The effect of high-skilled migrant hires and integration capacity on firm-level innovation performance: Is there a premium?

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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 the acculturation costs are relatively low for high-skilled migrants while the innovation-related benefits deriving from diversity are relatively high, innovation performance should increase a fortiori if the high-skilled migrant employees 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.
INTRODUCTION

Migration of high-skilled workers into advanced countries is an important feature of today’s world economy, and especially important economic sectors that are knowledge-based. 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 for 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 of a high-skilled “migrant innovation premium” which goes beyond the benefits from hiring high-skilled natives. In the case that we identify such a premium, we explore whether its impact differs according to the cultural proximity of the migrants and the host country, and whether there is 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. At the individual level, Almeida and Phene (2015) show that Indian immigrant inventors’ ability to draw on knowledge from their ethnic communities 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 increasing 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. Filatotchev et al. (2011) show that that Chinese returnee entrepreneurs create a significant spillover effect which promotes innovation in other local high-
The literature suggests also that high-skilled migration and entrepreneurship are linked (see for instance, Kenney and Patton, 2015; Lee and Eesley, 2018). At the organizational level, knowledge transfer success among returnee immigrants has been shown to depend on their embeddedness in both their home- and host-country workplaces (Wang, 2015). Similarly, Choudhury and Kim (2018) show that a national increase in the supply of first-generation ethnic migrant inventors increases patenting in the host firms of knowledge previously lodged in the home region cultural context. 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).

Nevertheless, in the context of firm-level strategies, we know little about the potential impact of hirings of high-skilled migrants on corporate innovation performance (however see, Gagliardi, 2015), and the contingencies that might affect this relationship. The learning-by-hiring literature shows that recruitment of high-skilled workers is an important source of knowledge which affects the hiring firm’s innovation-related problem-solving abilities (e.g., Almeida and Kogut, 1999; Song et al., 2003; Hoisl, 2007; Corredoira and Rosenkopf, 2010; Palomeras and Melero; Ganco et al., 2015), and innovation performance (Kaiser et al., 2018). However, to our knowledge this strand of work does not investigate the effects of hiring high-skilled migrant as opposed to high-skilled native workers. We address this question in the present paper.

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 derived from hiring high-skilled migrants with experience from different home countries, with respect to firm-level innovation performance. We argue that recruitment of migrants rather than natives with other types of experience allows different perspectives on innovation-related problem-solving and
access to other knowledge networks. Combined with the incumbent employees’ problem-solving abilities and networks, we posit that migrant hires should lead to superior firm-level innovation performance. Since a different approach to problem-solving and access to non-overlapping knowledge networks furthers innovation, we hypothesize that hiring high-skilled migrants from dissimilar cultures should contribute more to the firm’s innovation performance than recruiting high-skilled migrants from similar cultures. However, the acculturation involved in integrating and utilizing migrants has some costs (Berry, 2001). Therefore, and building on an organizational learning argument 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 in what we term “integration capacity”, produces variation in the firm-level net benefits for innovation from hiring high-skilled migrants.

Our contribution is novel compared to prior research on firm-level employment of high-skilled migrants and the effect on innovation performance. Gagliardi (2015) investigates the effect of highly skilled migrants in Britain on innovation outcomes at the regional and firm levels. While both our and Gagliardi’s (2015) papers analyze firm-level outcomes, there are important differences. First, while the latter studies the effect of the share of high skilled migrant employment in the firm, we investigate the firm’s annual inflows of high skilled migrants. Second, we rely on panel data whereas Gagliardi relies on cross-sectional data. Third, Gagliardi measures firm innovation outcome using a dummy variable for whether the firm introduced a product or process innovation while we use the firm’s patent applications and forward citations to measure firm-level innovation performance. Finally, unlike Gagliardi (2015) we establish and test contingency hypotheses related to important differences among both migrants and firms, and their effect on innovation performance.
We test our predictions using 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 movements of employees into the firms in our sample. We link these data to European Patent Office (EPO) patent and citations data which we use 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). We find support for our hypotheses.

THEORETICAL BACKGROUND

An important strand of work in the organizational learning literature highlights the significance of external learning involving the transfer of knowledge from other organizations and contexts (Easterby-Smith et al., 2008; Argote and Miron-Spektor, 2011). Employee mobility is an important mechanism of knowledge transfer (Levitt and March, 1988; Argote et al., 2000). However, Argote and Miron-Spektor (2011) point to major differences in the value of type of experience with respect to learning outcomes, and suggest that different types of experience can be substitutes for or complements to each other. In focusing on researcher mobility between geographies and consequent firm-level innovation performance, we argue that the type of experience brought to the firm will matter for the firm’s subsequent innovation performance. We propose that new hired high-skilled migrants embody different experience from new hired high-skilled natives. 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, and will increase the diversity in the hiring organization and in turn, increase innovation performance.

There are costs related to hiring migrants. In a seminal contribution, Berry (2001: 616) describes the psychological aspect of immigration in intercultural space as *acculturation*:
“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. In the conflict phase, immigrants experience difficulties. In contexts of high levels of conflict, their experience will be problematic and may result in acculturation stress. In the crisis phase, individuals employ strategies such as integration, assimilation, separation and marginalization to try to deal with problematic experiences. In the adaptation phase, immigrants’ behavioral change is less problematic, stress is likely to be minimal, and long-term adaptation is usually the 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 firm’s 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). However, in the context of innovation, diversity in human capital is important mainly because it results in different perspectives on problem-solving (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). Here, cultural diversity is understood as meaning involving different nationalities.

Our 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 perspectives 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 the confines of an innovation project. 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 benefit innovation.

Our second argument is that given that diversity brings the possibility of (re)combining different bodies of knowledge, a culturally diverse organization should increase the chances that organizational members can draw on different bodies of knowledge as they are likely to belong to different external networks often embedded in different types of social as well as national and ethnic communities. This is important because research shows that knowledge flows are localized in nature (e.g., Jaffe et al., 1993; Alcácer and Chung, 2007; Bell and Zaheer, 2007; Breschi and Lissoni,
2009; Knoben, 2009) with the result that knowledge flows are channeled mainly through social relationships among individuals within a 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 their networks perhaps in a (national) community (Almeida et al., 2015), and this knowledge is likely to be different from the knowledge possessed by native employees. Knowledge assumes national characteristics due to differences in 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 not only brings with it access to knowledge that circulates in the particular community but also the trust and saliency of the knowledge obtained (Almeida et al., 2015). Groups of high-skilled migrants from the same origin country living in the same host country can be expected to have more faith in 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 diversity 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 increase diversity in perspectives on problem-solving only marginally. If the networks to which the new hires belong are similar to those participated in by the incumbent native employees, then
migrant hiring will give access to only marginally different knowledge. However, the potential positive benefits from migrant recruitment will be much larger if the new hire brings substantially different experience and belongs to different networks compared to the incumbent employees. This is more likely if the new hire is from a dissimilar culture. However, such hirings will increase 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 a greater cultural distance implies a greater need to shed culture and cultural learning, and these greater differences could trigger negative intergroup attitudes and cultural conflicts. From this perspective, it is unclear whether there will be an increase in the net benefit from hiring an individual from a dissimilar culture compared to recruiting a similarly skilled person with experience of a more similar culture. However, in the particular case of the high-skilled migrants considered in this paper, we suggest that these net benefits are positive.

Our argument is that high-skilled migrants have university science degrees and often belong to the elite in their home countries. Their level of education implies that they are likely to have specialist science-based knowledge. Given the universalism of science (Gittelman, 2007) this knowledge is less context-specific than other types of knowledge. For instance, the same engineering and biology text books (even if translations) are used the world over. Thus, individual high-skilled job tasks in the recruiting organization will likely be familiar to the newly recruited migrant. In addition, highly educated people are likely to follow international media and are more likely also to have relatives and friends living in other countries. For these reasons, high-skilled migrants are likely to possess important knowledge about the functioning of other cultures, including that of the new host country. Highly-educated people are not only better
informed about foreign cultures but also as a result of their education are 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 educational background of their parents (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 lower than for other types of migrants. Given these lower 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 a dissimilar culture 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 very likely to outweigh the additional costs of employing migrant workers. However, there are other costs related to working with individuals with different attitudes, values, goals, knowledge, beliefs and behavior (Hofstede, 1980) from most of the firm’s employment. We argue 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, integration capacity with respect to innovation can be defined as the firm’s ability to identify and assimilate migrants productively into its organization and innovation process. A high integration capacity implies that the acculturation process speed can be increased for newly hired migrants. In other words, firms with good integration capacity should be able (compared to firms with a low integration capacity) to reap the innovation-related benefits of increased diversity from hiring high-skilled migrants while experiencing lower 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 also 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 be informative about which types of migrants should be recruited to benefit innovation. Also, existing migrant employees 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 identifying those migrants that will be the best fit for the firm with respect to increasing innovation performance.

The second antecedent is the work-organization effect which refers to having established 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). Work-organization to an important extent is likely 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 whose management will reduce problems in the workplace. For instance, the HR department’s experience of migrant employees will allow better management of new migrant hires, the firm may have developed practices which imply that natives and non-natives must collaborate, and the workplace may have a more international feeling which will make it more welcoming and accommodating for 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 located in the Netherlands during the period 2000 to 2010. We include all firms that applied for at least one European (EPO) patent during the period 2000-2010 and firms that are R&D active but did not apply for a patent during that period. The Netherlands is an interesting setting for our study because it attracts a significant number of high-skilled migrants. In 2015 and 2016, numbers of incoming high-skilled migrants were respectively 12,000 and 14,000 due in particular to the introduction of a simple and fast procedure for resident permits and provision of temporary tax benefits such as the 30% tax facility (Immigration and Naturalization Service Annual Report, 2015, 2016).

To collect the 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 may register patents under different names, e.g. 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 firms’ group structure such as the names and ownership of all Dutch subsidiaries. We chose Dutch enterprise group as the level of analysis.

Statistics Netherlands provided us with firm registry data from its Statistics for Non-financial Enterprises which contain sectoral affiliation, sales, book value of physical capital, and employee information such as end-of-year listings of all employees and their 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. 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 al., 1987; Hagedoorn and Clooût, 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 obtain a comparable citation window across patents. We include all patent citations (in patents filed with various patent offices) to the 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 (SSB) are used to define *high-skilled workers* with expertise that contributes to the firm’s innovation output. This approach to defining skills is based on the concept of knowledge workers; 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 educational background of all workers in the Netherlands, to proxy for skills we use wage data rather than the more commonly used information on education (e.g.,
Kaiser et al., 2015; Kaiser et al., 2018). The literature suggests a close relationship between education and wages (e.g., Mincer, 1958; Farber and Gibbons, 1996) which justifies our use of wages to proxy for employee skills. To control for the 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 with at least 12 months’ duration. High-skilled workers are defined as equal to or above the 75% percentile of the wage distribution.

Figure 1 depicts the relationship between education level and employee rankings 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 SOI education codes: primary and lower-secondary education (low education), higher-secondary education and post-secondary education (medium education) and higher education (high education). Figure 2 shows the close relationship between the level of education of employees 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 the migration database maintained by Statistics Netherlands which provides data on 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) added 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 one of the six other countries 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 split further 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 it employs a higher number 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, $\ln(\# \text{ high-skilled workers})$ which is the natural logarithm of the total number of high-skilled workers. Second, $\ln(\text{capital})$ expressed as the natural logarithm of the firm’s physical capital. Third, we control for sector by including six categories reflecting 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). Fourth, we include year dummies and control for number of fully controlled firm subsidiaries and the number of industry segments (NACE 3 digit level) in which the firm is active. Five, we control also for possible state dependence in innovation output. In line with Kaiser, Kongsted and Rønde (2015), we include a dummy for whether the firm patented in t-1. Sixth, 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 Rønde (2015). This relies on use of 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 high-skilled workers (L) in a firm is constituted by three categories of workers: high-skilled stayers (L_{st}), new high-skilled migrant hires (L_M), and new high-skilled native hires (L_N).\textsuperscript{1} This can be written as follows:

\[ L = L_{st} + \gamma_M L_M + \gamma_N L_N \]  
\[ L = L \left(1 + (\gamma_M - 1) \frac{L_M}{L} + (\gamma_N - 1) \frac{L_N}{L}\right) \] 

The coefficients \( \gamma_M \) and \( \gamma_N \) indicate the contribution of a newly hired high-skilled migrant and a newly hired high-skilled native to the total pool of high-skilled workers relative to the contribution of a high-skilled stayer (for which the 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:

\[
E(P) = \exp \left[ \ln(A) + \alpha \ln(L) + \alpha_M \frac{L_M}{L} + \alpha_N \frac{L_N}{L} + \beta \ln(K) \right]
\]

where \( \alpha_M = \alpha(\gamma_M - 1) \) and \( \alpha_N = \alpha(\gamma_N - 1) \), \( E(P) \) is the expected citation weighted patent count, \( K \) is physical capital, and \( A \) is the remaining determinants of \( P \) (sector, year, firm group structure, sales diversification, and pre-sample average). We estimate coefficients \( \alpha_N \) and \( \alpha_M \) but refer to the productivity ratios \( \gamma_N \) and \( \gamma_M \) to obtain an indication of the size effects of hiring high-skilled native and migrant workers.

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 that many firms have zero patent counts during

\textsuperscript{1} 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.
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 that the model fit is better using zero-inflated negative binomial instead of the standard negative binomial models.

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. The advantage of pseudo fixed effect models is that unlike conventional fixed effects 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, i.e., for firms entering the dataset in 2002 this would be the period 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, 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, firms on average hire four times more migrants from dissimilar compared to similar cultures. On average, the firms in our sample are active in 1.8 sectors and have 2.5 subsidiaries. The correlations between the explanatory variables included simultaneously in the regressions are generally low,

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2 We have added a value equal to one before the logarithmic transformation
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 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.

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. For an indication of the size effect of hiring migrants, we calculate the productivity ratio of hiring migrants ($\gamma_M$) where $\gamma_M = 1 + \frac{\alpha_M}{\alpha}$. The productivity ratio $\gamma_M$ equals 7.03 which implies that a new high-skilled migrant hire contributes seven times more to the firm’s innovation performance than a high-skilled stayer. 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.

In addition to the focal variables, total high-skilled workers 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 hiring
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 = 0.06) which
lends support to Hypothesis 2. In terms of size effects, we find that a new high-skilled migrant
hire from a dissimilar culture contributes 8.14 times more to the firm’s innovation performance
than a high-skilled stayer; we found no innovation performance premium for a new high-skilled
migrant recruited from a similar culture compared to a high-skilled stayer.

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 2.6 times higher for the high integration capacity sample compared to the low integration
capacity sample. A t-test shows that the coefficients differ (p-value = 0.019). 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 while a new high-skilled migrant hire is 5.38 times more
productive than a high-skilled stayer for firms with low integration capacity, this innovation
premium increases to 10.55 for firms with high integration capacity. In line with prior results, we
found no innovation performance premium for new high-skilled native hires compared to high-
skilled stayers.
For completeness, we checked 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 are positive and significant for hiring culturally dissimilar migrants. The coefficient of hiring migrants from dissimilar cultures is 2.6 times higher in the high integration capacity group compared to the low integration capacity sample. A t-test shows that the coefficients differ (p-value = 0.016). Hence, the firm’s integration capacity seems to matter in the case of hiring migrants from dissimilar rather than similar cultures.

ALTERNATIVE EXPLANATIONS AND ROBUSTNESS CHECKS

In this section, we discuss possible alternative explanations that potentially might be driving our findings, and the results of a number of alternative models to check the robustness of our findings (results not included here for reasons of space). One alternative explanation for our main research finding that there is an innovation premium from hiring high-skilled migrants rather than high-skilled natives, might be that this premium is not driven by the migrants’ unique experience but is the outcome of remaining unobserved differences in the quality of the highly-skilled migrants and natives (not controlled for using wage distributions to identify equally high-skilled migrants and natives). For example, it might be that firms are only willing to incur the acculturation costs associated to hiring migrants if those migrants are (perceived to be) more skilled than the best available native workers.

To test which explanation is driving our results, we examine whether the premium from migrant hiring depends on the recency of their foreign (origin) experience. Here, we differentiate between recently arrived and longer resident migrants in the host country.3 In the case that our

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3 We define recent as arriving in the new host country less than three years ago.
experience-based explanation holds, we can expect a stronger effect of hiring recent compared to non-recent migrants on firms’ innovation performance. This is because more recent migrants will embody unique experience (perspectives and networks) acquired in their home countries. If the alternative skill-based explanation is driving our results, we can see no clear reason to expect performance differences between these groups of newly hired migrants. The coefficients of hiring recent and non-recent migrants are both positive and significant. In line with our experience-based explanation, the coefficient of hiring recent migrants is much larger (5.4 times) than the coefficient of hiring non-recent migrants. A Wald-test shows that both coefficients are statistically different (p-value = 0.025) from each other. These results allow minimize concerns about the skill-based alternative explanation for our results.

A second alternative explanation for our finding of an innovation premium from hiring high-skilled migrants rather than high-skilled natives may 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 jointly be determining innovation performance and hiring high-skilled migrants. This type of unobserved time-varying heterogeneity is not accounted for in our main estimations (which do include a presample mean to control for time-constant firm effects). Therefore, we ran a general method of moments (GMM) regression for our main regression (Model 1) 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 effects and lagged dependent variables. We instrument migrant hiring, native hiring, and the total number of high-skilled workers with information on the (average) yearly percentage
change in (non-Dutch) migrant inflows in the OECD countries excluding the Netherlands. The idea of this instrument is that the growth in migration flows across other countries may be the result of exogenous shocks (e.g. rules, changes in economic growth, macroeconomic policy shocks, etc.) that affect changes in migration flows to the Netherlands. The additional instruments we use are based on Kaiser et al. (2015) and include the firm’s own lagged labor variables values, average hiring variables values for all other firms in the Netherlands in the same sector (NACE 2 level), and sector and year dummies. Running the GMM regression reduces the sample to 63,185 observations due to using lagged variables as instruments. The GMM results are similar to the presample mean estimations: the coefficient of hiring high-skilled natives is insignificant but is positive and significant for hiring high-skilled migrants.

We performed a number of checks to test the sensitivity of our results. First, we examined the robustness of our findings to restricting our sample to firms that filed a patent at the EPO at least once during the period 2002-2010. The rationale for this robustness check is that not all firms patent their innovations. This reduced the sample hugely — from 71,092 to 8,858 observations. Nevertheless, our empirical findings are supported if we restrict the sample only to patenting firms. Second, there is a strong concentration of patenting activity among a small number of sectors and firms, especially the electrical and electronics sectors (NACE 26-27) in the Netherlands. Therefore, we analyzed the robustness of our results to removing the firms in these two sectors. The results are comparable to those reported in Table 2.

We investigated also whether our main result holds if we use total factor productivity (TFP) growth instead of citation-weighted patent counts to indicate firm innovation performance. TFP growth is calculated as a Solow residual and measures change in output which can be explained by all 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 handles endogeneity of the right hand side variables by using their lagged values (in first differences and levels) as instruments. In using the specification in Model 1, the significant effect of hiring skilled migrants is again confirmed, and the effect of hiring high-skilled natives remains insignificant.

Finally, we checked the robustness of our findings to a different definition of countries culturally similar to the Netherlands. Specifically, we added to the group of culturally similar countries former colonies of the Netherlands among which Surinam and Netherlands Antilles are countries of origin of a high proportion of high-skilled migrants; in 2010 these two countries accounted for some 15% of new high-skilled migrant hires by our sample firms. We reclassified migrants from Surinam and Netherlands Antilles into the group of culturally similar countries and re-estimated our regression models. Again, the results are very similar to those presented in Table 2.

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. 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 leveraged the organizational learning argument to argue that since integrating and utilizing migrants is likely to be costly due to the problems migrants may experience during the acculturation process, firms with more 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 migration and mobility literatures by proposing a theoretical and empirical framework which both specifies why firms innovation performance can benefit from hiring high-skilled migrants, and highlights some important conditions under which firms can benefit from recruiting these workers. Our focus 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 the recent call 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 respond 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. More precisely, we found a much stronger effect of hiring recent compared to non-recent migrants on firms’ innovation performance. This suggests that our results are driven by the increased heterogeneity in the workforce rather than the quality of the migrant human capital recruited.

We suggested that integrating migrant hires in the innovation process might be costly due to the acculturation process required. However, we proposed that different experience of migrant hiring among firms matters for achieving a smoother acculturation process. 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 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 by
the recruiting firm and learning how best to 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 concern 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 is a limitation. 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 should look more deeply into firms’ specific investments in ways to integrate high-skilled migrants in the innovation process. These means might include specific procedures and work-practices aimed at integrating a diverse set of high-skilled employees.

Finally, our dependent variable reflects firms’ (quality-adjusted) total innovation performance. 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>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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<th>(10)</th>
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<td>(2) Hiring migrants</td>
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<td>0.088</td>
<td>0.088</td>
<td>1</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(3) Hiring migrants from similar culture</td>
<td>0.006</td>
<td>0.036</td>
<td>0.041</td>
<td>0.431</td>
<td>1</td>
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<td></td>
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<td>(4) Hiring migrants from dissimilar culture</td>
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<td>(8) Pseudo fixed effect</td>
<td>0.038</td>
<td>0.242</td>
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<td>(10) Number of firm subsidiaries</td>
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<td>-0.002</td>
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<td>0.158</td>
<td>0.227</td>
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Table 2: Newly hired high-skilled migrants and firms’ innovation output

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<tr>
<th>Dependent variable: Citation-weighted patent counts</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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<td>Highly skilled employment shares</td>
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<td>0.299</td>
<td>0.363</td>
<td>0.299</td>
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<tr>
<td>(2) Hiring migrants</td>
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<td>0.752</td>
<td>4.449***</td>
<td>1.094</td>
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<td>(3) Hiring migrants from similar culture</td>
<td>0.485</td>
<td>1.184</td>
<td>3.061***</td>
<td>0.865</td>
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<tr>
<td>(4) Hiring migrants from dissimilar culture</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital and highly skilled labor</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) ln(total highly skilled workers)</td>
<td>0.429***</td>
<td>0.055</td>
<td>0.429***</td>
<td>0.055</td>
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<tr>
<td>(6) ln(capital shock)</td>
<td>0.016</td>
<td>0.034</td>
<td>0.013</td>
<td>0.034</td>
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<tr>
<td>Lagged patent status and pseudo fixed effect</td>
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<tr>
<td>(7) Patent dummy in t-1</td>
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<td>0.131</td>
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<td>(8) Pseudo fixed effect</td>
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<td>(10) Number of firm subsidiaries</td>
<td>-0.037***</td>
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<td>Sector dummies</td>
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<td>(11) High-technology manufacturing</td>
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<td>(12) Medium-high-technology manufacturing</td>
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<td>(14) Knowledge-intensive services</td>
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<td>(15) Less knowledge-intensive services</td>
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<td>Wald chi2</td>
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<td>1505.65***</td>
<td>1006.14***</td>
<td>756.48***</td>
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Hypotheses tests

<table>
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<tr>
<th>Hypothesis 1:</th>
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<td>(1) = (2)</td>
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<table>
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<th>Hypothesis 2:</th>
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<td>(3) = (4)</td>
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<th>Hypothesis 3:</th>
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<td>(2) of model 3_high &gt; (2) of model 3_low</td>
<td>2.084</td>
<td>0.019</td>
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<tr>
<td>(4) of model 4_high &gt; (4) of model 4_low</td>
<td>2.134</td>
<td>0.016</td>
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</table>

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.