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Abstract

We study the role of firm productivity in explaining earnings disparities between immigrants and natives using population-wide matched employer-employee data from Sweden. We find substantial earnings returns to working in firms with higher persistent productivity, with greater gains for immigrants from non-Western countries. Moreover, the pass-through of within-firm productivity variation to earnings is stronger for immigrants in low-productive, immigrant-dense firms. But immigrant workers are underrepresented in high-productive firms and less likely to move up the productivity distribution. Thus, sorting into less productive firms decreases earnings in poor-performing immigrant groups that would gain the most from working in high-productive firms.

Keywords: Firm productivity; Immigrant-native earnings gaps; Wage inequality

JEL Codes: J15; J31; J62

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1 Introduction

The extent, sources, and remedies of immigrant labor market disadvantages seen in many Western economies are topics of intense scholarly and political debates. A vast literature documents wage and employment gaps relative to native workers, greater among recent migrants but present for decades.[1] Lack of country-specific human capital, such as language skills, is a commonly proposed explanation to why outcomes are particularly poor among the recently arrived. Other sources of inequalities are less immigrant-specific, but highly relevant. Substantial bodies of work investigate factors like employer discrimination, residential segregation, and the importance of networks and contacts.[2]

A much smaller but growing literature considers the role of firms and their hiring and pay-setting practices. These studies are partly motivated by two empirical observations: (i) there are significant and growing differences in wages and earnings across firms and establishments (Skans et al., 2007; Card et al., 2013; Barth et al., 2016), and firm practices increase inequality across groups in general (Card et al., 2016; Card et al., 2018; Gerard et al., 2021); (ii) there is substantial origin-based workplace segregation, which is also correlated with economic outcomes of individuals and groups (Hellerstein and Neumark, 2008; Åslund and Skans, 2010).

This study focuses on a particular aspect of firms: productivity. Consistent with models of rent-sharing implying a positive relationship between wages and firm productivity (Manning, 2011), our population-wide linked employer-employee data for Sweden shows that persistent measures of firm value added per worker are strongly related to individual-level earnings. We study how this measure of productivity relates to the allocation and workplace mobility of immigrant and native workers, the group-specific earnings gains from working at more productive firms, and how these factors relate to overall immigrant-native earnings gaps.

Sweden provides an interesting case for several reasons. First, over the past decades the country has experienced substantial and diverse economic and humanitarian immigration, bringing the fraction of foreign-born close to 20 percent in 2020 (SCB, 2020). Second, the overall immigrant-native employment differentials are among the greatest in the OECD (OECD, 2021). Our data show that the raw earnings ratio decreased from about 0.92 to 0.86 between 1998 and 2017. However, in line with existing evidence on within- and across-firm wage dispersion, the within-firm earnings gap is smaller and has not increased over time. Third, the country has low wage dispersion, a high degree of unionization and extensive collective bargaining. Studying a context where institutions counteract firm differentials gives an indication on the potential impact of firm policies, and complements evidence from less regulated labor markets.

[1] See Kerr and Kerr (2011), Borjas (2014), and Duleep (2015) for overviews.

[2] See e.g. Neumark (2018) on discrimination, Gobillon et al. (2007) and Chetty et al. (2020) on segregation, and Dustmann et al. (2016) on networks.

We start by proposing an easy-to-implement way to rank firms which captures how well-performing they are based on persistent differences in firm productivity. One advantage of our ranking method as compared to alternatives based on estimated firm fixed effects from AKM regressions (Abowd et al., 1999), is that it is based on a readily-observable measure of firm productivity that is directly interpretable.[3]

We rank firms based on average productivity over our sample period, 1998 to 2017, from a regression of log value added per worker on firm and year fixed effects. This allows us to classify firms into a tractable number of groups (productivity percentiles) and is similar in spirit to Bonhomme et al. (2019), who bin firms into classes via k–means clustering. We find no indication that this measure is influenced by the composition of workers in the firm, including the share of immigrants the firm employs. We also show that firms' position in the ranking is stable when computing the ranking in different sub-periods. Firms of all sizes and in most industries are present in all parts of the productivity distribution. There is a positive association between size and productivity, but the very large firms are also over-represented in the lowest decile.

The data reveal an almost linear positive relationship between firm productivity and average earnings, starting from the 10th percentile of the firm productivity distribution. Using an AKM model to control for worker heterogeneity, we show a very strong association between estimated firm earnings premiums and the productivity rank across the entire distribution of firms. AKM results also suggest that firm effects explain more of the earnings variation among immigrants than natives.[4] In other words, where one works appears to be even more important for immigrant workers than for native workers.

Foreign-born workers are over-represented in low-productive firms and under-represented in the upper part of the productivity distribution. Comparing the 1998–2009 period to the 2010–2017 period, we find that this sorting has become stronger over time. This pattern holds also when controlling for compositional changes in the immigrant population, even though the increased under-representation in high-productive firms is to some extent related to changes in source countries. In general, people born outside Western countries (and thus less likely to be economic migrants) are relatively more concentrated in low-productive firms.

Estimates controlling for worker fixed effects suggest that the earnings returns to working in a firm of high persistent productivity are substantial and positive for both groups, but greater for immigrants. For example, for natives there is slightly less than an 8 log point difference between working in the fifth compared to the first decile. For

[3]In addition, using a firm productivity-based ranking allows us to include in our study immigrant- and native-segregated firms, which are important to understand the role of firms in explaining earnings gaps in our setting. Moreover, our approach allows us to abstract from estimation problems that are well-known in the AKM literature (Kline et al., 2020; Bonhomme et al., 2020) and might be exacerbated in the presence of a high degree of immigrant or native firm segregation.

[4]When we estimate AKM models separately for immigrants and natives, firm effects account for 11% (22%) of native (immigrant) earnings.

immigrants, the difference is 11 log points. The differential returns are most marked in the lower half of the productivity distribution, where the immigrant share of the workforce is higher. Returns tend to be greater for migrants from non-Western countries, but similar by years-since-migration. But greater returns do not mean that immigrants earn more than natives in high-productive firms; average earnings are higher among natives than immigrants in all firm productivity deciles.

The observed sorting and the estimated returns indicate that access to high-productive firms could be a factor in explaining immigrant-native disparities. An analysis of mobility to more productive firms points in the same direction. For all starting productivity deciles, natives are more likely to have moved upwards five years later. The immigrant-native difference in mobility is about 10 percentage points up to and including the 8th productivity decile, which is substantial relative to a baseline mobility of 20–30 percent. Differences are qualitatively similar across subgroups of the foreign-born, but greater among those who have been in Sweden for less than ten years and those first observed in non immigrant-dense firms.

To investigate rent-sharing as a mechanism for differential returns to firm productivity affecting the gap, we relate within-match (and thus within-firm) variation in firm value added per worker to individual earnings. All workers gain from improved firm performance, but the impact depends on the immigrant share of workers and on the average productivity of the firm. Immigrant rent-sharing is greater in firms where a large share of the workers are foreign-born than where there are few immigrant peers. This pattern is most marked in low-productive firms. Results signal the potential importance of local bargaining power and/or firm practices.[5]

Finally, we present a decomposition analysis to evaluate the contribution of firm productivity pay premiums to the immigrant-native earnings gap. The average premium is the sum of sorting across deciles, and a pay-setting component for working in a given decile (relative to working in the lowest productivity decile). This average is 0.8 percentage points higher for immigrants, amounting to 7% of the earnings gap in the overall sample. Importantly, however, sorting and pay-setting work in opposite directions. Assuming migrants had the same returns to firm productivity as natives, their over-representation in less productive firms increases the earnings gap by 22%. On the other hand, if the allocation across firm types had been the same among immigrant and native workers, the higher returns among immigrants would have reduced the gap by around 28%.

Previous studies show that between-workplace variation explains significant shares of immigrant-native earnings gaps (Barth et al., 2012; Damas de Matos, 2017; Dostie et al., 2020; Gorshkov, 2020). There is also evidence that workplaces are related to the assimilation process. Eliasson (2013) finds that most earnings convergence occurs within

[5] It is of course hard to tell whether generous pay-setting policies toward immigrants attract immigrant workers, or whether a strong presence of migrants affects policies.

establishments rather than through transitions between workplaces. Results in Ansala et al. (2021) suggest that workplace conditions are strongly related to entry job earnings and subsequent performance among immigrants. Arellano-Bover and San (2020) find that recent migrants tend to work in low-paying firms, while access to higher-paying firms over time explains a significant fraction of immigrant-native pay differences.[6]

In addition to an impact of sorting over well- and badly-performing firms, the immigrant-native earnings gap can also be influenced by systematic cross-group differences in the premium from working in a specific type of firm. The latter phenomenon can for example arise if firms have more market power over immigrants.[7] Manning (2020) highlights that when labor markets are less competitive, wages will be more closely linked to reservation wages than to worker productivity. Hirsch and Jahn (2015) find that immigrants supply labor to the firm less elastically than natives. Bassier et al. (2020) show that the degree of monopsony power is higher in low-wage labor markets.

Preferences may also play a role. In the static monopsony model developed by Card et al. (2018), workers differ in their valuations of non-wage amenities and firms share rents due to information asymmetries. When there is room for discretion in wage setting, employers may discriminate based on preferences so that natives receive a larger share of rents than immigrants do (see Dostie et al., 2020).[8]

How do our results connect to theory? We find that: (i) more productive firms pay higher wages; (ii) immigrants are concentrated in low-productivity firms, and have lower rates of upward mobility; (iii) earnings gains from across-firm variations in productivity are greater for immigrants, especially in groups with poor average labor market positions; (iv) within-firm variations in productivity over time are strongly related to earnings for all groups of workers, but immigrant-native differences depend on peer density and persistent firm productivity.

The relative concentration in low-productive firms and lower upward mobility rates fit predictions of ethnically segregated and segmented labor markets (Reich et al., 1973; Massey and Denton, 1993).[9] Higher returns to working in a firm with persistently higher productivity are consistent with greater monopsony power over immigrants in the lower part of the firm productivity distribution (as discussed above). A greater earnings gap at the lower end means a steeper gradient to the pay offered by more productive firms. Of course, the results could also reflect stricter local enforcement of collective bargaining norms or inequality aversion in better-performing firms.

Since immigrants gain more from entering better firms but do so less frequently, it

[6]Immigration can also drive positive assortative matching between workers and firms, with consequences for the overall wage structure (Orefice and Peri, 2020).

[7]Closely linked are mechanisms linked to employer discrimination and immigrants having worse bargaining positions.

[8]See also Rosen (1986) for the influences of preferences among workers.

[9]The broader literature on transitions of workers up the job ladder and on worker sorting across firms also finds differences across groups of workers (Haltiwanger et al., 2018).

seems likely that there are thresholds for immigrants to climb the productivity ladder. There are of course many potential candidates for such thresholds; for example language barriers or manager hiring practices following ethnic delineations (Åslund et al., 2014). The fact that the association between within-firm productivity changes and individual earnings depends on peer density signals that firm-specific practices matter. Even though average outcomes are poorer in immigrant-dense firms, the observation that rent-sharing and upward mobility is greater in such contexts signals that there may also be advantages to working among peers.

From a policy perspective, it is particularly striking that immigrant groups with poor labor market positions deviate the most from natives in sorting, mobility, and returns. This speaks against voluntary sorting due to worker preferences, and signals the individual and societal gains from more equal employer access.

The rest of the paper proceeds as follows. In Section 2 we outline the data and main sample. Section 3 we present evidence on the immigrant-native earnings ratio, focusing on the role of firms in explaining the gap. Section 4 explains how we measure firm productivity. Our main results are included in Section 5. We analyze the sorting of immigrants and natives across the firm productivity distribution, as well as the earnings returns associated with working in more productive productive firms. This section also considers potential mechanisms: mobility up the productivity distribution and rent-sharing following productivity variations within firms. Section 6 presents a decomposition of the earnings premium. Section 7 concludes.

2 Data and main sample

We use data for the entire Swedish working-age population over the period 1998 to 2017, combining information from several administrative registers collected by Statistics Sweden. The RAMS matched employer–employee database is used to construct an employer-employee panel with yearly information on firm size in November, industry and total earnings paid by the firm. Statistics Sweden's business register on firm-level accounts provides information on value added (VA) for private firms. VA is defined as total value added at each production stage net of costs for intermediate goods and services, and is equal to total revenues minus intermediate consumption of goods and services. We divide the total firm VA by the number of employees reported in the balance sheet registers to obtain the measure of VA per worker used to rank firms.[10]

We complement this information with a rich set of socioeconomic characteristics from the Louise/Lisa database. Since the analysis focuses on firm productivity, we sample workers employed at private sector firms that have at least two employees in November.

[10]Firm accounts are available until 2015. Excluding firms for which VA information is missing results in about 12% of employee-year observations being dropped from the initial sample.

For each employee aged between 18 and 65, we compute total annual earnings, job tenure, and total number of months worked at the primary employer.[11] All monetary values are deflated to 2010 Swedish Kronor (SEK). To diminish the influence of extreme values and potential measurement error, earnings are winsorized at the 99$^{\text{th}}$ percentile of their yearly distribution. Moreover, we drop individual histories if log-earnings in any year are three standard deviations or more above the sample mean.[12] To focus on workers sufficiently attached to the labor market, we drop observations where earnings from the primary employer are lower than the yearly Price Base Amount (PBA).[13] Our main outcome of interest is monthly earnings from the primary employer, obtained by dividing annual earnings by the number of months worked.

Immigrants are defined as foreign-born with two foreign-born parents. People born abroad to at least one Swedish-born parent are excluded from the sample. We also present results where immigrants are divided into "West" (i.e. Western Europe, USA and Australia) and "Rest of the world" based on country of birth.[14]

Table 1 shows summary statistics for our main analysis sample. Panel A shows worker-level characteristics. At the start of the sample period, 9% are immigrants. Out of these, 51% were born in the West while 49% were born in the Rest of the World. The share of immigrants has doubled over the sample period. This change is driven primarily by an increase in non-Western migrants. 18% of employees work at firms that are completely segregated: 6% of immigrants work at all-immigrant firms, and 20% of natives work at all-native firms.

As a consequence of focusing on private sector employees, there is a gender imbalance: 64% are men. The average age is 40. Over time, the educational level has increased; this is reflected by a decline in the share with only compulsory education and an increase in the share with upper secondary education. Real monthly earnings increased from 21,000 SEK to 28,000 SEK between 1998 and 2017.

Turning to firm characteristics in Panel B, there are approximately 137,000 firms per year in the sample (somewhat fewer in the beginning and at the end of the period). The mean share of immigrants per firm has evolved roughly in line with the mean share of immigrants in the population. The mean masks the fact that there is a large portion

[11] The primary employer is defined as the firm paying the highest yearly earnings. To compute job tenure we use data from 1985 onward.

[12] Given that earnings are winsorized at the top, this second restriction only affects a residual number of workers.

[13] PBA is used to calculate benefits and fees in Sweden. Ruist (2018) argues that an earnings level equal to three times the PBA is a threshold for being self-supporting. Therefore, one PBA is a rather low threshold.

[14] "West" consists of the Nordics (Denmark, Finland, Norway and Iceland but not Sweden), Western Europe (Ireland, the UK, Germany, Greece, Italy, Malta, Monaco, Portugal, San Marino, Spain, the Vatican Sate, Andorra, Belgium, France, Liechtenstein, Luxembourg, the Netherlands, Switzerland and Austria), Canada, USA, Australia and New Zealand. "Rest of World" are countries that are not in the West.

of completely segregated firms: 62% of firms are native-segregated and 4% of firms are immigrant-segregated. The share of firms that are native-segregated has declined over time while the share that are immigrant-segregated has increased. There are on average 17 employees per firm (the median is 4). Mean firm size has increased over time, from 15 in 1998 to 22 in 2017.

Table 1: Summary statistics, analysis sample

	1998–2017	1998	2017
	(1)	(2)	(3)
Panel A: Employees			
Immigrant	0.133	0.094	0.183
Immigrant from West	0.039	0.048	0.034
Immigrant from Rest of World	0.094	0.046	0.149
Native-segregated firms	0.177	0.221	0.118
Immigrant-segregated firms	0.008	0.003	0.011
Male	0.643	0.664	0.624
Age	40.289	39.917	40.215
Age ≤ 30	0.266	0.267	0.287
Age ≥ 50	0.269	0.264	0.278
Education, compulsory	0.158	0.246	0.109
Education, secondary	0.548	0.539	0.530
Education, tertiary	0.288	0.210	0.349
Education, missing	0.007	0.005	0.013
Monthly earnings (2010 SEK)	24,665.686	20,864.961	28,014.769
No. observations	46,511,478	1,869,061	2,481,798
Panel B: Firms			
Fraction immigrants at employer	0.128	0.084	0.184
Yearly employer size	16.968	15.175	22.226
Share native-segregated firms	0.625	0.710	0.506
Share immigrant-segregated firms	0.045	0.024	0.065
No. observations	2,741,093	123,168	111,662

3 The immigrant-native earnings ratio

We start by analyzing the immigrant-native earnings gap and how it has evolved over time. Figure 1 reports the yearly immigrant–native earnings ratio between 1998 and 2017. It is given by the exponential of the coefficient θ_t from the following yearly regressions:

$$ln(e_{it}) = c_t + \theta_t imm_i + \beta_t X_{it} + \varepsilon_{it} \quad (1)$$

$ln(e_{it})$ are log monthly earnings for worker i in year t at the primary employer. Included in X_{it} are controls for age, age squared, gender, level of education (dashed line), as well as industry dummies $\lambda_{ind,t}$ (dotted line) or firm fixed effects $\lambda_{f,t}$ (triangles). The figure shows that there is a persistent earnings gap between natives and immigrants in all years. The raw immigrant-native earnings ratio has been declining over time; the gap in earnings has widened by approximately six percentage points between 1998 and 2017. Adjusting for age, gender, and education, the gap has widened even more. Including industry fixed effects indicates that the widening gap is present also within industries. However, adding firm fixed effects, the earnings ratio is higher in all years and even rises slightly over the period. It follows that earnings differences are substantially lower within than between firms. This suggests that the increase in the earnings gap is driven by differences between rather than within firms (see e.g. Tomaskovic-Devey et al., 2020), which motivates focusing on firms as a key element for understanding immigrants-native earnings differentials.[15]

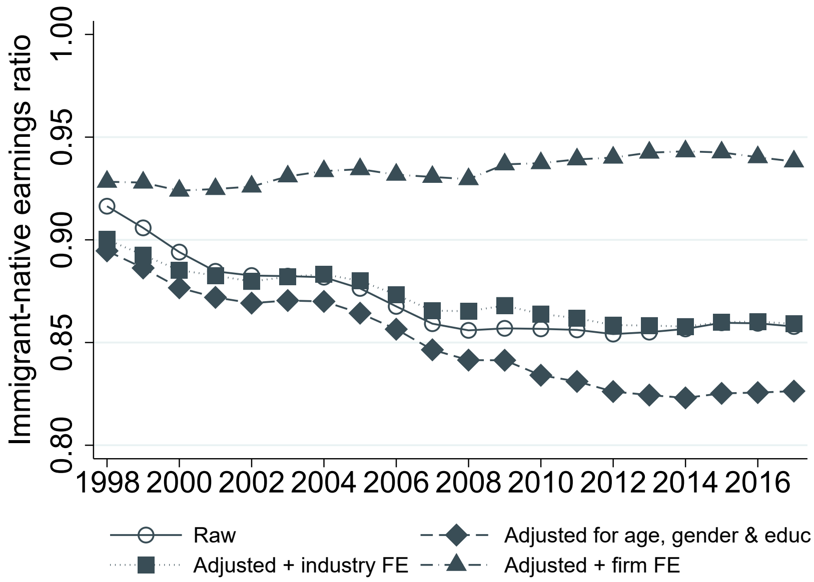


Figure 1: Immigrant–native earnings ratio

Estimating AKM models separately for immigrants and natives confirms that place of work is important for earnings. Full results, including an outline of the AKM model, are included in Appendix Table A.1. Even though differences in skills that are rewarded equally across firms may be the the most important component, the large standard deviation of the estimated firm effects for both natives and immigrants indicates that firms are also key in explaining earnings differences across workers.

[15] Appendix Figure A.1 plots the earnings ratio of immigrants compared to natives separately for Western countries and Rest of World countries. The West/native earnings ratio is flat and equal to approximately 0.97 throughout the period, once we include controls. The Rest of World/native earnings ratio is about 0.80–0.85 throughout the period. The overall earnings gap within firms has been closing over time when we compare the Rest of World immigrants to natives. Thus, at least some of the overall trends are driven by differences in the composition of migrants, bearing in mind that the share of Rest of World migrants has increased over time (see Table 1). For an analysis of occupational and task differences explaining immigrant-native wage differentials in Sweden, see e.g. Baum et al. (2020).

Decomposing the overall variance of log earnings, firm effects are found to account for 11% of the overall variance in earnings for natives, and 22% for immigrants (see the bottom of Table A.1). The covariance of person and firm effects accounts for a further 4% for natives. For immigrants, there is if anything a negative sorting but with very limited explanatory power.

For the remainder of the paper, we focus on a measure of firm productivity based on value added per worker, as opposed to the AKM firm fixed effects. This choice allows us to give an explicit interpretation to the relationship between firms and the immigrant-native pay gap, as well as include segregated firms in all results (segregated firms are relatively common in Sweden, as discussed above; see Table 1).[16] As we show in the next section, the firm fixed effects from an AKM model are strongly correlated with firm productivity based on value added per worker.

4 Firm productivity ranking

In the previous section, we showed that there are substantial immigrant-native earnings gaps, particularly between firms. Differences in firm productivity could potentially explain this finding.[17] This section presents our procedure for capturing firm value added, describes how this measure of persistent firm productivity is related to firm size and industry, and analyzes its association with earnings at the firm level.

4.1 Ranking procedure

In order to obtain a measure of persistent firm productivity that abstracts from fluctuations due to the business cycle and productivity shocks, we start by estimating the following model:

$$\ln(VA/N)_{ft} = \lambda_f + \lambda_t + \varepsilon_{ft} \tag{2}$$

where the fixed effects λ_f capture the permanent component in firm-level productivity and λ_t account for yearly effects common across all firms.

We estimate equation (2) using all firms for which information on both value added and firm size is available in at least two years in the matched employer-employee panel during 1998–2015, after restricting firm size to be larger than one.[18] Next, we use the empirical distribution of the $\widehat{\lambda}_f$ firm effects to rank firms into deciles or percentiles. Similar to the clustering procedure used by Bonhomme et al. (2019), grouping firms in

[16] We also avoid using firm fixed effects due to known possible incidental parameter problems when estimating the AKM (Andrews et al., 2008). Recent papers have proposed ways to tackle these problems (Kline et al., 2020; Bonhomme et al., 2020), but in our context, due to the smaller size of the group of immigrants, the bias may be particularly severe, further complicating how to interpret the results.

[17] For an extensive overview of why productivity differs between firms, see Syverson (2011).

[18] Dropping the firm size restriction leaves the results qualitatively unaffected.

this way aims to improve the tractability of our analyses. By construction, each firm's position in the productivity distribution is fixed over time. Even though value added per worker is only available until 2015, we thus obtain a measure of persistent productivity until 2017 (as long as the firm exists in earlier years).[19]

4.1.1 Robustness of the ranking

Table 2 compares the firm productivity ranking used in the main analysis with alternative ranking procedures. Panel A shows rank correlation coefficients for alternative specifications. Panel B reports the share of firms classified higher or lower in the ranking by at least 10 percentiles as compared to the baseline. Reassuringly, we find that the baseline ranking is robust to including additional controls or using different methods to generate the ranking.

Columns (1)–(3) of Table 2 show results when either producing the ranking by industry or controlling for the share of immigrants, or both. In general, this leaves the ranking qualitatively unaffected. For the ranking done by industry, despite some 11% firms being classified as belonging to a lower decile of the firm productivity distribution, the correlation with the baseline ranking is strong (0.95).

Log value added per worker may to some extent mechanically reflect that high-skilled workers are concentrated in certain firms, i.e. firm productivity may be a function of worker productivity. Column (4) reports results when we re-estimate equation (2) by including staff-composition characteristics averaged at the firm-year level (share of men, share of workers in each education category, average tenure at the firm, share of immigrants).[20] In Column (5) we alternatively control for worker fixed effects averaged at the firm-year level (estimated from an AKM model on log-monthly earnings). In both cases the productivity ranking is virtually unaffected.[21]

Thus, the measure of firm productivity used in the analysis is strongly related to earnings at the firm level, and is robust to alternative procedures and competing explanations. Most importantly, it captures firm productivity as opposed to worker productivity.

[19] When separately re-computing the ranking of firms in 1998-2009 and 2010-2017 for the firms operating in both periods, the correlation of the two rankings is of 0.70 and the share of firms moving up or down by at least 10 percentiles is about 0.25. The correlation of the 1998-2009 ranking with the baseline full-period ranking is of 0.93, with the share of upwards (downwards) movers being 0.13 (0.01); similar results are obtained when comparing the 2010-2017 ranking with the baseline one (0.89, 0.14, and 0.02). Moreover, results are virtually unaffected when re-computing the full-period ranking by including only the firms operating in both periods.

[20] Throughout our main analysis on the returns to working in more productive firms, we condition on individual-level fixed effects.

[21] As mentioned earlier, we also tested the stability of the ranking of firms when re-computing the ranking before and after 2010. Results show that the ranking is not affected when we only focus on early or later years to rank firms.

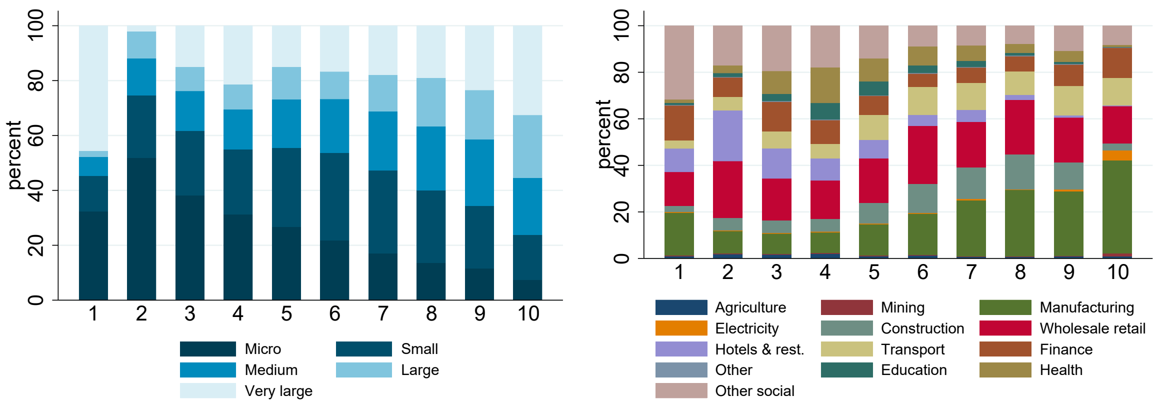
Table 2: Robustness of the firm ranking

	Industry	Share of immigrants	Industry and share of immigrants	Staff composition	Worker FEs
	(1)	(2)	(3)	(4)	(5)
Panel A: Correlation with baseline ranking					
	0.9542	0.9977	0.9519	0.9895	0.9754
Panel B: Share of firms moving in the ranking					
moving down	0.1123	0.0001	0.1212	0.0060	0.0372
moving up	0.0631	0.0116	0.0751	0.0185	0.0302
No. of firms	323,072	323,072	323,072	313,828	278,323

Notes: Panel A reports Spearman's rank correlations between the baseline productivity ranking percentiles and the following alternative measures: Column (1): ranking firms by industry; Column (2): controlling for the yearly share of immigrants at the firm; Column (3): ranking firms by industry and controlling for the share of immigrants at the firm; Column (4): controlling for education categories, gender, age, tenure, share of immigrants averaged at the firm-year level; Column (5): controlling for average worker FEs estimated via AKM model. Panel B reports the share of firms moving at least 10 percentiles in the ranking as compared to the baseline.

4.2 Firm productivity and other characteristics

To understand what types of firms are found in each productivity decile, Figure 2 shows the distribution of employees by firm size (Panel a) and by industry (Panel b) within each productivity decile of the $\widehat{\lambda}_f$ distribution.



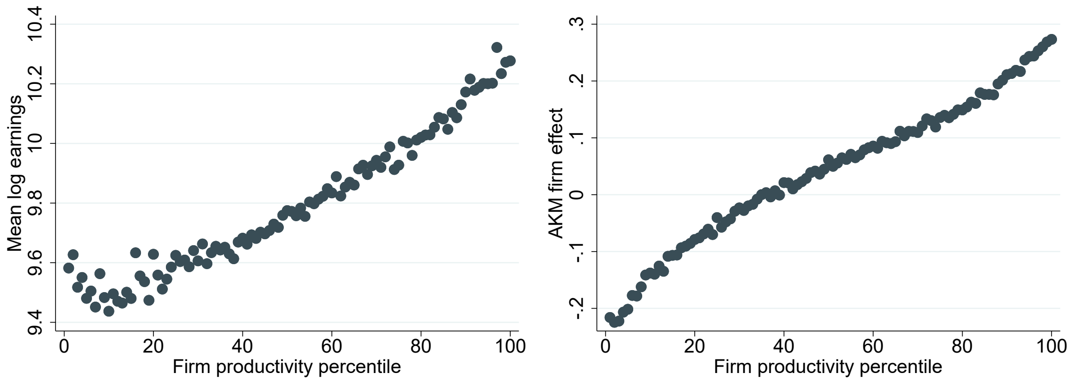
(a) Firm size

(b) Industry

Figure 2: Employment distribution within decile rank, by firm size or industry (1998–2017)

We group firms into five size bands: up to 9 employees (micro), up to 50 employees (small), up to 250 employees (medium), below 1000 employees (large) and 1000 employees and above (very large). Panel (a) shows that small and micro firms tend to be common in the lower deciles, whereas large and very large firm are more prevalent in the upper part of the distribution. Note, however, that the first decile is strongly dominated by the largest and smallest firms. Panel (b) additionally shows that virtually all industries are found in each productivity decile. Thus, working in more productive firms does not only reflect working in specific industries. Instead, the whole range of firm productivity types tends to be represented in the different industries.

Figure 3, Panel (a), shows log earnings averaged by each percentile of the firm productivity distribution. The results indicate that there is a positive and close to linear relationship between earnings and productivity ranking.[22] To understand how the common component of firm earnings relates to firm productivity above and beyond individual worker heterogeneity, Panel (b) plots the firm fixed effects obtained from a pooled AKM regression against productivity percentiles. This measure of a common firm-specific pay premium is strongly correlated with the productivity rank over the entire distribution of firms.[23] The pattern remains when using firm ranks weighted by the number of employees (Figure A.7). Our main results in Section 5 below are robust to using the alternative employee-weighted ranking.[24]



(a) Log earnings

(b) AKM firm fixed effects

Figure 3: More productive firms pay higher earnings

[22]The tendency to higher mean earnings in firms in the lowest percentiles could arise for several reasons. For example, the consistently positive slope in Panel (b) of Figure 3 indicates the presence of some "high-wage workers" in low-productive firms.

[23]When we rank firms using AKM fixed effects from an earnings regression and correlate this with the firm productivity-based ranking, we find a correlation of 0.41. Since the AKM firm fixed effects capture firm-level premiums attributable to several other time-fixed components on top of persistent productivity, the observed degree of correlation between the AKM- and the productivity-based rankings appears to be sizable.

[24]Plotting AKM firm fixed effects directly against mean log valued added per worker (Figure A.6) suggests that there is no rent-sharing at very low levels of firm productivity, which is similar to Card et al. (2016).

5 Sorting and returns to working in productive firms

The relationship between productivity and earnings for immigrants compared to natives can operate through several channels. First, it could be related to sorting: immigrants and natives may work in different types of firms. Second, it could be related to pay setting: in firms of a given productivity, immigrants and natives may be offered or negotiate different earnings (Card et al., 2016, Dostie et al., 2020). This can for example arise because firms have market power over workers and consequently are able to set lower wages to groups of individuals with more inelastic labor supply to the firm. This section first considers sorting of immigrants and natives and then turns to the earnings returns.

5.1 Distribution of workers in the firm productivity distribution

Figure 4 presents the distribution of immigrants and natives across the firm productivity distribution. For native workers, the number of workers per percentile grows steadily with productivity. For immigrants, this pattern is weaker, resulting in a relative over-representation in low-productive firms.

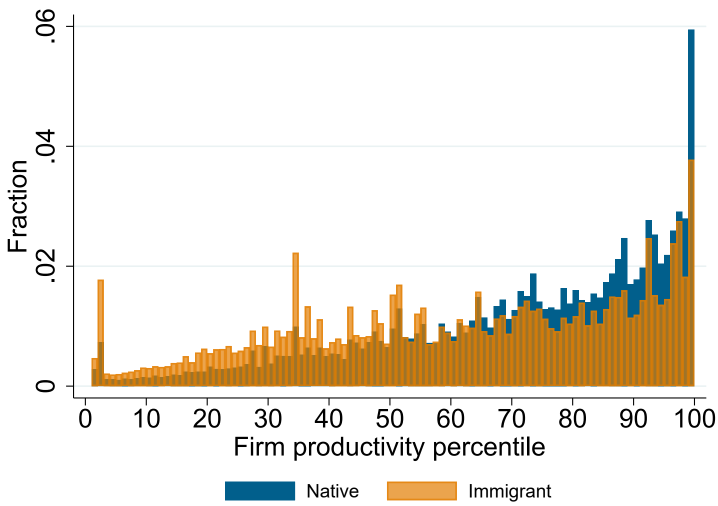


Figure 4: Distribution of immigrants and natives across productivity percentiles

To investigate how sorting has developed over time, we break the data into the sub-periods 1998–2009 and 2010–2017. We then estimate the following linear probability model separately by sub-period p:

$$imm_i = \alpha_p + \sum_{d=2}^{10} \beta_{dp} decile_d + \varepsilon_{ip} \tag{3}$$

where $decile_d$ refers to productivity decile. The first decile is omitted from the regressions such that the immigrant shares in a particular decile are estimated relative to the bottom decile.

Figure 5 plots $\hat{\beta}_{dp}$ from the regressions. It shows that immigrants have become relatively more concentrated in firms with lower productivity over time, compared to the share in the first decile. In particular, the second period estimates (shown by the dark blue squares) are above the first period (orange dots) at the bottom deciles and vice versa at the top.[25] There may be compositional changes in the immigrant population, which affect sorting. To account for this, we weight the second sub-period to match the first in terms of either country of birth (CoB) or years since migration (YSM) to Sweden. Weights are constructed as the ratio of the share in each respective country of birth or years since migration cell. The development of sorting appears not to be driven by changes in these variables.

However, the composition of workers with regards to country of birth explains part of the declining relative representation in the most productive firms. This is consistent with an increasing fraction of immigrants from the "Rest of the World" and the group's much stronger relative concentration to low-productivity firms; see Figure A.2. In fact, Western migrants are found in similar shares in all productivity deciles and there is no change over time. The presence of "Rest of the World" migrants increased over time in all deciles, but much more in the lower part of the productivity distribution.

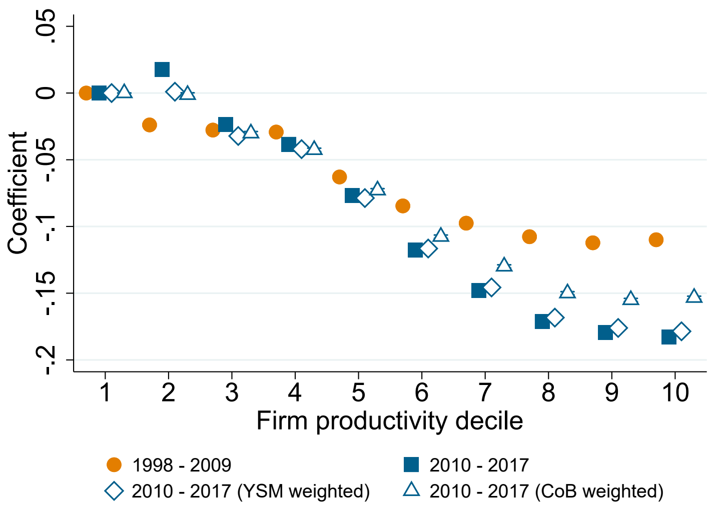


Figure 5: Sorting of immigrants across productivity deciles

5.2 Earnings returns to working in more productive firms

Figure 6 presents statistics capturing the main messages of our study. First, in line with the discussion above, the immigrant share falls strongly with productivity. The

[25]The overall immigrant share was 11.3% 1998–2009 and 16.0% in 2010–2017. The expected impact on absolute differentials across deciles from an increasing overall share is not obvious. However, sorting increased also measured relative to the overall share.

foreign-born account for 20 to 25% of employment in the lowest four deciles. At the top of the distribution, the figure is about 10%. Second, immigrants on average earn less in all deciles of firm productivity. Third, average earnings for natives as well as immigrants increase strongly with firm productivity. Since the immigrant-native gap tends to be greater at the lower end of the productivity distribution, the returns for immigrants could be even greater. At face value, this indicates that immigrants enter more productive firms less often, but may have the most to gain from doing so.

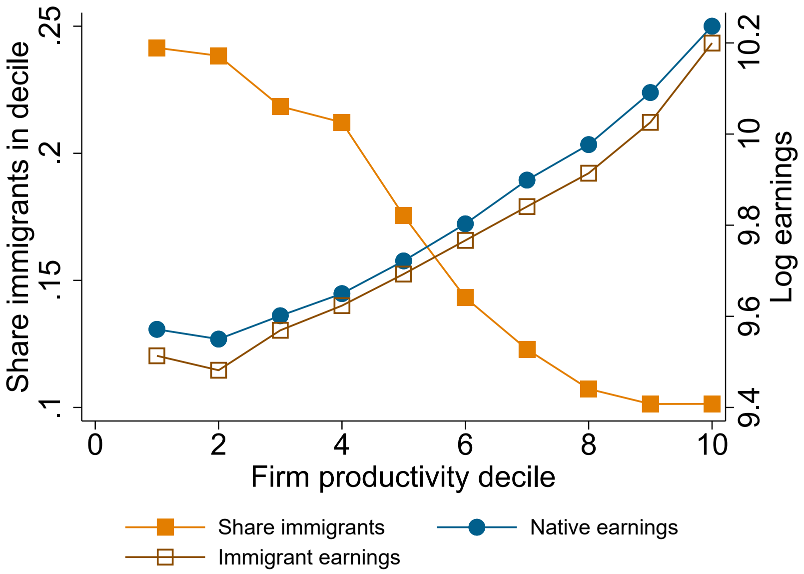
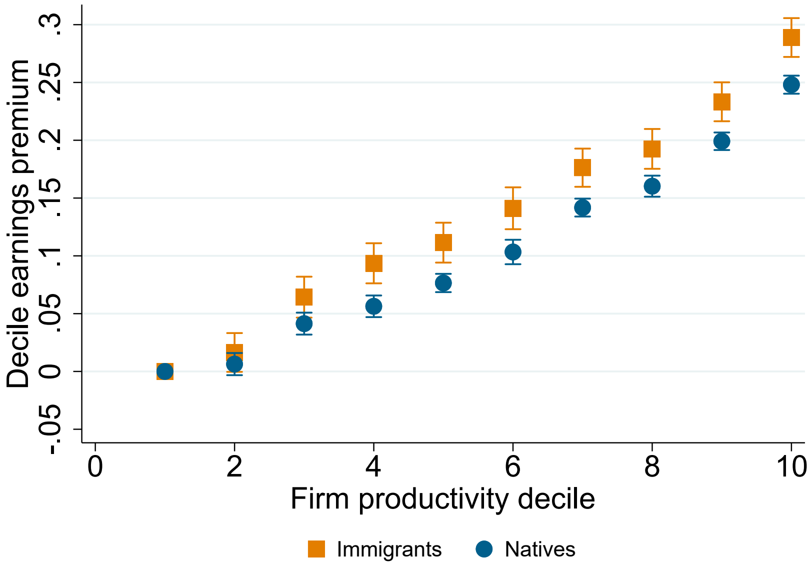


Figure 6: Share immigrants and raw log earnings by productivity decile

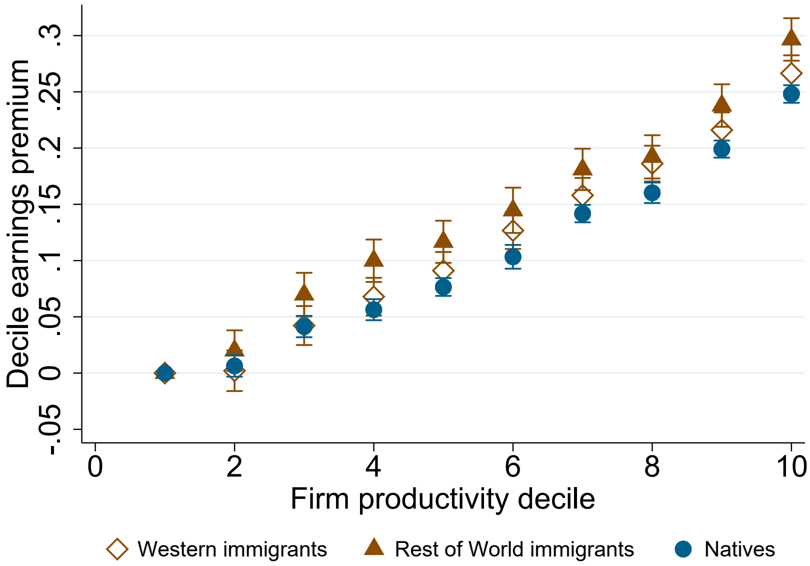
To more formally understand how earnings returns differ for immigrants and natives across the firm productivity distribution, we regress log earnings $\ln(e_{it})$ on the firm productivity decile $decile_d$ and on the interaction of the decile and an immigrant dummy imm_i:

$$\ln(e_{it}) = c + \sum_{d=2}^{10} \theta_d decile_d + \sum_{d=2}^{10} \gamma_d decile_d \cdot imm_i + \alpha_i + \lambda_t + \beta X_{it} + \varepsilon_{it} \tag{4}$$

The estimand $\hat{\theta}_d$ ($\hat{\theta}_d + \hat{\gamma}_d$) are the earnings returns to natives (immigrants) of working in relatively more productive firms, compared to natives (immigrants) working in the first productivity decile. Thus, $\hat{\gamma}_d$ is the differential return to immigrants of working in more productive firms. We include individual fixed effects α_i to control for individual heterogeneity in earnings. The identification of the return by productivity is consequently only based on individuals that have transitioned across productivity deciles. We include controls X_{it} for age polynomials (age squared and age cubed), as well as the same controls interacted with the immigrant dummy to allow differential effects for immigrants and natives.[26] We cluster standard errors at the firm level.



(a) All immigrants



(b) By immigrant group

Figure 7: Earnings returns to working in more productive firms

Note: Panel (a) plots $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4) for the full sample of natives and immigrants. Panel (b) plots $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4) for: (i) the full sample (circles); (ii) the full sample of natives and Western immigrants (diamonds); and (iii) the full sample of natives and Rest of World immigrants (triangles). All specifications include individual fixed effects, year fixed effects and controls as specified in Section 5.2. Table A.2 displays point estimates.

[26]Specifications excluding worker fixed effects give similar results, but the estimated coefficients $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ are much larger in size. Adding controls for education has virtually no impact.

The results are included in Figure 7. Panel (a) is for the full sample of immigrants, while Panel (b) splits the comparison to natives into the Rest of the World and the West birth region groups. The blue dots show returns to natives ($\hat{\theta}_d$) while the orange dots show returns to immigrants ($\hat{\theta}_d + \hat{\gamma}_d$).

For both immigrants and natives, there is a clear positive earnings return to working in more productive firms. For example, for the full sample in Panel (a), the estimated return to natives of working in the fifth decile compared to the first is 7.6 log points, and to immigrants nearly 11.1 log points. The return in the tenth decile is 25 log points for natives and almost 29 log points for immigrants. The differential return increases gradually in the lower part of the productivity distribution. From the fourth decile, the gap relative to the first remains about 3–4 log points. In other words, moving up one more decile is then associated with similar gains for natives and immigrants.[27] Recall that there is a persistent raw earnings gap between immigrants and natives across the whole productivity distribution (Figure 6). Even though some rungs on the ladder are taller for immigrants, it does not mean that immigrants have higher earnings than natives in more productive firms.

The returns to firm productivity may differ across groups of migrants. Panel (b) of Figure 7 shows that the differential returns are clearest for immigrants from the Rest of the World. Immigrants from the West have earnings returns more similar to natives, although it should be noted that the point estimates are greater in all deciles from the fourth and above. Another important component is years since migration. As discussed in the introduction, a large literature suggests that immigrants become more similar to natives with years spent in the host country. However, separate estimates for immigrants that have spent less than (at least) 10 years in Sweden suggest similar returns to firm productivity, in both cases greater than for natives (see Figure A.9).

5.3 Mechanisms: mobility and rent-sharing

5.3.1 Upward mobility in the productivity distribution

The returns to working in more productive firms are higher for immigrants than natives, but immigrants are less likely to work in more productive firms. These two findings raise the question as to which workers do actually climb up the productivity ladder.

[27] Results from estimating equation (4) using the employee-weighted ranking are included in Appendix Figure A.8.

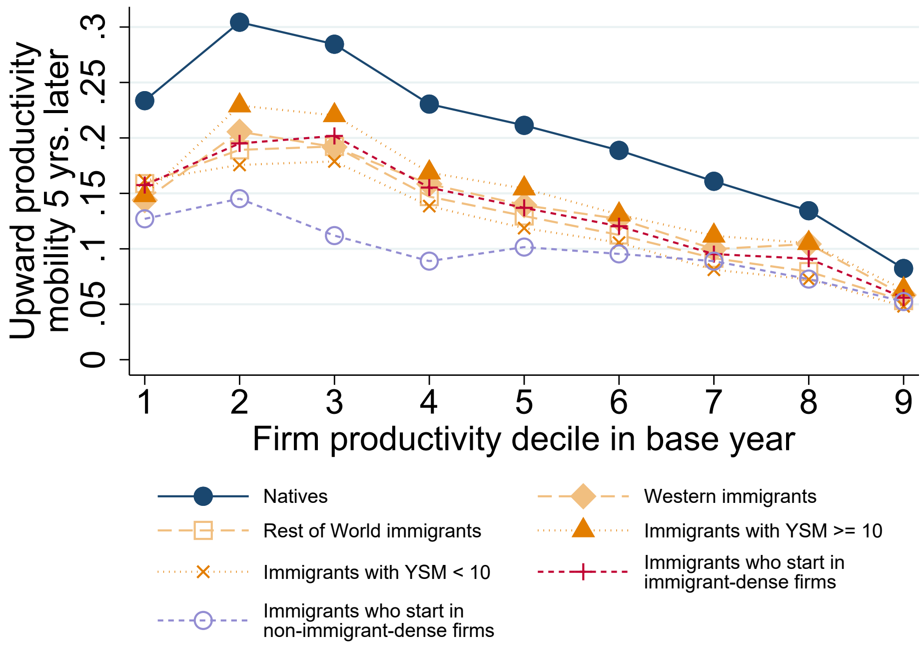


Figure 9: Upward mobility, natives vs. various groups of immigrants

Figure 9 plots the share of immigrants in various groups and natives who move up the productivity ranking, conditional on where they start (in our sample).[28] We define upward mobility as working in a higher productivity decile five years later compared to when the individual is first observed.[29] We see that, for all groups, the likelihood of moving up decreases with initial firm productivity (from the second decile). However, immigrants are less likely than natives to move at all, and this essentially holds across the whole productivity distribution and for all groups of immigrants.

The analysis shows that upward mobility is less common among immigrants starting in non-immigrant-dense firms, especially in the lower half of the productivity distribution. Differences between Western than Rest of World immigrants are limited, but immigrants with 10 or more years in the host country are more mobile than those who arrived more recently.

Could it be that mobility differences are related to differential selection of natives and immigrants? In order to test this hypothesis, we study the average person fixed effects

[28] We look at the following groups: Western immigrants, Rest of World immigrants, recently-arrived immigrants (YSM less than 10 years), immigrants with YSM more than 10 years, immigrants who start in immigrant-dense firms, defined as firms in the top quartile in the distribution of the immigrant share, and immigrants who start in non-immigrant-dense firms (all other firms; the median share of immigrants is 0 in all years). Note that the immigrant groups are not mutually exclusive. For example, there is likely overlap between the group of Rest of World immigrants and the group of recent arrivals, or between the group of recent arrivals and those in immigrant-dense firms.

[29] The outcome variable takes the value 1 if the productivity decile five years later is *strictly* higher than in the initial year, and 0 otherwise. Since by construction the outcome does not vary for those that start off in the highest decile, we disregard these individuals.

for immigrants and natives across the productivity distribution.[30] Figure A.3 shows that upward movers are positively selected and more so in lower productivity deciles. There is also a substantial immigrant-native difference in average person fixed effects. However, the differences are similar across the firm distribution, as are the patterns for movers vs. all workers. There is thus no evidence that the selection on worker productivity into firm productivity and mobility differs between the two groups.

5.3.2 Within-firm variation in productivity and earnings

Our main definition of productivity is based on log value added per worker, where one firm is assigned a constant productivity rank throughout the sample period. The estimates presented in section 5.2 are based on comparisons across firms. Here, we instead consider how within-firm variation in log value added is related to earnings.

We estimate a model allowing for different rent-sharing between immigrants and natives, and let the association between earnings and firm value added vary between three groups: Rest of the World, Western, and natives. We also interact this categorization with immigrant density, defined as the firm being under or above the 75th percentile in the calendar-year specific distribution of the immigrant share. The analysis allows us to gauge how changes in value added at the firm over time translate into changes in earnings, and whether this differs across groups. This keeps the sorting of workers to firms constant, and controls for time-invariant worker and firm heterogeneity:

$$\begin{aligned}\ln(e_{ift}) = c + \lambda_t + \lambda_{if} + \delta_1 \ln(VA/N)_{ft} + \delta_2 ImmDense_{ft} \\ + \boldsymbol{\delta}_3 ImmDense_{ft} \cdot ImmGr_g + \delta_4 ImmDense_{ft} \cdot \ln(VA/N)_{ft} \\ + \boldsymbol{\delta}_5 \ln(VA/N)_{ft} \cdot ImmGr_g + \boldsymbol{\delta}_6 \ln(VA/N)_{ft} \cdot ImmGr_g \cdot ImmDense_{ft} + \varepsilon_{ift}\end{aligned} \tag{5}$$

where $\ln(e_{ift})$ are log earnings for worker i in year t at firm f, $\ln(VA/N)_{ft}$ is a time-varying measure of log value added per worker at the firm-level, λ_{if} is a firm-worker match FE, $ImmDense_{ft}$ is an indicator variable for immigrant-dense firms, and g indexes the immigrant group (Western, Rest of the world (main effects captured by λ_{if})). Vector coefficients are reported in bold.

Table 3 reports the estimated coefficients on all terms that include $\ln(VA/N)_{ft}$ ($\widehat{\delta}_1$, $\widehat{\delta}_4$, $\widehat{\boldsymbol{\delta}}_5$ and $\widehat{\boldsymbol{\delta}}_6$). The column (1) specification does not include any additional controls, while column (2) includes individual time-varying controls (age squared, age cubed, and tenure).[31] As before, individual controls are also interacted with the immigrant group to allow the coefficients to vary for natives and immigrants.

[30] The person fixed effects are taken from an AKM model estimated on the pooled sample of immigrants and natives.

[31] To compute tenure we use data back to 1985. Because we have observed workers in 1998 for fewer years than workers in 2015, the tenure variable is left-truncated. We therefore include tenure in six bands: 1 year (omitted category), 2-3 years, 4-6 years, 7-9 years, 10-13 years and 14+ years.

The results indicate that firms indeed share profits with their employees: a 1% increase in value added per worker is associated with close to a 0.04% increase in earnings for natives. Since the within-firm standard deviation is approximately 0.36, the estimate is economically significant. If a firm moves from low to high productivity (increases its log value added by two within-firm standard deviations), earnings are expected to increase by 2.7 percent. If one is willing to extrapolate to across-firm variations, the earnings increase would be more than 4 percent.[32]

The evidence on heterogeneous returns reveals that workplace characteristics matter. For natives, working in immigrant-dense firms means less rent sharing. For immigrants, on the other hand, working in non-immigrant-dense firms means a significantly weaker association between earnings and within-firm changes in value added. But in immigrant dense firms the link for immigrants is much stronger. Splitting the sample into high- and low-productive firms (based on the persistent measure), columns (3) and (4) reveal that this heterogeneity is driven primarily by low-productive firms. In the upper half of the distribution, returns in general and differences across groups are smaller.

Immigrant density is obviously not exogenous; we do not know whether firms sharing rents with immigrants attract immigrant workers, or if they share more rents because they have more immigrants in the work force. But the findings are at least consistent with employers having more monopsony power over immigrants when they constitute a small minority in the firm, but that immigrant bargaining power increases in immigrant-dense environments. The fact that the differential returns are greater in the lower part of the productivity distribution is in line with the across-firm estimates suggesting that immigrants have the most to gain from not working in firms with very low productivity. Note also that the findings do not necessarily suggest that immigrants are better off working with other immigrants. On the contrary, average earnings are lower in immigrant-dense firms across the productivity distribution (see Figure A.5).

[32] The overall and between standard deviations in the firm-year sample is 0.61 and 0.56, respectively. The within-firm standard deviation is 0.36.

Table 3: Rent-sharing among immigrants and natives

	(1)	(2)	(3)	(4)
log VA/N	0.039***	0.037***	0.047***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)
Rest of World × log VA/N	-0.012***	-0.010***	-0.037***	-0.007**
	(0.003)	(0.003)	(0.005)	(0.003)
Western × log VA/N	-0.015***	-0.005*	-0.035***	-0.003
	(0.004)	(0.003)	(0.004)	(0.003)
Immigrant-dense × log VA/N	-0.014***	-0.018***	-0.019***	-0.019***
	(0.004)	(0.003)	(0.004)	(0.004)
Rest of World × Immigrant-dense × log VA/N	0.025***	0.020***	0.061***	0.006*
	(0.003)	(0.003)	(0.005)	(0.003)
Western × Immigrant-dense × log VA/N	0.027***	0.023***	0.074***	0.014***
	(0.004)	(0.003)	(0.005)	(0.003)
R^2	0.764	0.775	0.728	0.762
N	36,402,251	36,402,251	7,681,586	28,720,665
Decile	1-10	1-10	1-5	6-10
Year FE	Yes	Yes	Yes	Yes
Spell FE	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes

Note: This table provides the results of estimating equation (5). Individual controls are age squared, age cubed, and tenure. Controls are also interacted with the immigrant group. Standard errors are clustered by firm and reported in parentheses. Columns (1) and (2) include firms in all productivity deciles. Column (3) only includes firms in decile 1 to 5, and column (4) only in decile 6 to 10.

6 Decomposition of the immigrant-native earnings gap

This section presents a decomposition of the earnings premium associated with working in more productive firms, and how it relates to the immigrant-native earnings gap.[33] Building on our framework from section 5.2, assume that the earnings of worker i in group g in time t are given by:

$$\ln e_{git} = \alpha_{gi} + \theta_d^g + X_{git}\beta^g + \varepsilon_{git} \tag{6}$$

where α_{gi} is a person effect, θ_d^g is a group-specific earnings premium in productivity decile d compared to the first decile, X_{git} is a vector of time-varying controls (age squared, age cubed and year effects) and β_g a vector of coefficients. ε_{git} captures all remaining determinants of earnings. Let D_{git} indicate whether an individual i in group g is employed in time t. Let $\bar{X}_{It}$ and $\bar{X}_{Nt}$ constitute the means of the observed covariates for employed immigrants (I) and natives (N) in year t, and let π_{It} and π_{Nt} denote the fractions of the

[33]The decomposition closely follows Dostie et al. (2020), who instead decompose a firm-specific earnings premium that differs for immigrants and natives.

two groups employed in decile d in year t. Assuming $E[\varepsilon_{git}|D_{git}=1]=0$, we can express mean immigrant and native earnings in the following way:

$$E[\ln e_{Iit}] = E[\alpha_{Ii}|D_{Iit}=1] + \bar{X}_{It}\beta_I + \sum_d \theta_d^I \pi_{Iit}$$
$$E[\ln e_{Nit}] = E[\alpha_{Ni}|D_{Nit}=1] + \bar{X}_{Nt}\beta_N + \sum_d \theta_d^N \pi_{Nit}$$

and the mean immigrant-native gap in year t is then:

$$\begin{aligned} E[\ln e_{Nit}] - E[\ln e_{Iit}] &= E[\alpha_{Ni}|D_{Nit}=1] - E[\alpha_{Ii}|D_{Iit}=1] \\ &+ \bar{X}_{Nt}\beta_N - \bar{X}_{It}\beta_I \\ &+ \sum_d \theta_d^N \pi_{Nit} - \sum_d \theta_d^I \pi_{Iit} \end{aligned}$$

Since we are interested in the part of the earnings gap explained by the productivity decile premiums, we focus on the third term. A simple decomposition (Oaxaca, 1973; Blinder, 1973) of the third term gives:

$$\sum_d \theta_d^N \pi_{Nit} - \sum_d \theta_d^I \pi_{Iit} = \underbrace{\sum_d \theta_d^N (\pi_{Ndt} - \pi_{Idt})}_{sorting} + \underbrace{\sum_d (\theta_d^N - \theta_d^I)\pi_{Idt}}_{pay-setting} \tag{7}$$
$$= \underbrace{\sum_d \theta_d^I (\pi_{Ndt} - \pi_{Idt})}_{sorting} + \underbrace{\sum_d (\theta_d^N - \theta_d^I)\pi_{Ndt}}_{pay-setting} \tag{8}$$

The contribution of the productivity decile premiums to the immigrant-native earnings gap is given by a weighted average of the differences in employment shares of immigrants and natives (weighted by the earnings premium of natives per decile) and a weighted average of the differences in decile earnings premiums (weighted by the share of immigrants per decile). The first component in the expression in equation (7) (sorting) shows the effect of differences in sorting across the productivity distribution, assuming immigrants were paid the same premiums as natives. It will be positive if natives are more likely to work in more productive firms which pay higher premiums. The second component (pay-setting) shows how differences in the coefficients across the productivity distribution (relative to working in the first decile of firm productivity), affects the premium gap.[34]

Table 4 shows the decomposition results for the overall group of natives and immi-

[34]It is well-known that what is here labeled the pay-setting component is in general dependent on the choice of reference category (Fortin et al., 2011). We believe that relating to the least productive firms provides an intuition for the premium calculations. If we instead use the fifth or tenth decile as reference, the immigrant-native difference in the pay-setting component is small.

grants and for sub-samples categorized by gender, age, region of origin and education level. Column (1) shows the mean log earnings gap between immigrants and natives in different groups. Columns (2) and (3) show the mean decile premium received by natives and immigrants, respectively. Column (4) gives the difference between column (2) and column (3), while columns (5) and (6) show the sorting and within-decile pay-setting effects, respectively.[35] Starting with the first row, we see that, on average, the decile premium immigrants get is slightly higher than the decile premium natives get (16.7 vs. 15.9 percent), which is in line with our results from Figure 7. The difference of 0.8 percentage points reduces the overall gap by 7%. But this net effect combines two strong opposing components. The sorting effect in column (5) is positive (i.e. increases the gap) and accounts for around 22% of the earnings gap. The pay-setting term, instead, reduces the gap by around 28%.[36]

In the next rows, we show how the decomposition results vary for different subgroups. In most dimensions, similar patterns emerge: the sorting component increases the gap whereas the pay-setting component reduces it. Western immigrants in our sample have an earnings advantage over natives, and the pay-setting effect appears to be an important part of this. The pay-setting component is similar for Rest of World immigrants, but their concentration in the bottom deciles yields a premium that is on average similar to those of natives. The earnings gap is much larger for men than for women, and the net premium gap amounts to as much as 28 percent in the latter group. But the sorting and pay-setting components are of the same order magnitude in absolute terms for both genders. Immigrant workers below age 30 and above age 50 have slightly more favorable sorting than those age 31–50.[37]

[35]Table A.3 repeats the decomposition exercise when doing the employee-weighted ranking of firms. The results reported here are consistent with the fact that when using the employee-weighted ranking the bottom half of the productivity distribution is characterized by low decile premiums.

[36]The signs on these effects are in line with those in Dostie et al. (2020), who decompose *firm-specific* as opposed to decile-specific premiums using a similar method; the magnitudes are not directly comparable.

[37]Note that since we do not fit separate models for these different subgroups, these results do not account for the fact that firms may set different earnings premiums for the different subgroups. As we saw above, premiums may differ for immigrants depending on their country of birth. This aspect is also particularly important in the case of men and women, as previous research finds that firm pay differentials explains an important part of the gender gap (Card et al., 2016; Bruns, 2019).

Table 4: Decomposition of immigrant-native earnings gap

	Earnings gap (1)	Mean decile premium natives (2)	Mean decile premium immigrants (3)	Premium gap (4)	Sorting (5)	Pay-setting (6)
All	0.121	0.159	0.167	-0.008	0.026	-0.034
By gender						
Male	0.154	0.166	0.173	-0.006	0.028	-0.034
Female	0.043	0.146	0.158	-0.012	0.021	-0.033
By age group						
Up to age 30	0.039	0.144	0.156	-0.012	0.021	-0.033
Between 31 and 50	0.194	0.166	0.169	-0.003	0.031	-0.034
50 and above	0.133	0.163	0.174	-0.011	0.023	-0.033
By region of origin						
West	-0.041	0.159	0.191	-0.032	0.003	-0.035
Rest of World	0.188	0.159	0.157	0.002	0.035	-0.033
By education						
Compulsory	0.129	0.147	0.148	-0.001	0.030	-0.032
Secondary	0.097	0.153	0.164	-0.011	0.022	-0.034
Upper secondary	0.174	0.179	0.184	-0.006	0.029	-0.035

Notes: Column (1) shows the mean log earnings gap between immigrants and natives in different groups. Columns (2) and (3) show the mean decile premium received by natives and immigrants, respectively. Column (4) gives the difference between column (2) and column (3). We decompose the gap in column (4) into a between-decile sorting effect (column (5)) and a differential within-decile pay-setting effect.

7 Conclusion

The role of firms in determining immigrant-native earnings differentials is potentially important but under-explored. When firms differ in characteristics and practices, the average earnings of immigrants relative to those of natives may depend both on the firms in which immigrants and natives work, and on how the two groups fare in a given type of firm.

This paper focuses on firm productivity as a potential key to understanding labor market differences across groups of workers. We use population-wide linked employer-employee data for Sweden between 1998 and 2017 to study the sorting and earnings of immigrants and natives across the firm productivity distribution. Our primary measure of firm productivity builds on persistent value added per worker. We find no indication that this ranking of firms is influenced by the composition of workers in the firm, including the share of immigrants that the firm employs and differences in permanent worker characteristics.

First, we show that immigrants are concentrated in low-productivity firms relative to natives and have lower rates of upward mobility in the firm productivity distribution. This is in line with previous research that finds that immigrants do not have access to the same workplaces as natives. Second, more productive firms pay higher earnings. The earnings gains from working in more productive firms are substantial for all, but tend to be greater for immigrants. That is, the individual increase in earnings for a worker who climbs the productivity ladder is steeper for immigrants than for natives. This result is clearest for immigrant workers born outside Western countries. Within-firm variations in productivity are strongly associated with individual earnings, and the association depends on group- and workplace characteristics. Native workers have more rent-sharing when there are fewer migrant workers, whereas the opposite is true for immigrants. These differences are starkest in the lower half of the productivity distribution.

Decomposing the contribution of firm productivity pay premiums to the immigrant-native earnings gap, we find that the premiums reduce the earnings gap by 7%. Sorting and pay-setting work in opposite directions, which reduces the average premium gap. But it is noteworthy that the over-representation of immigrants in less productive firms is estimated to widen the gap by 22%. Since immigrant labor market assimilation is a major policy concern in many countries, our results clearly suggest that a better understanding of firm-level factors is needed. So far, the number of studies analyzing the contribution of firm hiring patterns and pay-setting policies to immigrant-native differentials is small. Productivity, technology, and competition, as well as their interactions with structural change and institutions, appear to be relevant areas for further research.

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A Appendix

A.1 Additional description and results

We estimate AKM models (Abowd et al., 1999) of the following form, separately for two groups g: immigrants and natives (see e.g. Dostie et al., 2020).

$$\ln(e_{git}) = \alpha_{gi} + \psi^{g}_{f(g,i,t)} + X_{git}\beta^{g} + \varepsilon_{git} \tag{9}$$

α_{gi} captures individual time-invariant skills and other factors that are rewarded equally across all firms; $\psi^{g}_{f(g,i,t)}$ captures a group-specific firm pay premium that is rewarded equally across individuals in a group within the same firm; X_{git} are time-varying individual controls; and the error term ε_{git} captures random match effects, human capital shocks, and other unobservables.[38] A summary of the estimated parameters and model fit are included in Table A.1 below.

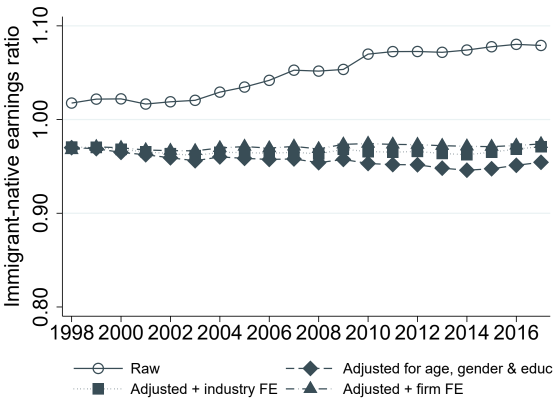
For reference, we include in Table A.1 estimates from the pooled model as well.

Table A.1: Summary of estimated AKM models

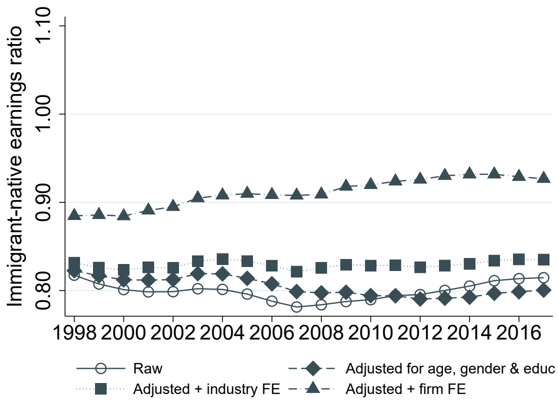
	Pooled (1)	Natives (2)	Immigrants (3)
Standard deviation of log earnings	0.595	0.593	0.592
Number of person-year observations	52,778,984	45,874,144	6,784,280
Panel A: Summary of parameter estimates			
Number of person effects	5,585,428	4,564,718	991,160
Number of firm effects	467,845	431,949	206,291
Std. dev. of person effects (across person-yr. obs.)	0.349	0.345	0.377
Std. dev. of firm effects (across person-yr. obs.)	0.205	0.200	0.277
Std. dev. of Xb (across person-yr. obs.)	0.229	0.234	0.192
Correlation of person/firm effects	0.115	0.095	-0.016
RMSE of model	0.326	0.325	0.321
Adjusted R-squared of model	0.660	0.663	0.643
Correlation native/immigrant firm effects		0.628	
Panel B: Share of variance of log earnings due to			
Person effects	0.345	0.338	0.407
Firm effects	0.119	0.114	0.219
Covariance of person and firm effects	0.047	0.037	-0.009
Xb and associated covariances	0.189	0.211	0.089
Residual	0.301	0.300	0.294

Notes: Results from two-way fixed effects models estimated for the full sample (column 1) and separately for natives (column 2) and immigrants (column 3). Models include year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies. The correlations of native and immigrant firm effects are calculated for the subset of dual-connected firms.

[38] The firm- and worker-specific fixed effects are separately identified by job-to-job transitions of workers across firms. Cross-firm mobility is therefore crucial for identification (see e.g. Card et al., 2013). Under exogenous mobility, both job-to-job transitions and the job assignment process depend solely on time-invariant unobservable characteristics of workers and firms, along with time-varying observables in X_{it}.

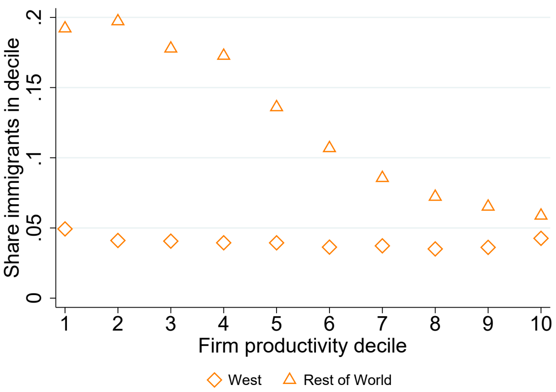


(a) West

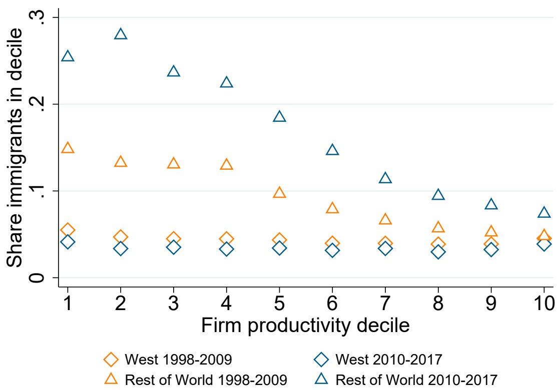


(b) Rest of World

Figure A.1: Immigrant–native earnings ratio – by region of birth



(a) Full period



(b) By sub-period

Figure A.2: Share immigrants in productivity decile – by country of birth

Table A.2: Earnings returns to working in more productive firms

Decile	Natives (1)	All immigrants (2)	Western immigrants (3)	Rest of World immigrants (4)
2	0.006 (0.005)	0.016 (0.009)	0.002 (0.009)	0.020 (0.009)
3	0.041 (0.005)	0.064 (0.009)	0.042 (0.009)	0.070 (0.010)
4	0.056 (0.005)	0.094 (0.009)	0.068 (0.009)	0.100 (0.010)
5	0.076 (0.004)	0.111 (0.009)	0.091 (0.009)	0.117 (0.010)
6	0.103 (0.005)	0.141 (0.009)	0.127 (0.008)	0.145 (0.010)
7	0.142 (0.004)	0.176 (0.008)	0.158 (0.008)	0.181 (0.009)
8	0.160 (0.005)	0.193 (0.009)	0.186 (0.008)	0.192 (0.010)
9	0.199 (0.004)	0.233 (0.009)	0.216 (0.008)	0.238 (0.010)
10	0.248 (0.004)	0.289 (0.009)	0.266 (0.008)	0.297 (0.010)

Notes: Columns (1) and (2) show $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4) for the full sample of natives and immigrants, respectively. Columns (3) and (4) show $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4) for the full sample of natives and Western immigrants, and the full sample of natives and Rest of World immigrants, respectively.

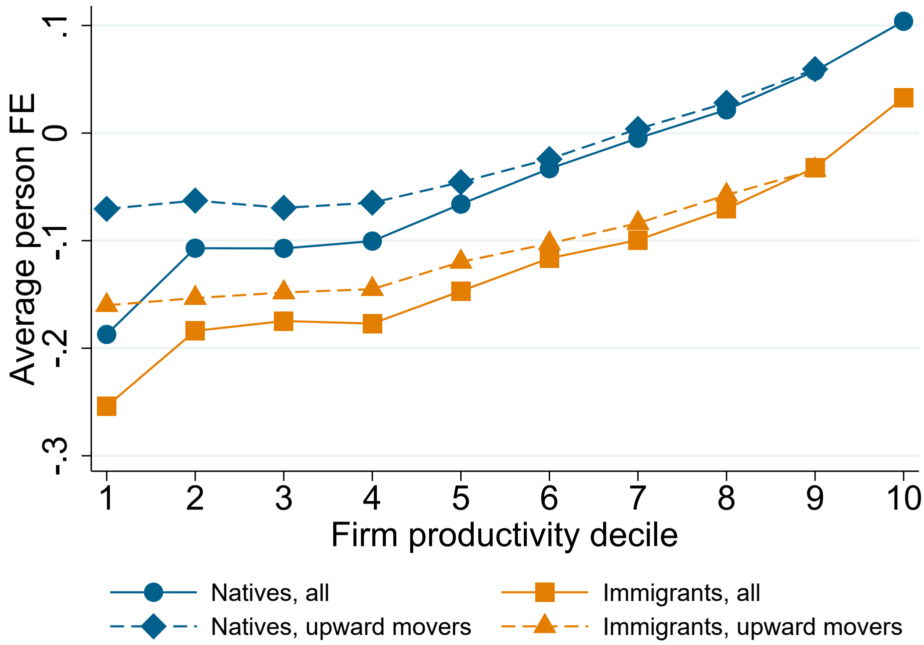
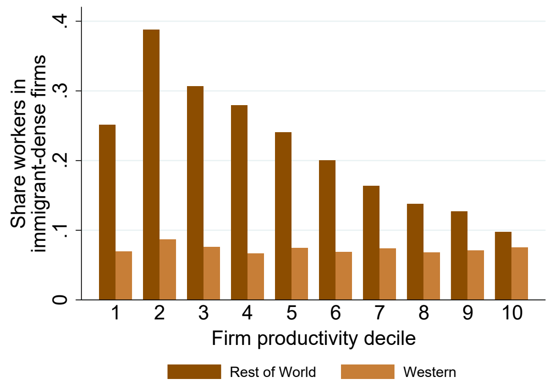
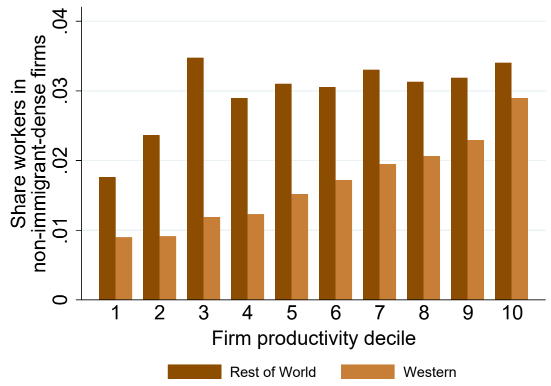


Figure A.3: Average person fixed effects, natives vs. immigrants, by mobility



(a) in immigrant-dense firms, by immigrant group



(b) in non-immigrant-dense firms, by immigrant group

Figure A.4: Distribution across immigrant-dense firms, by immigrant group

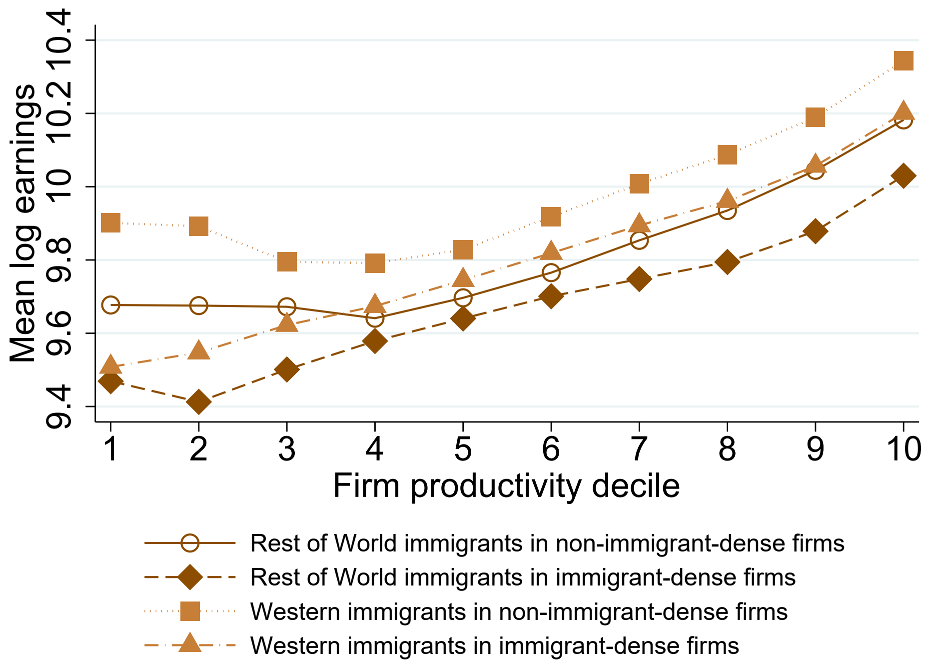


Figure A.5: Log earnings by immigrant density and immigrant group

Table A.3: Decomposition of immigrant-native earnings gap

	Earnings gap	Mean decile premium natives	Mean decile premium immigrants	Premium gap	Sorting	Pay-setting
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.121	0.163	0.160	0.003	0.028	-0.024
By gender						
Male	0.154	0.170	0.165	0.005	0.030	-0.025
Female	0.043	0.149	0.151	-0.002	0.022	-0.024
By age group						
Up to age 30	0.039	0.146	0.147	-0.001	0.023	-0.024
Between 31 and 50	0.194	0.170	0.161	0.009	0.033	-0.025
50 and above	0.133	0.167	0.167	-0.001	0.024	-0.025
By region of origin						
West	-0.041	0.163	0.186	-0.023	0.003	-0.026
Rest of World	0.188	0.163	0.149	0.014	0.038	-0.024
By education						
Compulsory	0.129	0.150	0.140	0.010	0.033	-0.023
Secondary	0.097	0.156	0.156	-0.001	0.024	-0.024
Upper secondary	0.174	0.183	0.178	0.005	0.031	-0.026

Notes: Column (1) shows the mean log earnings gap between immigrants and natives in different groups. Columns (2) and (3) show the mean decile premium received by natives and immigrants, respectively. Column (4) gives the difference between column (2) and column (3). We decompose the gap in column (4) into a between-decile sorting effect (column (5)) and a differential within-decile pay-setting effect.

A.2 Additional robustness checks

Relationship between AKM firm FE and firm productivity

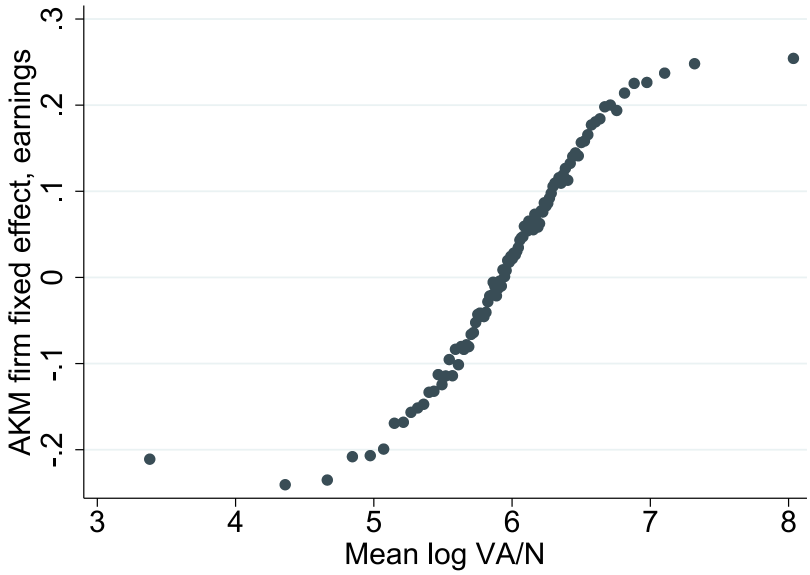
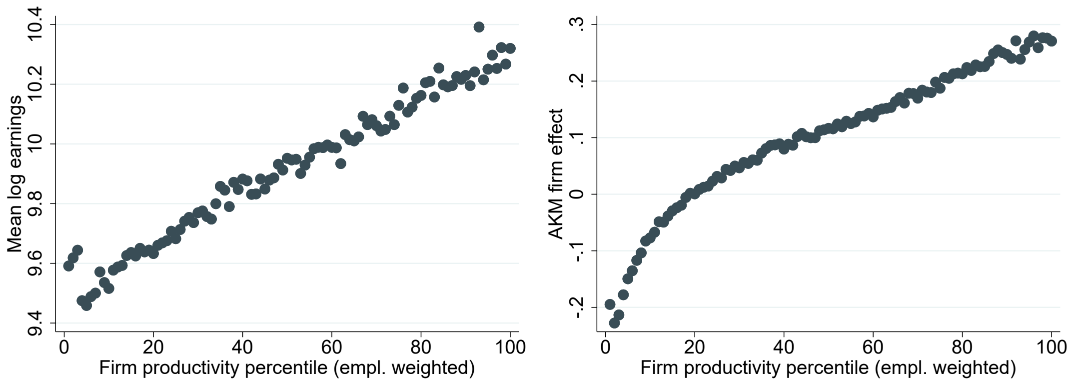


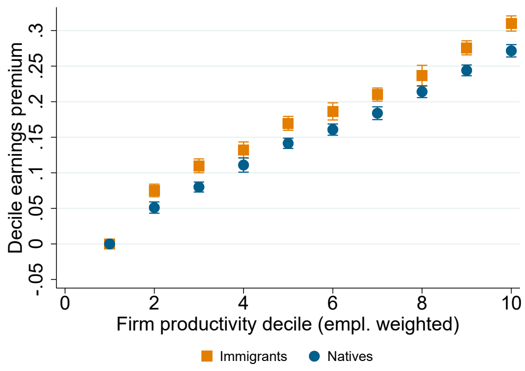
Figure A.6: AKM firm FE by log value added per worker (100 bins)



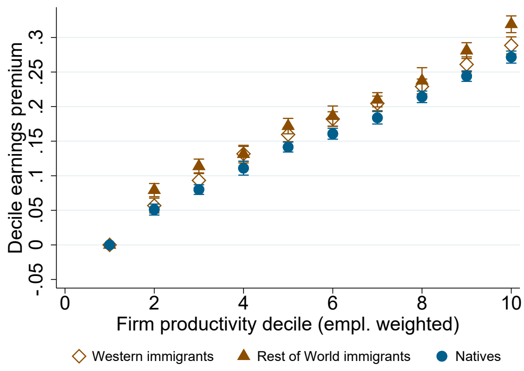
(a) Log earnings against productivity ranking (b) AKM firm FE against productivity ranking

Figure A.7: More productive firms pay higher earnings (employee-weighted)

Earnings returns by productivity decile – employment weighted ranking



(a) All immigrants



(b) By immigrant group

Figure A.8: Earnings returns to working in more productive firms (employment weighted ranking)

Note: The figure plots $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4) using the employee-weighted ranking of firms.

Earnings returns by productivity decile – by years since migration

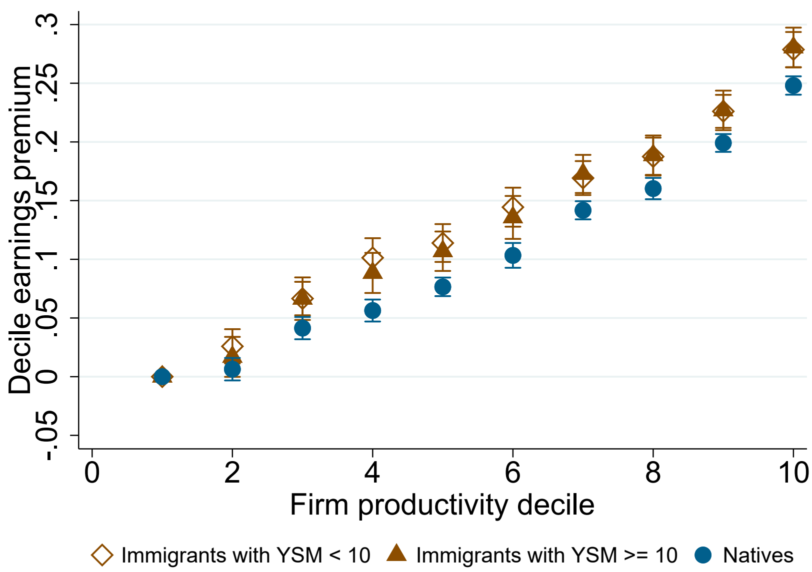


Figure A.9: Earnings returns to working in more productive firms – YSM

Note: The figure plots $\hat{\theta}_d$ and $\hat{\theta}_d + \hat{\gamma}_d$ from equation (4), where the immigrant group is split by their years since migration (YSM).