Firm productivity, manager origin, and immigrant-native earnings disparities*

Olof Åslund† Cristina Bratu‡ Stefano Lombardi§ Anna Thoresson¶

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The role of firm heterogeneity and workplace segregation for the substantial immigrant-native labor market inequalities seen in many countries is not well understood. We show that the earnings returns to working in firms with higher persistent productivity are especially high for immigrants, who benefit the most from avoiding the least productive firms in which they are strongly over-represented. While immigrant-native skill differences can partly explain the differential sorting across firms, our results also suggest group-specific barriers to climbing the firm productivity ladder. The combined balance sheet and population-wide employer-employee data reveal that manager-worker homophily is an important mechanism that reinforces the unequal access to high-productive firms and differential ability of extracting firm rents.

Keywords: Firm productivity; Immigrant-native earnings gap; Wage inequality; Managers

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†Corresponding author. Uppsala University, IFAU, CReAM, IZA. Email: olof.aslund@nek.uu.se

‡VATT Institute for Economic Research, Uppsala Center for Labor Studies (UCLS). Email: cristina.bratu@vatt.fi

§VATT Institute for Economic Research, IFAU, IZA, UCLS. Email: stefano.lombardi@vatt.fi

¶Reykjavik University, IFAU, UCLS. Email: annat@ru.is

1 Introduction

The persistent immigrant-native labor market inequalities seen in many countries are commonly associated with crime, segregation, and other social problems.[1] Despite receiving limited scholarly attention compared to, e.g., country-specific human capital and residential segregation, two factors suggest that firms are central for understanding the labor market integration of immigrants. First, in labor markets where employers have monopsony power, firm pay policies can explain a substantial part of the earnings gap between men and women (Card et al., 2016) or minority and majority workers (e.g. Dostie et al., 2023, Gerard et al., 2021). Second, ethnic workplace segregation is widespread in many countries (Hellerstein and Neumark, 2008; Åslund and Skans, 2010; Glitz, 2014; Andersson et al., 2014).

We study the role of firm productivity in explaining the immigrant-native earnings gap using longitudinal matched employer-employee data from Sweden. Quantifying the contribution of firm characteristics and policies to earnings gaps is particularly challenging when segregation is widespread, which is typical in the case of immigrant and native workers. We consider segregation in terms of employee country of origin and find that 60 percent of the firms in our setting are completely native-segregated (i.e. have no immigrant employees). We propose a firm ranking procedure that allows us to include fully-segregated firms in the analysis, thus not relying on dual-connected sets of immigrant and native workers, as required for AKM estimations (Abowd et al., 1999).[2]

To group firms based on persistent differences in firm productivity, we use balance sheet data over the 1998–2017 period and rank firms based on a regression of log value added per worker on firm and year fixed effects. The approach allows us to bin firms into a tractable number of groups while accounting for business cycle fluctuations and productivity shocks. While grouping firms could lead to loss of information, we provide evidence that using deciles of persistent firm productivity still captures a large degree of firm heterogeneity.[3] In addition, we test the robustness of the ranking in several ways and find no indication that the method

[1] Immigrants tend to earn less than observationally similar natives, even decades after arrival. See Kerr and Kerr (2011), Borjas (2014), Duleep (2015), Dustmann and Görlach (2015), and Rho and Sanders (2021) for overviews of the literature on labor market integration.

[2] In a complementary analysis, we show that imposing a dual-connected set restriction affects the sample substantially, yet maintains the key takeaways from the analysis.

[3] For instance, while high-productive firms tend to be larger and on average pay more, firms of all sizes and in all industries are found at all levels of productivity.

captures factors other than persistent firm productivity.

The ranking reveals that immigrants strongly sort into the lowest productivity deciles: the within-decile share of non-Western workers decreases from almost 20 percent at the bottom to 6 percent at the top of the productivity ranking. Assortative matching between high-productive firms and high-skill workers, combined with skill differences across groups, on average explains about 25 percent of the immigrant-native allocation differences.[4] Thus, skills matter but the majority of the sorting remains unexplained.

We then use the firm ranking to estimate the earnings returns to working in more productive firms conditional on worker fixed effects. While both immigrants and natives benefit from working in more productive firms, the corresponding returns are greater for immigrants at the lower end of the productivity distribution, precisely where the immigrant workforce is over-represented. For example, the estimated return to working in the fifth decile relative to the first is 8.5 log points for natives and 12.1 log points for immigrants. Moreover, within the group of immigrant workers, the greater returns to firm productivity are driven by non-Western workers. Differences in returns are not related to years since migration. They are also not explained by heterogeneity within the firm productivity bins.

To gauge the contribution of firm productivity pay premiums to the 12.9% overall earnings gap seen in our data, we decompose the average premium into a combination of sorting across deciles and a pay-setting component for working in a given decile relative to the lowest one. We find that sorting and pay-setting work in opposite directions. If immigrants' returns to firm productivity were the same as natives', immigrants' over-representation in less productive firms would increase the earnings gap by 21 percent. If the allocation across firm types was instead the same among immigrant and native workers, the higher returns among immigrants would reduce the earnings gap by 25 percent. When combining these two opposing forces, the resulting average premium is 0.5 percentage points higher for immigrants than natives, amounting to a mere 4 percent of the gap.

The fact that immigrants gain more from avoiding less productive firms but are concentrated in precisely those types of firms suggests the existence of group-specific barriers to climbing the productivity ladder. A potential explanation for these results is manager-worker similarity,

[4]We adapt this type of exercise from Gerard et al. (2021), who use it in the context of racial pay differences in Brazil. We capture skills by using individual fixed effects from earnings regressions.

which has been shown to affect hiring practices and thus sorting (Åslund et al., 2014; Kerr and Kerr, 2021).[5] We show that immigrant managers are over-represented in firms at the bottom of the productivity distribution and are under-represented at the top, despite only limited differences in manager quality by origin. Moreover, immigrant managers are 2.5 times more likely than native managers to hire immigrants in firms at the bottom of the productivity distribution.

The sorting of workers into firms where management shares their background may be driven by limited opportunities to be hired elsewhere. But it is also possible that such homophily reflects the ability to extract firm rents. Results from rent-sharing specifications exploiting within-employment spell variation in earnings and firm value added suggest that worker remuneration is indeed linked to firm performance. Furthermore, this association is significantly stronger for non-Western workers under immigrant management, a pattern that is particularly pronounced in the low-productive firms where immigrants work more often. Overall, this result signals a particularly close connection between firm and immigrant worker performance in specific types of low-productive workplaces.

Our work relates to a growing literature on the role of firms in wage inequality that builds on general insights on imperfectly competitive labor markets (Card, 2022). In the context of immigrant-native earnings disparities, evidence on the role of firms is still relatively scarce. Previous studies based on job ladder models that account for individual unobserved heterogeneity (Abowd et al., 1999) show that between-workplace variation explains significant shares of the earnings gap (Damas de Matos, 2017; Dostie et al., 2023; Arellano-Bover and San, 2023; Gorshkov, 2023).[6]

Our contribution to the literature is twofold. First, we study immigrant-native earnings differences via a job ladder model based on a firm productivity grouping that allows us to include fully-segregated firms in the analysis. To the best of our knowledge, this has not been done before in this literature and the approach could be more broadly applied when studying pay gaps in highly-segregated labor markets. An alternative firm grouping method, proposed by Bonhomme et al. (2019), uses k–means clustering to bin firms based on how similar their

[5] Sorting along origin lines can either come about through job search networks (Dustmann et al., 2016; Currarini et al., 2009) or employer discrimination (Fang and Moro, 2011; Neumark, 2018).

[6] A related literature analyzes the role of employers in the assimilation of immigrants without accounting for worker heterogeneity via individual fixed effects (as it is instead done in the job ladder literature). See for instance Aydemir and Skuterud (2008), Pendakur and Woodcock (2010), Barth et al. (2012), Carneiro et al. (2012), and Ansala et al. (2022). Immigrant-native productivity differences have also been related to culture (Ek, 2024).

earnings distributions are. Our approach takes advantage of the fact that value added is a readily observable and directly interpretable measure of firm heterogeneity (Syverson, 2011; Lentz and Mortensen, 2010). Moreover, our rent-sharing analysis, which exploits within-employment spell variation in value added, aligns naturally with ranking firms based on persistent value added.[7] Overall, our analysis shows that firm value added information can be leveraged to perform a comprehensive assessment of earnings gaps.

Second, by studying the role of managers, our analysis offers new insights into the mechanisms underlying the sorting of workers into workplaces. We thus provide a first attempt at building a bridge between the job ladder and the manager origin literatures. In doing so, we also provide novel estimates that relate worker-manager similarity to rent-sharing within firms (see Card et al., 2018, for a review of the rent-sharing literature). Empirical evidence on immigrant-native differences in rent-sharing is scarce. The only work that we are aware of in this context is by Amior and Stuhler (2024), who do not analyze the role of managers.

The paper proceeds as follows. In Section 2 we describe the analysis sample. Section 3 lays out the econometric framework. We then present our results in Section 4. Section 5 concludes.

2 Data and analysis sample

2.1 Institutional setting

Over the past decades, Sweden has experienced substantial and diverse economic and humanitarian immigration, which makes it an interesting case study for the analysis of immigration. In the 1950s and 1960s labor migration, often from neighboring countries, dominated. This phase was followed by humanitarian and family-related migration from the 1970s onward, bringing the fraction of foreign-born close to 20 percent by 2020 (SCB, 2020). Migrants have been more prone to move to cities, and our data reveal that nearly 54% of immigrants reside in the three main metropolitan areas in Sweden (Stockholm, Gothenburg and Malmö), compared to 36% of natives.

The country has had relatively generous regulations for refugee (Parusel, 2016) as well as

[7] Our ranking also relates to that of Bartolucci et al. (2018), who, by contrast, group firms based on average profits without adjusting for idiosyncratic shocks over the business cycle.

for family migration (Borevi, 2015). Following a surge in asylum applications that peaked in 2015, policies have become more restrictive.[8] Despite substantial improvements among the foreign-born in the post-pandemic recovery, the overall immigrant-native employment differential remains one of the largest in the OECD (OECD, 2024). Our data reveals a substantial raw earnings gap between immigrants and natives of 12.9% (20.7% when focusing on non-Western migrants). This earnings gap is driven by differences between rather than within firms, highlighting the importance of studying firm heterogeneity (see Figure 1 in Åslund et al., 2021). Another relevant feature of the Swedish labor market is its high degree of unionization and extensive collective bargaining (Olsson and Skans, 2024; Schnabel, 2020). Studying a context where institutions may limit firm monopsony power complements evidence from less regulated labor markets.

The empirical analysis hinges on mobility across firms of different productivity. Freedom of secondary mobility has applied to most immigrants to Sweden. Refugees and family reunification migrants have historically not faced residential mobility restrictions even under government dispersal policies (Edin et al., 2003). A 2008 reform introduced a demand-driven and unusually open system for labor migration from outside the EU/EEA (OECD, 2011). Even though initial permits for this specific group of workers were tied to the first employer, there was no restriction against changing employer by filing another application. Furthermore, the worker could start the new job before a decision was received. Thus, over a long time period, the formal institutions have been similar for immigrant and native workers covered by our data. As will be discussed below, this does of course not necessarily mean that the de facto conditions facing different groups of workers are the same.

2.2 Data and sample selection

Our analysis is based on a matched employer-employee panel that covers the period 1998 to 2017, and combines data from several administrative registers collected by Statistics Sweden. The firm tax records (RAMS register) provide information on annual earnings paid to each worker (deflated to 2010 Swedish Kronor, SEK), start and end dates of each employment spell, as well as industry and geographic location.We use employment spells to compute firm size

[8] Our data ends in 2017, therefore our sample is largely unaffected by these reforms.

based on the stock of workers employed in November.

For each firm also present in Statistics Sweden's business register on firm-level accounts, we add information on value added (VA). 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.[9] We compute value added per worker by dividing VA by the firm size measure. Finally, we complement this information with worker-level demographics (age, gender, education level, country of birth, immigration year) from the Louise/Lisa database.

Our main outcome of interest is log monthly earnings from the primary employer, obtained by dividing annual earnings by the number of months worked. The primary employer is defined as the firm paying the highest annual earnings.

We restrict the sample to workers aged between 18 and 65, who work in private sector firms that have at least two employees in November. To diminish the influence of extreme values, we winsorize earnings at the 99$^{\text{th}}$ percentile of their yearly distribution and drop worker histories if log earnings in any year are three standard deviations or more above the sample mean. Finally, to focus on workers sufficiently attached to the labor market, we drop observations where earnings are lower than the yearly Price Base Amount (PBA). The PBA is used to calculate benefits and fees in Sweden. An earnings level equal to three times the PBA is often considered enough for being self-supporting (Ruist, 2018). One PBA is thus a rather low threshold.

The sample includes both natives and immigrants. Immigrants are defined as foreign-born with two foreign-born parents. We present results where immigrants are divided into "West" (i.e. Western Europe, USA and Australia) and "Rest of World" based on country of birth.[10]

2.3 Sample description

Table 1 shows summary statistics separately for natives and immigrants. Overall, 13 percent of observations are immigrants, most of whom are born in non-Western countries (71 percent).

[9]Firm accounts are available until 2015 and exclude financial companies. Excluding firms for which VA information is missing results in about 12 percent of employee-year observations being dropped from the sample.

[10]"West" consists of the Nordics except Sweden (Denmark, Finland, Norway, Iceland), Western Europe (Ireland, UK, Germany, Greece, Italy, Malta, Monaco, Portugal, San Marino, Spain, the Vatican Sate, Andorra, Belgium, France, Liechtenstein, Luxembourg, the Netherlands, Switzerland. Austria), Canada, USA, Australia and New Zealand. "Rest of World" are non–Western countries.

Segregation is prevalent, with 6 percent of immigrants working at all-immigrant firms, and 20 percent of natives at all-native firms. To put this in perspective, under random allocation of workers of different origin (preserving the immigrant share and the firm size distribution), we would expect to find only 1% of immigrants and less than 12% of natives in fully segregated firms (Table A.1).

Table 1: Summary statistics (1998–2017)

	Immigrants			Natives
	Total	West	Rest of World	Total
Immigrant from West	0.293	1.000	0.000	0.000
Immigrant from Rest of World	0.707	0.000	1.000	0.000
In native-segregated firms	0.000	0.000	0.000	0.203
In immigrant-segregated firms	0.055	0.021	0.069	0.000
Male	0.615	0.621	0.612	0.648
Age	40.795	45.879	38.692	40.215
Share age ≤ 30	0.218	0.104	0.265	0.273
Share age ≥ 50	0.253	0.416	0.185	0.272
Education, compulsory	0.203	0.218	0.196	0.151
Education, secondary	0.437	0.427	0.441	0.565
Education, post secondary	0.318	0.308	0.322	0.283
Education, missing	0.043	0.047	0.041	0.001
Monthly earnings (2010 SEK)	22315.297	26063.057	20763.998	25042.991
No. observations	6,154,384	1,801,470	4,351,188	40,241,618

Notes: The unit of observation is worker $\times$ year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants).

While Western immigrants slightly outearn natives, non-Western immigrants on average earn 17 percent less, despite the fact that the figures on educational attainment do not suggest major skill differences across groups in our sample. However, the groups likely differ in labor market experience, as Western immigrants are somewhat older and Rest of World immigrants somewhat younger on average than natives.

3 Econometric framework

This section outlines the econometric framework. We first describe our proposed method of classifying employers based on differences in persistent productivity. In the spirit of the firm clustering approach of Bonhomme et al. (2019), our method keeps the number of groups tractable. Moreover, it provides an easily interpretable and intuitive grouping procedure. We then estimate the returns to working in deciles of firms of different productivity.

3.1 Firm ranking procedure

We classify firms based on persistent differences in log VA. To this aim, we use firm-year level data on firms with two or more employees in at least two years to estimate the following model:

$$\ln(VA/N)_{ft} = \lambda_f + \lambda_t + \varepsilon_{ft} \tag{1}$$

where $\ln(VA/N)_{ft}$ is log VA per worker for firm f in year t (1998-2015), λ_f are firm fixed effects, λ_t are year fixed effects, and ε_{ft} is an error term. λ_f capture the permanent component in firm-level productivity and λ_t account for year effects common across all firms, due to, for instance, business cycle fluctuations or productivity shocks. We then use the empirical distribution of the estimated firm effects $\widehat{\lambda}_f$ to rank firms into deciles. Since by construction each firm's position in the productivity distribution is fixed over time, we obtain a measure of persistent productivity for the entire 1998–2017 observation period.

The value added-based ranking that we propose has some advantages compared to alternative rankings based on firm fixed effects à la Abowd et al. (1999). First, and importantly in our setting, the productivity ranking allows us to include immigrant- and native-segregated firms in firm premium decompositions. Since fully-segregated firms would not be part of a dual-connected set, they would be discarded when ranking employers based on AKM firm fixed effects. Given that about 60 percent of firms in our sample are fully segregated, their inclusion is important for getting a representative picture of how firms relate to the immigrant-native earnings gap. In Appendix C, we provide a more thorough discussion of this by showing how our results compare to those for workers in the dual-connected set, as well as to AKM decompositions. Overall, it appears that applying a dual-connected set restriction in our analysis affects the sample composition and the magnitudes of some of the main results. At the same time, it is reassuring that the main message of the analysis is generally preserved.

Second, the approach makes it possible to abstract from well-known incidental parameter estimation problems (Kline et al., 2020; Bonhomme et al., 2023), which would be exacerbated in the presence of a high degree of immigrant or native firm segregation. These advantages apply also more generally to studies on other groups of workers that are significantly separated from each other on the labor market. Third, value added is a readily-observable and directly interpretable measure of firm productivity, which is a key dimension of firm heterogeneity. Lastly, in a complementary analysis we exploit yearly changes in firm-level valued added to obtain rent-sharing estimates, which further justifies our choice of value-added-based groups.

Table 2: Robustness of the firms ranking

	Staff composition	Worker FEs	Industry	Share of immigrants	Industry and share of immigrants
	(1)	(2)	(3)	(4)	(5)
Panel A: Correlation with baseline ranking					
	0.9917	0.9880	0.9365	0.9991	0.9365
Panel B: Share of firms moving in the ranking					
moving down	0.0001	0.0083	0.1383	0.0001	0.1369
moving up	0.0019	0.0068	0.0666	0.0001	0.0666
No. of firms	287,734	278,329	287,740	287,740	287,740

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

We perform a number of robustness checks to analyze whether our grouping procedure captures factors other than persistent firm productivity. Firstly, log value added per worker in equation (1) may mechanically reflect the fact that high-skilled workers are concentrated in certain firms, i.e. firm productivity may be a function of worker productivity. Column (1) in Panel A of Table 2 reports results when we re-estimate equation (1) by including staff 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). In Column (2) of Panel A we alternatively control for worker fixed effects averaged at the firm-year level (estimated from an AKM model on log-monthly earnings).[11] In both cases the correlation between the baseline ranking and these alternative rankings is very high (0.98-0.99). Moreover, very few firms are classified at

[11] See Table A.2 for a summary of the estimated AKM model.

least 10 percentiles higher or lower in the ranking when compared to the baseline (columns 1 and 2 in Panel B).

Two additional concerns are that i) some industries have less scope for being high-productive than others (e.g. hotels and restaurants) and that ii) the share of immigrant workers may affect firm productivity (see e.g. Parrotta et al., 2014). Columns (3)–(5) of Table 2 show that producing the ranking by industry, controlling for the share of immigrants, or doing both leaves the ranking qualitatively unaffected.

Given that the ranking is calculated over a long time span, a final concern is that a time-fixed position might be affected by firm life-cycle dynamics (entry and exit). To assess whether this is the case, we re-compute the ranking separately for 1998–2009 and 2010–2017, respectively, for the sample of firms operating in both periods. The correlation between the 1998–2009 ranking and the baseline full-period ranking is 0.93, with the share of upward (downward) movers at 12 percent (1 percent); similar results are obtained when comparing the 2010–2017 ranking with the baseline (0.89, 13 percent, and 2 percent, respectively). The correlation is virtually 1 when re-computing the full-period ranking by including only the firms that operate in both periods.

All in all, it appears that equation (1) captures a component of firm productivity which is largely independent of worker-level heterogeneity and robust to alternative specifications. We therefore use the baseline ranking in the empirical analysis.

3.2 Estimating and decomposing firm productivity decile premiums

The returns to working in more productive firms are estimated by using the firm ranking in the following way. We assume that the earnings of worker i in group g in time t are given by:

$$\ln e_{git} = \alpha_{gi} + X'_{git}\beta^{g} + \theta^{g}_{D(g,i,t)} + \varepsilon_{git} \tag{2}$$

where α_{gi} is a person fixed effect, X_{git} is a vector of time-varying controls (year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies), θ^{g}_{d} is an earnings premium paid in productivity decile d to workers in group g, $D(g,i,t)$ is a vector of index functions indicating the given productivity decile d of worker i in group g in year t, and ε_{git} captures all remaining determinants of earnings.

We estimate model (2) separately for four groups: natives, immigrants, immigrants from Western countries and immigrants from the Rest of the World. The main coefficients of interest $\theta^g_{D(g,i,t)}$ capture the return to working in decile d, relative to working in the first decile. The model is identified by cross-decile movers and requires that worker histories are independent of the error term (exogenous mobility assumption). In Appendix B, we show that this assumption is likely to hold since earnings are similar among upward and downward movers between decile pairs, which suggests that high-wage workers are not more likely to transition to better firms.

To understand how differences in productivity decile premiums $\theta^g_{D(g,i,t)}$ relate to the overall earnings gap between immigrants and natives, we perform a decomposition of the decile premiums (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973) as follows:[12]

$$\sum_d \theta^N_d \pi_{Nd} - \sum_d \theta^I_d \pi_{Id} = \underbrace{\sum_d \theta^N_d (\pi_{Nd} - \pi_{Id})}_{sorting} + \underbrace{\sum_d (\theta^N_d - \theta^I_d)\pi_{Id}}_{pay-setting} \tag{3}$$

where π_{Nd} and π_{Id} denote the fractions of natives and immigrants employed in decile d.

Equation (3) shows that 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) plus a weighted average of the differences in decile earnings premiums (weighted by the share of immigrants per decile). The sorting component accounts for differences in sorting across the productivity distribution, assuming immigrants were paid the same premiums as natives. The pay-setting component shows how differences in the coefficients for natives and immigrants within each productivity decile affect the premium gap, given the distribution of immigrants across productivity deciles. The pay-setting component is sensitive to the normalization used (Fortin et al., 2011). We normalize using the first productivity decile, and thus assume that the premiums to both immigrants and natives in the least productive firms is zero.

The contribution of sorting to the immigrant-native earnings gap in equation (3) is positive if natives are more likely to work at highly productive firms that offer higher wage premiums.

[12] Taking expectations of equation (2), we can express mean immigrant and native earnings as $E[\ln e_{Iit}] = \alpha_I + \bar{X}'_I\beta_I + \sum_d \theta^I_d \pi_{Id}$ and $E[\ln e_{Nit}] = \alpha_N + \bar{X}'_N\beta_N + \sum_d \theta^N_d \pi_{Nd}$ respectively, where $\alpha_g = E[\alpha_{gi}]$ and $\bar{X}_g = E[X_{git}]$. The mean immigrant-native gap is then given by the following expression, of which we decompose the third term: $E[\ln\ \mathrm{e}_{Nit}] - E[\ln e_{Iit}] = \alpha_N - \alpha_I + \bar{X}'_N\beta_N - \bar{X}'_I\beta_I + \sum_d \theta^N_d \pi_{Nd} - \sum_d \theta^I_d \pi_{Id}$.

The educational differences between natives and immigrants shown in Table 1 indicate that under assortative matching of high-productive workers and firms, allocation differences could occur even if employers treat both groups equally. We therefore isolate skill-based sorting from other forms of sorting.[13] We categorize workers into twenty age-by-skill groups, defined by five age ranges (18–24, 25–34, 35–44, 45–54, 55+) and four skill levels (quartiles of the person effects distribution or four education levels). To also accommodate geographic and time variations in the supply of workers and jobs, we define a cell as the combination of local labor market region, year, age group, and skill group. Denoting the number of workers in cell c working in decile d by N_{cd}, and the overall immigrant share in cell c by S_c^I, we calculate an expected immigrant fraction for each decile:

$$\hat{F}_d^I = \sum_c (N_{cd} \cdot S_c^I) \tag{4}$$

For natives, the analogous fraction is:

$$\hat{F}_d^N = \sum_c (N_{cd} \cdot S_c^N)$$

Finally, we obtain the predicted shares of immigrants in each decile, assuming that employers within each decile aim to maintain the age and skill distribution of their workforce but otherwise hire workers randomly within age-skill groups, without considering immigrant status, in the local labor market (region) for a given year:

$$\hat{S}_d^I = \frac{\hat{F}_d^I}{\hat{F}_d^I + \hat{F}_d^N} \tag{5}$$

We use $\hat{S}_d^I$ to contrast expected with actual allocation. For the decomposition, we divide the expected number of immigrants per decile ($\sum_c (N_{cd} \cdot S_c^I)$) by the total number of immigrants to get π_{Id}^*. The native counterfactual share, π_{Nd}^*, is calculated similarly. We use the counterfactual employment shares of immigrants and natives to build the following modified version of the first term in equation (3), which measures the counterfactual *skill-based sorting* component and

[13] This method is based on Gerard et al. (2021) and builds on the workplace segregation literature (Hellerstein and Neumark, 2008; Åslund and Skans, 2010).

captures how much of the observed sorting component of the earnings gap is due to differences in age and skill:

$$\sum_d \theta_d^N (\pi_{Nd}^* - \pi_{Id}^*) \tag{6}$$

To obtain a measure of sorting that consists of practices that disproportionately affect immigrants (including for instance discrimination), we take the difference between the sorting effect from equation (3) and the skill-based sorting effect from equation (6); we call this term *residual sorting*:

$$\sum_d \theta_d^N (\pi_{Nd} - \pi_{Id}) - \sum_d \theta_d^N (\pi_{Nd}^* - \pi_{Id}^*) \tag{7}$$

4 Results

4.1 Worker and employer characteristics across the firm productivity distribution

Table 3 summarizes the characteristics of firms and workers in each productivity decile and highlights three findings that motivate the subsequent analyses. First, the value added classification of firms captures a large degree of firm heterogeneity. The ranking reflects the empirical fact that firm productivity increases with size (see, e.g., Lentz and Mortensen, 2010). At the same time, firms in all industries, all regions, and of all sizes are found in each firm productivity decile. Thus, working in more productive firms does not mechanically reflect working in specific sectors, nor does it reflect geographic sorting.

Second, firm segregation is widespread. In particular, the fraction of fully native-segregated firms is above 60 percent and stable across productivity deciles. By contrast, the fraction of fully immigrant-segregated firms is on average 5 percent, but significantly higher in the bottom than in the top productivity deciles. The data thus confirm the importance of using an approach that allows us to include fully-segregated firms in the analysis.

Third, more productive firms tend to pay more and to employ more highly-educated workers, which indicates positive assortative matching. Moreover, the average share of immigrants at the firms decreases dramatically across productivity deciles; from 22 percent in decile 1 to less than 9 percent in decile 10, a pattern driven by immigrants from the Rest of the World. The total number of workers increases with productivity, a gradient much steeper for natives (Figure A.1). Immigrants, instead, have become more concentrated in low-productive firms over time, a development partly explained by changing country of birth composition (Figure A.2).

Table 3: Summary statistics by productivity decile

	1	2	3	4	5	6	7	8	9	10
Panel A: Firm statistics										
Number of firms × year	174,951	217,421	244,414	269,609	277,440	291,024	299,636	303,811	307,017	303,456
Mean yearly firm size	11.886	12.209	16.711	18.852	21.248	20.244	25.290	26.490	30.647	42.336
Firm size 2-9	0.807	0.764	0.716	0.665	0.642	0.607	0.585	0.575	0.579	0.570
Firm size 10-49	0.169	0.203	0.242	0.287	0.299	0.329	0.339	0.338	0.328	0.315
Firm size 50-249	0.022	0.028	0.036	0.042	0.050	0.056	0.066	0.074	0.076	0.090
Firm size 250-999	0.002	0.004	0.005	0.005	0.007	0.006	0.009	0.010	0.013	0.019
Firm size $\geq$ 1000	0.000	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.003	0.006
Mean fraction immigrants at firm	0.225	0.200	0.166	0.142	0.125	0.113	0.103	0.095	0.089	0.085
Share native-segregated firms	0.631	0.630	0.636	0.631	0.631	0.623	0.618	0.618	0.617	0.603
Share immigrant-segregated firms	0.131	0.095	0.065	0.045	0.036	0.031	0.026	0.022	0.019	0.016
Share immigrant managers	0.224	0.198	0.158	0.132	0.112	0.098	0.086	0.079	0.074	0.070
Share Western managers	0.049	0.045	0.041	0.040	0.039	0.036	0.034	0.034	0.036	0.038
Share Rest of World managers	0.176	0.153	0.117	0.092	0.074	0.062	0.051	0.045	0.038	0.032
Manufacturing	0.079	0.086	0.104	0.116	0.143	0.159	0.166	0.157	0.138	0.107
Construction	0.061	0.086	0.111	0.136	0.177	0.204	0.185	0.152	0.112	0.060
Retail and trade	0.300	0.298	0.282	0.251	0.251	0.231	0.222	0.211	0.207	0.227
Transport	0.036	0.050	0.059	0.059	0.066	0.070	0.094	0.107	0.111	0.068
Hotels and restaurants	0.194	0.180	0.124	0.084	0.065	0.044	0.032	0.023	0.015	0.006
Other social	0.073	0.066	0.062	0.046	0.037	0.032	0.025	0.024	0.023	0.022
Stockholm	0.294	0.254	0.238	0.235	0.222	0.216	0.219	0.230	0.264	0.329
Gothenburg	0.155	0.161	0.169	0.162	0.167	0.166	0.171	0.174	0.167	0.168
North Sweden	0.107	0.122	0.127	0.128	0.129	0.128	0.128	0.121	0.107	0.078
Panel B: Worker statistics										
Number of workers × year	1,249,390	1,377,254	2,282,699	3,031,797	3,858,841	4,080,823	5,776,369	6,290,203	7,647,112	10,801,514
Share immigrants	0.242	0.242	0.212	0.211	0.160	0.139	0.119	0.106	0.099	0.102
Share immigrants: West	0.048	0.041	0.039	0.041	0.038	0.037	0.036	0.035	0.037	0.043
Share immigrants: Rest of World	0.195	0.201	0.173	0.170	0.122	0.102	0.083	0.071	0.062	0.059
Share male	0.542	0.522	0.497	0.477	0.588	0.649	0.644	0.697	0.706	0.690
Share age $\leq$ 30	0.252	0.380	0.374	0.342	0.326	0.306	0.276	0.264	0.225	0.197
Share age $\geq$ 50	0.329	0.212	0.213	0.231	0.250	0.254	0.274	0.274	0.289	0.285
Share compulsory educ.	0.268	0.203	0.181	0.182	0.185	0.174	0.166	0.161	0.143	0.116
Share secondary educ.	0.524	0.567	0.582	0.583	0.599	0.605	0.593	0.582	0.518	0.467
Share tertiary educ.	0.192	0.213	0.223	0.223	0.208	0.214	0.236	0.252	0.335	0.412
Mean log earnings	9.548	9.548	9.618	9.654	9.742	9.825	9.910	9.985	10.104	10.234
Std. dev. log earnings	0.582	0.595	0.570	0.558	0.547	0.538	0.534	0.536	0.530	0.546
Imm/native earnings gap	-0.057	-0.056	-0.023	-0.023	-0.020	-0.053	-0.059	-0.056	-0.065	-0.038

Notes: The unit of observation in the top panel is firm × year, and in the bottom panel it is worker × year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants). The included industries are not exhaustive. *Other social* includes industries like sewage and refuse disposal, membership organization activities, cultural and sporting activities, and services such as hairdressing. Regions in the middle and south of Sweden are omitted from the table.

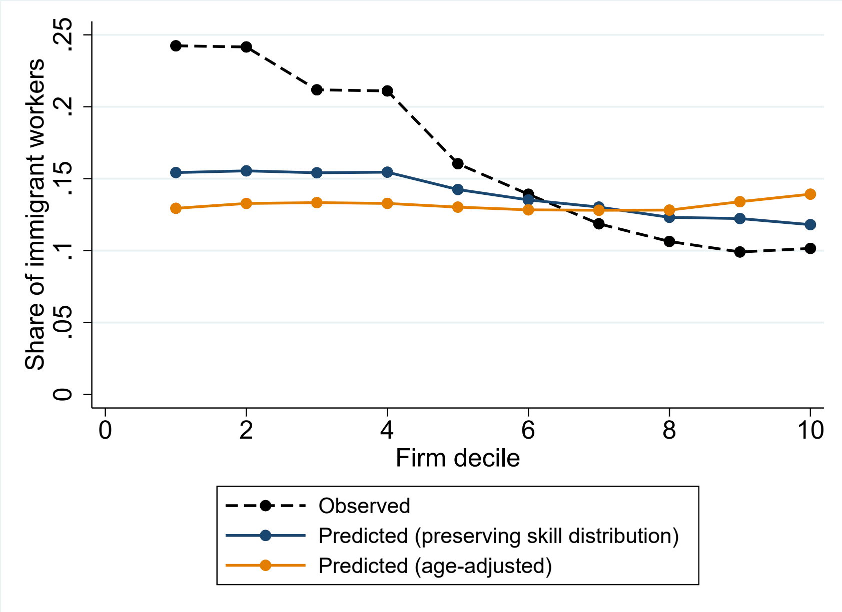
4.2 Do skill differences explain worker sorting?

As Table 3 shows, immigrants are over-represented in low-productive firms and workers in more productive firms are on average more educated. If high-productive firms tend to disproportionately hire high-skilled workers, and natives are on average more skilled than immigrants, then the immigrant-native sorting that we observe may simply reflect differences in skill demand and not group-specific firm pay policies or barriers to entry. We therefore investigate how much of the sorting can be explained by accounting for skill differences across groups (see section 3.2).

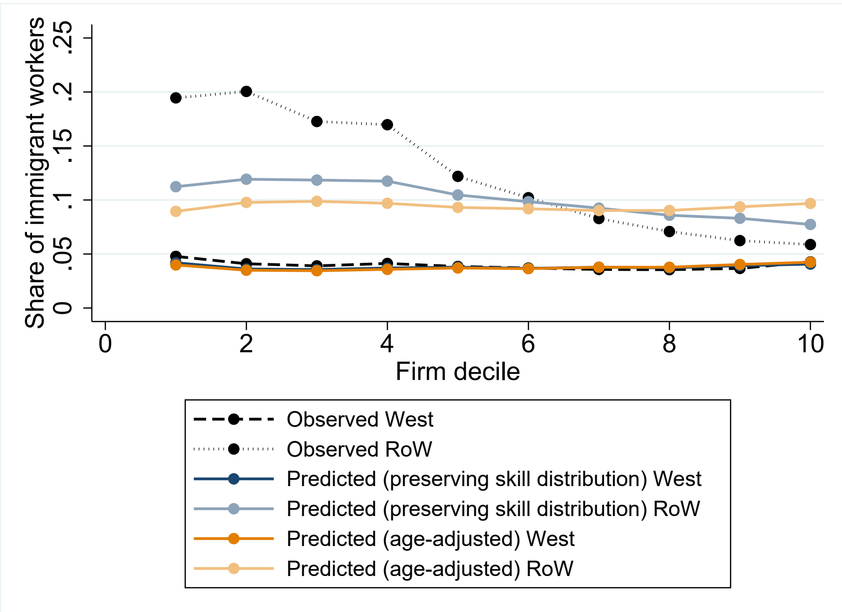
In Figure 1a, the black dashed line shows the observed share of immigrants in a given decile (as in Table 3); the orange line gives the expected share of immigrants if employers in a given decile were to hire based on age only (*age-adjusted prediction*); and the blue line shows the expected share of immigrants if employers hired based on age and skills captured by individual earnings fixed effects (*preserving skill distribution*), based on equation (5). According to the age-adjusted prediction, we would find roughly equal shares of immigrants within each decile across the firm productivity distribution if age was the only hiring criterion. The relative distances between the observed and the two predicted shares provide a measure of skill-sorting. In deciles 1–4, where immigrant concentration is relatively high, skills explain 20–28 percent of the difference between the observed shares and the age-adjusted expectations.[14]

The qualitative result of Figure 1a – that the majority of the sorting remains unexplained by skill compositions as captured by quartiles of the person effects – is confirmed when skill is instead defined by four education categories (although this measure explains somewhat less of the overall sorting; see Figures A.3a and A.3c). Figure 1b further shows that both the overall sorting and the explanatory power of the skill-preserving prediction can be attributed to Rest of World workers. We will further consider skill-based sorting in the decomposition of earnings differences related to firm productivity (Section 4.4). Also, the fact that there is a lot of systematic sorting which cannot be attributed to skill differences motivates our analysis on manager-related sorting in Section 4.5.

[14]This is computed by taking the mean across deciles d of $(I_{d,skill-adjusted} - I_{d,age-adjusted})/(I_{d,observed} - (I_{d,age-adjusted})$, where I is share of immigrant workers (available in Table A.6). This measure captures the mean distance between the age-adjusted and observed shares explained by adjusting for skill.



(a) All immigrants



(b) By immigrant group

Figure 1: Skill-based sorting

Notes: The figure shows the observed distribution of immigrants within firm productivity deciles, as well as two predicted distributions. The age-adjusted distribution maintains the age distribution of each decile. The skill-preserving distribution maintains the joint age-skill distribution of each decile (see equation 5). Skill is given by quartiles of the person fixed effects estimated in equation (2). Panel (a) uses the person fixed effects from a regression where the group of immigrants is pooled, while Panel (b) uses the person fixed effects from separate regressions for Western and Rest of World immigrants.

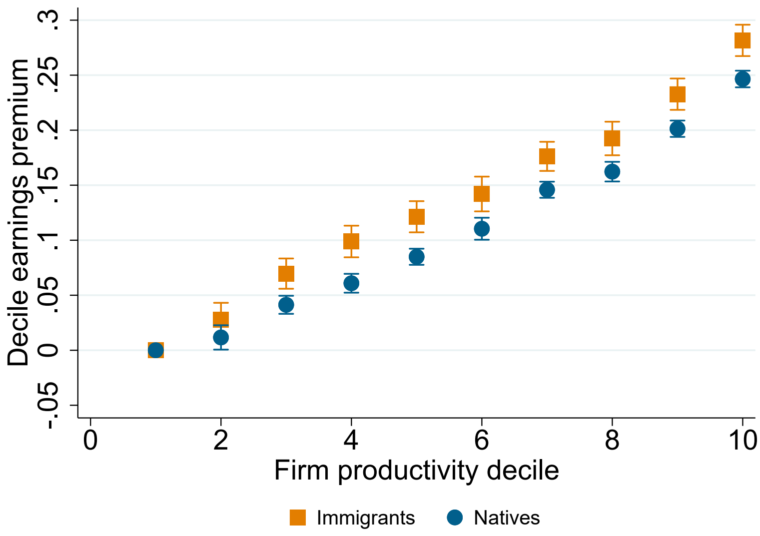
4.3 Earnings returns to working in more productive firms

The importance of productivity-related sorting depends on the earnings returns to firm productivity for different groups of workers across the distribution of firms. To investigate this, we estimate Equation (2) using the firm ranking while accounting for worker fixed effects. Figure 2 plots the estimated decile earnings premiums $\hat{\theta}_D^g$ (Table A.3 presents the corresponding estimates). Panel (a) compares natives to immigrants, while Panel (b) compares natives to the sample of immigrants split into West and Rest of the World.

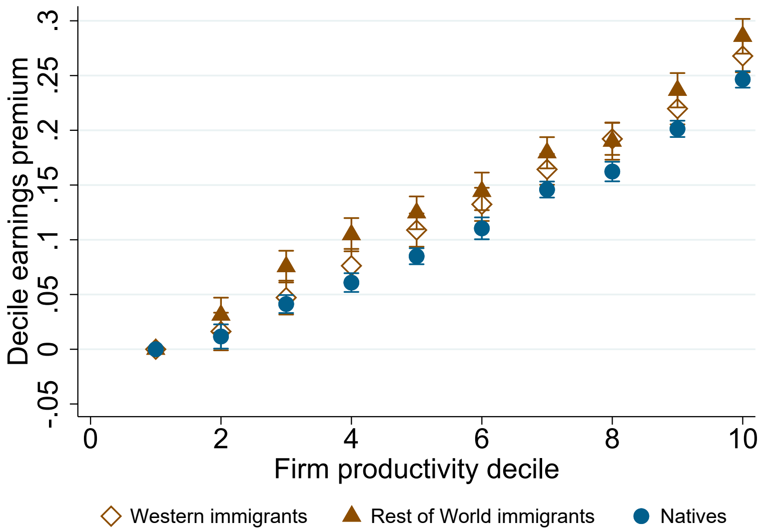
There are substantial positive returns to working in more productive firms for all groups of workers and across the productivity distribution. Moreover, immigrants gain relatively more from avoiding firms at the very bottom of the productivity distribution. For example, the estimated return to working in the fifth decile compared to the first is 8.5 log points for natives and 12.1 log points for immigrants. From the fourth decile and up, each step up on the productivity ladder results in similar gains for natives and immigrants (i.e. the difference relative to decile one is constant).[15]

We saw in Figure 1b that Rest of the World immigrants are relatively more concentrated in the bottom part of the productivity distribution. Panel (b) of Figure 2 shows that the differential returns from avoiding the low-productive firms are primarily driven by this group of immigrant workers. By contrast, immigrants from the West have earnings returns that are more similar to those of natives. While region of origin clearly matters, time spent in Sweden does not seem to be a crucial determinant of the returns to firm productivity: separate estimates for immigrants that have spent less than vs. at least 10 years in Sweden highlight similar returns to firm productivity, in both cases greater than for natives (Figure A.5).

[15]Results are similar when accounting for the unequal distribution of the total number of workers in different deciles as seen in Figure A.1 by using an employee-weighted productivity ranking (Figure A.4).



(a) All immigrants



(b) By immigrant group

Figure 2: Earnings returns to working in more productive firms

Notes: Panel (a) plots $\hat{\theta}_D$ from equation (2) for the sample of natives and immigrants. Panel (b) plots $\hat{\theta}_D$ from the same equation for the sample of natives (circles), Western immigrants (diamonds), and Rest of World immigrants (triangles). All specifications include individual fixed effects, year fixed effects and controls as specified in Section 3. Table A.3 displays point estimates.

Clustering firms into ten categories may hide firm heterogeneity and worker sorting within these categories. We investigate this possibility by inspecting the distribution of immigrants and natives within deciles, and by estimating the earnings returns using ventiles instead of deciles. Figure A.6 suggests that within each productivity decile, immigrant and native workers are similarly distributed. This finding supports the idea that the ten-group classification captures relevant aspects of firm heterogeneity and worker sorting. Furthermore, Figure A.7 shows that the steady returns to firm productivity found in Figure 2 are also present with the finer grouping of firms.[16]

4.4 Decomposition of decile premiums into sorting and pay-setting

We now turn to evaluating the contribution of productivity decile-specific pay premiums to the immigrant-native earnings gap according to equation (3). Table 4 shows the decomposition results for both the overall group of natives and immigrants and separately for immigrants from West and Rest of World countries.

Starting with the first row, we see that the average decile premium of immigrants is quite similar to that observed for natives (16.2 vs. 15.7 percent). This similarity hides two opposing forces. The sorting component in column (5) is positive (i.e. increases the gap) and amounts to around 21 percent of the overall earnings gap between immigrants and natives. The pay-setting component in column (8) instead reduces the gap by around 25 percent. Thus, the fact that immigrants work in lower-productivity firms is on average fully compensated by their higher returns to firm productivity.[17] Recall that the pay-setting component is dependent on choice of reference category, while the sorting component is not (Fortin et al., 2011). Relating to the firms with the lowest productivity is a natural reference category as these are the firms with the lowest rents. If, however, the firms in the lowest decile pay a premium to natives over immigrants, the pay-setting component would rise accordingly: A 3 percent pay premium to natives over immigrants in the lowest decile would drive the pay-setting component to 0 and

[16] For all groups of workers, the estimates suggest negative returns to moving from the lowest productivity ventile to the second and third ventiles. Table A.4 suggests that this result may relate to firm size, since the first ventile contains a comparatively greater number of large firms, which on average pay higher earnings. While there may be additional firm-related factors affecting earnings such as firm size, the overall picture of the earnings returns to firm productivity for different groups of workers remains.

[17] The signs on these effects are in line with those in Dostie et al. (2023), who decompose *firm-specific* as opposed to decile-specific premiums using a similar method.

mean that the contribution of the mean decile premiums to the overall gap is driven by sorting only.[18]

Columns (6) and (7) further decompose the sorting component into skill-based and residual sorting (cf. Section 3.2). The figures suggest that approximately 40 percent of the sorting component of the earnings gap can be explained by differential firm allocation due to skill differences between immigrants and natives (as captured by individual fixed effects from earnings regressions).

The second and third rows of Table 4 separate immigrants by region of origin. Western immigrants in our sample have a slight earnings advantage over natives, and the pay-setting effect accounts for a substantial part of this. For Rest of the World migrants, the pay-setting component is similar in magnitude to that of Western migrants, but the sorting component is remarkably different. In particular, the concentration of these immigrants in firms of low productivity yields an overall productivity decile premium – when sorting and pay-setting are combined – that is on average similar to that of natives.

Table 4: Decomposition of immigrant-native earnings gap

	Earnings gap	Mean decile premium			Sorting			Pay-setting
		Natives	Immigrants	Gap	Total	Skill-based	Residual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.121	0.157	0.162	-0.005	0.026	0.010	0.015	-0.030
West	-0.041	0.157	0.174	-0.016	0.003	0.001	0.002	-0.019
RoW	0.188	0.157	0.155	0.002	0.035	0.014	0.021	-0.033

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 within-decile pay-setting effect (column 8). We further decompose the sorting effect into skill-based sorting (column 6) and residual sorting (column 7).

[18] Although magnitudes vary, in Appendix Table C.3 we show that a comparable result – that sorting and pay-setting are of similar magnitude and opposite signs – is obtained if we instead perform decompositions on the dual-connected set using firm fixed effect estimates from an AKM model.

4.5 The role of manager origin: sorting and rent-sharing

4.5.1 Immigrant hiring by manager background

The fact that immigrants are less likely to work in high-productive firms despite the relatively higher returns to doing so indicates that there may be immigrant-specific barriers affecting the types of firms that immigrants work in. One such barrier can be due to hiring practices that favor workers who share the manager's/owner's background (Raphael et al., 2000; Åslund et al., 2014; Hsu Rocha and Dias, 2021; Miller and Schmutte, 2023). If immigrant managers are more likely to be found in the bottom of the firm productivity distribution – which Panel A of Table 3 confirms to be the case in our setting – then an increased likelihood of hiring other immigrants could contribute to the concentration of immigrant workers in low-productive firms.[19,20]

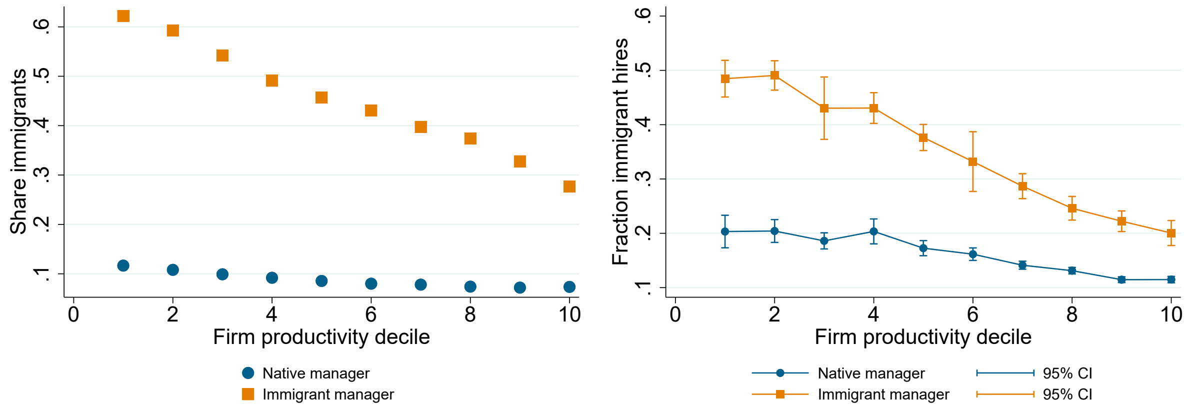
Panel (a) of Figure 3 shows that the share of immigrant workers at immigrant-managed firms vastly exceeds the share at native-managed firms throughout the firm productivity distribution.[21] A potential concern is that these manager-worker sorting patterns are picking up unobservable characteristics of the firm rather than the effect of manager origin per se. To address this, Panel (b) of Figure 3 plots how the fraction of immigrant hires varies by manager background and productivity decile, after controlling for firm characteristics such as size and industry. We restrict the estimation sample to new hires that are never managers, where a new hire is defined as a worker who has not had the firm as its primary employer in the preceding year. The estimates show that immigrant managers are significantly more likely to hire immigrants than native managers are. In relative terms, immigrant managers at the bottom of the firm productivity distribution are 2.5 times more likely to hire an immigrant, compared to native managers. The absolute gap is much smaller at the top, but the ratio is still close to 2. While the magnitudes are much smaller and the identifying variation changes, the pattern that

[19]We define a manager as the person with the highest yearly earnings at the firm. Previous work using this definition on Swedish data suggests a strong correlation between highest wage and manager occupational classification (Åslund et al., 2014).

[20]A natural question is why immigrant managers are over-represented in the bottom part of the firm productivity distribution. While we leave a deeper analysis of this for future research, Figure A.9a neither suggests that immigrants in general are "poor" managers nor that "poor" managers disproportionately hire immigrants. Thus, differences in manager quality by origin are unlikely to drive the sorting of workers across firms.

[21]Our relatively coarse classification for immigrant groups appears to capture sorting along manager origin lines: Figure A.8 shows that across the productivity distribution, the share of Rest of World (Western) workers is much higher under Rest of World (Western) management than in firms with another manager origin.

immigrant managers are more likely to hire immigrants holds even when controlling for firm fixed effects (Appendix Table A.5).



(a) Share immigrants

(b) Estimated immigrant hires

Figure 3: Firm productivity and manager background

Notes: Panel (a) shows the leave-out-manager share of immigrants in each firm productivity decile, by manager background. Panel (b) plots the estimated fraction of immigrant hires by manager background from the regression $ImmHire_{ift} = \alpha + \upsilon_d Decile_d + \Omega_d Decile_d \cdot ImmManager_{ft} + \beta X_{ft} + \varepsilon_{ft}$. The native manager (immigrant manager) line shows the linear combination of $\hat{\alpha} + \hat{\upsilon}_d$ ($\hat{\alpha} + \hat{\upsilon}_d + \hat{\Omega}_d$). Controls include firm size (in five groups) and year-by-region-by-industry fixed effects. Full results are available in Table A.5.

How much of worker sorting across productivity deciles can manager sorting explain? To assess this, we calculate the counterfactual share of immigrant workers in each decile under the assumption that hiring is driven solely by manager-worker homophily. This is given by $(I_d S_I + N_d S_N)/(I_d + N_d)$, where I_d (N_d) is the number of workers in decile d under immigrant (native) management, and S_I (S_N) is the overall immigrant share under immigrant (native) management across firm productivity deciles. Assuming that the allocation of managers across productivity deciles precedes that of workers, the exercise suggests that manager-related sorting accounts for a significant share of the disproportionate presence of immigrants in low-productive firms. For example, the immigrant share in the second decile would be 16.9 percent if hiring was based on manager-worker homophily. This is substantially higher than the age-adjusted prediction of 13.3, and thus closer to the observed 24.2 percent. On average, relative to the baseline age-adjusted prediction, the allocation of workers to same-origin managers accounts for more than a third of the sorting. Full results are available in Table A.6.

4.5.2 Rent-sharing

To relate the earnings gains from working in more productive firms to manager background, we estimate rent-sharing specifications (Card et al., 2018) exploiting variation in log value added per worker within employment spells. This analysis also complements the results based on persistent across-firm differences in productivity (Section 4.3). We let rent-sharing potentially differ between workers *and* managers of different origin, which has not been done before to the best of our knowledge. The estimation keeps the sorting of workers to firms constant, and controls for time-invariant worker and firm heterogeneity:

$$\begin{aligned}\ln(e_{ift}) = c + \lambda_t + \lambda_{if} + \delta_1 \ln(VA/N)_{ft} + \delta_2 ImmManager_{ft} \\ + \boldsymbol{\delta}_3 ImmManager_{ft} \cdot ImmGr_g + \delta_4 ImmManager_{ft} \cdot \ln(VA/N)_{ft} \\ + \boldsymbol{\delta}_5 \ln(VA/N)_{ft} \cdot ImmGr_g + \boldsymbol{\delta}_6 \ln(VA/N)_{ft} \cdot ImmGr_g \cdot ImmManager_{ft} + \varepsilon_{ift}\end{aligned} \tag{8}$$

$\ln(e_{ift})$ 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 fixed effect, $ImmManager_{ft}$ is an indicator variable for immigrant managers, and g indexes the immigrant group (Western, Rest of World). We exclude from the analysis workers who become managers at some point during our sample period.

Table 5 reports the estimated coefficients on all terms that include $\ln(VA/N)_{ft}$. The column (1) specification does not include any additional controls, while column (2) includes individual time-varying controls (age squared, age cubed, and tenure), all interacted with immigrant group.[22] Column (3) only includes firms in productivity deciles 1 to 5, and column (4) only includes firms in productivity deciles 6 to 10, based on our earlier classification of firms.

The estimate of 0.020 in column (1) suggests that if a firm moves from low to high productivity (increasing its log value added by two within-firm standard deviations), earnings of native workers are expected to increase by 1.4 log points.[23,24] This association is substantially

[22] 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.

[23] The within-firm standard deviation in log value added is approximately 0.37. The overall and between standard deviations in the firm-year sample are 0.60 and 0.53, respectively.

[24] Compared to other studies (see overview in Card et al., 2018), this elasticity is at the lower end of the spectrum. A possible contributing factor is that we control for worker fixed effects.

Table 5: Rent-sharing among immigrants and natives

	(1)	(2)	(3)	(4)
Log VA per worker	0.020***	0.018***	0.017***	0.018***
	(0.002)	(0.002)	(0.002)	(0.003)
Rest of World × Log VA per worker	0.001	-0.002	0.006*	-0.006**
	(0.003)	(0.002)	(0.003)	(0.003)
Western × Log VA per worker	-0.004**	0.003*	0.008***	0.001
	(0.002)	(0.002)	(0.003)	(0.002)
Immigrant manager × Log VA per worker	-0.004	-0.002	-0.005	-0.002
	(0.003)	(0.003)	(0.005)	(0.004)
Rest of World × Immigrant manager × Log VA per worker	0.013***	0.011***	0.023***	0.004
	(0.004)	(0.004)	(0.006)	(0.005)
Western × Immigrant manager × Log VA per worker	0.004	0.001	0.006	-0.001
	(0.003)	(0.003)	(0.007)	(0.004)
R^2	0.759	0.770	0.728	0.753
N	29,353,492	29,353,492	6,190,895	23,162,597
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 8. 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 deciles 1 to 5, and column (4) only includes firms in deciles 6 to 10.

greater for Rest of World workers under immigrant management, a pattern that is primarily driven by low-productive firms (see the comparison between columns 3 and 4). The results suggest that productivity changes spill over onto changes in earnings, particularly where there is homophily. That rent-sharing is higher for immigrants in less productive firms (see column 3) echoes our results in Section 4.3, where the gap in earnings returns between immigrants and natives opened up in the bottom half of the persistent firm productivity distribution.

The results show that worker pay responds to productivity variations not only when moving across employers, but also within firms. In certain settings immigrants appear to be particularly able to bargain over their wages. Note, however, that the rent-sharing estimates do not suggest that immigrants are better off in absolute terms: they disproportionately work in firms where both the size of rents and level of earnings are lower. Moreover, immigrants may be subject to larger decreases in earnings if value added decreases in bad times, and not just extract more rents in good times. In any case, the estimates point to immigrant workers being more connected to changes in firm performance in immigrant-managed firms, particularly when these firms are less productive.

5 Discussion and conclusion

We examine how firm productivity contributes to the earnings disparities between immigrants and natives using Swedish balance sheet data and population-wide employer-employee records. Our analysis shows that immigrants, particularly those from non-Western countries, are over-represented in less productive firms, which negatively affects their earnings. At the same time, their returns to productivity are at least as high as those of natives. This suggests that immigrants are able to reap the benefits of employment in high productivity firms once they actually reach that step on the job ladder, but face barriers in doing so.

What drives the differential sorting of immigrant and native workers in different firms? Part, but far from all, of the sorting can be explained by skills, as reflected in worker earnings fixed effects or level of education. We also document striking worker-manager homophily that explains a substantive part of the worker allocation. The importance of manager origin is confirmed by a complementary analysis that exploits within employment spell variation in value added. The rent-sharing results show that the pass-through of value added changes to workers' earnings is higher among non-Western immigrants if the manager shares their background.

One way to interpret our findings is in the context of monopsonistic labor markets. The presence of earnings gains associated with working in more productive firms is consistent with firms, rather than markets, setting wages (Card, 2022; Manning, 2020). The dual result that immigrants are concentrated in low-productivity firms, but have at least as high returns as natives in high-productivity firms, points to a potential combination of two factors: immigrants face barriers to climbing the job ladder, and firms exert varying degrees of monopsony power over different groups of workers. Our results are consistent with the theoretical framework by Amior and Stuhler (2024), where the driving force behind immigrant-native wage differentials is firm pay-setting practices coupled with recent immigrants' lower reservation wages. This creates a segregated labor market: non-discriminating low-wage firms hire low reservation wage workers over high reservation wage workers (i.e. natives), creating a low-pay immigrant-dominated sector in equilibrium. Consistent with what we find, the sorting patterns are not solely due to skill-differences between immigrants and natives, but also relate to firms' monopsony power.[25]

Our decomposition shows that if the returns for immigrants and natives are the same, the over-representation of immigrants in less productive types of firms increases the overall earnings gap between immigrants and natives by 2.6 percentage points (21%). This type of between-firm sorting effect (or, in our case, between-decile sorting effect) is of similar magnitude to Dostie et al. (2023), who instead rely on firm fixed effects in an AKM-framework and find that sorting across firms contributes to 20% of the overall immigrant-native earnings gap in Canada. Indeed, sorting across different types of firms as a key contributor to the earnings gap also holds for other groups, such as men and women (Card et al., 2016; Bruns, 2019) or race-based demographic groups (Gerard et al., 2021).

Assuming instead the same allocation of immigrants and natives across the productivity distribution, our results suggest that the higher returns for immigrants decreases the overall earnings gap by 3 percentage points (25%). Unlike the sorting component, this result relies on the assumption that the least productive firms are non-discriminatory. If, however, the firms in the lowest decile pay more to natives than immigrants, the contribution of the pay-setting component to the overall earnings gap would go to zero, or even serve to widen the gap.

The existence of firm productivity premiums may not (only) be about monopsonistic labor markets, but also about institutions, networks, and geographical segregation. Conditional on accessing a high-productive firm, immigrants with poorer outside options could, for instance, gain more from firm policies that benefit all employees in similar ways (e.g. due to relatively high union density and general egalitarian social norms in Sweden). The importance of managers points to ethnic networks being potentially important, and our finding that worker-manager origin similarity is related to the extent of rent-sharing within firms suggests that there are also group-specific, intra-firm mechanisms at work. Moreover, as our data show, immigrants are not only segregated by firm type but also by geographic location, potentially affecting the set of employers within the local labor market and thus the career ladders of the workers. In line with this, Eckert et al. (2022) study Danish refugees and find that returns to experience are

[25] Our results also echo work by Hirsch and Jahn (2015), who conjecture that search costs may be greater for immigrants than natives and find that immigrants supply labor to the firm less elastically than natives, and Bassier et al. (2022) who find that the firm monopsony power is higher for low-wage workers and in low-wage sectors.

substantially higher in Copenhagen than elsewhere, driven by sorting into high-skill jobs at high-productive firms.

From a policy perspective, it is particularly striking that immigrant groups with poor labor market positions deviate the most from natives in sorting and returns. This speaks against voluntary sorting due to worker preferences and signals the potential individual and societal gains from more equal employer access. Overall, our results suggest that a better understanding of the role firms play in immigrant labor market integration is needed.

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A Appendix

A.1 Additional figures and tables

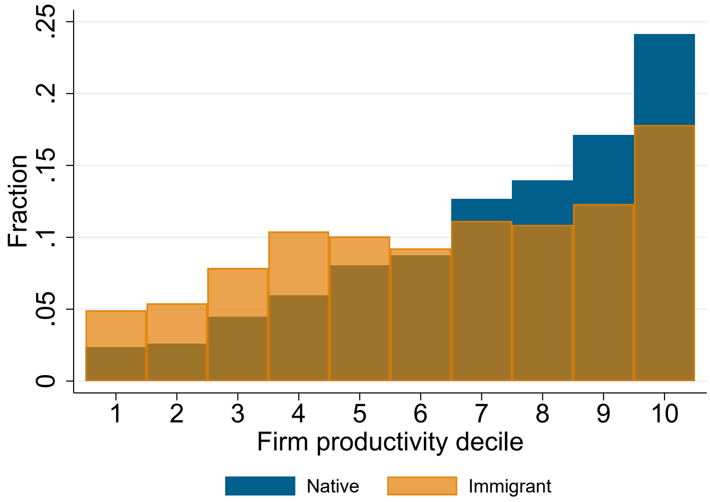


Figure A.1: Distribution of immigrants and natives across productivity deciles

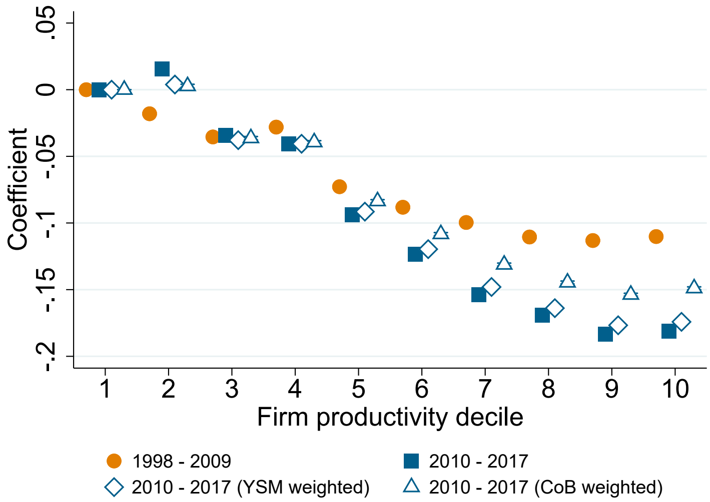
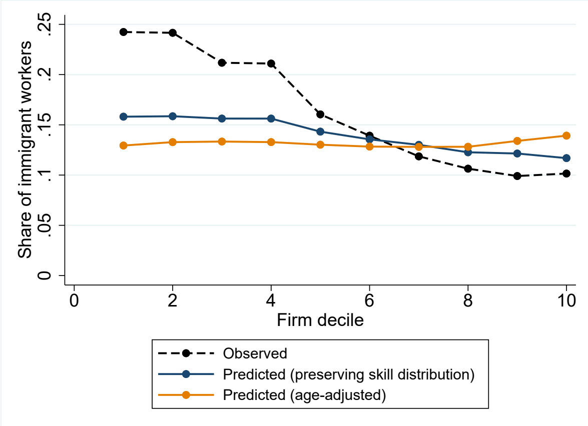
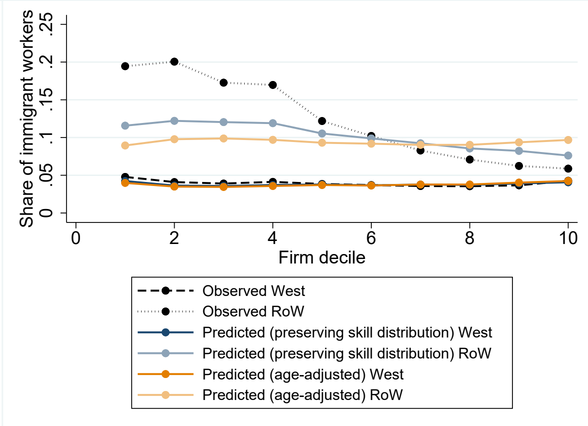


Figure A.2: Sorting of immigrants across productivity deciles

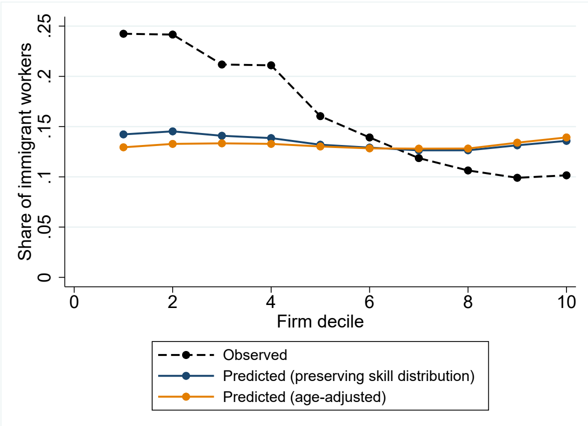
Notes: The figure plots the estimated β_{dp} coefficients from estimating the following regression, separate by two sub-periods p (where imm_i is an indicator variable for being an immigrant and $decile_d$ refers to productivity decile): $imm_i = \alpha_p + \sum_{d=2}^{10} \beta_{dp} decile_d + \varepsilon_{ip}$. The first decile is omitted such that the immigrant shares in a particular decile are estimated relative to the bottom decile. The hollow dots re-weight the second sub-period (2010–2017) to match the first (1998–2009) either in terms of the country of birth (CoB) composition or the years since migration (YSM) composition.



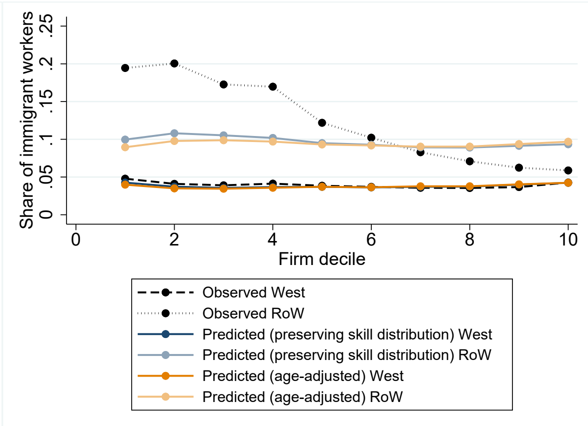
(a) All immigrants, deciles of person fixed effects



(b) By immigrant group, deciles of person fixed effects



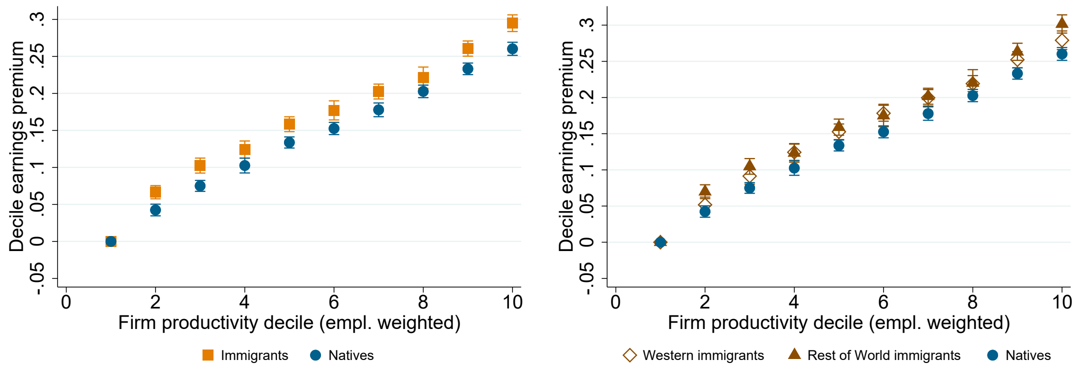
(c) All immigrants, education groups



(d) By immigrant group, education groups

Figure A.3: Skill-based sorting using alternative skill measures

Notes: The figures show the observed distribution of immigrants across firm productivity deciles, as well as two predicted distributions. The naive distribution maintains the age distribution of each decile. The skill-preserving distribution maintains the joint age-skill distribution of each decile. Skill is given by deciles of the person fixed effects estimated in equation (2) in the top panel and by four education groups (missing, compulsory, secondary and tertiary) in the bottom panel. Panels (a) and (c) show the distributions for the pooled group of immigrants and panels (b) and (d) break the group down into West and Rest of World.



(a) All immigrants (b) By immigrant group

Figure A.4: Earnings returns to working in more productive firms (employee-weighted ranking)

Notes: The figure plots $\hat{\theta}_D$ from equation (2) for the sample of natives and immigrants respectively, using the employee-weighted ranking of firms. All specifications include individual fixed effects, year fixed effects and controls as specified in Section 3.

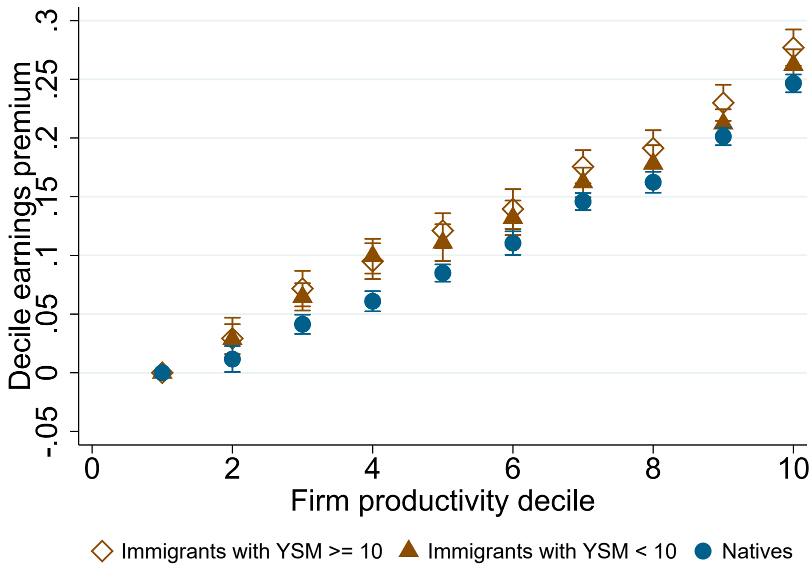
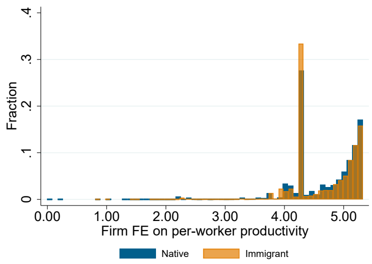
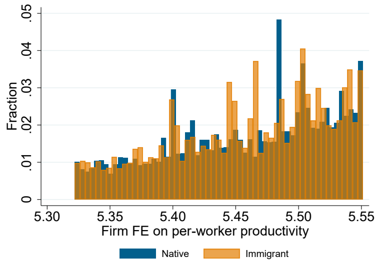


Figure A.5: Earnings returns to working in more productive firms – YSM

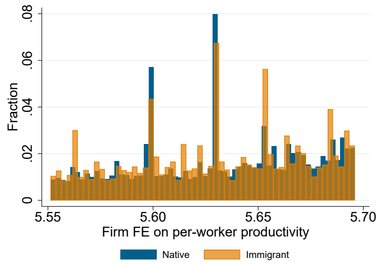
Notes: The figure plots $\hat{\theta}_D$ from equation (2) for the sample of natives and immigrants respectively, where the immigrant group is split by their years since migration (YSM). All specifications include individual fixed effects, year fixed effects and controls as specified in Section 3.



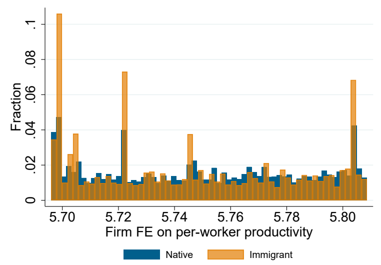
(a) Decile 1



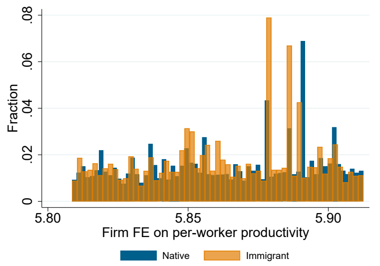
(b) Decile 2



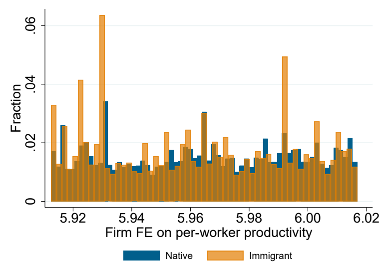
(c) Decile 3



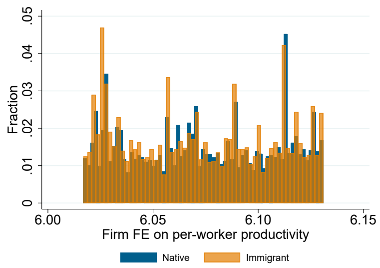
(d) Decile 4



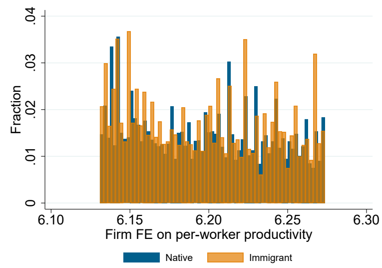
(e) Decile 5



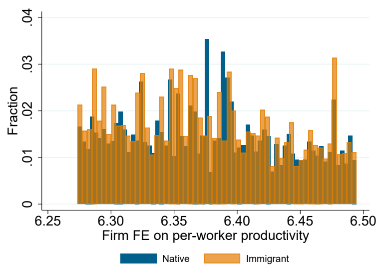
(f) Decile 6



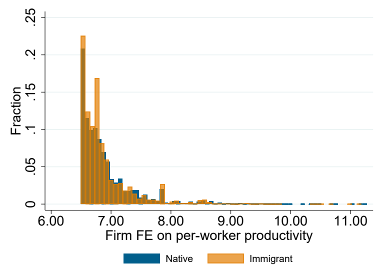
(g) Decile 7



(h) Decile 8

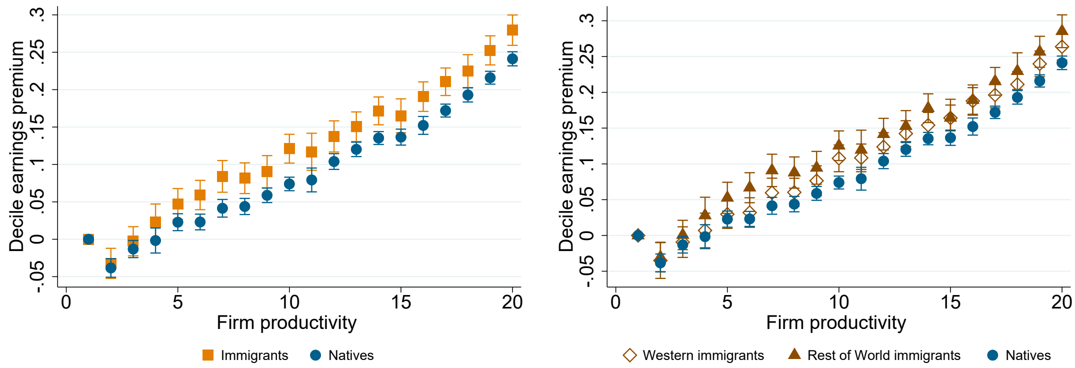


(i) Decile 9



(j) Decile 10

Figure A.6: Within-decile distribution of immigrants and natives

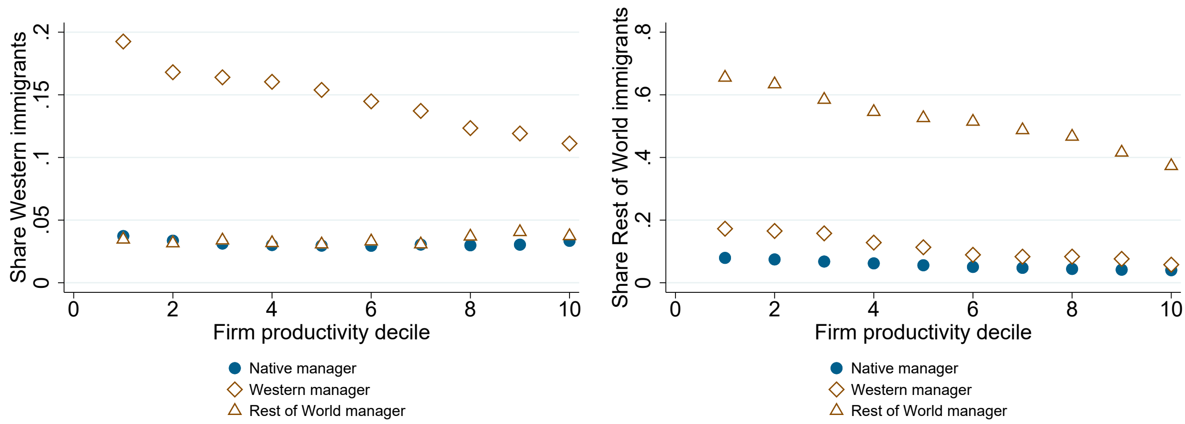


(a) All immigrants

(b) By immigrant group

Figure A.7: Earnings returns to working in more productive firms (ventiles)

Notes: The figure plots $\hat{\theta}_D$ from equation (2) for the sample of natives and immigrants respectively, using ventiles of firm productivity. All specifications include individual fixed effects, year fixed effects and controls as specified in Section 3.



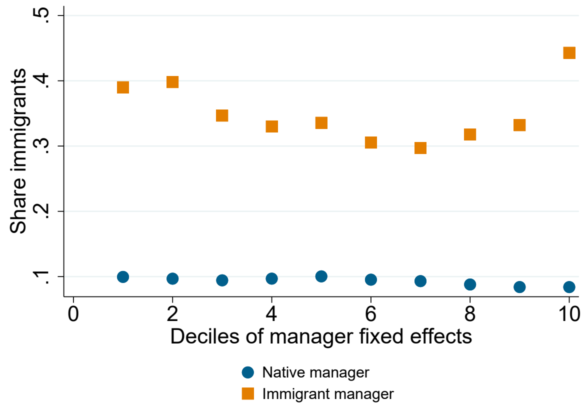
(a) Share Western immigrants, by manager type and firm productivity

(b) Share Rest of World immigrants, by manager type and firm productivity

Figure A.8: Manager and worker interactions by subgroups

Notes: Panel (a) shows the leave-out-manager share of Western immigrants in each firm productivity decile, by manager type. Panel (b) shows the leave-out-manager share of Rest of World immigrants in each firm productivity decile, by manager type.

(a) Manager fixed effects distribution, by immigrant status



(b) Share immigrants, by manager quality

Figure A.9: Manager quality

Notes: Panel (a) shows the distribution of manager fixed effects $\lambda_{manager}$ estimated from the following equation on the largest connected set of firms linked by manager mobility (see, e.g., Graham et al., 2012): $\ln(VA/N)_{ft} = \alpha_t + \gamma_f + \lambda_{manager} + \beta X_{ft} + \varepsilon_{ft}$, where α_t are year fixed effects, γ_f are firm fixed effects, X_{ft} is a vector of time-varying firm-level characteristics (the same that we use in Column 1 of Table 2). Panel (b) shows the leave-out-manager share of immigrants, by manager quality and type.

Table A.1: Firm segregation under random allocation of immigrant status

	Immigrants	Natives
	Total	Total
In native-segregated firms	0.000	0.116
In immigrant-segregated firms	0.010	0.000
Male	0.643	0.643
Age	40.301	40.291
Share age ≤ 30	0.266	0.266
Share age ≥ 50	0.269	0.269
Education, compulsory	0.158	0.158
Education, secondary	0.547	0.548
Education, post secondary	0.288	0.288
Education, missing	0.007	0.007
Monthly earnings (2010 SEK)	24682.539	24680.959
No. observations	6,057,757	40,338,245

Notes: Immigrant status randomly assigned preserving the share of immigrants and the firm size distribution observed in the analysis sample. The unit of observation is worker $\times$ year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants).

Table A.2: 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	52,778,912	45,874,100	6,784,253
Panel A: Summary of parameter estimates			
Number of person effects	5,585,418	4,564,717	991,151
Number of firm effects	467,855	431,954	206,295
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
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). The regression model is $\ln(e_{git}) = \alpha_{gi} + \psi^{g}_{f(g,i,t)} + X_{git}\beta^{g} + \varepsilon_{git}$, where e_{git} are monthly earnings; α_{gi} are individual fixed effects; $\psi^{g}_{f(g,i,t)}$ are firm fixed effects; X_{git} are time-varying individual controls; and ε_{git} is an error. g denotes the group, which is natives or immigrants. Models include year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies.

Table A.3: Earnings returns to working in more productive firms

Decile	Natives (1)	All immigrants (2)	Western immigrants (3)	Rest of World immigrants (4)
2	0.012 (0.006)	0.028 (0.008)	0.016 (0.009)	0.031 (0.008)
3	0.041 (0.004)	0.070 (0.007)	0.047 (0.008)	0.075 (0.007)
4	0.061 (0.004)	0.099 (0.007)	0.076 (0.008)	0.105 (0.008)
5	0.085 (0.004)	0.121 (0.007)	0.109 (0.008)	0.125 (0.008)
6	0.110 (0.005)	0.142 (0.008)	0.132 (0.008)	0.144 (0.009)
7	0.146 (0.004)	0.176 (0.007)	0.164 (0.007)	0.180 (0.007)
8	0.162 (0.005)	0.192 (0.008)	0.192 (0.007)	0.190 (0.009)
9	0.201 (0.004)	0.233 (0.007)	0.220 (0.007)	0.237 (0.008)
10	0.247 (0.004)	0.282 (0.007)	0.268 (0.008)	0.286 (0.008)

Notes: Columns (1) and (2) show $\hat{\theta}_D$ from equation (2) for the full sample of natives and immigrants, respectively. Columns (3) and (4) show $\hat{\theta}_D$ from equation (2) for Western immigrants and Rest of World immigrants, respectively. All specifications include individual fixed effects, year fixed effects and controls as specified in Section 3.

Table A.4: Summary statistics by productivity ventile, ventiles 1-10

	1	2	3	4	5	6	7	8	9	10
Panel A: Firm statistics										
Number of firms × year	79,084	95,867	104,505	112,916	118,093	126,321	135,614	133,995	137,502	139,938
Mean yearly firm size	15.303	9.067	11.336	13.017	15.399	17.937	20.387	17.298	20.819	21.669
Firm size 2-9	0.811	0.804	0.777	0.752	0.726	0.706	0.658	0.673	0.652	0.632
Firm size 10-49	0.165	0.173	0.193	0.213	0.233	0.250	0.297	0.276	0.289	0.308
Firm size 50-249	0.021	0.022	0.026	0.030	0.036	0.037	0.038	0.045	0.049	0.052
Firm size 250-999	0.002	0.002	0.003	0.004	0.004	0.006	0.006	0.005	0.007	0.007
Firm size $\geq$ 1000	0.001	0.000	0.000	0.001	0.001	0.001	0.002	0.001	0.002	0.001
Mean fraction immigrants at firm	0.225	0.225	0.210	0.190	0.175	0.158	0.146	0.138	0.129	0.120
Share native-segregated firms	0.631	0.630	0.628	0.633	0.633	0.638	0.623	0.639	0.636	0.626
Share immigrant-segregated firms	0.136	0.126	0.107	0.085	0.070	0.060	0.046	0.045	0.040	0.033
Share immigrant managers	0.223	0.225	0.209	0.187	0.169	0.149	0.135	0.129	0.118	0.107
Share Western managers	0.050	0.048	0.044	0.046	0.043	0.040	0.041	0.039	0.040	0.037
Share Rest of World managers	0.173	0.177	0.164	0.142	0.126	0.109	0.094	0.091	0.078	0.069
Manufacturing	0.081	0.077	0.084	0.087	0.099	0.108	0.107	0.126	0.139	0.148
Construction	0.053	0.067	0.080	0.092	0.104	0.118	0.118	0.154	0.166	0.188
Retail and trade	0.295	0.305	0.302	0.295	0.287	0.278	0.245	0.257	0.252	0.250
Transport	0.032	0.039	0.046	0.053	0.060	0.059	0.056	0.063	0.067	0.066
Hotels and restaurants	0.190	0.197	0.193	0.168	0.139	0.110	0.089	0.078	0.072	0.058
Other social	0.077	0.069	0.067	0.066	0.064	0.060	0.050	0.043	0.040	0.034
Stockholm	0.306	0.284	0.259	0.249	0.246	0.230	0.241	0.230	0.218	0.226
Gothenburg	0.156	0.154	0.159	0.163	0.168	0.170	0.160	0.163	0.165	0.168
North Sweden	0.099	0.115	0.120	0.123	0.126	0.127	0.126	0.131	0.129	0.130
Panel B: Worker statistics										
Number of workers × year	820,535	428,855	606,631	770,623	977,607	1,305,092	1,653,107	1,378,690	1,767,584	2,091,257
Share immigrants	0.243	0.242	0.240	0.243	0.221	0.205	0.227	0.192	0.161	0.160
Share immigrants: West	0.051	0.043	0.041	0.041	0.043	0.036	0.041	0.041	0.038	0.039
Share immigrants: Rest of World	0.192	0.200	0.199	0.201	0.178	0.169	0.185	0.151	0.124	0.120
Share male	0.549	0.528	0.531	0.514	0.495	0.498	0.452	0.508	0.569	0.605
Share age $\leq$ 30	0.187	0.378	0.377	0.383	0.375	0.373	0.344	0.340	0.349	0.307
Share age $\geq$ 50	0.391	0.211	0.216	0.209	0.211	0.215	0.227	0.237	0.230	0.267
Share compulsory educ.	0.306	0.197	0.204	0.201	0.189	0.176	0.188	0.175	0.177	0.192
Share secondary educ.	0.507	0.558	0.564	0.569	0.579	0.584	0.577	0.591	0.596	0.602
Share tertiary educ.	0.176	0.225	0.213	0.212	0.217	0.228	0.223	0.222	0.219	0.199
Mean log earnings	9.584	9.480	9.540	9.554	9.596	9.634	9.639	9.672	9.715	9.766
Std. dev. log earnings	0.563	0.610	0.602	0.590	0.573	0.568	0.562	0.552	0.548	0.546
Imm/native earnings gap	-0.052	-0.067	-0.060	-0.053	-0.024	-0.020	-0.022	-0.020	-0.043	0.001

Notes: The unit of observation in the top panel is firm × year, and in the bottom panel it is worker × year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants). The included industries are not exhaustive. *Other social* includes industries like sewage and refuse disposal, membership organization activities, cultural and sporting activities, and services such as hairdressing. Regions in the middle and south of Sweden are omitted from the table.

Table A.5: Hiring by manager type

	(1)	(2)
Immigrant manager × Decile 1	0.281***	0.032***
	(0.022)	(0.005)
Immigrant manager × Decile 2	0.286***	0.042***
	(0.015)	(0.005)
Immigrant manager × Decile 3	0.244***	0.020***
	(0.030)	(0.005)
Immigrant manager × Decile 4	0.227***	0.026***
	(0.017)	(0.006)
Immigrant manager × Decile 5	0.204***	0.019***
	(0.014)	(0.007)
Immigrant manager × Decile 6	0.170***	0.016***
	(0.028)	(0.005)
Immigrant manager × Decile 7	0.146***	0.017***
	(0.012)	(0.004)
Immigrant manager × Decile 8	0.115***	0.007*
	(0.011)	(0.004)
Immigrant manager × Decile 9	0.108***	0.009***
	(0.010)	(0.003)
Immigrant manager × Decile 10	0.086***	0.016**
	(0.011)	(0.008)
Decile 2	0.001	
	(0.018)	
Decile 3	-0.017	
	(0.017)	
Decile 4	0.000	
	(0.019)	
Decile 5	-0.031*	
	(0.017)	
Decile 6	-0.042**	
	(0.016)	
Decile 7	-0.062***	
	(0.016)	
Decile 8	-0.072***	
	(0.016)	
Decile 9	-0.089***	
	(0.016)	
Decile 10	-0.088***	
	(0.016)	
Constant	0.203***	0.167***
	(0.015)	(0.000)
R^2	0.073	0.205
N	8,433,931	8,399,056
Year by region by industry FE	Yes	No
Firm size	Yes	Yes
Firm FE	No	Yes
Year FE	No	Yes

Note: This table provides the results of a linear probability model that regresses a dummy for hiring an immigrant on the productivity deciles interacted with immigrant manager, as follows: $ImmHire_{ift} = \alpha + \upsilon_d Decile_d + \Omega_d Decile_d \cdot ImmManager_{ft} + \beta X_{ft} + \varepsilon_{ft}$. The sample is restricted to new hires only, and workers that ever become managers are dropped from the analysis. A new hire is defined as someone who works for the firm in year t but does not work for the firm in t-1. Standard errors are clustered by firm and reported in parentheses.

Table A.6: Share immigrants by decile

	1	2	3	4	5	6	7	8	9	10
Panel A: All immigrants										
Observed	0.242	0.242	0.212	0.211	0.160	0.139	0.119	0.106	0.099	0.102
Preserving skill distribution	0.154	0.155	0.154	0.155	0.142	0.135	0.130	0.123	0.122	0.118
Age-adjusted	0.129	0.133	0.133	0.133	0.130	0.128	0.128	0.128	0.134	0.139
Manager allocation	0.138	0.169	0.159	0.140	0.122	0.119	0.115	0.114	0.113	0.116
Panel B: Western immigrants										
Observed	0.048	0.041	0.039	0.041	0.038	0.037	0.036	0.035	0.037	0.043
Preserving skill distribution	0.042	0.036	0.036	0.037	0.038	0.037	0.038	0.037	0.039	0.041
Age-adjusted	0.040	0.035	0.035	0.036	0.037	0.036	0.038	0.038	0.040	0.042
Manager allocation	0.036	0.037	0.037	0.037	0.036	0.035	0.036	0.037	0.036	0.037
Panel C: Rest of World immigrants										
Observed	0.195	0.201	0.173	0.170	0.122	0.102	0.083	0.071	0.062	0.059
Preserving skill distribution	0.112	0.119	0.118	0.117	0.105	0.098	0.092	0.086	0.083	0.077
Age-adjusted	0.089	0.098	0.099	0.097	0.093	0.092	0.090	0.090	0.094	0.097
Manager allocation	0.101	0.133	0.119	0.098	0.081	0.080	0.072	0.069	0.069	0.070

Notes: The table shows observed and predicted shares of immigrant workers by decile. The Preserving skill distribution and Age-adjusted predicted shares are discussed in Section 4.2. The Manager allocation predicted shares are discussed in Section 4.5.

B Exogenous mobility

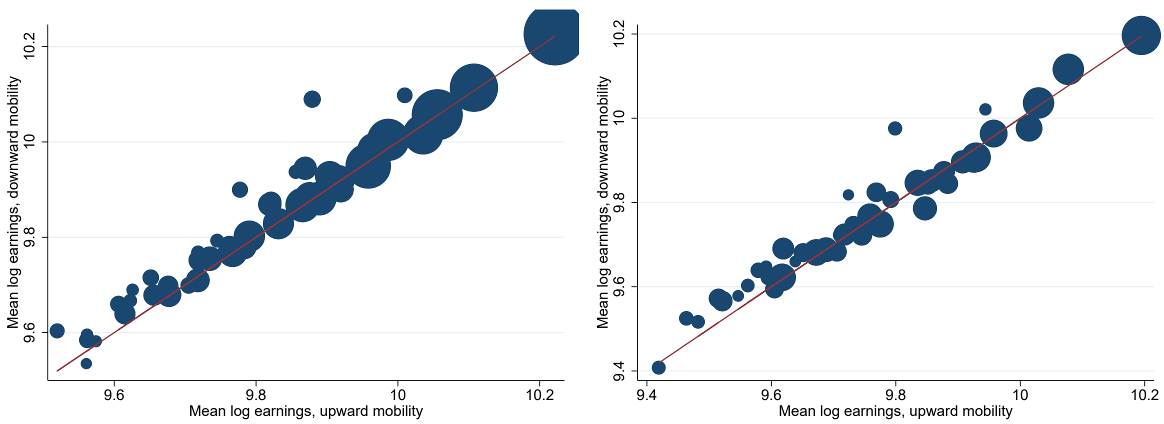
To estimate our main regression (equation 2), we require variation coming from workers moving across firm productivity deciles. In particular, in order for OLS to return a consistent estimator, worker history needs to be independent of the error term (the exogenous mobility assumption in the context of two-way fixed effect models a la Abowd et al., 1999). We here show that the assumption is likely to hold in our context.

To test this assumption, we restrict our attention to workers who move across firms at least once in 2000–2016 and who are employed for at least four consecutive years at firms with non-missing productivity ranking: two years at their pre-move employer and two years at the new employer. We then apply the same sampling restrictions adopted in the main analyses.[26] Figure B.1 shows regression-adjusted log-earnings averaged between the year of a decile move and the year before for each pair of downward and upward firm productivity decile movers (the test is akin to that in Bonhomme et al., 2019). For instance, for the combination of deciles 1 and 2, one dot represents the average log-earnings of the 2-to-1 (downward) movers on the y-axis paired with the corresponding outcome of the 1-to-2 (upward) movers on the x-axis.

Intuitively, for the additive model with exogenous mobility to hold, it is necessary that workers who move towards opposite deciles exhibit symmetric earnings changes (same magnitude and opposite sign). Log-earnings are adjusted for education dummies, quadratic age, the interaction between the two, and calendar year. We estimate the model separately by year and immigrant status using the sub-sample of decile-stayers, and use it to predict the outcome for the decile-movers using their observable characteristics. For both immigrants and natives the upward and downward mobility across firm productivity deciles is approximately symmetric across the decile transitions. We find similar results when plotting raw, unadjusted log-earnings, although for immigrants the average log-earnings of the upward movers appear slightly larger than those of downward movers (Figure B.2). Results are also similar when using earnings information only in the decile move year rather than averaging earnings the year of the move and that before. Overall, the results support that exogenous mobility holds in our

[26] Figure B.3 shows group-specific transition matrices which give, conditional on the pre-move decile, the shares of individuals moving to each of the ten deciles. For both groups, the least mobile are those in the bottom and top deciles, but there is otherwise a non-trivial amount of movement across deciles. The patterns are similar between immigrants and natives.

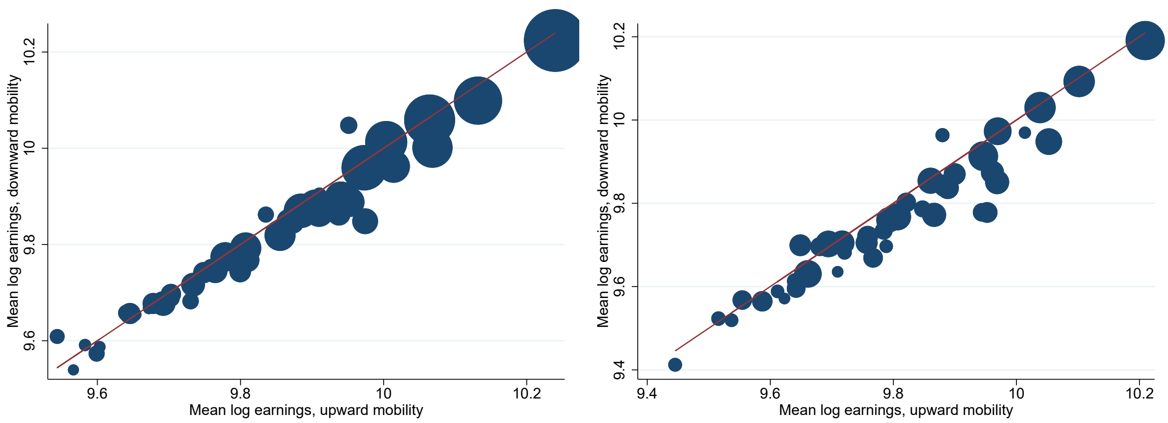
setting.



(a) Natives (b) Immigrants

Figure B.1: Average log-earnings for downward vs. upward decile movers

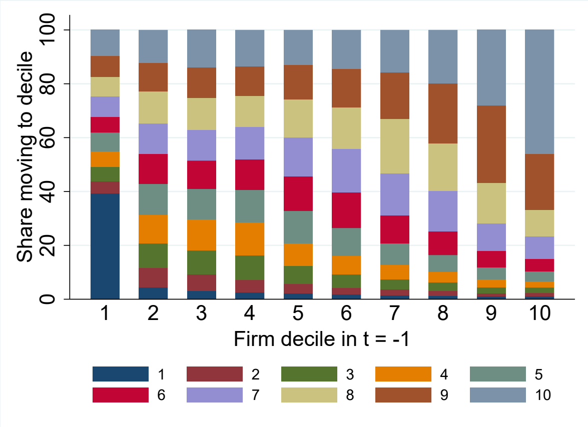
Notes: Each dot reports regression-adjusted log-earnings averaged the year of a firm productivity decile move and the year before for the pair of downward and opposite upward movers. The regression adjustment is implemented by estimating a log-earnings model adjusting for calendar year, education dummies, quadratic age, and education and quadratic age interacted. The model is separately estimated by year and for immigrants and natives with decile-stayers observations. The estimated model is then used predict the outcome for the decile-movers. Dot size is proportional to the number of observations in the year of the move. 45-degree line in red.



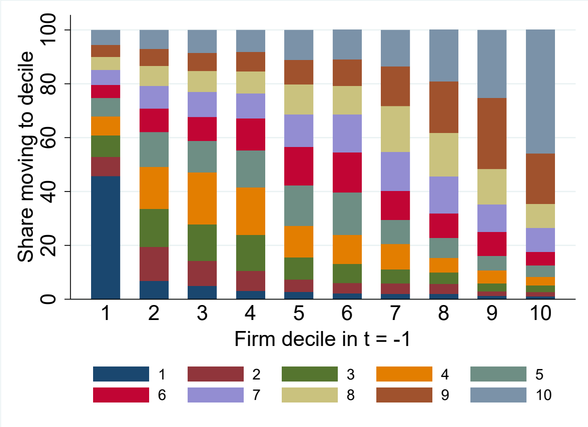
(a) Natives (b) Immigrants

Figure B.2: Unadjusted average log-earnings for downward vs. upward decile movers

Notes: Each dot reports raw (unadjusted) log-earnings averaged between the year of the move and that before for the pair of downward and opposite upward movers. Dot size is proportional to the number of observations in the year of the move. 45-degree line in red.



(a) Natives



(b) Immigrants

Figure B.3: Mobility across firm productivity deciles

C Dual-connected set and AKM comparisons

Estimating two-way fixed effects models with worker and firm fixed effects – AKM models (Abowd et al., 1999) – requires workers and firms to be connected by worker mobility, i.e. to be part of the same connected set. When estimating models separately by groups, such as immigrants and natives, attention is restricted to dual-connected sets in order not to violate common support in decompositions; that is, only workers and firms that are in the connected sets for *both* groups are included in the analysis. In a segregated labor market, this often leads to a substantial portion of workers and firms being dropped from the analysis.

In this appendix we explore how our main sample and decomposition results compare to those performed on the dual-connected set. The dual-connected set is defined at the worker-firm level and includes the set of firms linked by worker mobility for both immigrants and natives. We also provide AKM-decompositions.[27] Summary statistics by productivity deciles are provided in Table C.1, decomposition results for our main model estimated on the dual-connected set (based on equation 3) in Table C.2, and standard AKM decompositions in Table C.3. We show that (i) the sample changes substantively when restricting to the dual-connected set, but even so (ii) the key takeaways from the decomposition results are not sensitive to the exact definition of the sample or method used. We provide more details on these findings below.

Regarding the sample, 4% of the immigrant worker-year observations and 12% of the native worker-year observations are lost in the dual-connected set compared to our main sample. This despite the fact that we have 20 years of data. The pattern is driven by the omission of workers in segregated firms: the number of workers (immigrants as well as natives) in segregated firms is about half in the dual-connected set compared to our main sample. Because there are many more natives than immigrants, the share of native-segregated firms in the dual-connected set falls relative to the main sample, and the share of firms with immigrant managers increases. Focusing on the dual-connected set thus only captures part of the labor market, and it is not *a priori* obvious how this will affect the results.

[27] AKM decompositions are based on decomposing the firm (as opposed to firm decile) premiums from the following regression, estimated separately by group g (immigrant or native): $\ln(e_{git}) = \alpha_{gi} + \psi^{g}_{f(g,i,t)} + X_{git}\beta^{g} + \varepsilon_{git}$, where 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 ε_{git} captures random match effects, human capital shocks, and unobservables. Results of the estimation are summarized in Table A.2. The firm fixed effects are normalized to be 0 in hotels and restaurants in the decompositions.

Turning to the earnings gap, the overall earnings gap is slightly larger in the dual-connected set (0.128 compared to 0.121), and the productivity decile premiums are lower for natives (0.136 compared to 0.157) and to some extent also for immigrants (0.156 compared to 0.162). The descriptives suggest that there is a set of segregated firms at higher productivity deciles that are beneficial for the earnings of the workers at the segregated firms, and particularly so for natives. Omitting these firms lowers the decile earnings premiums. Although the sorting component in the decompositions is similar in both samples, the pay-setting component is much larger in the dual-connected set. This is in line with the segregated firms being especially beneficial for natives (the pay-setting component increases to the benefit of immigrants when these firms are omitted).

Overall, the qualitative patterns from the decompositions hold regardless of sample (dual-connected or our main sample) or method (grouping firms into productivity deciles or the AKM methodology). By this we mean that the sorting component is positive and increases the earnings gap, while the pay-setting component is negative and decreases the earnings gap, in all three decompositions. However, the magnitudes differ. Moreover, we also find that the sorting component is substantive for Rest of World migrants, and close to zero for Western migrants, in all three sets of results. While we maintain that the inclusion of segregated firms is important in our context, we show here that the key takeaways are not sensitive to the exact construction of the sample or method.

Table C.1: Summary statistics by productivity decile in dual-connected set

	1	2	3	4	5	6	7	8	9	10
Panel A: Firm statistics										
Number of firms × year	90,902	113,067	129,718	136,231	143,230	150,530	155,562	158,029	160,506	162,791
Mean yearly firm size	21.156	22.431	32.523	29.471	35.569	34.127	41.357	41.014	51.354	71.114
Firm size 2-9	0.639	0.584	0.514	0.488	0.448	0.415	0.390	0.383	0.373	0.358
Firm size 10-49	0.304	0.345	0.400	0.413	0.442	0.469	0.470	0.462	0.461	0.440
Firm size 50-249	0.051	0.061	0.072	0.086	0.095	0.102	0.120	0.133	0.135	0.157
Firm size 250-999	0.005	0.008	0.011	0.011	0.012	0.012	0.017	0.018	0.025	0.035
Firm size $\geq$ 1000	0.001	0.002	0.003	0.002	0.003	0.003	0.004	0.004	0.005	0.010
Mean fraction immigrants at firm	0.343	0.294	0.238	0.210	0.183	0.161	0.149	0.139	0.130	0.122
Share native-segregated firms	0.342	0.364	0.380	0.385	0.379	0.384	0.376	0.377	0.370	0.357
Share immigrant-segregated firms	0.140	0.092	0.059	0.044	0.036	0.028	0.024	0.021	0.018	0.014
Share immigrant managers	0.343	0.289	0.221	0.191	0.157	0.135	0.119	0.110	0.103	0.096
Share Western managers	0.078	0.071	0.065	0.061	0.057	0.054	0.051	0.051	0.053	0.054
Share Rest of World managers	0.264	0.217	0.156	0.130	0.100	0.082	0.068	0.059	0.050	0.042
Manufacturing	0.068	0.083	0.105	0.139	0.174	0.195	0.205	0.205	0.180	0.136
Construction	0.039	0.067	0.084	0.119	0.158	0.182	0.158	0.129	0.092	0.044
Retail and trade	0.233	0.227	0.212	0.223	0.228	0.220	0.221	0.223	0.226	0.259
Transport	0.041	0.063	0.067	0.071	0.072	0.078	0.094	0.097	0.089	0.056
Hotels and restaurants	0.299	0.254	0.164	0.118	0.087	0.058	0.045	0.030	0.020	0.008
Other social	0.072	0.066	0.055	0.042	0.034	0.027	0.023	0.023	0.024	0.023
Stockholm	0.358	0.315	0.298	0.281	0.268	0.254	0.259	0.271	0.314	0.385
Gothenburg	0.146	0.163	0.162	0.168	0.167	0.168	0.174	0.173	0.170	0.161
North Sweden	0.082	0.096	0.093	0.096	0.099	0.103	0.095	0.096	0.068	0.056
Panel B: Worker statistics										
Number of workers × year	1,163,246	1,341,547	2,425,659	2,383,745	3,440,035	3,687,274	5,032,708	5,142,454	6,789,849	9,944,898
Share immigrants	0.266	0.269	0.251	0.204	0.182	0.146	0.124	0.114	0.105	0.105
Share immigrants: West	0.053	0.048	0.044	0.045	0.042	0.041	0.038	0.040	0.039	0.044
Share immigrants: Rest of World	0.213	0.221	0.206	0.158	0.140	0.104	0.086	0.074	0.066	0.061
Share male	0.543	0.508	0.452	0.504	0.590	0.634	0.644	0.691	0.704	0.687
Share age $\leq$ 30	0.272	0.417	0.376	0.354	0.321	0.309	0.273	0.261	0.222	0.198
Share age $\geq$ 50	0.313	0.180	0.207	0.225	0.253	0.250	0.274	0.271	0.289	0.282
Share compulsory educ.	0.267	0.186	0.183	0.172	0.182	0.167	0.162	0.159	0.138	0.115
Share secondary educ.	0.524	0.564	0.572	0.588	0.590	0.607	0.579	0.573	0.511	0.463
Share tertiary educ.	0.194	0.232	0.232	0.229	0.221	0.219	0.254	0.263	0.346	0.417
Mean log earnings	9.583	9.590	9.634	9.675	9.761	9.850	9.936	10.002	10.121	10.241
Std. dev. log earnings	0.581	0.609	0.577	0.561	0.553	0.544	0.536	0.535	0.528	0.545
Imm/native earnings gap	-0.075	-0.055	-0.013	-0.028	-0.018	-0.062	-0.060	-0.046	-0.070	-0.041

Notes: The unit of observation in the top panel is firm × year, and in the bottom panel it is worker × year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants). The included industries are not exhaustive. *Other social* includes industries like sewage and refuse disposal, membership organization activities, cultural and sporting activities, and services such as hairdressing. Regions in the middle and south of Sweden are omitted from the table.

Table C.2: Decomposition of immigrant-native earnings gap in dual-connected set

	Earnings gap	Mean decile premium			Sorting			Pay-setting
		Natives	Immigrants	Gap	Total	Skill-based	Residual	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.128	0.136	0.156	-0.020	0.027	0.010	0.017	-0.047
West	-0.030	0.136	0.173	-0.037	0.005	0.001	0.005	-0.043
RoW	0.194	0.136	0.148	-0.012	0.036	0.014	0.022	-0.048

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 (column 8). We further decompose the sorting effect into skill-based sorting (column 6) and residual sorting (column 7).

Table C.3: Decomposition of immigrant-native earnings gap from AKM regressions

	Earnings gap	Mean firm premium natives	Mean firm premium immigrants	Premium gap	Sorting	Pay-setting
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.128	0.276	0.269	0.007	0.068	-0.061
West	-0.030	0.276	0.334	-0.058	0.005	-0.063
Rest of World	0.194	0.276	0.242	0.035	0.095	-0.060

Notes: Column (1) shows the mean log earnings gap between immigrants and natives in different groups. Columns (2) and (3) show the mean firm 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-firm sorting effect (column (5)) and a differential within-firm pay-setting effect.