

HIGH-GROWTH FIRMS AND THE LABOR MARKET ENTRY OF FIRSTGENERATION IMMIGRANTS

SVEN-OLOV DAUNFELDT & HANS SEERAR WESTERBERG

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The number of refugees in Europe has increased dramatically in recent years, and many countries are facing great challenges to integrating these refugees into their societies. A small group of high-growth firms have at the same time attracted attention because they create the most new jobs at any given point in time. Using matched employer-employee data from Statistics Sweden, we find that these high-growth firms in general are more likely to recruit first-generation immigrants that are unemployed. This provides support for the hypothesis that managers in high-growth firms, to greater extents, recruit marginalized individuals because they want to take advantage of their growth opportunities and therefore do not wait for the best match. Rapidly growing firms are thus less selective in their hiring decisions, and policies that are focused on increasing the number of high-growth firms might also help immigrants who face difficulties entering the labor market.

Keywords: Firm growth; Gazelles; High-growth firms; Immigration; Integration; Labor market; Matching models; Resource based theory; Interaction effects; Logit; Odds ratio

JEL classification: D22; J15, L25, L26.

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1. Introduction

The matching process in the labor market is characterized by asymmetric information and high search costs (Mortensen and Pissarides, 1999). Asymmetric information occurs because employers have more information about the positions that they offer than jobseekers, while the latter group has more information about their particular skills. The matching process is further complicated by the fact that job-seekers have incentives to hide information that might prevent them from getting the position that they seek, while employers have incentives to hide facts to get the best job applicants.

Coad et al. (2014a) argued that high-growth firms (HGFs) under such circumstances are more likely to recruit individuals who have difficulties entering the labor market than other firms. The reason is that HGF-managers want to take advantage of their growth opportunities and therefore focus more on the pace of growth when recruiting new personnel. This implies that HGF-managers are less likely to wait for the best match and will recruit individuals who are more readily available on the labor market with less regard to their specific skills and prior experience. They found some support for their hypothesis by investigating the recruitment of HGFs in the Swedish knowledge-intensive industries, finding that HGFs were more likely to recruit immigrants and low-educated workers compared to non-HGFs.

However, Coad et al. (2014a) made no distinction between immigrants and natives that were unemployed, and they also found that HGFs were less likely to hire unemployed individuals. The unemployment rate is in general higher among first-generation immigrants than native workers and immigrants tend to be hired from other companies and not from the pool of unemployed (Daunfeldt et al., 2019). Immigrants' likelihood of being hired by an HGF might thus depend on whether they are unemployed or not, which means that we still lack knowledge on whether HGFs provide jobs for those immigrants that have difficulties entering the labor market.

We contribute to the literature by investigating the interaction effect between region of birth and employment status using a framework that was suggested by Buis (2010). We believe this to be important considering that first-generation immigrants have difficulties in establishing themselves in the labor market. As an example, the employment rate of non-EU migrants is more than 10% lower than for workers that are born in Europe (Eurostat, 2019). The large inflow of refugees in recent years, which constitutes one of

the greatest demographical changes in Europe since World War II (OECD, 2015), has also made the immigrant-native labor market gap even more alarming.¹

In total, we analyze 267,020 recruitments in 2015 by 53,168 firms that were active during the 2012-2015 period. Our study builds on an employer-employee dataset from Statistics Sweden that provides information on all residents in Sweden that are at least 16 years old. We believe that Sweden is of particular interest to study because of its high share of immigrants and its high inflow of refugees compared to other European countries.² Immigrants also have documented difficulties entering the Swedish labor market (Ekberg, 2009; Ekberg, 2012), and their problems seem to be large compared to other countries within Europe (Koopmans, 2010).³

We find that the 5% fastest growing firms in Sweden are more likely to hire immigrants from Africa and Asia, irrespective of whether HGFs are defined in terms of employment or sales growth, which support Coad et al.'s (2014a) previous findings. However, we also find that HGFs are more likely to recruit first-generation immigrants from Africa and Asia that are unemployed compared to non-HGFs. HGFs are thus more likely to provide jobs for marginalized groups, which indicates that they are less selective in their hiring decisions. Policies that stimulate risk-taking and high-growth entrepreneurship (see, e.g., Henrekson & Johansson, 2009) might thus also be important for improving the labor market position of unemployed first-generation nonwestern immigrants.

The rest of the paper is organized as follows. The description of how we have defined HGFs is presented in the next section, and the matched employer-employee dataset is described in Section 3. The estimated model and the results are then presented in Section 4. Finally, Section 5 summarizes and concludes.

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¹ The number of refugee arrivals exceeded one million both in 2015 and 2016 (EASO, 2017).

² The number of asylum seekers in Sweden reached, for example,163,000 in 2015 (Migrationsverket, 2016), which corresponded to more than three times as many asylum seekers per capita as in Germany (Eurostat, 2016).

³ The unemployment rate among foreign-born individuals in Sweden (16-64 years) was, for example, 17.3% in June 2019, while the corresponding figure for native-born workers was only 4.6%. As much as 29.6% of all unemployed immigrants are long-term unemployed, i.e., had been unemployed for more than 27 weeks. The employment rate is also significantly higher among native-born individuals (83.6%) than among foreign-born individuals (68%) (Statistics Sweden, 2019).

2. Defining high-growth firms

As noted by Davidsson and Delmar (1997), researchers that want to investigate HGFs need to make choices regarding the following: (i) the growth indicator, (ii) the growth measurement (relative vs. absolute change), (iii) the length of the study period, and (iv) the growth process.

To make our results comparable to Coad et al. (2014a), we follow their ways of defining HGFs. The number of employees and sales are the two most commonly used growth indicators (Delmar et al., 2003; Daunfeldt et al., 2014), and Coad et al. (2014a) use both of these growth indicators in their analysis. Although employment and sales growth are modestly correlated (Shepherd and Wiklund, 2009; Coad, 2010), the results are in general not sensitive to which one is chosen (Daunfeldt et al., 2014). However, they represent two different growth phenomena (Delmar et al., 2003). The growth in the number of employees shows how resources grow within the firm, whereas sales growth indicates product or service acceptance in the market.

Following Coad et al. (2014a), we also identify HGFs with respect to their relative growth rates. It is well known that relative growth rates tend to favor smaller firms, whereas absolute growth measures are biased toward larger firms (Delmar et al., 2003). Relative growth can be measured in various ways, e.g., percentage changes, taking log-differences or scaling down by initial size. Coad et al. (2014a) use Tornqvist et al.'s (1985) recommendation to use the log difference to calculate firms' growth rates, which we follow. The log difference has the advantage that the growth measure becomes symmetric for positive and negative growth rates, i.e., real changes in either indicator give the same percentage change, regardless of being positive or negative.

Regarding the length of the study period, most previous studies have used a three- or four-year period when identifying HGFs. However, the results do not seem particularly sensitive to the length of the growth period (Coad et al., 2014b). Coad et al. (2014a) use three-year growth periods when defining HGFs, which we thus follow.

The final choice relates to the researchers' ability to distinguish between organic and acquired growth in the data. Organic growth refers to growth that is internal to a firm, and acquired growth refers to growth that occurs through external acquisitions or mergers. In accordance with Coad et al. (2014a), we cannot distinguish between these

growth modes in the data and so we use a total growth measure (i.e., the sum of organic and acquired growth) when defining HGFs.

Given the choices that are described above, HGFs can be identified in two different ways. The first method defines HGFs as a certain share of the fastest growing firms during a particular period, i.e., the top 1% or 3% of firms that had the highest growth rates. One disadvantage with this method is that it cannot be used to compare the shares of HGFs across time or across countries (Coad et al., 2014b). The second approach defines HGFs as firms growing at or above a particular pace. Eurostat and the OECD have, for example, recommended that HGFs be defined as firms with at least 10 employees at the start-year and annualized employment growth exceeding 20% during a 3-year period (Eurostat-OECD, 2007). This definition is used in many studies (Bravo-Biosca, 2010; Du and Temouri, 2015; Nordic Council of Ministries, 2010; Hölzl, 2014; Teruel Carrizosa and De Wit, 2011) but has been criticized because the use of the firm size threshold level means that many firms are excluded from the analysis (Daunfeldt et al., 2015). Coad et al. (2014a) used the first approach and identified HGFs as the top 1% and 5% fastest growing firms, and we therefore adopt this definition as well.4

 $^{^{44}}$ The results are similar if we use the 3% fastest growing firms instead. The results are available upon request.

3. Data and descriptive statistics

We investigate the hiring decisions of HGFs in 2015 using matched employer-employee data from Statistics Sweden (SCB) covering the period from 2012 to 2015. The data are from LISA (Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier), a database that covers all legal residents of Sweden that are at least sixteen years old. It contains a wealth of demographic and financial information that is generated from a number of registers, such as individual tax statements, financial records, birthplace registries, and school records. We use this database to control for the individual characteristics that might influence whether the individual was hired by an HGF, including the region of birth, age, gender, education and family composition.

We use the register data from the Swedish Public Employment Service (*Arbetsförmedlingen*) to define employment status. This means that all individuals who were registered as full-time unemployed or participating in a labor market program by the end of November are defined as unemployed. An individual is defined as employed if she is not registered as full-time unemployed or participating in a labor market program but is registered with an association to a firm through a firm identification number.

Firm-specific data are collected from *Företagsdatabasen* (FTG), a database that includes information on corporate firms, excluding the financial sector, collective owned housing enterprises (*bostadsrättsföreningar*) and businesses engaged in the farming, forestry and hunting sectors. For a meaningful comparison between firms, we have restricted our sample to only include limited liability companies. Limited liability firms are selected because we want to focus our analysis on firms that are more likely to accept risk and pursue growth (Bradley et al., 2011). We also omit firms that had zero sales throughout the study period, since we want to focus our analysis on active firms.⁵ Finally, we use data on firm age from *Företagens och arbetsställenas dynamik* (FAD), a database that compiles information on firm structure changes, such as new entries and bankruptcies.

We use the region of birth of the individual to distinguish between different types of immigrants and to identify whether the individual is a second-generation immigrant. The

⁵ These firms correspond to about 5% of the observations in *FTG*.

following independent variables are included in our analysis to capture immigrant status (variable names in *italics*).

- *Second*. A dummy variable that captures whether the individual is a second-generation immigrant. It equals one if the individual was born in Sweden and both parents were born outside Sweden, and otherwise it is zero.
- *Nordic*. A dummy variable that equals one if the individual was born in Norway, Finland, Denmark or Iceland, and otherwise it is zero.
- *EU25*. A dummy variable that equals one if the individual was born in a country that belonged to the European Union in 2004 (excluding Finland, Denmark and Sweden), and otherwise it is zero.
- *Eur*. A dummy variable that equals one if the individual was born in another country in Europe other than the Nordic countries and the EU25, and otherwise it is zero. Note that this variable captures immigrants who were born in Romania and Bulgaria since they joined the EU in 2007. Individuals who were born in Turkey are also included here.
- *Africa*. A dummy variable that equals one if the individual was born in Africa, and otherwise it is zero.
- *South Am*. A dummy variable that equals one if the individual was born in South America, and otherwise it is zero.
- *Asia*. A dummy variable that equals one if the individual was born in Asia, and otherwise it is zero.
- Other. A dummy variable that equals one if the individual was born in a country
 that is not captured by the variables above, and otherwise it is zero. Individuals
 who were born in the former Soviet Union, North America, and Oceania, as well as
 unknowns and foreign-born individuals with at least one Swedish parent, are
 included here.

Following Coad et al. (2014a), we also control for other characteristics, both individual and firm-specific, that might influence the hiring decisions of high-growth firms. More specifically, we include the following controls in the estimated equation.

- *Female*. A dummy variable that equals one if the individual is a woman and zero if the individual is a man.
- Age. Age of individuals who are 16 years or older.

- *Married*. A dummy variable that equals one if the individual is married or cohabiting and zero if single.
- *Child*. A dummy variable that equals one if children under the age of 18 are present in the household, and otherwise it is zero.
- *Educational attainment. Primary*=1 if the individual completed primary school, *High* =1 if the individual completed a 3-year high-school education, and *Uni*=1 if the individual completed a university program of at least three years. The baseline is those individuals who have less than 9 years of schooling, i.e., did not complete primary school.
- *Firm age.* This variable ranges from 4 to 25 years. Firm age is in most cases calculated by subtracting the entry year from the observation year.⁶
- *Firm size*. Number of employees in year *t-1*, i.e., the year before hiring.

3.4 Summary statistics for incumbent employees in HGFs

Our sample is restricted to individuals who were hired by a limited liability firm in 2015 but were classified as unemployed or employed in another firm in 2014. The final sample consists of 267,020 individuals, of whom 855 % were job changers and 19.7% were unemployed in 2014. The descriptive statistics for all new hires that were hired by non-HGFs, employment-HGFs and sales-HGFs are presented in Table 1.

[Table 1 about here]

The shares of hired immigrants are similar among HGFs and non-HGFs, while employees who were hired by HGFs, on average, had less schooling than those who were recruited by non-HGFs. The descriptive statistics also show that individuals who were hired by HGFs were more likely to be recruited by a young and small firm compared to those individuals who were hired by non-HGFs.

Next, to investigate whether HGFs are more likely to hire unemployed immigrants than non-HGFs, we exclude job-switchers and reduce our sample to those individuals who were unemployed in 2014 and became employed during 2015 (Table 2). The results then

⁶ Firms that are not recorded in FAD but are observed in FTG are considered new firms once they enter FTG (11-12 % of the matched sample). Finally, firms that in FAD are founded at a later point but previously appear in FTG are recoded according to their first appearance (11-14 % of the matched sample).

show that the share of Swedish born individuals is twelve percentage points lower among non-HGFs and up to 19 percentage points lower among HGFs compared to all hires (Table 1). It is thus more common that foreign-born individuals are hired from unemployment, and this difference is even more apparent among firms that are rapidly growing. Note, finally, that the composition of foreign-born workers is marginally different if we choose to define HGFs in terms of employment or sales.

[Table 2 about here]

4. Empirical Method

We are capturing the recruitment decisions of HGFs by using the dichotomous variable HGF_{i2015} that takes the value one if an individual i is hired by an HGF in year 2015 and zero if the individual is hired by a non-HGF. Coad et al. (2014a) analyzed the same dependent variable using a Probit model but did not include any interaction effects. These effects are difficult to interpret in nonlinear models because the full interaction effect is different from the marginal effect of the interaction term in a nonlinear model (Ai and Norton, 2003; Norton et al., 2004).⁷ The Probit model is thus not suitable when investigating if the effect of unemployment on the likelihood of being hired by an HGF is moderated by the region of birth.

One possible way to solve this problem, which was proposed by Buis (2010), is to estimate a logit model where the dependent variable is measured using odds and then use a margins command in Stata to obtain the interaction effects for every possible combination of the immigrant term. We follow this approach and assess how being an immigrant (I_i =1) influences the odds of being hired by HGFs compared to the odds of being hired by non-HGFs in the following way:

$$\frac{p(HGF_{i,2015} = 1 | I_i = 1)}{1 - p(HGF_{i,2015} = 1 | I_i = 1)} = \exp(\beta_I + \beta' X), \tag{1}$$

where X is a vector of variables that are assumed to influence the odds of being hired by an HGF. It includes an unemployment dummy ($U_{i,2014}$) that takes the value of one if the

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⁷ Despite this difficulty, interaction effects are often used in nonlinear models. Ai and Norton (2003), for example, found 72 papers in economics journals from 1980-2000 that analyzed interaction terms in a nonlinear model. However, none of them correctly interpreted the interaction effects.

individual was unemployed in 2014 and zero if employed by another firm. It also includes the individual's gender, age, marital status, educational attainment, and the presence of children in the household in 2014. Following Coad et al. (2014a), we also include a vector of firm-specific characteristics to control whether the decision to be hired by an HGF is related to the age or the size of the firm. Finally, vectors of industry- and region-specific fixed effects are included to control for the time-invariant heterogeneity at the industry and regional levels, respectively.

The odds for nonimmigrants being hired by HGFs are as follows:

$$\frac{p(HGF_{i,2015} = 1 | I_i = 0)}{1 - p(HGF_{i,2015} = 1 | I_i = 0)} = \exp(\beta' X).$$
 (2)

The odds ratio for being an immigrant is then the odds for immigrants being hired by HGFs divided by the odds for nonimmigrants being hired by HGFs:

$$\frac{\exp(\beta_I + \boldsymbol{\beta}' \boldsymbol{X})}{\exp(\boldsymbol{\beta}' \boldsymbol{X})} = \exp(\beta_I)$$
 (3)

The odds ratio thus measures the expected number of immigrants being hired by an HGF for every immigrant being hired by a non-HGF. Note that the estimated coefficient will measure the effect of being an immigrant, holding all other variables constant at zero.

We include an interaction term, $I_i * U_i$, in the vector of explanatory variables, X, because we want to investigate if the effect of unemployment on the odds of being hired by an HGF is different for immigrants and natives. However, the estimated coefficient of the interaction term will only measure the odds of being hired by an HGF for immigrants who are unemployed (I_i =1; U_i =1) compared to the baseline. To study if the effect of unemployment on the odds of being hired by HGFs differs between immigrants and nonimmigrants, we follow Buis' (2010) recommendation to use the margins command to calculate every combination of the interaction term.

5. Results

Estimates regarding which individuals are hired by HGFs are presented in Table 3 for both employment-HGFs and sales-HGFs. Note that the interaction effects are excluded to

save space⁸ and that all results are presented as odds ratios, which means that an estimated coefficient less than one indicates that its corresponding variable is negatively related to the probability of being hired by an HGF, whereas an estimate larger than one indicates a positive association.

[Table 3 about here]

We find that the odds of first-generation immigrants of several regional origins are up to 52% higher than those of natives in regard to recruitment by the top 1% fastest growing employment-HGFs. Specifically, we find positive and significant effects among immigrants from the EU (31.9%), Eastern Europe (52%) and Africa (51%). We find no such recruitment patterns when we investigate the top 5% fastest growing employment-HGFs. With respect to sales-HGFs, we find no evidence of higher odds among immigrant groups for being hired by the 1% fastest growing firms. In contrast, the odds are higher among first-generation immigrants from the EU (19.3%) and Africa (33.4%) in regard to recruitment by the 5% fastest growing firms in terms of sales.

Note, however, that immigrants who are switching job positions are included in the estimated effect of being an immigrant on the odds of being hired by an HGF. Therefore, we cannot conclude from the estimates above how being an unemployed immigrant affects the probability of being hired by an HGF. The results that are presented in Table clearly show that the odds of being hired by HGFs are lower for unemployed individuals. According to the results that are presented in Table 4, the odds decrease by (0.824-1)*100 = -17.6%, (0.74-1)*100 = -26%, and (0.865-1)*100 = -13.5% for both the top 1% and 5% fastest growing employment-HGFs and the top 5% fastest growing sales-HGFs, respectively. Thus, HGFs are not a general recruitment base for individuals who are unemployed and have difficulties entering the labor market. Note finally that the effect of unemployment on the likelihood of being hired by a sales HGFs is not significant for the top 1% fastest growing firms.

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⁸ We have also estimated the model without any interaction effects, and these results are comparable to those presented by Coad et al. (2014a). The effects of immigrant status then become somewhat more significant, but the results are otherwise qualitatively similar to those presented in Table 3. These results are available from the authors upon request.

With respect to our control variables, females and those that have completed a higher education have lower odds of being hired by any type of HGF. Finally, individuals who are hired by HGFs are more likely to be hired by young and small firms compared to those who are hired by non-HGFs. This result supports previous findings (Henrekson and Johansson, 2010; Daunfeldt et al., 2014), indicating that most HGFs typically are young and small.

The results that are presented in Table 3 are similar to those that were obtained by Coad et al. (2014), who also found that HGFs were more likely to *employ* first-generation immigrants and young, less educated and unemployed individuals compared to non-HGFs. However, they also found that the recruitment pattern appears to change in later stages of the growth period, which is in line with the results in this paper. Although immigrants are overrepresented among new hires, individuals from other firms were hired at this point, as opposed to hires from unemployment. However, it still remains an open question as to whether the effect of being unemployed and being recruited by an HGF differs between native born and first-generation immigrants.

To investigate if the effect of being unemployed on the odds of being hired by HGFs is different for immigrants and nonimmigrants, we include an interaction term in the empirical model ($I_i * U_i$). The interaction effect measures how much the effect of being unemployed differs depending on the immigrant status of the individual. Following the recommendation of Buis (2010), we compute the predicted probabilities of attaining a job in an HGF given every combination of regional origin and employment status. As such, we are able to distinguish the odds of being recruited for individuals of a given regional origin that were unemployed in 2014 from those of individuals with the same regional origin that were employed in 2014. We can furthermore distinguish the marginal effect of being unemployed in 2014 given regional origin as the difference between the odds of being unemployed and employed in 2014. The odds difference can thus tell us whether unemployment in 2014 influences the odds of being hired by an HGF in 2015 depending on regional origin.

The estimated odds of attaining a job in an HGF are presented in Figures 1 (employment-HGFs) and 2 (sales-HGFs), together with their associated 95% confidence intervals. Figure 1 shows that the odds of being hired by an HGF are consistently higher among first-generation immigrants from Africa and Asia compared to Swedish-born individuals,

given their employment status. It is thus shown that the immigrant status of these immigrant groups explains their increased likelihood of being recruited by an employment-HGF and not whether they have a job or are unemployed. Note also that the magnitude of these results is larger when analyzing the top 5% fastest growing firms. However, first-generation immigrants from the EU and Eastern Europe have lower odds of being hired by the top 1% fastest growing employment-HGFs if they are unemployed, while unemployed natives, second-generation immigrants and first-generation immigrants from Nordic countries have lower odds of being hired by a top 5% fastest growing employment HGF.

The results are less clear for sales-HGFs (Figure 2), where we cannot distinguish any effects of unemployment and region of birth on the odds of being hired by a top 1% fastest growing sales-HGF. However, the results for the top 5% fastest growing sales-HGFs are more in line with the results for employment-HGFs, showing that the odds of being hired is higher among first-generation immigrants from Africa and Asia, irrespective of whether they have a job or are unemployed.

Our results thus support Coad et al.'s (2014a) conclusion that HGFs are more likely than non-HGFs to recruit nonwestern immigrants but also that this result is robust for nonwestern immigrants that are unemployed and thus have proven difficulties entering the labor market. Taking into account that recruitment from unemployment is a marginal event, the finding that HGFs are less likely to hire unemployed individuals is not driven by nonwestern immigrants. Rather, this result stems from Swedish-born, second-generation immigrants, and immigrants born in a European country, all of which are immigrant groups that, in general, have less difficulties establishing themselves in the labor market.

Finally, it is worth mentioning that the marginal effect of being unemployed in 2014 (although not always significant) is greater when growth is defined as the 5% fastest growing firms, both in terms of sales and in terms of employment. This is an indication that the more rapid growth a firm encounter, they are more unable or unwilling to make discriminatory decisions based on employment status.

[Figures 1 and 2 about here]

5. Conclusions

The number of refugees that seek asylum in Europe has increased dramatically in recent years, and countries within the European Union are facing great challenges to integrate and assimilate these refugees into their societies. Coad et al. (2014a) previously argued that HGFs can be of special importance for these immigrants because HGF-managers want to take advantage of their growth opportunities and therefore are less likely to wait for the best match.

However, previous studies give us no clear answers regarding whether HGFs are more likely than non-HGFs to hire nonwestern immigrants that are unemployed and thus have proven difficulties entering the labor market. Coad et al. (2014a) found that HGFs in the Swedish knowledge-intensive service industries were more likely to recruit nonwestern immigrants and low-educated individuals compared to non-HGFs, which supported their hypothesis. In addition, they also found that HGFs in general were less likely to hire unemployed individuals than non-HGFs. The aim of our paper has been to complement Coad et al.'s (2014a) analysis and investigate if HGFs are also more likely to hire immigrants that are unemployed.

Using matched employer-employee data from Statistics Sweden, we have investigated the interaction effects between employment status and being a first- or second-generation immigrant using the framework that was suggested by Buis (2010). Our results support Coad et al.'s (2014a) conclusion and indicate that HGFs are more likely to recruit first-generation immigrants but not unemployed individuals in particular. However, first-generation immigrants from the EU, eastern Europe and Africa were more likely to be hired by an HGF in 2015 irrespective of their employment status in the preceding year. It thus seems that rapidly growing firms do not have time to find perfect matches and instead provide newly recruited employees with more on-the-job training.

Earlier contributions suggest that HGFs are important because they create most new jobs at any given point in time. We have contributed to the literature by investigating if HGF-managers are also more likely to provide jobs for unemployed immigrants or if they prefer to recruit immigrants that already are employed. Our results show that most new employees are recruited from other employers rather than from unemployment, but that HGFs are more likely to hire unemployed first-generation immigrants than non-HGFs.

Policies that focus on increasing risk-taking and high-growth entrepreneurship might therefore also be important for the labor market integration of immigrants that are unemployed.

We believe that more research is needed to understand why HGFs are more likely than non-HGFs to hire unemployed first-generation immigrants. Future studies should also consider investigating more homogenous samples, such as new ventures, and investigating hiring practices along the whole growth rate distribution. In particular, we need a deeper understanding of how policies can be designed to stimulate high-growth entrepreneurship and the labor market integration of first-generation immigrants.

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Table 1: Summary statistics for the data set investigating individuals *hired* in 2015 for non-HGFs and various definitions of HGFs (top 5% or top 1% sales or employment growth)

	Mean									
		SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Swe	.74	(.44)	.77	(.42)	.72	(.45)	.76	(.43)	.74	(.44)
Second	.051	(.22)	.049	(.22)	.055	(.23)	.051	(.22)	.051	(.22)
Nordic	.014	(.12)	.015	(.12)	<u>.014</u>	(.12)	.013	(.11)	.014	(.12)
Eu25	.031	(.17)	.028	(.16)	.025	(.16)	.031	(.17)	.031	(.17)
Eur	.044	(.21)	.035	(.18)	.034	(.18)	.037	(.19)	.044	(.21)
Africa	.027	(.16)	.019	(.14)	.03	(.17)	.025	(.16)	.027	(.16)
S_Am	.012	(.11)	.011	(.11)	.022	(.15)	.012	(.11)	.012	(.11)
Asia	.068	(.25)	.06	(.24)	.085	(.28)	.066	(.25)	.068	(.25)
Other	.0088	(.09)	.0086	(.09)	.012	(.11)	.0096	(.01)	.0088	(.093)
unemployed	.19	(.39)	.17	(.38)	.2	(.4)	.19	(.39)	.19	(.39)
Female	.38	(.49)	.37	(.48)	.44	(.5)	.38	(.48)	.38	(.49)
Married	.27	(.44)	.27	(.45)	.23	(.42)	.25	(.44)	.27	(.44)
Child	.35	(.48)	.35	(.48)	.32	(.47)	.34	(.47)	.35	(.48)
No educ	.029	(.17)	.023	(.15)	.027	(.16)	.027	(.16)	.029	(.17)
Primary	.096	(.29)	.091	(.29)	.097	(.3)	.09	(.29)	.096	(.29)
High	.66	(.47)	.63	(.48)	.61	(.49)	.64	(.48)	.66	(.47)
Uni	.22	(.41)	.26	(.44)	.27	(.44)	.24	(.43)	.22	(.41)
Start-ups	.59	(.49)	.46	(.5)	.71	(.45)	.63	(.48)	.59	(.49)
Young firms	.36	(.48)	.4	(.49)	.25	(.43)	.32	(.47)	.36	(.48)
Middle-aged firms	.021	(.14)	.088	(.28)	.038	(.19)	.031	(.17)	.021	(.14)
Old firms	.024	(.15)	.047	(.21)	.0039	(.062)	.018	(.13)	.024	(.15)
Micro firms	.23	(.42)	.25	(.44)	.17	(.38)	.26	(.44)	.23	(.42)
Small firms	.35	(.48)	.33	(.47)	.33	(.47)	.38	(.49)	.35	(.48)
Medium-sized firms	.32	(.46)	.25	(.44)	.44	(.5)	.25	(.44)	.32	(.46)
Large firms	.039	(.19)	.14	(.35)	0	0	.046	(.21)	.039	(.19)
Observations	224,304		10,930		41,492		1,802		12,589	

Table 2: Summary statistics for the data set investigating individuals *hired* from unemployment in 2015 for non-HGFs and various definitions of HGFs (top 5% or top 1% sales or employment growth)

	Non- HGFs	•	Emp (1%)	. ,	Emp (5%)		Sales (1%)		Sales (5%)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Swe	.65	(.48)	.58	(.49)	.6	(.49)	.58	(.49)	.58	(.49)
Second	.061	(.24)	.064	(.24)	.057	(.23)	.066	(.25)	.061	(.24)
Nordic	.015	(.12)	.016	(.12)	.014	(.12)	.016	(.13)	.015	(.12)
Eu25	.03	(.17)	.031	(.17)	.037	(.19)	.022	(.15)	.032	(.18)
Eur	.067	(.25)	.07	(.26)	.072	(.26)	.06	(.24)	.07	(.26)
Africa	.043	(.2)	.072	(.26)	.054	(.23)	.063	(.24)	.064	(.24)
S_Am	.014	(.12)	.014	(.12)	.016	(.12)	.022	(.15)	.013	(.11)
Asia	.11	(.31)	.14	(.35)	.14	(.34)	.16	(.36)	.15	(.36)
Other	.01	(.1)	.0088	(.093)	.012	(.11)	.016	(.13)	.01	(.099)
unemployed	1	0	1	0	1	0	1	0	1	0
Female	.36	(.48)	.35	(.48)	.37	(.48)	.42	(.49)	.36	(.48)
Married	.16	(.36)	.17	(.37)	.17	(.38)	.14	(.35)	.17	(.37)
Child	.18	(.39)	.19	(.39)	.2	(.4)	.17	(.38)	.19	(.39)
No educ	.036	(.19)	.047	(.21)	.043	(.2)	.049	(.22)	.05	(.22)
Primary	.12	(.33)	.13	(.34)	.12	(.33)	.14	(.35)	.13	(.34)
High	.68	(.47)	.66	(.47)	.65	(.48)	.6	(.49)	.63	(.48)
Uni	.16	(.37)	.16	(.37)	.18	(.39)	.21	(.41)	.19	(.39)
Start-ups	.15	(.35)	.7	(.46)	.54	(.5)	.68	(.47)	.71	(.46)
Young firms	.33	(.47)	.27	(.44)	.38	(.48)	.3	(.46)	.26	(.44)
Middle-aged firms	.26	(.44)	.021	(.14)	.054	(.23)	.016	(.13)	.022	(.15)
Old firms	.26	(.44)	.016	(.12)	.026	(.16)	.0055	(.074)	.0083	(.091)
Micro firms	.16	(.36)	.23	(.42)	.28	(.45)	.15	(.36)	.26	(.44)
Small firms	.25	(.43)	.36	(.48)	.34	(.47)	.3	(.46)	.37	(.48)
Medium-sized firms	.21	(.41)	.28	(.45)	.25	(.43)	.49	(.5)	.25	(.43)
Large firms	.38	(.49)	.059	(.24)	.11	(.31)	0	0	.054	(.23)
Observations	45,297	· ·	2,045	. ,	7,225	, ,	366		2,404	

Table 3: Logistic regression for the odds ratio of being hired by an HGF. HGFs are defined as the top 1% and 5% fastest growing firms in terms of number of employees (Employment-HGFs) and sales (Sales-HGFs).

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VAR	Emp (1%)	Emp (5%)	Sales (1%)	Sales (5%)
Second	1.00069	0.96176	0.91726	0.96708
	(0.054)	(0.029)	(0.115)	(0.048)
Nordic	0.90447	0.99648	0.92403	0.89438
	(0.091)	(0.055)	(0.214)	(0.085)
Eu25	1.31909***	0.99640	0.99554	1.19329**
	(0.089)	(0.041)	(0.176)	(0.077)
Eur	1.51983***	1.05707	1.00298	1.12781
	(0.094)	(0.042)	(0.175)	(0.073)
Africa	1.51323***	1.04082	1.07783	1.33353**
	(0.139)	(0.064)	(0.211)	(0.117)
S_Am	1.14169	1.00234	1.47811*	0.98211
_	(0.120)	(0.064)	(0.282)	(0.098)
Asia	1.10969	0.92518*	1.11426	0.91572
	(0.060)	(0.030)	(0.130)	(0.048)
Other	1.12891	0.89994	1.13611	1.09309
	(0.139)	(0.065)	(0.301)	(0.122)
<u>Controls</u>	(0.200)	(====)	(====	()
Unemployed	0.82350***	0.73892***	0.90291	0.86531***
	(0.028)	(0.014)	(0.072)	(0.028)
Baseline	0.00038***	0.01251***	0.00005***	0.00037***
	(0.000)	(0.004)	(0.000)	(0.000)
Female	0.85772***	0.89586***	0.67044***	0.82051***
1 0	(0.021)	(0.012)	(0.037)	(0.018)
Married	0.96751	0.98619	0.86904*	0.96922
	(0.027)	(0.016)	(0.059)	(0.026)
Child	1.00509	1.01740	0.94170	1.00616
	(0.025)	(0.015)	(0.057)	(0.024)
Primary	0.88572	0.87942**	0.95651	0.82672**
	(0.065)	(0.040)	(0.170)	(0.058)
High	0.87568*	0.85946***	0.91581	0.83803**
g	(0.059)	(0.036)	(0.149)	(0.054)
Uni	0.70191***	0.83918***	0.90887	0.73834***
0711	(0.049)	(0.036)	(0.152)	(0.049)
Start-up firm	43.80186***	21.57825***	190.91350***	49.60165***
beare appirm	(2.870)	(0.568)	(74.137)	(3.467)
Young firm	13.88247***	8.33845***	41.43435***	13.51175***
roung jirm	(0.905)	(0.213)	(16.076)	(0.945)
Middle aged firm	1.10837	2.19950***	10.44825***	1.85349***
Madic aged min	(0.101)	(0.063)	(4.177)	(0.156)
micro firm	2.23301***	2.00313***	3.70575***	2.35104***
micro ju m	(0.091)	(0.041)	(0.442)	(0.088)
Small firm	3.06783***	2.03791***	5.09689***	2.97610***
Oman min	(0.114)	(0.037)	(0.559)	(0.103)
Medium -sized firm	4.16042***	2.38430***	8.67466***	3.04093***
Medium -Sizeu milli	(0.150)	(0.043)	(0.915)	(0.105)
N	265,878	266,413	263,675	265,878
IN	203,070	200,413	203,073	203,070

Figure 1: Odds ratio of being hired by employment-HGFs for all combinations of regional origin and unemployment status in 2014. HGFs are defined as the top 1% and 5% fastest growing firms, respectively.

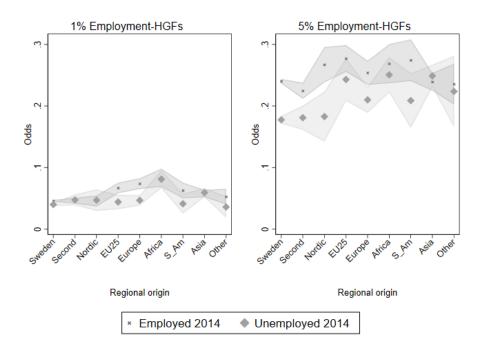


Figure 2: Odds ratio of being hired by sales-HGFs for all combinations of regional origin and unemployment status in 2014. HGFs are defined as the top 1% and 5% fastest growing firms, respectively.

