
EduDiv	0.11***	0.15***	0.11***	0.11***	0.13***	0.11***	0.05***	0.08***	0.05***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Search breadth	0.08***	0.10***	0.08***	0.07***	0.08***	0.07***	0.05***	0.07***	0.06***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
EduDiv * Search breadth		-0.04***			-0.02***			-0.03***	
		(0.01)			(0.01)			(0.01)	
EthnDiv * Search breadth			-0.01			-0.01			-0.01
			(0.01)			(0.01)			(0.01)
Women share	-0.25***	-0.24***	-0.25***	-0.23***	-0.22***	-0.23***	-0.12***	-0.12***	-0.12***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
PhD share	0.03	0.05	0.04	0.06	0.07	0.06	-0.11	-0.09	-0.10
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.08)	(0.08)	(0.08)
Research intensity	0.23***	0.23***	0.23***	0.19***	0.19***	0.19***	0.08***	0.08***	0.08***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
ROA	-0.06***	-0.06***	-0.06***	-0.04*	-0.04*	-0.04*	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Young firm	0.05***	0.05***	0.05***	0.03***	0.03***	0.03***	0.03**	0.02**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Independent	-0.01	-0.01	-0.01	-0.00	0.00	-0.00	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Domestic group	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Domestic Multinationals	0.03**	0.03**	0.03**	0.04***	0.04***	0.04***	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.19***	-0.21***	-0.19***	-0.27***	-0.28***	-0.27***	-0.26***	-0.28***	-0.26***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
Observations	7,389	7,389	7,389	7,389	7,389	7,389	7,389	7,389	7,389
left censored	4033	4033	4033	4980	4980	4980	5120	5120	5120
right censored	154	154	154	74	74	74	37	37	37
Log lik.	-3476.0	-3460.6	-3475.7	-2790.2	-2783.2	-2789.9	-2655.0	-2643.0	-2654.6

Note. In all models clustered robust standard error is reported in parentheses, * ,** or *** indicate statistical significance at the 10%, 5%, 1% level, respectively.

Table 5- Probit analysis of effect of ethnical and education diversity on innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Innovation			Radical innovation			Incremental innovation		
EthnDiv	0.11	0.11	0.12	0.16**	0.16**	0.19**	-0.06	-0.06	-0.03
	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
EduDiv	0.44***	0.48***	0.44***	0.36***	0.43***	0.36***	0.18***	0.24***	0.18***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Search breadth	0.39***	0.43***	0.39***	0.30***	0.34***	0.31***	0.08***	0.12***	0.08***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
EduDiv* Search breadth		-0.06**			-0.07***			-0.06**	
		(0.03)			(0.03)			(0.03)	
EthnDiv *Search breadth			-0.01			-0.03			-0.03
			(0.05)			(0.04)			(0.04)
Women share	-0.59***	-0.58***	-0.59***	-0.67***	-0.66***	-0.67***	-0.04	-0.03	-0.04
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
PhD share	-1.13***	-1.09***	-1.12***	-0.47*	-0.44	-0.45	-0.74**	-0.70**	-0.72**
	(0.31)	(0.31)	(0.31)	(0.27)	(0.27)	(0.27)	(0.32)	(0.31)	(0.32)
Research intensity	0.62***	0.62***	0.62***	0.56***	0.56***	0.56***	0.02	0.03	0.02
	(0.18)	(0.18)	(0.18)	(0.13)	(0.13)	(0.13)	(0.06)	(0.06)	(0.06)
ROA	0.08	0.08	0.08	0.05	0.05	0.05	0.05	0.05	0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Young firm	-0.05	-0.05	-0.05	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Independent	-0.12*	-0.12*	-0.12*	-0.03	-0.03	-0.03	-0.14**	-0.14**	-0.14**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Domestic group	-0.10*	-0.09*	-0.10*	-0.10*	-0.10*	-0.10*	-0.01	-0.00	-0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Domestic Multinationals	0.06	0.06	0.06	0.09*	0.09*	0.09*	-0.04	-0.04	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.57***	-0.59***	-0.57***	-0.83***	-0.87***	-0.84***	-1.34***	-1.38***	-1.35***
	(0.14)	(0.14)	(0.14)	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.16)
Observations	7,389	7,389	7,389	7,389	7,389	7,389	7,389	7,389	7,389
Pseudo R-squared	0.200	0.201	0.200	0.168	0.169	0.168	0.022	0.023	0.022
Log lik.	-4085.1	-4082.2	-4085.0	-3912.1	-3907.2	-3911.7	-2890.4	-2887.2	-2890.2
Chi-squared	1201.0	1236.9	1202.0	1161.5	1174.1	1162.8	114.3	119.5	114.7

Note. In all models clustered robust standard error is reported in parentheses, *, ** or *** indicate statistical significance at the 10%, 5%, 1% level, respectively.

Table 6- Tobit panel analysis of effect of ethnical and education diversity on innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Turnino			**Turnradical**			**Turnincremental**	
EthnDiv	0.05*	0.05	0.03	0.06**	0.06*	0.05	0.02	0.02	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
EduDiv	0.11***	0.14***	0.12***	0.12***	0.14***	0.12***	0.05***	0.07***	0.05***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Search breadth	0.06***	0.07***	0.05***	0.05***	0.06***	0.05***	0.04***	0.05***	0.04***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
EduDiv # Search breadth		-0.03***			-0.02***			-0.02***	
		(0.01)			(0.01)			(0.01)	
EthnDiv # Search breadth			0.01			0.01			0.01
			(0.01)			(0.01)			(0.01)
Women share	-0.22***	-0.21***	-0.22***	-0.20***	-0.20***	-0.20***	-0.10***	-0.10***	-0.10***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
PhD share	-0.03	-0.02	-0.04	0.05	0.05	0.04	-0.19**	-0.18**	-0.19**
	(0.11)	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)
Research intensity	0.26***	0.26***	0.26***	0.19***	0.19***	0.19***	0.10***	0.10***	0.10***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
ROA	-0.05**	-0.05**	-0.05**	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Young firm	0.05***	0.05***	0.05***	0.04***	0.04***	0.04***	0.02**	0.02*	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Independent	-0.03	-0.03	-0.03	-0.00	0.00	-0.00	-0.03*	-0.03*	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Domestic group	-0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Domestic Multinationals	0.04**	0.04**	0.04**	0.04**	0.04***	0.04**	-0.00	-0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Firm size	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.20*	-0.22**	-0.19*	-0.33***	-0.35***	-0.32***	-0.18**	-0.19**	-0.18**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)	(0.09)
Observations	4,025	4,025	4,025	4,025	4,025	4,025	4,025	4,025	4,025
left censored	2,032	2,032	2,032	2,560	2,560	2,560	2,677	2,677	2,677
right censored	57	57	57	33	33	33	8	8	8
Log lik.	-1481.5	-1475.7	-1481.0	-1286.4	-1281.9	-1286.3	-1184.4	-1180.5	-1184.3
Chi-squared	716.1	725.3	717.1	554.8	559.5	555.2	336.9	342.7	337.0

Note. In all models robust standard error is reported in parentheses, *, ** or *** indicate statistical significance at the 10%, 5%, 1% level, respectively.