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Abstract

STEM-focused industries are critical to the innovation-driven economy. As many firms are running short of STEM workers, international immigrants are increasingly recognized as a potential for high-tech job recruitment. This paper studies STEM occupations in Sweden 2011–2015 and tests hypotheses on new recruitment and the economic impact of foreign STEM workers. The empirical analysis shows that the probability that a new employee is a STEM immigrant increases with the share of STEM immigrants already employed, while the marginal effect on average firm wages is positively associated with the share of immigrant STEM workers. We also document heterogeneity in the results, suggesting that European migrants are more attractive for new recruitment, but non-EU migrants have the largest impact on wage determination.

Keywords: STEM, migration, employment, wages, correlated random effects
JEL Codes: C23, J24, J61, O14, O15

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1 Introduction

Advances within high-tech fields of the economy have an important role for sustained productivity and growth (Siegel & Griliches 1992, Jones 1995). Already by the 1940s, attention was drawn to the need to provide industry with skilled STEM-educated workers for this purpose (Bush 1945). Ever since then, there have been a number of policy measures throughout OECD countries to satisfy the labor market's needs for these key competences. However, many industrialized countries experience a shortage of high-skilled employees in STEM-focused industries. For instance, the US is not able to produce enough STEM workers in key fields such as computer science and electrical engineering, despite its leading role in university education in STEM-related subjects (Atkinson & Mayo 2010). As many firms are running short of STEM workers, international immigrants are increasingly recognized as a potential for high-tech job recruitment.

In this paper, we consider STEM jobs in Sweden during the recovery period 2011–2015, after the financial crisis, and test hypotheses on new recruitments and the economic impact of international STEM migrants. To do so, we exploit employer-employee data provided by Statistics Sweden (SCB) that contain extensive information on all workers and firms. The goal of our research is to assess the impact of skilled foreign workers on the wages of all STEM workers in the economy. This allows us to gain insight into the contribution of foreign workers to development of STEM competence as a driver of firms' technological progress. If hiring foreign STEM workers increases all STEM workers' wages, they may also increase firms' productivity and growth potential. By analyzing the causality in the other direction, Peri, Shih & Sparber (2015) find that immigrant STEM workers enhance local firms' productivity in U.S. cities with possible local effects on both growth and wages.

Hunt & Gauthier-Loiselle (2010) discuss conditions and mechanisms for integration of international migrants' scientific and engineering knowledge into firms' development processes. A greater concentration of high-tech skilled immigrants is considered to be favorable, and also testable. In the present study, we would expect the importance of skilled immigrants to increase with the proportion of foreign STEM workers in a company. Another argument for recruiting foreign STEM workers, besides shortages of labor, proposed by Hunt & Gauthier-Loiselle (2010) is that they may provide complementary skills to the native workers. In addition, there are fewer language and cultural barriers when both education and expert knowledge are similar between domestic and foreign STEM workers.

We begin our analysis by examining the presence of STEM immigrants in the Swedish economy. However, there is no widely recognized definition of STEM jobs. By limiting STEM to professional industries and STEM-educated employees only, STEM workers account for about 5% percent of total U.S. employment. With a more inclusive definition that considers the importance of STEM knowledge in the economy, the share increases to 20% percent of all jobs (Rothwell 2013).

In Sweden, STEM workers with occupations that require a university education in physics and chemistry, mathematics and statistics, biology, engineering and IT, or a professional background as a technician or IT operator, constitute around 10% of the total employment in the private sector, corresponding to nearly 300,000 people. International migrants are increasingly important for the supply of these STEM categories in both manufacturing and service industries. In 2011, they accounted for almost 6% of all STEM workers in the private sector and 26.9% of all newly recruited STEM workers. Four years later, the corresponding figures were 9% and 28.4%. Almost half of the immigrants have a refugee background.

In the empirical analysis, we consider recruitment and estimate the probability that the newly employed worker is a STEM immigrant. We find a significant positive association with the share of STEM immigrants already employed by the firm. We then employ a correlated random effects model to study the importance of immigrant STEM workers on firm performance, captured by normalized wage income as the ratio of monthly wage earnings to median monthly wage earnings. The estimates shows that normalized wage earnings are an increasing function of the fraction of immigrant STEM workers in the firm's workforce.

The existing literature on immigration and wages mainly focuses on the relative supply of different kinds of skills in local labor markets. Some examples from a very extensive literature include Basso & Peri (2015), Card (2009), Dustmann, Fabbri & Preston (2005), or more recently occupational tasks in regional labor markets (see, e.g., Peri & Sparber (2009)), and substitutability between natives and immigrants of similar education and experience level (Ottaviano & Peri (2012)). There are only a few papers specifically addressing the wage impact of STEM immigrants, perhaps due to lack of data for systematic analyzes. To circumvent this problem, Bound, Braga, Golden & Khanna (2015) employ a dynamic simulation approach and estimate the optimal recruiting choice between computer scientists from recently graduated college students, STEM workers working in other occupations, or a pool of foreign talent. The model predicts that that wages for native computer scientists are negatively correlated with a greater number of foreign hires, while increases in employment have the opposite effect. There are also a few studies, similar to our paper, that rely on employer-employee data for research on foreign STEM workers. For instance, Pekkala Kerr & Kerr (2013) use information on both individual STEM immigrants in the U.S. and their workplaces. However, they do not consider wages but rather employer transition.[1].

Our current knowledge about the importance of STEM immigrants' importance for wages and productivity is clearly limited. Our paper therefore contributes to several understudied areas within the STEM literature. First, we doc-

[1]Related to our paper is also a large number of studies on migration and innovation, however mainly not based on representative microeconomic data. For a recent survey, see Breschi, Lissoni & Temgoua (2016)

ument the universe of international STEM migrants in the private sector of a developed economy and distinguish between economic and refugee migrants, as well as between migrants from different regional areas. Second, we study both domestic and foreign STEM workers and observe their personal characteristics as well as the characteristics of their workplaces. Third, we examine whether firms appear to deal with labor shortages by hiring foreign STEM workers, and the possible heterogeneity within this category of employees. Forth, the paper assesses economic effect at the firm level of foreign STEM-workers.

In Section 2 the empirical approach is outlined, focusing on the correlated random effects approach. Data and descriptive evidence are discussed in Section 3. Section 4 presents the empirical results and section 5 concludes.

2 Empirical Approach

Using the correlated random effects (CRE) approach (Mundlak 1978, Wooldridge 2010), we estimate the determinants of wage earnings at the individual level. As we have an employer-employee dataset, we can also include firm characteristics as control variables in the estimated model. The CRE approach has the advantage over fixed effects models in that it enables inclusion of time-invariant variables, such as an individual belonging to a specific cohort. Furthermore, it relaxes the restrictive assumptions of the random effects model in that unobserved heterogeneity and the other explanatory variables may be correlated. In the presence of such correlation, the CRE method decomposes the random effect into a component correlated with the regressors and a remainder which is orthogonal to the regressors.

Formally, the CRE model can be written as follows (Schunck 2013, Schunck & Perales 2017):

$$y_{it} = \beta_0 + \beta_w x_{it} + \beta_c c_i + \pi \bar{x}_i + \mu_i + \epsilon_{it} \tag{1}$$

where y_{it} measures the normalised monthly wage earnings of person i, where monthly wage earnings are expressed as a ratio to median STEM monthly wage earnings in the private sector. The c_i variables are time-invariant factors, while β_w correspond to the within estimates, $\bar{x}_i$ are group specific means of variables and π indicates the difference between within and between estimates, $\pi = \beta_w - \beta_b$. The μ_i are the part of the individual random effects which is uncorrelated with the error term ϵ_{it} and with the other explanatory variables x_{it} of the model. It is worth noting that if we cannot reject $H_0 : \pi = 0$, a standard random effects model would be appropriate, in which the random effect is assumed to be uncorrelated with the regressors. Evidence in support of the alternative $H_1 : \pi \neq 0$ supports the CRE specification, allowing for such correlation. Testing this hypothesis in the context of the augmented regression model is equivalent to a Hausman test on the random effects versus fixed effects specification.

As Schunck (2013) has pointed out, the CRE model is numerically equivalent to a so-called hybrid model formulation from which both within and between estimates can be directly obtained:

$$y_{it} = \beta_0 + \beta_w(x_{it} - \bar{x}_i) + \beta_c c_i + \beta_b \bar{x}_i + \mu_i + \epsilon_{it}. \tag{2}$$

As the between-group estimates have a direct interpretation, we prefer the hybrid model formulation over the CRE specification. While the within estimate shows the effect of a variable which varies over time on the outcome for an individual, the between estimates can be interpreted as expressing the long-term outcomes which are obtained from the cross-sectional dimension (see Baltagi 2013, chap. 10.4).

3 Data and descriptive evidence

The unit of observation in our data is the worker-year. We can classify individuals as STEM workers using the codes of the SSYK scheme (see Table 1). STEM occupations are further designated as high-skill STEM, which generally require theoretical knowledge from a university course, or low-skill STEM, with professional qualifications. We can identify whether each worker is native-born or an immigrant STEM worker. For those who are immigrants, we can further classify their status as an economic migrant from the EU, an economic migrant from outside the EU, and an immigrant with refugee status. We record the worker's educational attainment on a six-point scale; their age in one of six brackets; their marital status, number of children 0-3 years and 4-6 years, and their number of years of experience, as well as their gender.

From the linked employer data, we identify the share of foreign STEM workers in total STEM employment, and create indicators for whether the firm has been granted patents, trademarks, exports its products, and whether it has a foreign owner. Firms are classified into six categories of skill levels, from high-tech manufacturing to low-tech knowledge intensive services. Firm size is captured by a five-point scale, and workplace location by a four-point scale ranging from urban to rural. Further details on the classification schemes for worker and firm variables are presented in Table 2.

Table 3 presents summary statistics for two categories of STEM workers: the native-born and immigrants, as well as the firms where they are employed. The measure of normalised wage earnings show that native-born STEM workers earn higher wages than immigrant STEM workers. This differential may reflect the fact that the native-born STEM worker has almost twice as much experience as the immigrant, and is older on average. In contrast, the immigrant STEM worker is much more likely to have earned a university degree at bachelors, masters or doctoral levels. They are also more likely to work in a metropolitan location.

Turning to the employer data, Table 3 illustrates that foreign STEM workers make up 8.4% of the STEM labor force. The share of those workers from other EU countries is 1.8%, while the share of workers from outside the EU is 4.3%. Interestingly, 2.3% of STEM workers have refugee status in Sweden. Firms hiring foreign STEM workers are more likely to be foreign-owned, more likely to own patents and trademarks, and more likely to export. STEM immigrants are also more likely to be working in larger firms, with 250 employees or more.

To provide an overview of the prevalence of native-born and immigrant STEM workers, Table 4 illustrates the growing share of foreign-born STEM workers over the period studied. Among the newly employed, the percentage of foreign-born STEM workers is much higher, as Table 5 illustrates. We can also characterize the immigrant workers by region of origin and refugee status in Table 6. In Table 7, data for the most recent year show that immigrant STEM workers are more likely to be found in engineering and IT fields with a university degree. The location of native and immigrant STEM workers is classified by skill level in Table 8, where we see that the immigrant workers are twice as likely to be found in high-tech manufacturing firms than their native counterparts.

4 Empirical analysis

The first empirical findings in our analysis of these detailed employee-employer data are derived from a binomial logit model of the probability that a newly employed worker in a STEM field will be an immigrant. The models in Table 9 are based on 16,000–20,000 newly employed STEM workers over the 2011–2015 period. The table presents average marginal effects from the logit model. Our key finding is the importance of the foreign STEM share, which has a positive and significant effect across all four specifications. This illustrates that a firm with a higher fraction of immigrant STEM workers is more likely to hire an additional immigrant STEM worker. This finding is robust across the overall foreign STEM share and the three categories (EU labor immigrant, non-EU labor immigrant, or refugee). We note that the largest effect among these categories comes from the share of EU immigrant workers. This clear finding appears after controlling for firm characteristics, skill level, firm size and individual characteristics.

In summary, private firms that have dealt with labor shortages by hiring STEM immigrant workers appear to consider that to be a good strategy, so that firms with a higher fraction of immigrant STEM workers are more likely to augment their number. This perhaps represents the tradeoff between the lower average experience of the immigrant worker (perhaps leading to a lower wage offer) combined with the generally higher level of educational attainment that immigrant STEM workers display.

The second set of empirical results, presented in Table 10, apply the correlated random effects (CRE) model of Eq. (2) to explain STEM workers' normalised wage earnings: the worker's average monthly wage earnings as a ratio to median monthly wage earnings of STEM workers in the private sector. The estimates are based on over one million worker-year observations, corresponding to approximately 350,000 workers' employment histories. The four columns of this table consider the role of the overall foreign STEM share in each worker's firm, followed by the shares of non-EU, EU and refugee STEM workers in each workplace. Both the within-effects and between-effects coefficients are positive and statistically significant in all models, implying that cet.par., a higher share of foreign STEM workers is associated with higher wage earnings for all workers. The impact on foreign STEM workers is reduced by the coefficient on migrant STEM workers (a time-invariant covariate), reflecting the lower normalised wage for foreign STEM workers presented in Table 3. However, as we noted in the univariate analysis, foreign STEM workers generally have fewer years of experience and higher educational qualifications than their native-born counterparts.

The impact of foreign STEM workers' share in these models is robust to controlling for firm characteristics, such as patenting, exporting, firm size and skill levels. Individual characteristics, such as experience, education, gender also play an important role in the estimated model. There are increasing returns to higher education, as one would expect, and a sizable gender differential in favor of male workers. Although not reported in the estimates, other worker characteristics, such as age and number of pre-school children, are also included among the controls.

Our summary findings from these estimates indicate that there are very significant wage impacts from the employment of foreign STEM workers in Swedish firms in the private sector, for both native-born and foreign STEM workers.

5 Conclusions

This paper reports on the initial steps of our analysis of STEM employment in the private sector in Sweden. Despite a robust technical education system in Swedish universities, firms have increasingly turned to foreign STEM workers to fill their high skill level jobs. In contrast to populist sentiment that questions the benefits of immigration, our analysis suggests that foreign STEM workers are an important component of Swedish firms' success in meeting the challenges of high-technology manufacturing and services. Firms with a significant foreign STEM component in their workforce are likely to hire more of them, and higher shares of foreign STEM workers are associated with higher wages for all STEM workers, native-born and foreign. Our analysis can reach these clear conclusions because it is based upon the full population of employees and private-sector employers rather than more limited survey data. Although this paper is the first report from this research project, it should be clear that these data and detailed classifications will support more thorough analysis of these key phenomena in the context of technological change, and could be fruitfully repeated in other Nordic economies with detailed administrative data.

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A Tables

Table 1: Definition of STEM occupations, SSYK codes

SSYK code	Description
From 2014	SSYK 2012 (ISCO-08)
211	Physics and Chemistry (university)
212	Mathematics and Statistics (university)
213	Biology (university)
214	Engineering (university)
251	IT (university)
311	Technician (professional)
351	IT operation (professional)
Before 2014	SSYK 1996 (ISCO 88)
211	Physics and Chemistry (university)
212	Mathematics and Statistics (university)
213	IT (university)
214	Engineering (university)
311	Technician and Engineer (professional)

Notes: There was a change of occupational classification system in 2014. University means that the occupation requires theoretical special knowledge which a person usually acquires from a university education.

Table 2: Variable descriptions

Variable	Definition
STEM immigrant	**0=native-born STEM worker**, 1=immigrant STEM worker
high-skill STEM	STEM occupations that require theoretical knowledge obtained by university degree (or equivalent)
foreign STEM share	share of foreign STEM workers in total STEM employment at firm level without individual i
patent	firm has granted patents
trademark	firm has granted trademarks
export	firm is exporting
foreign	firm has a foreign owner
educ	highest educational attainment: **1=primary school**, 2=secondary school, 3=tertiary education (below university degree), 4=bachelor's degree, 5=master's degree, 6=doctoral degree
female	1=women, **0=men**
age	current year minus birth year. In regression models, age is included as categorical variable, 1=age <30, 2=age 30-34, 3=age 35-39, 4=age 40-49, 5=age 50-59, **6=age>59**
married	marital status: 1=married, **0=unmarried**
kids age 0-3	number of children with age 0-3 years, winsorized at 2, ref category **0 children**
kids age 4-6	number of children with age 4-6 years, winsorized at 2, ref category **0 children**
wage	monthly wage earnings relative to median monthly wage earnings in all STEM occuptation. Trimmed at 1% to remove outliers.
experience	number of years after exam year
ind	1=high-tech manufacturing, 2=medium-tech manufacturing, 3=low-tech manufacturing, 4=high-tech knowledge intensive services (kis), 5=market kis, **6=less knowledge intensive services**
fsize	number of firm's employees, 1=micro$<$1-9, 2=small 10-49, 3=medium 50-249, 4=large 250-999, **5=big$\geq$1000 employees**
muni	settlement type of municipality where a person's workplace is located, 1= metropolitan area/larger city, 2=densely populated, close to larger city, 3=densely populated remote region, **4=rural remotely located region**

Notes: reference category of a categorical variable is shown in **bold.**

Table 3: Descriptive statistics of main variables, 2011–2015

variable	STEM natives mean	STEM natives se(mean)	STEM immigrants mean	STEM immigrants se(mean)
individual characteristics				
normalised wage earnings	1.050	.00026	1.013	.00094
high-skill STEM worker	.554	.00038	.686	.00129
female	.198	.00030	.269	.00123
experience	18.76	.01049	10.70	.02936
educ: secondary	.325	.00036	.096	.00085
educ: tertiary	.290	.00035	.261	.00127
educ: bachelor	.111	.00024	.214	.00118
educ: master	.204	.00031	.314	.00134
educ: doctoral	.028	.00013	.105	.00088
married	.519	.00038	.563	.00138
age <30	.087	.00022	.174	.00106
age 30-34	.107	.00024	.225	.00116
age 35-39	.137	.00026	.177	.00106
age 40-49	.268	.00034	.258	.00122
age 50-59	.180	.00029	.134	.00095
age >59	.220	.00032	.032	.00049
muni: metro/city	.508	.00041	.712	.00130
muni: dense close city	.369	.00039	.234	.00121
muni: rural close city	.043	.00016	.022	.00042
muni: remote rural region	.080	.00022	.032	.00050
firm characteristics				
foreign STEM share (all)			.084	.00040
foreign STEM share (EU)			.018	.00012
foreign STEM share (non-EU)			.043	.00036
foreign STEM share (refugee)			.023	.00011
foreign owner	.223	.00032	.269	.00123
patent	.197	.00030	.289	.00126
trademark	.187	.00030	.196	.00111
exporting firm	.535	.00038	.638	.00134
fsize: 1-9	.135	.00028	.090	.00081
fsize: 10-49	.231	.00034	.177	.00109
fsize: 50-249	.271	.00036	.266	.00126
fsize: 250-999	.318	.00038	.365	.00137
fsize: >999	.044	.00017	.103	.00087

Table 4: Share of STEM workers by immigration background in Sweden, broad STEM classification

year	native %	foreign %	# obs
2011	94.3	5.7	409,975
2012	93.7	6.3	421,952
2013	93.3	6.7	432,425
2014	91.6	8.4	278,535
2015	91.1	8.9	297,055
# obs	1,710,877	129,065	1,839,942

Notes: Change of occupational classification system from SSK96 to SSK2012 in 2014 which causes a break in the time series.

Table 5: Share of newly employed STEM workers in Sweden by immigration background

year	native %	foreign %	# obs
2011	73.2	26.8	6,699
2012	72.1	27.9	6,460
2013	70.6	29.4	5,748
2014	74.6	25.4	5,140
2015	71.6	28.4	4,546
# obs	20,705	7,888	28,593

Notes: see previous Table.

Table 6: Origin and immigration status of STEM workers in Sweden, 2011–2015

	%	obs
labor EU immigrant	20.1	14,004
labor non-EU immigrant	34.6	24,086
refugee status immigrant	45.3	31,612
# obs	100.0	69,702

Table 7: STEM occupations of natives and immigrants in Sweden, 2015

STEM occupations	native %	immigrant %	# obs
211: phys/chem (university)	1.7	4.4	5,822
212: math/stat (university)	0.5	0.7	1,631
213: biology (university)	2.1	2.4	6,281
214: engineering (university)	24.5	29.7	74,017
251: IT (university)	29.4	30.9	87,789
311: technician (professional)	28.5	22.4	83,013
351: IT operations (professional)	13.3	9.5	38,502
Total	100	100	297,055

Table 8: STEM workers across industries in Sweden, 2015

industry	native %	immigrant %	# obs
high-tech manu	6.5	13.6	21,114
medium-tech manu	15.4	12.3	44,866
low-tech manu	3.2	1.6	9,177
high-tech kis	18.8	19.6	55,937
market kis	22.8	24.0	67,954
low-tech service	33.4	28.9	98,007
	100	100	297,055

Notes: manu: manufacturing industries, kis: knowledge intensive service sectors.

Table 9: Average marginal effects on the probability for an individual to be a newly employed STEM immigrant worker in Sweden, 2011–2015

dep var: Pr[newly employed]	(1)	(2)	(3)	(4)
foreign STEM share (all)	0.639***			
	[0.031]			
foreign STEM share (non-EU)		0.201***		
		[0.023]		
foreign STEM share (EU)			0.586***	
			[0.032]	
foreign STEM share (refugee)				0.100***
				[0.018]
patent=1	0.023***	0.011***	0.027***	-0.005
	[0.008]	[0.003]	[0.005]	[0.005]
trademark=1	-0.040***	-0.009***	-0.024***	0.001
	[0.008]	[0.003]	[0.005]	[0.004]
foreign owner=1	0.004	0.007***	0.006	0.003
	[0.006]	[0.002]	[0.004]	[0.003]
exporting firm=1	-0.015**	0.005	-0.000	-0.006*
	[0.006]	[0.003]	[0.005]	[0.003]
fsize: 1-9	-0.036**	-0.002	-0.016	0.004
	[0.018]	[0.007]	[0.012]	[0.009]
fsize: 10-49	-0.064***	-0.006	-0.043***	0.008
	[0.016]	[0.006]	[0.011]	[0.008]
fsize: 50-249	-0.036**	-0.000	-0.024**	0.010
	[0.016]	[0.006]	[0.010]	[0.008]
fsize: 250-999	-0.013	0.003	-0.015	0.007
	[0.015]	[0.005]	[0.009]	[0.008]
ind: high-tech manu	0.110***	0.022***	0.088***	-0.007
	[0.017]	[0.008]	[0.013]	[0.010]
ind: medium-tech manu	-0.011	-0.007	0.007	0.000
	[0.010]	[0.004]	[0.008]	[0.006]
ind: low-tech manu	-0.033*	-0.023***	-0.025**	0.024*
	[0.019]	[0.004]	[0.012]	[0.014]
ind: high-tech kis	-0.005	0.001	0.016**	-0.015***
	[0.008]	[0.004]	[0.006]	[0.004]
ind: market kis	-0.042***	-0.007**	-0.015***	-0.007*
	[0.007]	[0.003]	[0.005]	[0.004]
high-skill STEM	0.014**	-0.002	0.038***	-0.005
	[0.006]	[0.003]	[0.005]	[0.003]
experience	0.001**	0.004***	0.004***	-0.002***
	[0.001]	[0.000]	[0.001]	[0.000]
educ: secondary	-0.034*	-0.001	-0.007	-0.036**
	[0.021]	[0.002]	[0.007]	[0.018]
educ: tertiary	0.035*	0.005**	0.045***	-0.029
	[0.021]	[0.002]	[0.008]	[0.018]

cont.

dep var: Pr[newly employed]	(1)	(2)	(3)	(4)
educ: bachelor	0.199***	0.077***	0.123***	0.000
	[0.022]	[0.006]	[0.009]	[0.019]
educ: master	0.166***	0.050***	0.104***	-0.014
	[0.022]	[0.005]	[0.009]	[0.018]
educ: doctoral	0.207***	0.156***	0.165***	-0.041**
	[0.028]	[0.023]	[0.019]	[0.019]
female=1	0.011*	-0.012***	-0.018***	-0.014***
	[0.006]	[0.003]	[0.004]	[0.004]
married=1	0.121***	-0.000	0.062***	0.024***
	[0.006]	[0.003]	[0.004]	[0.004]
age: 30-34	0.020**	-0.005	-0.028***	0.015***
	[0.008]	[0.008]	[0.007]	[0.004]
age: 35-39	-0.060***	-0.049***	-0.091***	0.004
	[0.010]	[0.011]	[0.009]	[0.005]
age: 40-49	-0.109***	-0.077***	-0.125***	0.019***
	[0.011]	[0.013]	[0.010]	[0.007]
age: 50-59	-0.141***	-0.088***	-0.146***	0.044***
	[0.014]	[0.013]	[0.009]	[0.015]
age: >59	-0.187***	0.000	-0.150***	0.046
	[0.015]	[.]	[0.009]	[0.028]
muni: metro/city	0.075***	0.012***	0.025***	0.016***
	[0.011]	[0.005]	[0.008]	[0.005]
muni: dense close city	0.035***	0.004	0.009	0.008
	[0.011]	[0.005]	[0.008]	[0.005]
muni: rural close city	0.013	0.004	0.000	0.006
	[0.018]	[0.008]	[0.013]	[0.008]
year=2012	-0.000	0.000	0.011**	-0.007*
	[0.007]	[0.004]	[0.005]	[0.004]
year=2013	-0.005	-0.000	-0.002	-0.003
	[0.008]	[0.004]	[0.005]	[0.004]
year=2014	-0.014*	-0.018***	-0.019***	-0.000
	[0.008]	[0.003]	[0.005]	[0.004]
year=2015	-0.005	-0.024***	0.006	-0.001
	[0.008]	[0.003]	[0.006]	[0.005]
# obs	20,942	16,658	18,219	17,167
df(m)	35	34	35	35
pseudo R^2	0.19	0.31	0.38	0.05
χ^2	4177.0	1171.3	4139.0	250.1
p-value	0.000	0.000	0.000	0.000

Notes: Estimation by binomial logit. Average marginal effects derived by the delta method. Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (1) all STEM migrants included, (2) only EU STEM migrants, (3) only non-EU STEM migrants, (4) only refugee STEM migrants, reference group native STEM workers. Only private sector firms included.

Table 10: Determinants of normalised wage earnings of STEM workers in Sweden, correlated random effects model of Eq. (2)

dep var: normalised wage earnings	(1)	(2)	(3)	(4)
foreign STEM share (all) (w)	0.039***			
	[0.007]			
foreign STEM share (all) (b)	0.116***			
	[0.010]			
foreign STEM share (non-EU) (w)		0.133***		
		[0.018]		
foreign STEM share (non-EU) (b)		0.532***		
		[0.036]		
foreign STEM share (EU) (w)			0.076***	
			[0.013]	
foreign STEM share (EU) (b)			0.183***	
			[0.017]	
foreign STEM share (refugee) (w)				-0.023**
				[0.011]
foreign STEM share (refugee) (b)				-0.149***
				[0.017]
migrant STEM worker (c)	-0.062***	-0.007	-0.084***	-0.055***
	[0.002]	[0.006]	[0.004]	[0.003]
patent=1 (w)	-0.001	-0.001	-0.001	-0.001
	[0.002]	[0.002]	[0.002]	[0.002]
patent=1 (b)	0.009***	0.008***	0.009***	0.010***
	[0.001]	[0.001]	[0.001]	[0.001]
trademark=1 (w)	0.001	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
trademark=1 (b)	-0.001	-0.001	-0.002	-0.003**
	[0.001]	[0.001]	[0.001]	[0.001]
foreign owner=1 (w)	-0.002***	-0.002***	-0.002***	-0.002***
	[0.001]	[0.001]	[0.001]	[0.001]
foreign owner=1 (b)	0.052***	0.050***	0.051***	0.051***
	[0.001]	[0.001]	[0.001]	[0.001]
exporting firm=1 (w)	0.001	0.000	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
exporting firm=1 (b)	0.024***	0.022***	0.024***	0.023***
	[0.001]	[0.001]	[0.001]	[0.001]
fsize: 1-9 (b)	-0.149***	-0.149***	-0.150***	-0.154***
	[0.003]	[0.003]	[0.003]	[0.003]
fsize: 10-49 (b)	-0.029***	-0.028***	-0.027***	-0.031***
	[0.003]	[0.003]	[0.003]	[0.003]
fsize: 50-249 (b)	-0.034***	-0.034***	-0.034***	-0.037***
	[0.003]	[0.003]	[0.003]	[0.003]
fsize: 250-999 (b)	0.000	-0.000	0.001	-0.002
	[0.002]	[0.003]	[0.003]	[0.003]

cont.

dep var: normalised wage earnings	(1)	(2)	(3)	(4)
ind: high-tech manu (b)	0.053***	0.053***	0.052***	0.057***
	[0.002]	[0.002]	[0.002]	[0.002]
ind: medium-tech manu (b)	-0.034***	-0.036***	-0.036***	-0.035***
	[0.002]	[0.002]	[0.002]	[0.002]
ind: low-tech manu (b)	-0.012***	-0.011***	-0.013***	-0.013***
	[0.002]	[0.002]	[0.002]	[0.002]
ind: high-tech kis (b)	0.024***	0.021***	0.021***	0.023***
	[0.001]	[0.002]	[0.002]	[0.002]
ind: market kis (b)	0.012***	0.010***	0.011***	0.012***
	[0.001]	[0.001]	[0.001]	[0.001]
high-skill STEM (b)	0.119***	0.120***	0.119***	0.121***
	[0.001]	[0.001]	[0.001]	[0.001]
experience (w)	0.002***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
experience (b)	0.007***	0.007***	0.007***	0.007***
	[0.000]	[0.000]	[0.000]	[0.000]
educ: secondary (b)	0.002	0.003	0.002	0.003
	[0.004]	[0.004]	[0.004]	[0.004]
educ: tertiary (b)	0.083***	0.083***	0.083***	0.083***
	[0.004]	[0.004]	[0.004]	[0.004]
educ: bachelor (b)	0.130***	0.131***	0.132***	0.129***
	[0.004]	[0.004]	[0.004]	[0.004]
educ: master (b)	0.184***	0.189***	0.189***	0.189***
	[0.004]	[0.004]	[0.004]	[0.004]
educ: doctoral (b)	0.272***	0.273***	0.276***	0.277***
	[0.005]	[0.006]	[0.006]	[0.006]
female (c)	-0.119***	-0.121***	-0.120***	-0.121***
	[0.001]	[0.001]	[0.001]	[0.001]
married=1 (w)	0.002**	0.001	0.002*	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
muni: metro/city (b)	0.093***	0.093***	0.094***	0.095***
	[0.002]	[0.002]	[0.002]	[0.002]
muni: dense close city (b)	0.016***	0.016***	0.016***	0.016***
	[0.002]	[0.002]	[0.002]	[0.002]
muni: rural close city (b)	0.008***	0.008***	0.008***	0.008***
	[0.002]	[0.003]	[0.003]	[0.003]
year effects (w and b)	yes	yes	yes	yes
age, kids effects (w and b)	yes	yes	yes	yes
industry, region, fsize effects (w)	yes	yes	yes	yes
high-skill STEM, education (w)	yes	yes	yes	yes
married (b)	yes	yes	yes	yes
constant	0.805***	0.802***	0.802***	0.806***
	[0.009]	[0.010]	[0.010]	[0.010]

cont.

dep var: normalised wage earnings	(1)	(2)	(3)	(4)
# obs	1,142,517	1,073,896	1,080,349	1,088,375
σ_u	0.24	0.24	0.24	0.24
σ_ϵ	0.12	0.12	0.12	0.12
ρ	0.79	0.79	0.79	0.79
# individuals	373,589	349,702	352,433	354,268
df(model)	78	78	78	78
R^2 (w)	0.061	0.059	0.060	0.059
R^2 (b)	0.367	0.368	0.367	0.367

Notes: Cluster-robust standard errors by individual in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (1) all STEM migrants included, (2) only EU STEM migrants, (3) only non-EU STEM migrants, (4) only refugee STEM migrants, reference group native STEM workers. Only private sector firms included. (w) indicates within estimates, (b) between estimates and (c) time-invariant estimates from the CRE model. σ_u denotes random effects, σ_ϵ the error term component, $\rho = \sigma_u/(\sigma_u + \sigma_\epsilon)$.