Mounting corporate innovation performance: The effects of high-skilled migrant hires and integration capacity

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Abstract. We adopt an organizational learning approach to examine how firms' recruitment of high-skilled migrants contributes to subsequent firm-level innovation performance. We argue that due to migrants' often different experience from that of native high-skilled workers, their perspectives on problem-solving and access to non-overlapping knowledge networks will also differ. The implied complementarity between these worker types makes migrant hires a particularly valuable resource in the context of firm-level innovation. We hypothesize also that since acculturation costs of high-skilled migrants are relatively low while the innovation-related benefits deriving from diversity are relatively high, innovation performance should increase a fortiori if the high-skilled migrant hires are from a dissimilar culture. Finally, we conjecture that firms with high integration capacity as a function of prior experience of employing high-skilled migrants should derive more innovation-related benefits from migrant hiring than firms with a low integration capacity. We track the inward mobility of high-skilled workers empirically using patents and matched employer-employee data for 16,241 Dutch firms over an 11-year period. We find support for our hypotheses.

Keywords: High-skilled migration, innovation, dissimilar culture, integration capacity.

INTRODUCTION

Migration of high-skilled workers into advanced countries is an important feature of today's world economy, especially in knowledge-based economic sectors. In recent decades, migration of high-skilled workers into the OECD countries has increased much more than migration of other types of workers (Kerr et al., 2016). The innovation process requires high-skilled workers, and in the US for instance, the distribution of science and engineering degrees among immigrants and natives is disproportionate, making immigrants a valuable input to the innovation process (Hunt and Gauthier-Loiselle, 2010). Innovation is argued to be a central driver of prosperity and growth across countries, industries, firms and individuals. In this paper, we investigate the presence and impact of a high-skilled-migrant innovation premium which exceeds the benefits derived from hiring high-skilled natives. We explore whether its impact differs according to the cultural proximity of the migrant's home and host countries, and the heterogeneity among firms with respect to the ability to reap innovation-related benefits from migrant hirings.

The recent literature provides several important insights into the effects of high-skilled migration on the innovation process and its outcomes (for detailed reviews of the literature, see Nathan, 2014a; Kemeny, 2017). At the individual level, Nathan (2014b) shows for the UK context that the diversity of inventor communities helps to increase individual patenting. For the US case, Almeida and Phene (2015) show that Indian immigrant inventors' ability to draw on knowledge from their ethnic community can increase the quality of their inventions (see also Breschi et al., 2017 for an analysis of individual-level knowledge flows pertaining to migrants). Cooke and Kemeny (2017) demonstrate that increased immigrant diversity in cities and workplaces is related to higher wages for workers engaged predominantly in complex problem solving and tasks involving high levels of innovation. Also, at the industry and region levels high-skilled migrants have been shown to affect knowledge transfer and innovation output (see for instance, Hunt and Gauthier-Loiselle, 2010; Fassio et al., 2018). Using data on Chinese and Indian herbal patents filed in the US, Choudhury and Kim (2018) show that a national increase in the supply of first-generation ethnic migrant inventors increased patenting in the US of knowledge transferred from the home region cultural context. In a study of returnee immigrants, Wang (2015) shows that knowledge transfer success depends on migrants' embeddedness in both the home and host country workplaces.

At the firm level, several studies analyze the potential impact of a high-skilled, ethnically/culturally diverse workforce on corporate innovation performance (e.g., Østergaard et al., 2011; Nathan and Lee, 2013; Ozgen et al., 2013; Parrotta et al., 2014; Gagliardi, 2015; Lee, 2015). This stream of work — whether based on innovation survey or patent data — is in line mostly with the finding that ethnic/cultural diversity is a determinant of innovative performance. However, the literature does not consider the effect on the focal firm of hiring high-skilled migrants. Studying the effect of migrants from the point of view of recruitment of foreign workers as opposed to the effect of a culturally diverse firm workforce allows us to compare the effects of hiring high-skilled migrants versus high-skilled native workers. Such an approach can also reveal important heterogeneity among migrants and firms in relation to the effect on innovation performance. Holding workforce cultural diversity constant, we complement the migration and innovation literature by adopting a learning-by-hiring approach to study the marginal benefits of hiring migrants or natives, and the firm-level heterogeneity which might affect this relationship.

The learning-by-hiring literature shows that the recruitment of high-skilled workers from firms and other organizations such as universities, is an important source of knowledge which affects innovation-related problem-solving and the hiring firm's innovation output (e.g., Almeida and Kogut, 1999; Song et al., 2003; Hoisl, 2007; Ganco et al., 2015; Kaiser et al., 2015; Kaiser et al., 2018). More specifically, using an organizational learning lens (Levitt and March, 1988; Easterby-Smith et al., 2008; Argote and Miron-Spektor, 2011), we analyze the extent of the heterogeneity in the benefits to firm-level innovation performance derived from hiring high-skilled migrants with experience from different home countries. In line with the diversity and innovation literature (see, Nathan, 2014a), we argue that the recruitment of migrants rather than natives with different experience enables diverse approaches to innovation-related problem-solving, and access to other knowledge networks. We suggest that the experience embedded in migrant hires combined with the incumbent employees' problem-solving abilities and networks should lead to superior firm-level innovation performance. Since a different approach to problem-solving and ability to access non-overlapping knowledge networks furthers innovation, we hypothesize that high-skilled migrants recruited from dissimilar cultures should contribute more to the firm's innovation performance than recruitment from similar cultures. However, since the acculturation of migrants has some costs (Berry, 2001), in line with the organizational learning literature, we posit that firms with more experience of recruiting and retaining high-skilled migrants will more easily integrate and utilize them in their innovation processes. We argue also that this heterogeneity reflected in what we describe as "integration capacity", produces variation in the firm-level net benefits to innovation from hiring high-skilled migrants.

We test our predictions on unique data on a panel of Dutch innovation-active firms and their employees over the period 2000-2010. The data allow us to track annual mobility of employees into the firms in our sample. We link these data to European Patent Office (EPO) patent and citations data used to measure firms' innovation performance. Our analysis includes 16,241 firms and 71,092 observations. To address econometric concerns about possible state dependence and time-invariant unobserved firm-level heterogeneity, we control for fixed effects by applying a pre-sample mean estimator (Blundell et al., 1995). To account for unobserved time-varying factors which affect both the firm's innovation performance and the hiring of high-skilled migrants we re-run our main regressions using a general method of moments (GMM) estimation where we instrument our migrant and native hiring variables. To investigate mechanism linking hiring of high-skilled migrants and innovation, we run a series of regressions using number of patents in new-to-the-firm technology fields as an alternative dependent variable. We find overall support for our hypotheses.

THEORETICAL BACKGROUND

An important strand of work in the organizational learning literature highlights the significance of external learning based on the transfer of knowledge from other organizations and contexts (Easterby-Smith *et al.*, 2008; Argote and Miron-Spektor, 2011). Hiring is an important knowledge transfer mechanism (Levitt and March, 1988; Argote et al., 2000). However, Argote and Miron-Spektor (2011) point to major divergences in the value of types of experience with respect to learning outcomes, and suggest that different types of experience can be substitutes or can be complementary. In focusing on mobility involving different geographic locations and consequent firm-level innovation performance, we argue that the type of experience brought to the firm matters for its subsequent innovation performance. We propose that new high-skilled migrant hires embody different experience from new high-skilled native hires. Given that initially firms typically employ high-skilled natives, we argue that new high-skilled migrant hires are likely to have strong complementarities with the existing workforce, will increase the diversity in the hiring organization and in turn, will increase innovation performance.

It is recognized that there are costs related to hiring migrants (see for instance, Alesina and La Ferrara, 2005). In a seminal contribution, Berry (2001: 616) describes the psychological aspect of immigration in intercultural space thus: "Acculturation is a process involving two or more groups, with consequences for both; in effect, however, the contact experiences have much greater impact on the non-dominant group and its members." Berry (1994) and Berry et al. (2002) propose four phases of acculturation: contact, conflict, crisis and adaptation. The first phase involves contact between the home and host countries which requires an appreciation of the origin society to understand the migration motivation, and examination of the host society to understand its general orientation towards cultural pluralism. Conflict refers to the difficulties experienced by the immigrant; high levels of conflict can produce acculturation stress. The crisis phase involves strategies such as integration, assimilation, separation and marginalization employed to deal with problematic experiences, and leads to adaptation in which phase, the immigrants' behavioral change is less problematic, stress becomes minimal, and long-term adjustment and integration the usual outcome.

These phases imply that while hiring migrants has benefits, the acculturation process is time consuming, and is unlikely to be costless for the recruiting firm. In turn, this means that there are likely to be stark differences in firms' capacities to integrate migrants into their business activities, and suggests that heterogeneity in previous experience of hiring and employing migrants will be a critical determinant of this capacity.

HYPOTHESES

Our theoretical arguments are based on the notion that innovation and diversity in individual experience are linked. There is a long tradition in innovation research (Schumpeter, 1912/1934; Nelson and Winter, 1982; Kogut and Zander, 1992; Fleming and Sorenson, 2004) of viewing innovation as the result of the integration of previously separate bodies of knowledge. Cultural diversity implies differences among individuals in terms of shared attitudes, values, goals, knowledge, beliefs and behavior (Hofstede, 1980; Hofstede, 1990). Here, we follow the literature on diversity and innovation (e.g., Østergaard et al., 2011; Ozgen et al., 2013; Nathan, 2014a; Lee, 2015), and assume that diversity in human capital is important mainly because it results in different problem-solving perspectives (Cox et al., 1991; McLeod et al., 1996; DiStefano and Maznevski, 2000) and gives access to different knowledge networks (Almeida et al., 2015; Bogers et al., 2018).

The first argument is that differences in culture and related experience mean that high-skilled migrants bring a perspective to problem-solving that is likely to differ from the view adopted by the firm's native employees. The perceptions of new hired high-skilled migrants may complement or challenge those of the incumbent native employees. In the context of problem-solving, Lyles and Schwenk (1992: 168) assert that "diversity may influence a firm's repertoire of the definitions and understandings of how to handle different situations and events." Indeed, cultural differences can lead to more comprehensive problem-solving in novel contexts (Priem, 1990; O'Reilly, 1993) such as innovation projects. Thus, increasing cultural diversity by hiring high-skilled migrants should improve the firm's overall problem-solving ability which in turn, should increase the chances of fruitful knowledge (re)combination to promote innovation.

The second argument is that since diversity facilitates the (re)combination of different bodies of knowledge, a more culturally diverse organization should increase the chances for employees to draw on different bodies of knowledge based on their likely belonging to different external networks embedded, perhaps in different types of social as well as national and ethnic communities. This is important because research shows that knowledge flows tend to be localized (e.g., Jaffe et al., 1993; Alcácer and Chung, 2007; Bell and Zaheer, 2007; Breschi and Lissoni, 2009; Knoben, 2009) and channeled mainly through social relationships among individuals within a particular social structure (Owen-Smith and Powell, 2004). Indeed, organizational members' access to external networks embedded in social communities can be of critical importance for successful innovation outcomes (Laursen et al., 2012; Almeida et al., 2015; Dahlander et al., 2016). High-skilled migrants are able to draw extensively on the innovation-relevant knowledge embedded in the networks in their (national) community (Nathan, 2014a; Almeida et al., 2015), and this knowledge is likely to be different from the knowledge possessed by native employees. Knowledge characteristics depend on differences in national institutional factors, culture, scientific and technological developments, resource endowments, demand and supply conditions and regulation (Phene et al., 2006). Note that membership of a national or ethnic community allows access to the knowledge circulating in the particular community and ensures it is both trustworthy and relevant (Almeida *et al.*, 2015). Groups of high-skilled migrants from the same origin country living in the same host country can be expected to rely more on the knowledge they obtain from each other. Almeida and Phene (2015: 202) state that knowledge "obtained from a trusted partner or collaborator is more likely to acquire saliency, to be acted upon, and influence subsequent decision making." We hypothesize that:

Hypothesis 1: New high-skilled migrant hires contribute more to firms' innovation performance than new high-skilled native hires.

We have argued that differences in the experience of high skilled workers stemming from their different cultural background contributes to innovation. The implication is that the diversity gained from migrant hiring will be limited if the new hire comes from a similar culture, and will only marginally increase diversity in approaches to problem solving. If the networks accessible to the new hires are similar to those that are accessible to the incumbent native employees, then migrant hiring will give access to only marginally different knowledge. The potential positive benefits from migrant recruitment will be much greater if the new hire brings substantially different experience and belongs to different networks compared to those accessible to incumbent employees. This is more likely if the new hire is from a dissimilar culture.

However, recruitment from a dissimilar culture increases the costs of acculturation. Berry

(1997) argues that the greater the cultural difference between the home and host countries, the less positive will be the migrants' experience of adaptation because of the need to shed culture and cultural learning. These greater differences could result in negative intergroup attitudes and cultural conflicts. From this perspective, the increased net benefit from hiring an individual from a dissimilar culture compared to recruiting a similarly skilled person with experience of a more similar culture is unclear. However, in the particular case of high-skilled migrants considered in this paper, we suggest that the net benefit will be positive.

We start by considering the acculturation costs involved in migrant recruitment but suggest that these costs will be relatively low in the case of high-skilled migrants. This is because high-skilled migrants have university science degrees and often belong to their home country elite. Given the universalism of science (Gittelman, 2007), scientific training helps to bridge cultural distance by creating a common platform for scientists from different cultures. In addition, more highly educated people are more likely to follow international media, and are more likely also to have relatives and friends living in other countries. Thus, high-skilled migrants are likely to possess important knowledge about the functioning of other cultures, including the new host country. Highly-educated people are both better informed about foreign cultures, and as a result of their education better equipped to cope with acculturation problems and to adapt to life in a new society (Berry, 1997). It has been shown empirically that the educational achievement of immigrant children is tied closely to the parents' education background (Card et al., 2000; Dustmann et al., 2012). This finding and the above arguments suggest that the acculturation costs of high-skilled migrants will be relatively low. Given these comparatively low acculturation costs and the larger innovation-related benefits from hiring migrants from dissimilar cultures, we hypothesize that:

Hypothesis 2: New high-skilled migrant hires from dissimilar cultures contribute more to firms' innovation performance than new high-skilled migrant hires from a similar culture.

We have argued that increasing the cultural diversity within firms has strong innovation-related benefits, and that in the case of high-skilled workers the benefits are likely to outweigh the additional costs of employing migrant workers. However, different environments may have different capacity for integrating migrants productively. For instance, extant research shows that the benefits derived from cultural diversity involving migrant recruitment will be higher in geographical locations with more inclusive social and economic institutions (Kemeny and Cooke, 2017). We argue also that firms will differ in their capacity to integrate high-skilled workers in their innovation activities. Analogous to Cohen and Levinthal's (1990) notion of absorptive capacity in the context of knowledge transfer, in the context of innovation *integration capacity* can be defined as the firm's ability to identify and to assimilate migrants productively into the organization and its innovation process. High integration capacity implies a speedy acculturation process for newly hired migrants. In other words, firms with good (poor) integration capacity will be more able (unable) to reap the innovation-related benefits of increased diversity from hiring high-skilled migrants while experiencing lower (higher) costs of the increased diversity.

We argue that integration capacity is largely a function of the firm's prior experience of hiring and assimilating high-skilled migrants. We posit that there are two effects/antecedents to firm integration capacity. The first is the recruitment effect, or experience of hiring high-skilled migrants which can help to identify which types of migrants should be recruited to benefit innovation. Existing migrant employees also can help to identify potential recruits, and inform potential candidates about the firm's integration capacity and related work conditions. This implies that firms with experience of hiring migrants should be better at distinguishing which types of migrants will be the best fit for the firm in the context of increasing innovation performance.

The second antecedent is the work-organization effect which refers to the existence of work-practices for integrating non-native high-skilled knowledge workers (see for instance, Cox and Stacy, 1991; Konrad and Linnehan, 1995; Kalev et al., 2006). These work-practices are likely to an important extent to be based on experience of previous hirings. The firm's previous experience may allow it to accommodate to employees with different norms and incentives which will reduce problems in the workplace. For instance, the HR department's experience of dealing with migrant employees will allow better management of new migrant hires while the firm may have put in place practices which imply collaboration between native and non-native workers. This can result in a workplace with a more international feel that is more welcoming and accommodating to non-natives. The mere presence of other migrants in the firm should reduce the negative stress of being different (Berry, 1997; Berry *et al.*, 2002). Therefore, we hypothesize that:

Hypothesis 3: New high-skilled migrant hires contribute more to firms' innovation performance if firms have high integration capacity.

METHODS

Data

We constructed a panel dataset of innovation-active firms in the Netherlands during the period 2000 to 2010. We include firms that applied for at least one European (EPO) patent during that period, and firms that did not apply for a patent but were R&D active during that period. The Netherlands is an interesting setting because it attracts significant numbers of high-skilled migrants. In 2015 and 2016, incoming high-skilled migrant numbers were respectively 12,000 and 14,000 due in particular, to the introduction of a simple and fast resident permit procedure, and temporary tax benefits such as the 30 percent tax for new migrants (The Immigration and Naturalisation Service, 2015; 2016).

To collect patents registered by the sample firms, we started with the population of patents filed at the EPO since 2000 with at least one applicant located in the Netherlands. Since firms can register patents under different names e.g., the name of the local subsidiary, we consolidated patent data at the firm group level. To match patents to firm group, we relied on annual General Business Register data published by Statistics Netherlands which provides information on group structure such as the name and ownership for all Dutch subsidiaries. We chose the Dutch enterprise group as the level of analysis.

Statistics Netherland's Statistics for Non-financial Enterprises data provide information on sectoral affiliation, sales, book value of physical capital, and employee information such as end-of-year listings and wages at the firm-group level. We identified R&D active firms using information on R&D investment or R&D labor obtained from the Community Innovation Survey (for the even years) and R&D surveys (for odd years) which are collated by Statistics Netherlands. We include only private sector firms and exclude (NACE 2 digit) sectors with no EPO patent applications in the sample period.[1] Our sample is unbalanced and includes 16,241 firms and 71,092 firm-year observations.

Dependent variable

Our dependent variable is the firm's *citation-weighted patent count*. Patents are used frequently as an indicator of innovation output (e.g., Ahuja and Lampert, 2001; Phene et al., 2006; Joshi and Nerkar, 2011; Leten et al., 2016) and have been shown to be correlated strongly to other innovation indicators such as new product announcements and expert rankings of firm innovation (Narin et

[1] In these sectors firms do not rely on patents to protect their innovations.

al., 1987; Hagedoorn and Cloodt, 2003). We weigh patent counts by number of patent citations received to control for differences in patent quality (Trajtenberg, 1990; Hall et al., 2005). We apply a fixed five-year citation window to allow comparison across patents. We include all patent citations (in patents filed with various patent offices) to EPO patents and their patent family equivalents (i.e., patent documents related to protection of the same invention). To calculate citation counts we integrated citing and cited patents at the DOCDB PATSTAT patent family level to avoid double counting of patents for similar inventions (Martínez, 2011). Citations are calculated based on PATSTAT data (March 2018 version).

Explanatory variables

Employee-employer data from the Social Statistics Database are used to define *high-skilled workers* with expertise that contributed to the firm's innovation output. We rely on a broad definition of high-skilled worker in line with the prior literature which considers that both technical workers and other high-skilled professionals in firms (such as sales people and business developers) contribute to firm innovation (see for instance, Lukas and Ferrell, 2000; Foss et al., 2011). Our definition of skills is based on the concept of knowledge workers (Horwitz et al., 2003); we classify workers into high-pay levels according to some threshold values based on the entire wage distribution. Since we do not have information on the education background of *all* workers in the Netherlands, we use wage data to proxy for skills (e.g., Kaiser et al., 2015; Kaiser et al., 2018). The literature suggests there is a close relationship between education and wages (e.g., Mincer, 1958; Farber and Gibbons, 1996) which justifies this choice. To control for confounding influences on wages of sector, year and seniority, we estimate different wage distributions per sector (NACE 2 digit), year and age cohort (<30 yrs, 31-40 yrs, 41-50 yrs, >50 yrs), relying on wage information for *all* workers in the Netherlands. To rank employees, we consider only tax paying employees with a current address in the Netherlands, and include full-time equivalent jobs of at least 12 months' duration. High-skilled workers are defined as equal to or above the 75th percentile of the wage distribution.

Figure 1 depicts the relationship between employee's education level and ranking in the wage distribution. It is based on data for a sample of 1.65 million people in full-time employment in non-agricultural sectors in the Netherlands in year 2011 for whom Statistics Netherlands has information on education background. In line with van Ark et al. (2008), we differentiate among three levels of education based on Dutch Standard Classification of Education (SOI) codes: primary and lower-secondary education (low education), higher-secondary education and post-secondary education (medium education) and higher (masters or doctoral degree) education (high education). Figure 1 shows the close relationship between employees' education level and their rankings in the wage distribution.

[INSERT FIGURE 1, JUST ABOUT HERE]

We differentiate between high-skilled *migrants* and high-skilled natives using information from Statistics Netherlands' migration database which provides details of date of registration and country of origin of migrants. We define migrant workers as workers born outside of the Netherlands who migrated to the Netherlands as adults i.e., we exclude foreign born workers with a Dutch parent who lived abroad temporarily, and foreigners already integrated in the Netherlands when they reached working age.

High-skilled migrants are split into two groups based on level of cultural similarity between the Netherlands and their country of origin: *high-skilled migrants from similar cultures* and *high-skilled migrants from dissimilar cultures*. We rely on the cultural groupings of countries in the GLOBE study (House et al., 2004) which provides survey data for 62 countries and 9 cultural dimensions: 1) power distance, 2) uncertainty avoidance, 3) institutional collectivism, 4) in-group collectivism, 5) gender egalitarianism, 6) assertiveness, 7) performance orientation, 8) future orientation, and 9) humane orientation. This resulted in 10 cultural clusters: 1) Anglo-Saxon, 2) Nordic-European, 3) Germanic-European, 4) Latin-European, 5) Eastern-European, 6) Latin-American, 7) Sub-Saharan African, 8) Middle-Eastern, 9) Confucian Asian and 10) South Asian. The Netherlands is included in the Germanic-European cluster together with Germany, Austria and Switzerland. Follow-up research (Mensah and Chen, 2012) adds Belgium, Luxembourg and Liechtenstein to this cluster. A migrant is defined as originating from a similar culture to the Netherlands if the country of origin is included in the Germanic-European cluster.

We separate the population of high-skilled workers by mobility status. We define *hires* as workers employed by different employers in t-1 and t. We differentiate between two main hire categories: i) high-skilled natives and ii) high-skilled migrants. High-skilled migrants is subdivided into: i) high-skilled migrants from similar cultures and ii) high-skilled migrants from dissimilar cultures. High-skilled stayers are defined as non-mobile high-skilled workers (i.e., employed by the same firm in t-1 and t). Finally, a firm is defined as having high *integration capacity* with respect to newly hired high-skilled migrants if in a given year it employs a higher share of high-skilled migrants than the average firm in the Netherlands that is active in the same sector (NACE 2 digit level).

Control variables

We include a set of control variables in our analyses. First, *ln(≠ high-skilled workers)* which is the natural logarithm of the total number of high-skilled workers. Second, *ln(capital)* expressed as the natural logarithm of the firm's physical capital. Third, *cultural diversity* which measures the cultural diversity of the firm's high-skilled workforce (excluding new hires). In line with Parrotta et al. (2014), cultural diversity is measured as (minus) a Herfindahl index of the distribution of the high-skilled workforce over a number of cultural clusters (10 GLOBE clusters plus the Netherlands). Fourth, we control for *sector* by including six categories for sectoral technological intensity: 1) low technology manufacturing, 2) medium-low technology manufacturing, 3) medium-high technology manufacturing, 4) high-technology manufacturing, 5) knowledge-intensive services and 6) less knowledge-intensive services (source: Eurostat classification). Fifth, we include *year* dummies and control for *number* of fully controlled *firm subsidiaries* and *number of industry segments* (NACE 3 digit level) in which the firm is active. Sixth, we control for possible state dependence for innovation output. In line with Kaiser et al. (2015), we include a dummy for whether the firm patented in t-1. Seventh, we control for unobserved time-invariant firm heterogeneity — as described below.

Empirical specification and estimation

To examine the (differential) effects of new high-skilled migrant hires and new high-skilled native hires on the firm's innovation performance, we adopt the empirical approach proposed by Kaiser, Kongsted and Ronde (2015). This relies on a Cobb-Douglas knowledge production function where the firm's innovation performance is determined by high-skilled labor and physical capital inputs, and high-skilled labor is decomposed linearly into different types.

The total number of the firm's high-skilled workers (L) includes three categories of workers: high-skilled stayers (L_{st}), new high-skilled migrant hires (L_M), and new high-skilled native hires (L_N).[2] This can be written as follows:

[2] In some models, newly hired high-skilled migrants are split into migrants from similar and dissimilar cultures which provides a simple extension to our model. All labor variables are 1-year lagged.

$$L = L_{st} + \gamma_M L_M + \gamma_N L_N \tag{1}$$

$$L = L\,(1 + (\gamma_M\text{-}1)\,\frac{L_M}{L} + (\gamma_N\text{-}1)\,\frac{L_N}{L}) \tag{2}$$

The coefficients γ_M and γ_N indicate the contribution to the total high-skilled workers of a newly hired high-skilled migrant and a newly hired high-skilled native relative to the contribution of a high-skilled stayer (whose effect is normalized to unity). After plugging equation (2) into the Cobb-Douglas knowledge production function, taking logs on both sides of the equation and using the approximation that ln(1+z) = z for small z, we get equation (3), which is our main regression model:

$$E(P) = \exp\left\lfloor \ln(A) + \alpha\ln(L) + \alpha_M\frac{L_M}{L} + \alpha_N\frac{L_N}{L} + \beta\ln(K)\right\rfloor \tag{3}$$

where $\alpha_M = \alpha(\gamma_M\text{-}1)$ and $\alpha_N = \alpha(\gamma_N\text{-}1)$, E(P) is the expected citation weighted patent count, K is physical capital and A are the remaining determinants of P (cultural diversity, sector, year, firm group structure, sales diversification, and pre-sample average). We opt for count data models to take account of the discreteness and non-negativity of our dependent variable: citation weighted patent count. We estimate negative binomial models which are robust to the over-dispersion common in patent data. An important feature of our data is the skewness of the dependent variable and the zero patent counts for many firms in some years. Among the 71,092 firm-year observations used in our estimations, only 2,308 have positive patent counts. To take account of the excess zeros, we use a *zero-inflated negative binomial model* (Cameron and Trivedi, 2010). Vuong tests for the different regression models indicate a better model fit using a zero-inflated negative binomial instead of the standard negative binomial model.

To control for time-invariant heterogeneity across firms not captured by the model variables, we include a *pseudo fixed effect* calculated as the natural logarithm of the pre-sample value of the dependent variable.[3] The advantage of pseudo fixed effect models is that unlike conventional fixed effect models they do not require strict exogeneity of the error terms (Blundell et al., 1995). The pseudo fixed effect is calculated as the average value of the dependent variable over the two years preceding the first year observed e.g., for firms entering the dataset in 2002 this is 2000-2001.

RESULTS

Table 1 presents firm-level descriptive statistics for the dependent and explanatory variables, and the correlation matrix of the explanatory variables. On average, the firms in our sample have three citation weighted patents per year. The average ratios of newly hired high-skilled natives, and newly hired high-skilled migrants, to all high-skilled employees are 0.249 and 0.030 respectively. In other words, for every 100 high-skilled employees, the average firm hires 24.9 new native and 3 new migrant workers per year. Among those high-skilled migrants, four times more migrants on average are from dissimilar compared to similar cultures. Also, the firms in our sample are active in 1.8 sectors and have 2.5 subsidiaries on average. The correlations among the explanatory variables included simultaneously in the regressions are generally low, and low correlation coefficients suggest that multicollinearity is unlikely to be a problem. Among the explanatory variables, the highest correlations are among log of capital, log of total highly skilled workers, number of sectors with sales and number of firm subsidiaries. These correlation coefficients vary between 0.55 and 0.85. Notice that excluding the log of skilled workers does not allow identification of our results. Therefore, as a robustness check, we re-ran the regression models omitting the variable *number of firm subsidiaries* but this did not affect the coefficients of the other variables.

[INSERT TABLES 1 AND 2, JUST ABOUT HERE]

[3] We added a value equal to 1 before the logarithmic transformation.

Table 2 presents the regression results. Model 1 tests Hypothesis 1 that new high-skilled migrant hires contribute more to firms' innovation performance than new high-skilled native hires. The coefficient of migrant hiring is positive and significant; the coefficient of native hiring is insignificant. The former is seven times larger than the latter, and a Wald test shows that the two coefficients differ from one another (p-value < 0.01). This supports Hypothesis 1. We calculate the productivity ratio of hiring migrants (γ_M) where $\gamma_M = 1 + \frac{\alpha_M}{\alpha}$. The productivity ratio γ_M equals 6.8 which implies that a new high-skilled migrant hire contributes almost seven times more than a high-skilled stayer to the firm's innovation performance. This is similar to the estimates in Kaiser et al. (2015) and Kaiser et al.(2018) for other knowledge-intensive worker groups. The insignificant coefficient of native hire means there are no significant differences in the contribution to the firm's innovation performance of new high-skilled native recruits and high-skilled stayers.

The marginal effect on quality-adjusted innovation output of adding one worker of type *k* in Model 1 depends on (i) the share of type *k* workers, (ii) the initial innovative output (number of patents applied for by the firm plus citations), and (iii) the initial number of high-skilled workers of all types (see, Kaiser et al., 2018). To provide interpretable marginal effects we follow Kaiser et al. (2018) and set the number of patents per worker applied for by the employing firm equal to the sample average, and set the number of workers of any mobile type other than *k* to zero. Then, the marginal effect of hiring one additional worker of type *k* depends on the share of type *k* workers in total high-skilled employment. Note that all marginal effects are downward-sloping, implying that if a firm already has (hired) a high share of a certain type of high-skilled worker, hiring additional workers of this type will yield relatively low marginal innovation output.

The marginal effects show that adding one high-skilled migrant hire is associated to 0.074 additional patents if the receiving firm hires workers of this type only. To properly gauge the economic significance of this result, we can compare the marginal effect of 0.074 to the sample average of quality-adjusted innovative output of 2.947. Hence, the effect of hiring a high-skilled migrant amounts to 2.5 percent of the overall sample average. We note that the change results from the addition of one worker which is a fairly large change given the sample average of 62 for the overall number of high-skilled workers employed.

In addition to the focal variables, total high-skilled workers, cultural diversity and pseudo fixed effect are positive and significant. No significant effect is found for the firm's capital stock, and the one-year lagged patent dummy has a negative effect which indicates that firms with patenting activity in the previous year patent less in the current year. Finally, we find that firms with fewer subsidiaries record higher innovation performance.

Model 2 tests Hypothesis 2 that newly hired high-skilled migrants from a dissimilar culture contribute more to the firm's innovation performance than newly hired high-skilled migrants from a similar culture. We find a positive and significant coefficient of migrant hires from a dissimilar culture, and an insignificant coefficient of migrants hired from a similar culture. A Wald test shows that these coefficients differ from each other (p-value = 0.037) which lends support to Hypothesis 2. In terms of marginal effects, adding one high-skilled migrant hire from a dissimilar culture is associated to 0.396 additional patents if the receiving firm hires workers of this type only. Again, we can compare the marginal effect of 0.396 to the sample average of quality-adjusted innovative output of 2.947. Hence, the effect of hiring a high-skilled migrant from a dissimilar culture amounts to 13.4 percent of the overall sample average.

Hypothesis 3 states that newly hired high-skilled migrants contribute more to the firm's innovation performance if the firm has a high level of integration capacity. To test this hypothesis, we conduct a split sample analysis (Model 3) where we differentiate between high and low integration capacity firms. The coefficient of migrant hiring on innovation performance is 2.5 times higher for the high compared to the low integration capacity sample. To compare the coefficients across the two models we rely on a chi square test obtained by employing the seemingly unrelated estimation and implemented using Stata's suest command. This test shows that the coefficients differ (p-value = 0.053). This is in line with Hypothesis 3. We found no significant effects for the native hiring variables in either sample. In terms of size effects, we find that a new high-skilled migrant hire by a firm with high integration capacity is almost twice as productive as a new high-skilled migrant hire by a firm with low integration capacity.

For completeness, we check for the differential effects of newly hired culturally similar and dissimilar migrants in the high and low integration capacity samples (results reported in Model 4). In both samples the coefficients of hiring culturally similar migrants are insignificant, and for hiring culturally dissimilar migrants are positive and significant. The coefficient of hiring migrants from dissimilar cultures is 2.4 times higher in the high integration capacity group compared to the low integration capacity sample. A chi square test (based on suest) shows that the coefficients differ (p-value = 0.049). Hence, the firm's integration capacity seems to matter for recruitment of migrants from dissimilar but not similar cultures.

ALTERNATIVE EXPLANATIONS AND ROBUSTNESS CHECKS

In this section, we discuss possible alternative explanations which potentially might be driving our findings and the results of a number of alternative models to check the robustness of our findings.

Alternative explanations

One explanation for our finding of an innovation premium from hiring high-skilled migrants rather than high-skilled natives may be that this premium is not driven by the migrants' unique problem-solving experience and access to different knowledge networks but rather is the result of unobserved differences between high-skilled migrants and high-skilled natives such as differences in skills (not fully accounted for in wages) and occupations. In the case of skills, it might be that migrants face higher labor market barriers, or that firms are willing to incur the acculturation costs associated to hiring migrants only if those migrants are (perceived to be) more skilled than the best available native workers. In the case of occupations, it may be that high-skilled migrants are employed relatively more in technical occupations which are expected to have the greatest impact on firm innovation.

To test whether our results are driven by alternative explanations based on skills and occupations, we rely on information from the 2010 Labor Force Survey (LFS). The LFS contains information on education background (SOI codes) and occupation (ISCO codes) for a sample of workers in the Netherlands. After matching information from the LFS with our sample firms, we obtained information on, respectively, 19,482 and 3,603 high-skilled native and migrant hires. If the explanation is skill-based, we would expect to find significantly higher percentages of high-skilled migrants (defined on the basis of wages) with high or medium level education. However, 56.3 percent of high-skilled migrants have a high education background, and this percentage is only slightly lower (53.7%) for high-skilled natives while the percentage of high-skilled workers with medium education is much lower for migrants (27.6%) than for natives (33%). A chi-square test comparing the percentages of high-skilled migrants and natives with low, medium and high education is not significant. To examine the technical occupation based alternative explanation, we classified a number of occupations (engineers and researchers, ICT specialists, medical and technical specialists) as technical occupations. We find no evidence of a technical occupation based alternative explanation since there is a smaller — rather than a higher — percentage of high-skilled migrants (16.4%) compared to high-skilled natives (18.5%) in technical occupations.

We conduct an additional analysis to test whether the suggested hiring high-skilled migrant mechanisms are at work. If the benefits from high-skilled migrants stem from their unique experience, hiring high-skilled migrants would likely result in diverging innovation trajectories reflected in firms entering new technology fields. The EPO classifies patents in at least one eight-digit technology field based on the International Patent Classification (IPC) system. Technology fields are aggregated into 628 broader four-digit IPC classes which we use in our paper. In line with prior work (e.g., Ahuja and Lampert, 2001; Leten et al., 2016) a technology field is defined as new-to-the-firm if the firm was not active (did not patent) in the technology field in the previous four years. For the sample firms, 47 percent of the patents filed between 2004-2010 were in at least one new technology field and are classified as new to a firm.

Table 3 reports the results of the main regression models using number of patents in new-to-the-firm technology fields as the dependent variable. The estimations cover the period 2004-2010 since a four year period is used to identify a new technology field. The Model 1 results show that new high-skilled migrant hires contribute more to innovation diversification into a new technology field than new high-skilled native hires. This effect is larger for newly hired high-skilled migrants from a dissimilar rather than similar culture (Model 2) and if the firm has high integration capacity (Model 3). These findings are in line with the suggested mechanisms allowing high-skilled migrants to influence firm innovation.

[INSERT TABLE 3, JUST ABOUT HERE]

Another explanation for our finding of an innovation premium from hiring high-skilled migrants rather than high-skilled natives might be that this result is driven by unobserved time-varying factors which affect both the firm's innovation performance and the hiring of high-skilled migrants. For example, firms that want to increase their innovation performance will make various types of R&D investments including hiring high-skilled migrants. These investments might be jointly determining innovation performance and hiring high-skilled migrants. This type of unobserved firm-level time-varying heterogeneity is not accounted for in our main estimations (which include a presample mean to control for time-constant firm effects). Therefore, we re-estimated our main regression using a GMM regression where we instrument the migrant and native hiring variables.

We use the Poisson estimator derived by Blundell et al. (2002) which accounts for both fixed effect and lagged dependent variables. We instrument migrant hiring, native hiring and the total number of high-skilled workers using information on the (average) yearly percentage changes in (non-Dutch) migrant inflows in the OECD countries excluding the Netherlands, and migrant inflows in the Netherlands. The idea of these instruments is that the growth in migration flows across countries may be the result of exogenous shocks (e.g., rules, changes in economic growth, macroeconomic policy shocks, etc.) which affect the opportunities for firms located in the Netherlands to hire high-skilled (migrant) workers. The additional instruments we use are based on Kaiser et al. (2015) and include the firm's lagged labor variables, average hiring variables for all other firms in the Netherlands in the same sector (NACE 2 level) and sector dummies. Running the GMM regression reduces the sample to 51,185 observations due to using lagged variables as instruments. The GMM results are reported in Table 4 and are similar to the presample mean estimations: insignificant coefficient of hiring high-skilled natives and positive and significant coefficient of hiring high-skilled migrants.

Robustness checks

We performed a number of checks to test the sensitivity of our results. First, we examined potential remaining heterogeneity amongst high-skilled migrants from dissimilar cultures in terms of their cultural distance to the Netherlands and the innovation benefits that accrue to the hiring firms. Using information on nine cultural dimensions from the GLOBE survey, we calculated the average cultural distance between the Germanic-European cultural cluster (which includes the Netherlands) and the other cultural clusters. This resulted in two dissimilar culture groups: 1) low dissimilar culture (including Nordic-European, Anglo-Saxon and Latin-European) and 2) high dissimilar culture (including Eastern-European, Latin-American, Sub-Saharan African, Middle-Eastern, Confucian Asian and South Asian). We re-estimated the main regression model which distinguishes high-skilled migrant hires from similar and dissimilar cultures. In this re-estimation we further subdivided migrant hires from dissimilar cultures into high-skilled migrant hires from low dissimilar and high dissimilar cultures (see Table 4). In line with the prior findings, we found no significant effect for migrants hired from similar cultures, and positive and significant coefficients of migrant hires from both low and high dissimilar cultures. While the coefficient of migrant hires from high dissimilar cultures is slightly higher than the coefficient of migrant hires from low dissimilar cultures, the difference is not statistically significant.

Second, we examined the robustness of our findings to restricting our sample to firms that filed a patent at least once during the period 2002-2010. The rationale for this is that not all firms patent their innovations. This restriction reduced the sample hugely — from 71,092 to 8,858 observations but our main research finding is still supported (see Table 4). Third, we investigated the sensitivity of our results to controlling for the firm's regional context (Trax et al., 2015; Kemeny and Cooke, 2018). We collected information from Statistics Netherlands' REGIO database which provides information from 2007 on location address (plant level) for almost all of the firms in the sample. We linked these addresses to the 12 Netherlands provinces, and estimated our main regression model for the period 2007-2010 including province dummies (see Table 4).[4] The province dummies are jointly significant but their inclusion has no real influence on the effects of our main variables.

[INSERT TABLE 4, JUST ABOUT HERE]

We conducted some additional robustness checks; the results are not reported here for reasons of space. First, we checked the robustness of our findings to controlling for — in addition to cultural diversity — the ratio of high-skilled migrant stayers in the firm's labor force. This generated comparable results: the coefficient of high-skilled migrant hires is positive and significantly higher than the coefficient of high-skilled native hires. The coefficient of high-skilled migrant stayers is positive and significant (compared to high-skilled native stayers) again demonstrating the innovation benefits from employing high-skilled migrants.

Second, we investigated whether our results hold if we use total factor productivity (TFP) growth instead of citation-weighted patent counts to measure firms' innovation performance. TFP growth is calculated as a Solow residual and measures the changes to output which can be explained by other factors not included explicitly in the production process. In a growth accounting approach, TFP growth is measured based on perfect competition and constant returns to scale. After trimming the data, for simplicity we used the system GMM which includes fixed effects and accounts for endogeneity of the right-hand side variables by using their lagged values (in first differences and levels) as instruments. The significant effect of hiring skilled migrants is confirmed, and the effect of hiring high-skilled natives remains insignificant.

[4] Since our unit of analysis is the consolidated firm-level and the REGIO database identifies plant-level locations for each firm, we weighed each plant by employment to identify the parent firm location since firms might have several plants in various locations.

Third, we checked the robustness of our findings to a different definition of countries culturally similar to the Netherlands. Specifically, we added former colonies to the group of culturally similar countries; we found that Surinam and Netherlands Antilles are the countries of origin of a significant proportion of high-skilled migrants. We reclassified migrants from former colonies into the group of culturally similar countries. Our results are robust to this reclassification. Fourth, since there is a strong concentration of patenting activity among a small number of sectors and firms in the Netherlands, especially the electrical and electronics sectors (NACE 26-27), we analyzed the robustness of our results to removing the firms in these two sectors. Our results are robust.

Finally, we explored whether there is heterogeneity over time in the main effects of hiring high-skilled migrants and high-skilled natives. We did this by estimating our main regression model for two subsequent time periods (2002-2006 and 2007-2010). The hiring high-skilled migrant variable is significant in both periods; we found no significant effect for hiring high-skilled natives in either period. While the coefficient of hiring high-skilled migrants is higher in the second than in the first period, the difference is not statistically significant.

CONCLUSION AND DISCUSSION

The analysis in this paper is premised on the fact that although our knowledge of the role of migrants as an input to the innovation process has increased markedly over recent years, we know very little about how hiring high-skilled migrants affects firm-level innovation or the factors that might moderate this relationship. Theoretically, we adopted an organizational learning perspective to investigate these important questions. We posited that firms' hirings of high-skilled migrants rather than high-skilled natives with other types of experience, should lead to higher firm-level innovation performance. In line with the literature on diversity and innovation, we argued that migrants provide different perspectives on innovation-related problem-solving and give access to different knowledge networks which complement (predominantly native) incumbent employees' problem-solving abilities and networks.

We conjectured that because of the greater heterogeneity among problem-solving perspectives and access to non-overlapping knowledge networks, new highly-skilled migrants from dissimilar cultures should contribute more to firms' innovation performance than new high-skilled migrants from similar cultures. We used the organizational learning argument to advance the idea that since integration and use of migrants is likely to be costly due to the problems migrants will tend to experience during their acculturation, firms with greater experience of recruiting and retaining high-skilled migrants should be better at integrating and assimilating migrants in their innovation processes. Using patent and matched employer-employee data for a sample of Dutch firms, we found empirical support for our predictions.

This paper makes two main contributions. First, we contribute to the literature on the firm-level effects of migration by proposing a theoretical and empirical framework which while controlling for within firm cultural diversity both specifies why firms innovation performance can benefit from hiring high-skilled migrants, and highlights some important conditions related to benefiting from recruiting such workers. Our focus in this context on cultural heterogeneity among migrants and differences in the "integration capacity" of host firms is novel.

Our second main contribution is that we add to the organizational learning literature by responding to call made in Argote and Miron-Spektor (2011: 1127) for more research to understand "when different types of experience are complements or substitutes for one other." We have responded by unpacking the effects of heterogeneity in types of experience based on an examination of whether that experience complements (or substitutes) in the context of mobility of high-skilled migrants and natives into innovation active firms. Our results are consistent with the idea that high-skilled migrants — because of their different problem-solving and networking experience — complement incumbent high-skilled workers in the context of innovation activity. We find an even stronger effect in the case of culturally distant compared to culturally similar migrants which highlights that differences in the experience of new hires compared to the experience of existing employees, are critical for innovation performance.

We suggest that integrating migrant hires in the innovation process might be costly due to the necessary acculturation process. However, we proposed that different experience of migrant hiring among firms matters for achieving smoother acculturation. We suggest that the integration capacity of firms varies depending on their prior experience of employing high-skilled migrants. Empirically, we found that the effect of hiring high-skilled migrants more than doubles for firms with high compared to low integration capacity. In the context of firm-level integration capacity, in line with the general theoretical arguments proposed here we show that integration capacity matters greatly for the subsequent innovation performance of culturally distant but not culturally similar migrants: Culturally similar migrants appear to require much less organizational attention (but contribute less to the innovation process).

The findings from our study have implications for managerial practice. First, it is clear that firms can achieve innovation-related benefits by increasing the diversity of their high-skilled workforce through the recruitment of migrants. However, our findings suggest also that these benefits are not costless; hiring migrants requires significant investment in integration activities from the recruiting firm, and learning about how best to identify and work with high-skilled migrant workers to benefit from the perspectives and networks they bring to the recruiting firm.

This research has some limitations. First, despite our best efforts, endogeneity might remain a problem; however, we believe that the empirical strategy we employed reduces concerns over unobserved heterogeneity and omitted variables bias. We used the pre-sample mean estimator to account for time-invariant unobserved heterogeneity. Also, as a robustness check to account for time-varying unobserved factors, we applied a GMM estimator and obtained very similar results to those obtained using the pre-sample mean estimator. In addition, we tested several alternative explanations for our results. We believe that these procedures greatly reduce concerns about alternative explanations.

Second, our high-skilled hires measures are based on wages. Although previous research suggests a strong link between wages and education level, we acknowledge that this proxy has some shortcomings. Third, our measure of firm integration capacity is relatively simple and reflects only the experience of firms that hired migrants in recent years. Future research could more deeply investigate firms' specific investments in the integration of high-skilled migrants in the innovation process. This might include specific procedures and work-practices aimed at integrating a diverse set of high-skilled employees. Fourth, due to data availability, we were forced to measure migrant diversity by country of origin. However, although there is no reason to believe that this should create systematic bias, it should be noted that diversity could depend on other factors such as race and ethnicity, and also, that there might be some workers with roots in more than one country.

Finally, our dependent variables reflect firms' (quality-adjusted) total innovation performance and firms' patents in new-to-the-firm technology fields. However, cultural diversity might be particularly important in the context of radical innovation. All of these issues require theoretical and empirical scrutiny in future research. However, we hope that the present paper will be considered a first step toward establishing an exciting research agenda which investigates further important individual-level and firm-level heterogeneity with respect to migrant mobility.

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FIGURES AND TABLES

Figure 1: Relationship between level of education and ranking in wage distributions

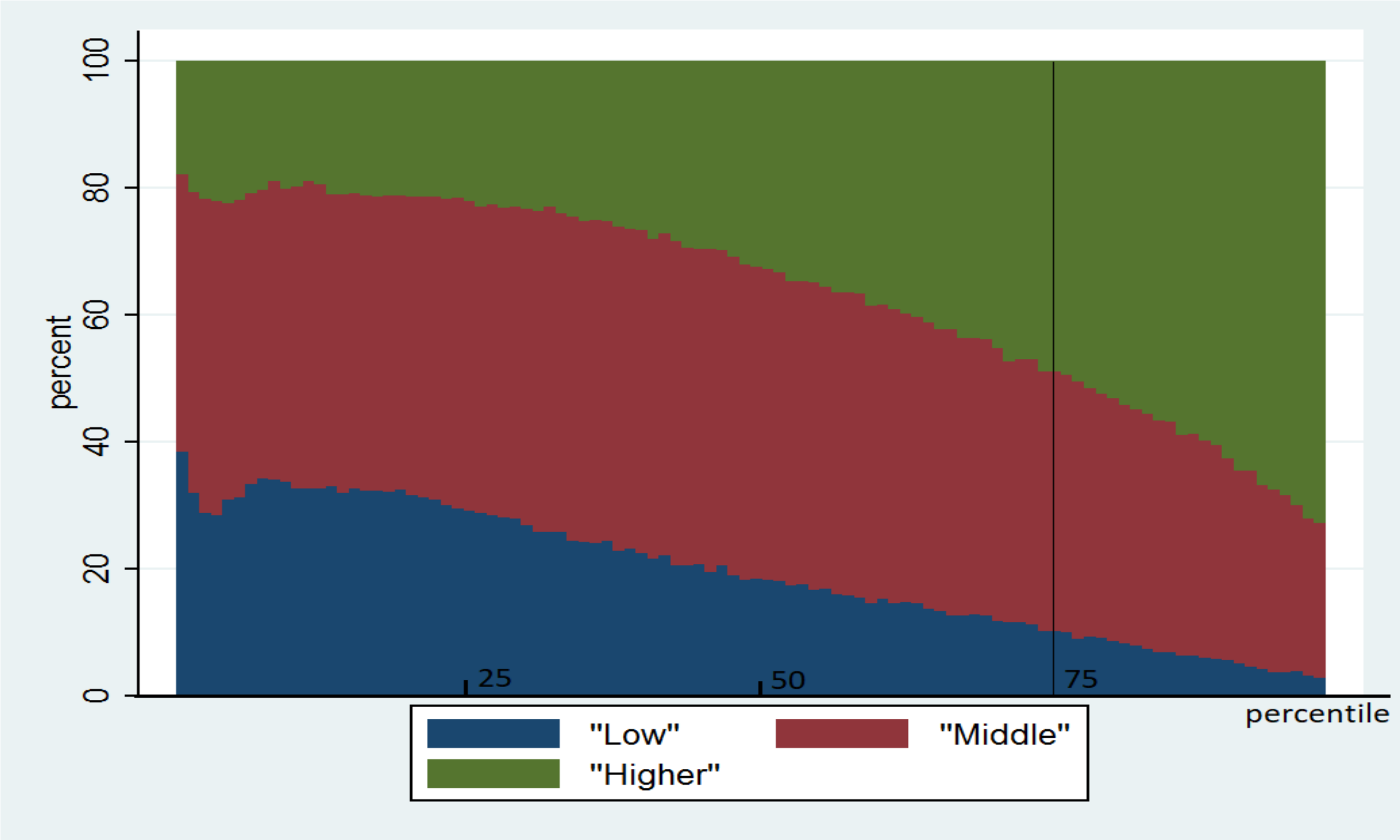

Table 1: Summary statistics and correlation table (n=71,092)

		Mean	Std.Dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Citation-weighted patent count	2.947	179.219											
(1)	Hiring natives	0.249	0.296	1										
(2)	Hiring migrants	0.030	0.088	0.088	1									
(3)	Hiring migrants from similar culture	0.006	0.036	0.041	0.431	1								
(4)	Hiring migrants from dissimilar culture	0.025	0.079	0.077	0.916	0.035	1							
(5)	ln(total highly skilled workers)	2.421	1.498	-0.065	0.004	-0.004	0.009	1						
(6)	ln(capital stock)	6.636	2.228	-0.081	-0.099	-0.022	-0.097	0.556	1					
(7)	Patent dummy in t-1	0.031	0.172	-0.025	0.004	0.004	0.003	0.147	0.116	1				
(8)	Pseudo fixed effect	0.038	0.242	-0.028	0.008	0.003	0.008	0.209	0.166	0.683	1			
(9)	Number of sectors with sales	1.765	1.701	0.005	-0.006	0.002	-0.007	0.416	0.359	0.168	0.243	1		
(10)	Number of firm subsidiaries	2.457	4.462	0.003	-0.002	0.002	-0.002	0.406	0.326	0.158	0.227	0.858	1	
(11)	Cultural diversity	-0.624	0.219	0.037	-0.002	0.008	-0.006	-0.082	-0.049	0.003	0.013	0.008	0.009	1

Table 2: Newly hired high-skilled migrants and firms' innovation output

	Dependent variable: Citation-weighted patent counts	Model 1		Model 2		Model 3				Model 4			
						High		Low		High		Low	
		Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
	Highly skilled employment shares												
(1)	Hiring natives	0.341	0.287	0.332	0.287	-0.477	0.424	0.399	0.296	-0.472	0.421	0.394	0.295
(2)	Hiring migrants	2.482***	0.726			4.225***	1.099	1.683**	0.743				
(3)	Hiring migrants from similar culture			0.311	1.093					0.835	2.068	0.110	1.072
(4)	Hiring migrants from dissimilar culture			2.968***	0.834					5.005***	1.232	2.067**	0.847
	Capital and highly skilled labor												
(5)	ln(total highly skilled workers)	0.425***	0.055	0.424***	0.055	0.458***	0.069	0.376***	0.102	0.454***	0.068	0.376***	0.102
(6)	ln(capital stock)	0.012	0.034	0.009	0.034	0.009	0.040	0.024	0.054	0.009	0.040	0.019	0.054
(7)	***Cultural diversity***	0.599**	0.237	0.612***	0.237	0.367	0.277	0.626	0.397	0.374	0.277	0.639	0.395
	Lagged patent status and pseudo fixed effect												
(8)	Patent dummy in t-1	-0.383***	0.129	-0.383***	0.128	-0.627***	0.174	0.029	0.196	-0.627***	0.173	0.031	0.196
(9)	Pseudo fixed effect	0.846***	0.056	0.848***	0.056	0.843***	0.069	0.979***	0.101	0.842***	0.069	0.987***	0.102
(10)	Number of sectors with sales	0.065	0.041	0.066	0.041	0.035	0.037	0.032	0.109	0.037	0.036	0.032	0.109
(11)	Number of firm subsidiaries	-0.036***	0.010	-0.037***	0.010	-0.032***	0.009	-0.018	0.029	-0.032***	0.009	-0.017	0.029
	Sector dummies												
(12)	High-technology manufacturing	0.741***	0.288	0.731**	0.289	0.125	0.357	1.478***	0.368	0.116	0.355	1.479***	0.369
(13)	Medium-high-technology manufacturing	0.350*	0.207	0.349*	0.207	0.400*	0.229	0.249	0.301	0.385*	0.229	0.265	0.302
(14)	Low-technology manufacturing	-0.028	0.219	-0.039	0.219	-0.023	0.226	0.056	0.375	-0.038	0.226	0.044	0.373
(15)	Knowledge-intensive services	0.908***	0.187	0.885***	0.187	0.867***	0.226	0.868***	0.269	0.846***	0.226	0.842***	0.271
(16)	Less knowledge-intensive services	0.190	0.181	0.180	0.181	0.097	0.239	0.173	0.239	0.078	0.240	0.165	0.239
	Year dummies	included		included		included		included		included		included	
	Number of observations	**71092**		**71092**		**33866**		**36819**		**33866**		**36819**	
	Non-zero obs	2308		2309		1515		793		1515		793	
	Wald chi2	1552.50		1548.24		1015.65		788.28		1007.46		784.97	
	Hypotheses tests												
	Hypothesis 1:	*Chi2*	*p-value*										
	(1) = (2)	7.65	0.006										
	Hypothesis 2:			*Chi2*	*p-value*								
	(3) = (4)			4.32	0.037								
	Hypothesis 3:					*Chi2*	*p-value*						
	(2) of model 3_high > (2) of model 3_low					3.681	0.053			*Chi2*	*p-value*		
	(4) of model 4_high > (4) of model 4_low									3.861	0.049		

Notes: ML-estimates with (robust) standard errors are reported. Statistical significance is indicated by stars (*: 10%, **: 5%, ***: 1% significance level). Reported is the estimation of the number of the (citation-weighted) patent counts based on the Negative Binomial distribution. Results corresponding to the zero inflation probability equation are not reported but are available upon request.

Table 3: Newly hired high-skilled migrants and firms' entry into new technology fields

	Dependent variable: new-IPC-entry patent counts	**Model 1**		**Model 2**		**Model 3**				**Model 4**			
						High		**Low**		**High**		**Low**	
		Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
	Highly skilled employment shares												
(1)	Hiring natives	0.339**	0.169	0.341**	0.170	-0.018	0.238	0.509**	0.206	-0.022	0.239	0.509**	0.206
(2)	Hiring migrants	2.489***	0.429			3.219***	0.659	1.364***	0.348				
(3)	Hiring migrants from similar culture			1.613***	0.521					1.709	1.444	1.365***	0.524
(4)	Hiring migrants from dissimilar culture			2.726***	0.495					3.531***	0.767	1.365***	0.404
	Capital and highly skilled labor												
(5)	ln(total highly skilled workers)	0.414***	0.037	0.412***	0.037	0.370***	0.048	0.628***	0.061	0.369***	0.048	0.628***	0.061
(6)	ln(capital stock)	0.059***	0.017	0.058***	0.017	0.049***	0.018	0.073**	0.029	0.048***	0.018	0.073**	0.029
(7)	***Cultural diversity***	0.424***	0.142	0.413***	0.142	0.189	0.158	0.791***	0.278	0.168	0.159	0.791***	0.278
	Lagged patent status and pseudo fixed effect												
(8)	Patent dummy in t-1	-0.103	0.072	-0.107	0.073	-0.065	0.087	-0.011	0.127	-0.067	0.087	-0.009	0.127
(9)	Pseudo fixed effect	0.442***	0.038	0.443***	0.038	0.451***	0.043	1.148***	0.132	0.450***	0.043	1.147***	0.133
(10)	Number of sectors with sales	0.038*	0.020	0.039*	0.020	0.053***	0.019	-0.101**	0.043	0.054***	0.019	-0.101**	0.043
(11)	Number of firm subsidiaries	-0.028***	0.006	-0.028***	0.006	-0.031***	0.006	0.012	0.012	-0.031***	0.006	0.012	0.012
	Sector dummies												
(12)	High-technology manufacturing	0.601***	0.193	0.602***	0.193	0.507**	0.226	1.096**	0.554	0.511**	0.227	1.103**	0.549
(13)	Medium-high-technology manufacturing	0.311***	0.107	0.313***	0.107	0.419***	0.103	-0.076	0.208	0.419***	0.103	-0.075	0.208
(14)	Low-technology manufacturing	-0.286***	0.107	-0.288***	0.107	-0.121	0.095	-0.606**	0.269	-0.124	0.095	-0.604**	0.269
(15)	Knowledge-intensive services	0.443***	0.099	0.435***	0.100	0.365***	0.109	0.599***	0.159	0.356***	0.110	0.599***	0.160
(16)	Less knowledge-intensive services	-0.202*	0.105	-0.203*	0.105	-0.374***	0.111	0.145	0.176	-0.377***	0.111	0.145	0.176
	Year dummies	included		included		included		included		included		included	
	Number of observations	**62020**		**62020**		**31028**		**30598**		**31028**		**30598**	
	Non-zero obs	3365		3365		2470		895		2470		895	
	Wald chi2	2220.17		2219.89		1543.84		607.17		1544.23		606.90	
	Hypotheses tests												
	Hypothesis 1:	*Chi2*	*p-value*										
	(1) = (2)	20.79	0.000										
	Hypothesis 2:			*Chi2*	*p-value*								
	(3) = (4)			3.52	0.061								
	Hypothesis 3:					*Chi2*	*p-value*						
	(2) of model 3_high > (2) of model 3_low					5.84	0.015			*Chi2*	*p-value*		
	(4) of model 4_high > (4) of model 4_low									5.96	0.015		

Notes: ML-estimates with (robust) standard errors are reported. Statistical significance is indicated by stars (∗: 10%, ∗∗: 5%, ∗∗∗: 1% significance level). Reported is the estimation of the number of patents in new-to-the-firm technology fields based on the Negative Binomial distribution. Results corresponding to the zero inflation probability equation are not reported but are available upon request.

Table 4: Additional analyses and robustness checks

	Dependent variable: Citation-weighted patent counts	Poisson GMM with instruments		High- vs. Low-dissimilar cultures		Sample of patenting firms		Include regional dummies	
		Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
	Highly skilled employment shares								
(1)	Hiring natives	-15.247	11.215	0.332	0.287	0.258	0.293	-0.382	0.328
(2)	Hiring migrants	12.605***	1.364			2.694***	0.821	2.444***	0.764
(3)	Hiring migrants from similar culture			0.308	1.096				
(4)	Hiring migrants from high-dissimilar culture			3.069***	1.036				
(5)	Hiring migrants from low-dissimilar culture			2.977**	1.191				
	Capital and highly skilled labor								
(6)	ln(total highly skilled workers)	1.785***	0.230	0.424***	0.055	0.411***	0.055	0.485***	0.079
(7)	ln(capital stock)	-0.067	0.056	0.008	0.035	0.019	0.035	0.029	0.053
(8)	***Cultural diversity***	0.012	0.819	0.608**	0.238	0.617***	0.239	1.309***	0.365
	Lagged patent status and pseudo fixed effect								
(9)	Patent dummy in t-1	0.683	0.614	-0.382***	0.128	-0.305**	0.137	-0.507**	0.209
(10)	Pseudo fixed effect			0.848***	0.056	0.803***	0.057	0.651***	0.097
(11)	Number of sectors with sales	0.082*	0.042	0.066	0.041	0.071*	0.041	0.038	0.073
(12)	Number of firm subsidiaries	-0.045**	0.018	-0.037***	0.010	-0.037***	0.010	-0.069***	0.025
	Sector dummies								
(13)	High-technology manufacturing	1.532**	0.656	0.729**	0.289	0.703**	0.284	0.819*	0.484
(14)	Medium-high-technology manufacturing	2.153***	0.434	0.348*	0.206	0.383*	0.210	-0.267	0.263
(15)	Low-technology manufacturing	1.394**	0.656	-0.040	0.219	0.007	0.217	-0.434	0.294
(16)	Knowledge-intensive services	-0.712	0.557	0.882***	0.187	0.852***	0.191	0.656**	0.279
(17)	Less knowledge-intensive services	-2.388***	0.695	0.178	0.181	0.127	0.184	0.021	0.287
	Year dummies	excluded		included		included		included	
	Regional dummies	excluded		excluded		excluded		included	
	Number of observations	**51165**		**71092**		**8858**		**25481**	
	Non-zero obs	-		2308		2308		776	
	Wald chi2	-		1551.97		1590.31		1726.49	
	Hypotheses tests								
	Hypothesis 1:	*Chi2*	*p-value*			*Chi2*	*p-value*	*Chi2*	*p-value*
	(1) = (2)	5.85	0.016			7.73	0.005	8.82	0.003
	Hypothesis 2:			*Chi2*	*p-value*				
	(4) = (5)			0.00	0.953				
	Hypothesis: all regional dummies=0							*Chi2*	*p-value*
								113.58	0.000

Notes: ML-estimates with (robust) standard errors are reported. Statistical significance is indicated by stars (∗: 10%, ∗∗: 5%, ∗∗∗: 1% significance level).