Firm productivity and immigrant-native earnings disparities*

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Abstract

We develop a grouping measure based on persistent firm productivity to study the role of employers in explaining the immigrant-native earnings gap. Using Swedish population-wide matched employer-employee data, we find substantial returns to working in more productive firms for all workers. However, the returns are particularly high for those immigrants concentrated in low-productive firms. The unequal sorting of workers across the firm productivity distribution explains one fifth of the immigrant-native earnings gap. Worker sorting cannot be explained by skill differences between native and immigrant workers. Instead, managerial hiring practices along origin lines reinforce the unequal access to high-productive firms.

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

JEL Codes: J15; J31; J61

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1 Introduction

Immigrants tend to earn less than observationally similar natives, even decades after arrival.[1] Two factors suggest that the role of employers is central in determining 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 groups of advantaged and disadvantaged workers, such as men and women (Card et al., 2016) or whites and nonwhites (Gerard et al., 2021). Second, ethnic workplace segregation is widespread in many host countries (Hellerstein and Neumark, 2008; Åslund and Skans, 2010; Glitz, 2014; Andersson et al., 2014). Yet, firms have received relatively little attention in the immigration literature.

In this paper, we study the role of employers in explaining the immigrant-native earnings gap after accounting for worker unobserved heterogeneity. We use population-wide matched employer-employee data from Sweden, a country where the earnings gap is large and where the majority of firms (60 percent) are native-segregated. In order to quantify the contribution of firm policies to the earnings gap, there needs to be overlap between where workers from different groups work, and overlap tends to be limited when workplace segregation is widespread. We propose a new method of grouping firms that allows us to include workers in fully-segregated firms in our analysis.

We group firms based on persistent differences in firm productivity. To do so, 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 (firm productivity deciles) while accounting for business cycle fluctuations and productivity shocks. We test the robustness of the ranking in several ways and find no indication that the method captures factors other than persistent productivity.

Our grouping method captures a large degree of firm heterogeneity. 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. In addition, the ranking reveals a strong concentration of immigrants in the lowest productivity deciles. The share of non-Western workers decreases from almost 20 percent at the bottom to less than 6 percent at the top of the productivity ranking. There is also a significant share of fully-segregated firms, with those employing only foreign-born workers much more often found in low productivity deciles.

We then use the grouping to estimate the earnings returns to working in more productive firms with a model specification that includes worker and productivity decile fixed effects. While average earnings are higher among natives than immigrants in all firm productivity deciles, the returns to working in a firm of high persistent productiv-

[1] See Kerr and Kerr (2011), Borjas (2014), Duleep (2015), and Dustmann and Görlach (2015) for overviews of the literature on labor market integration.

ity are substantial and positive for both natives and immigrants, but even greater for immigrants. For example, for natives there is about an 8 log point difference between working in the fifth compared to the first decile of firm productivity; this difference is 11 log points for immigrants. The returns to firm productivity are larger in the lower half of the productivity distribution, where the immigrant share of the workforce is also higher. 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.

To gauge the overall contribution of firm productivity pay premiums to the earnings gap, we decompose the average premium into the sum 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. Assuming migrants had the same returns to firm productivity as natives, their over-representation in less productive firms increases the earnings gap by 21 percent. On the other hand, if the allocation across firm types were the same among immigrant and native workers, the higher returns among immigrants would reduce the gap by 27 percent. The resulting average premium is 0.7 percentage points higher for immigrants than natives, amounting to 6 percent of the earnings gap.

We further document that immigrants are less likely than natives to climb the productivity ladder and to move across firms in the first place, especially those in the bottom of the productivity distribution. The fact that immigrants gain more from entering better firms but do so less frequently suggests the existence of group-specific thresholds to climbing the productivity ladder. We analyze two main channels that can explain immigrants' lack of upward mobility. A first potential channel is skill differences across groups and positive assortative matching between high-productive firms and high-skilled workers. Similarly to Gerard et al. (2021), we decompose the overall sorting into a skill-based component and a residual component. The exercise highlights that skill differences are only to a minor extent predictive of the differential allocation across firms. This finding holds robustly regardless of whether we use individual fixed effects from our main job ladder equation or education categories as the skill measure.

A second channel consists of manager hiring practices along origin lines (Åslund et al., 2014). We find that most immigrant managers are in firms at the bottom of the productivity distribution and few work at the top: 22 percent of the lowest-decile firms are led by immigrant managers, compared to 7 percent of the firms in the top decile. We also document substantial concentration of workers sharing the manager's background. For example, Rest of the World managers in the bottom third have more than 60 percent of their workers born in the same broad region, and the figure is still about 40 percent in the highest deciles. For native managers, the corresponding numbers are 5–10 percent.

These patterns suggest that workers strongly sort by manager ethnicity, which could explain their limited access to high-productive firms. At all levels of firm productivity, working under immigrant management means a lower probability of moving upwards. However, we show that the mobility gap between immigrant and native workers is independent of manager origin. Thus, concentration in immigrant managed firms hampers upward mobility among immigrants, but the data does not suggest that manager-worker similarity per se matters for transitioning to better firms.[2]

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. The three 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).[3] We make the following contributions to the literature. We are the first to study immigrant-native earnings differences via a job ladder model based on a firm productivity grouping. Moreover, our firm ranking method can be generally applied to settings where the interest lies in estimating earnings gaps between groups of workers; these include workers segregated in the labor market, such as immigrants and natives. This paper is also the first to investigate the mechanisms underlying the sorting channel for immigrant-native earnings gaps by means of a skill-based decomposition, and the first to do so while also analyzing the role of managers. As such, this makes us the first to build a bridge between the job ladder and the manager origin literatures.

Our work also relates to a recent literature that focuses on capturing firm heterogeneity while ensuring dimensionality reduction. Bonhomme et al. (2019) bin firms via *k*–means clustering based on how similar their earnings distributions are. One advantage of our method is that it is based on a readily observable and directly interpretable measure of firm heterogeneity (Syverson, 2011; Lentz and Mortensen, 2010). 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.

The rest of the paper proceeds as follows. In Section 2 we describe the analysis sample. Section 3 lays out the econometric framework. We present our main results in Section 4, while Section 5 analyzes potential mechanisms for the main results. Section 6 concludes.

[2]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).

[3]A related literature analyzes the role of employers for the assimilation of immigrants without accounting for worker heterogeneity via individual fixed effects, as it is typically 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).

2 Data and analysis sample

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. From firm tax records (RAMS register), we have 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.[4] We use employment spells to compute firm size 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) and value added per worker. 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.[5] Finally, we complement this information with worker-level demographics (age, gender, education level, country of birth, immigration year) from the Louise/Lisa database.

Our 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.

2.1 Sample selection

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 can be considered a threshold for being self-supporting (Ruist, 2018), therefore one PBA is a rather conservative threshold.

The sample includes both natives and immigrants. Immigrants are defined as foreign-born with two foreign-born parents. We exclude the limited number of people born abroad with at least one Swedish-born parent. Given the large heterogeneity in the group of immigrants, 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.[6]

[4] Firm region is given by where most employees live at the end of the year.

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

[6] "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,

2.2 Sample description

Table 1 shows summary statistics separately for natives and immigrants. Overall, 13 percent workers are immigrants, most of whom are born in non-Western countries (71 percent). Segregation is prevalent, with 6 percent of immigrants working at all-immigrant firms, and 20 percent of natives at all-native firms.

While natives and Western immigrants have similar earnings, non-Western immigrants earn 20 percent less on average than either of these groups, despite the fact that the figures on educational attainment do not suggest major skill differences across groups. 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.

Table 1: Summary statistics (1998–2017)

	Immigrants			Natives
	Total	West	Rest of World	Total
Immigrant from West	0.292	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	0.204
In immigrant-segregated firms	0.057	0.021	0.072	0.000
Male	0.615	0.621	0.613	0.648
Age	40.787	45.875	38.687	40.212
Share age ≤ 30	0.218	0.104	0.265	0.273
Share age ≥ 50	0.253	0.416	0.185	0.271
Education, compulsory	0.203	0.218	0.196	0.151
Education, secondary	0.436	0.427	0.440	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)	22290.320	26045.727	20739.065	25029.595
No. observations	6,179,022	1,806,043	4,371,248	40,332,456

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

Andorra, Belgium, France, Liechtenstein, Luxembourg, the Netherlands, Switzerland. Austria), Canada, USA, Australia and New Zealand. "Rest of World" are non–Western countries.

3 Econometric framework

This section outlines the econometric framework. We first propose a 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 data at the firm-year level 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 three main advantages compared to alternative rankings based on firm fixed effects à la Abowd et al. (1999). First, unlike AKM firm fixed effects, value added is a readily-observable and directly interpretable measure of firm productivity, which is a key dimension of firm heterogeneity. Second, 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. Lastly, the approach makes it possible to abstract from well-known incidental parameter estimation problems (Kline et al., 2020; Bonhomme et al., 2023), which might 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.

We perform a number of robustness checks to analyze whether our grouping procedure captures factors other than persistent productivity. A first concern with equation (1) is that log value added per worker 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[7]). In both cases the correlation between the baseline ranking and these alternative rankings is very high (0.95-0.99). Moreover, very few firms are classified at least 10 percentiles higher or lower in the ranking when compared to the baseline (columns 1 and 2 in Panel B).

Table 2: Robustness of the firms ranking

	Staff composition (1)	Worker FEs (2)	Industry (3)	Share of immigrants (4)	Industry and share of immigrants (5)
Panel A: Correlation with baseline ranking					
	0.9820	0.9660	0.9473	0.9944	0.9449
Panel B: Share of firms moving in the ranking					
moving down	0.0060	0.0372	0.0822	0.0001	0.1085
moving up	0.0185	0.0301	0.0631	0.0116	0.0740
No. of firms	313,827	278,329	323,072	323,072	323,072

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.

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

[7]See Table A.1 in Åslund et al. (2021) for a summary of the estimated AKM model.

correlation between the 1998-2009 ranking and the baseline full-period ranking is 0.93, with the share of upward (downward) movers at 13 percent (1 percent); similar results are obtained when comparing the 2010-2017 ranking with the baseline (0.89, 14 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

To estimate the returns to working in more productive firms, we use 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 A.1, we show that the 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:[8]

$$\sum_d \theta_d^N \pi_{Nd} - \sum_d \theta_d^I \pi_{Id} = \underbrace{\sum_d \theta_d^N (\pi_{Nd} - \pi_{Id})}_{sorting} + \underbrace{\sum_d (\theta_d^N - \theta_d^I)\pi_{Id}}_{pay-setting} \quad (3)$$

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) and 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 across the productivity distribution (relative to working in the first decile of firm productivity) affects the premium gap, given the distribution of immigrants across productivity deciles.

Assortative matching between high-productive firms and high-productive workers could determine differential allocation of immigrant and native workers. To investigate this possibility, we separate skill-based sorting from other types of sorting.[9] We divide workers into a total of twenty age-by-skill groups based on five age categories (18-24, 25-34, 35-44, 45-54, 55 and above) and four skill categories (either quartiles of person effects as estimated in equation (2) or four education categories). For each region and separately by year, we then calculate the number of workers in each firm productivity decile and age-by-skill group. We multiply this number by the share of immigrants among all workers in a region, year and age-by-skill group (across all deciles). We sum over the thus-obtained cell-level shares to construct decile-level counterfactual employment shares of natives and immigrants (π^*_{Nd} and π^*_{Id}), i.e. the shares that we would observe if employers only took into account age and skill, but not immigrant status, when making hiring decisions. Accordingly, a measure of the counterfactual *skill-based sorting* effect, which captures how much of the observed sorting is due to differences in

[8]Taking expectations of equation (2), we can express mean immigrant and native earnings as $E[\ln e_{Iit}] = \alpha_I + \bar{X}_I'\beta_I + \sum_d \theta_d^I \pi_{Id}$ and $E[\ln e_{Nit}] = \alpha_N + \bar{X}_N'\beta_N + \sum_d \theta_d^N \pi_{Nd}$ 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: $E[\ln e_{Nit}] - E[\ln e_{Iit}] = \alpha_N - \alpha_I + \bar{X}_N'\beta_N - \bar{X}_I'\beta_I + \sum_d \theta_d^N \pi_{Nd} - \sum_d \theta_d^I \pi_{Id}$.

[9]The exercise draws on Gerard et al. (2021) and relates to previous work on workplace segregation (Hellerstein and Neumark, 2008; Åslund and Skans, 2010).

age and skill, is the following modified version of the first term in equation (3):

$$\sum_d \theta_d^N (\pi^*_{Nd} - \pi^*_{Id}) \tag{4}$$

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 (4); we call this term *residual sorting*:

$$\sum_d \theta_d^N (\pi_{Nd} - \pi_{Id}) - \sum_d \theta_d^N (\pi^*_{Nd} - \pi^*_{Id}) \tag{5}$$

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. A first result is that the value added-based classification of firms is able to capture 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.

A second finding is that firm segregation is widespread, which reinforces the need for an approach that allows the inclusion of fully-segregated firms in the analysis. More specifically, the fraction of fully native-segregated firms is around 60 percent and is constant across all productivity deciles. By contrast, the fraction of fully immigrant-segregated firms is on average 5 percent, and is significantly higher in the bottom than in the top productivity deciles.

Third, more productive firms tend to pay more and to employ more highly-educated workers, which indicates positive assortative matching. Fourth and last, the average share of immigrants at the firm 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 (Panel A of Table 3). While the total number of workers increases with productivity, this gradient is much steeper for natives (Figure A.4). Immigrants, instead, have become more concentrated in low-productive firms over time, a development partly explained by changing country of birth composition (Figure A.5).

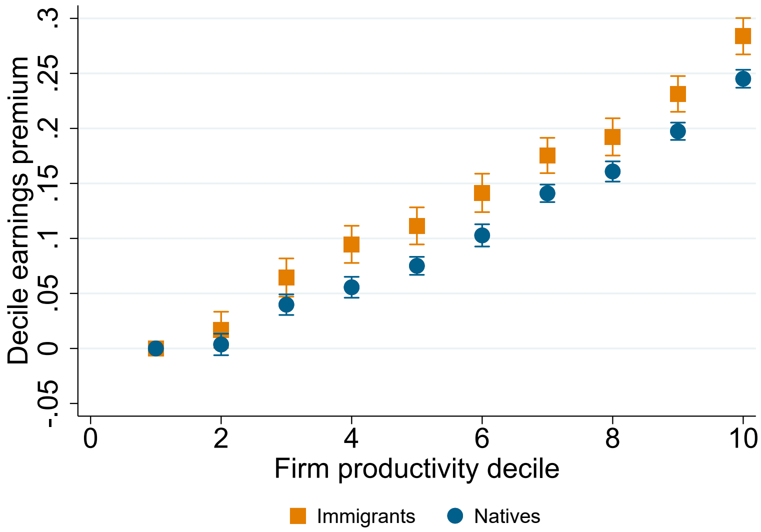
Table 3: Summary statistics by productivity decile (1998–2017)

	1	2	3	4	5	6	7	8	9	10
Panel A: Firm statistics										
Number of firms × year	149,551	208,458	241,521	275,804	284,838	298,082	309,096	319,588	326,531	327,569
Mean yearly firm size	11.610	10.667	14.815	18.946	19.384	20.628	23.663	26.761	29.991	41.870
Firm size 2-9	0.826	0.787	0.737	0.678	0.660	0.619	0.589	0.576	0.580	0.566
Firm size 10-49	0.153	0.186	0.224	0.277	0.284	0.321	0.339	0.338	0.328	0.319
Firm size 50-249	0.019	0.025	0.034	0.038	0.049	0.053	0.063	0.073	0.076	0.091
Firm size 250-999	0.002	0.003	0.004	0.005	0.006	0.006	0.008	0.010	0.013	0.019
Firm size $\geq$ 1000	0.000	0.000	0.001	0.002	0.001	0.001	0.002	0.002	0.003	0.005
Mean fraction immigrants at firm	0.222	0.207	0.176	0.148	0.131	0.116	0.105	0.097	0.089	0.085
Share native-segregated firms	0.646	0.638	0.639	0.632	0.636	0.627	0.618	0.617	0.619	0.600
Share immigrant-segregated firms	0.135	0.108	0.075	0.050	0.041	0.033	0.027	0.023	0.019	0.016
Share immigrant managers	0.220	0.206	0.170	0.138	0.120	0.102	0.088	0.079	0.075	0.070
Share Western managers	0.049	0.046	0.042	0.042	0.039	0.037	0.035	0.034	0.035	0.038
Share Rest of World managers	0.171	0.161	0.129	0.096	0.081	0.066	0.054	0.045	0.040	0.032
Manufacturing	0.077	0.079	0.097	0.105	0.131	0.144	0.157	0.153	0.135	0.105
Construction	0.062	0.080	0.103	0.123	0.167	0.200	0.189	0.159	0.113	0.061
Retail and trade	0.285	0.295	0.280	0.250	0.247	0.234	0.220	0.207	0.203	0.224
Transport	0.035	0.046	0.058	0.057	0.064	0.067	0.088	0.103	0.111	0.068
Hotels and restaurants	0.181	0.183	0.139	0.091	0.069	0.049	0.033	0.025	0.016	0.007
Other social	0.067	0.063	0.060	0.049	0.037	0.031	0.026	0.022	0.023	0.021
Stockholm	0.303	0.260	0.248	0.235	0.226	0.221	0.220	0.227	0.257	0.324
Gothenburg	0.156	0.162	0.164	0.163	0.165	0.165	0.170	0.173	0.169	0.169
North Sweden	0.104	0.119	0.126	0.126	0.129	0.129	0.129	0.122	0.109	0.081
Panel B: Worker statistics										
Number of workers × year	1,076,050	1,142,203	1,972,505	3,006,821	3,480,919	4,252,322	5,431,989	6,714,962	7,872,442	11,561,265
Share immigrants	0.241	0.238	0.218	0.212	0.175	0.143	0.123	0.107	0.101	0.101
Share immigrants: West	0.049	0.041	0.041	0.039	0.039	0.036	0.037	0.035	0.036	0.043
Share immigrants: Rest of World	0.192	0.197	0.178	0.173	0.136	0.107	0.086	0.072	0.065	0.059
Share male	0.546	0.535	0.506	0.475	0.571	0.619	0.656	0.681	0.702	0.693
Share age $\leq$ 30	0.223	0.381	0.382	0.343	0.334	0.308	0.290	0.263	0.232	0.197
Share age $\geq$ 50	0.356	0.211	0.208	0.230	0.242	0.258	0.261	0.277	0.287	0.286
Share compulsory educ.	0.281	0.201	0.188	0.186	0.179	0.180	0.169	0.161	0.146	0.117
Share secondary educ.	0.516	0.565	0.577	0.580	0.597	0.602	0.604	0.582	0.527	0.468
Share tertiary educ.	0.190	0.215	0.220	0.223	0.215	0.211	0.221	0.252	0.324	0.410
Mean log earnings	9.557	9.534	9.594	9.644	9.717	9.798	9.892	9.970	10.084	10.233
Std. dev. log earnings	0.579	0.600	0.575	0.564	0.546	0.544	0.536	0.534	0.529	0.545
Imm/native earnings gap	-0.058	-0.068	-0.032	-0.026	-0.029	-0.036	-0.058	-0.063	-0.065	-0.037

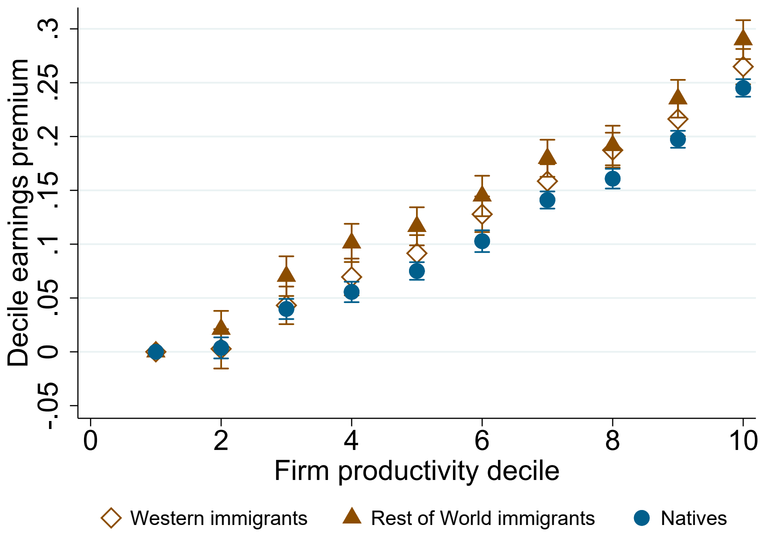
Notes: The unit of observation in the top panel is firm × year, and in the bottom panel it is worker × year. Native-segregated (immigrant-segregated) firms employ only natives (immigrants). The included industries are not exhaustive. *Other social* includes industries like sewage and refuse disposal, 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 Earnings returns to working in more productive firms

We now turn to analyzing the earnings returns to firm productivity. Figure 1 presents the estimated decile earnings premiums $\hat{\theta}_D^g$ from the main model (2); Table A.1 reports the corresponding estimates. Panel (a) of Figure 1 compares natives to immigrants, while Panel (b) compares natives to the sample of immigrants split into Rest of the World and West.



(a) All immigrants



(b) By immigrant group

Figure 1: 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.1 displays point estimates.

The returns to working in more productive firms conditional on unobserved individual heterogeneity are large and positive for both immigrants and natives, but larger for immigrants. For example, for the full sample in Panel (a), the estimated return to working in the fifth decile compared to the first is 7.5 log points for natives, and for immigrants 11.2 log points. The differential is largest in the lower part of the productivity distribution. Starting with the fourth decile, the gap relative to the first remains at about 3–4 log points, implying that moving up the productivity ladder results in similar gains for natives and immigrants from this point onward.[10]

We saw in Table 3 that Rest of the World immigrants are relatively more concentrated in the bottom part of the productivity distribution. Panel (b) of Figure 1 shows that the differential returns are primarily driven by this group of immigrant workers. By contrast, immigrants from the West have earnings returns that are more similar to 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.6).

A natural follow-up question is the extent to which the differential returns to higher firm productivity are explained by sorting of workers into firm types vs. group-specific pay setting. A first indication of employer-employee positive assortative matching is given by the variance decomposition exercise in table A.2, which shows a high correlation between person and firm productivity deciles (28.5 percent and 33.5 percent for natives and immigrants respectively). In the next section we formally quantify the relative importance of sorting vs. firm pay setting in explaining group differences in the estimated firm decile premiums.

4.3 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 on average the decile premium of immigrants is slightly higher than the decile premium of natives (16.5 vs. 15.8 percent), which is in line with the results in Figure 1. The difference of 0.7 percentage points reduces the overall gap by 6 percent. This net effect is the result of two opposing forces. The sorting component in column (5) is positive (i.e. increases the gap) and accounts for around 21 percent of the earnings gap between immigrants and natives. The pay-setting

[10] Results are qualitatively similar when accounting for the unequal distribution of the total number of workers in different deciles as seen in Figure A.4 by using an employee-weighted productivity ranking (Figure A.7).

component, instead, reduces the gap by around 27 percent.[11]

When analyzing how the decomposition results vary for different subgroups, Western immigrants have a slight earnings advantage over natives, and the pay-setting effect appears to be an important part of this. For Rest of the World migrants, the pay-setting component is similar in magnitude to 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 those of natives.

The exercise in this section allows us to pin down the relative importance of sorting and pay-setting for the group-specific mean decile premium; however, it is not informative of the extent to which workers sort into more productive firms based on their skills or along other dimensions. Understanding the drivers of sorting is a prerequisite for formulating appropriate policy interventions. In the next section we analyze the drivers of sorting by decomposing the overall sorting component (results reported in the right-hand side panel of Table 4) and by studying the role of manager origin.

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	0.158	0.165	-0.007	0.026	0.002	0.023	-0.033
West	-0.041	0.158	0.173	-0.015	0.003	-0.001	0.004	-0.018
RoW	0.188	0.158	0.159	-0.002	0.035	0.004	0.031	-0.037

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).

4.4 Drivers of sorting: Skills and manager origin

The fact that immigrants are less likely to work in more productive firms despite the higher returns to doing so indicates that there may be barriers to entry and mobility for immigrants. Figure A.8 indeed shows that at all levels of initial firm productivity immigrants are less likely to move upward in the firm productivity distribution five years later. Immigrants are also less likely than natives to move at all: natives are 5–10 percentage points more likely to move to a different firm from a given decile and are

[11] 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; the magnitudes are not directly comparable.

especially more mobile than immigrants in the bottom of the productivity distribution. To better understand the mechanisms underlying sorting and mobility, this section investigates the role of skills and manager origin.

4.4.1 Skill-based and residual sorting

Firms that are more productive may hire higher-skilled workers. In our sample, natives are on average more educated than immigrants (Table 1), and average education is higher in higher productivity deciles (Table 3). These skill differences may result in positive assortative matching between high-productive firms and natives, even in the absence of discriminatory practices against immigrants.

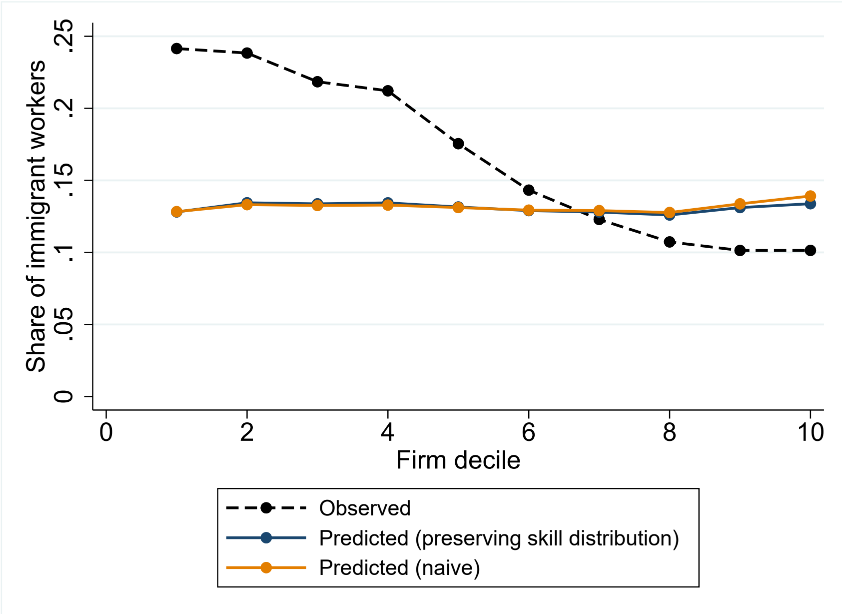
To understand how workers are allocated across firms, we decompose sorting into a skill-based component and a residual component (Section 3.2). In Figure 2a, the black line shows the observed share of immigrants in a given decile; the orange line gives the counterfactual share of immigrants if employers in a given decile were to hire based on age only (*naive prediction*), and the blue line the counterfactual share of immigrants if employers hired based on age and skill (*preserving skill distribution*). According to the naive prediction, we should find roughly equal shares of immigrants across the firm productivity distribution if age were the only hiring criterion. Remarkably, the skill-preserving prediction lies on top of the native prediction. That is, if hiring were based on the combination of age and skill, we would expect to observe an almost equal share of immigrants across the firm productivity distribution.[12] Figure 2b additionally shows that similarly to when pooling all immigrants, the skill-preserving prediction returns an even distribution for both Western and Rest of World workers.

Overall, the sorting decomposition exercise suggests that differences in skills between immigrants and natives cannot explain the observed sorting patterns across productivity deciles (Column 6 in Table 4). Since a large share of sorting is residual (Column 7) – especially for Rest of World immigrants, who drive the earnings gap – we next investigate a potential source of the residual sorting: origin-based manager hiring practices.

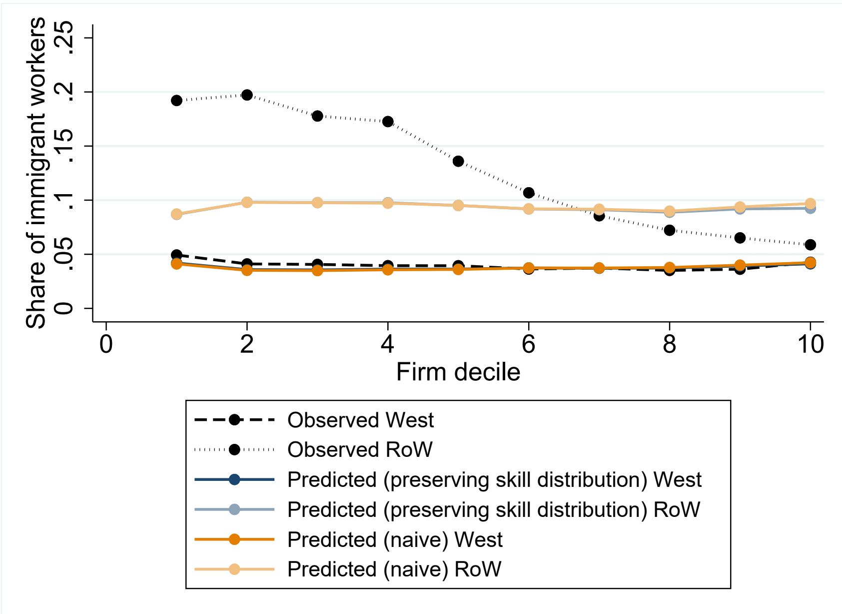
4.4.2 The role of managers

Manager hiring practices can play an important role in how workers sort across firms. Previous evidence suggests that hiring often follows ethnic or origin lines (Åslund et al., 2014; Kerr and Kerr, 2021). If immigrant managers are more likely to be found in the bottom of the firm productivity distribution, an increased likelihood of hiring

[12] We get very similar patterns when using deciles of the person effects or four education categories instead of the baseline skill measure (Figures A.9a and A.9c).



(a) All immigrants



(b) By immigrant group

Figure 2: Skill-based sorting

Notes: The figure shows 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 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.

other immigrants could contribute to the concentration of immigrant workers in low-productive firms.[13]

[13]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

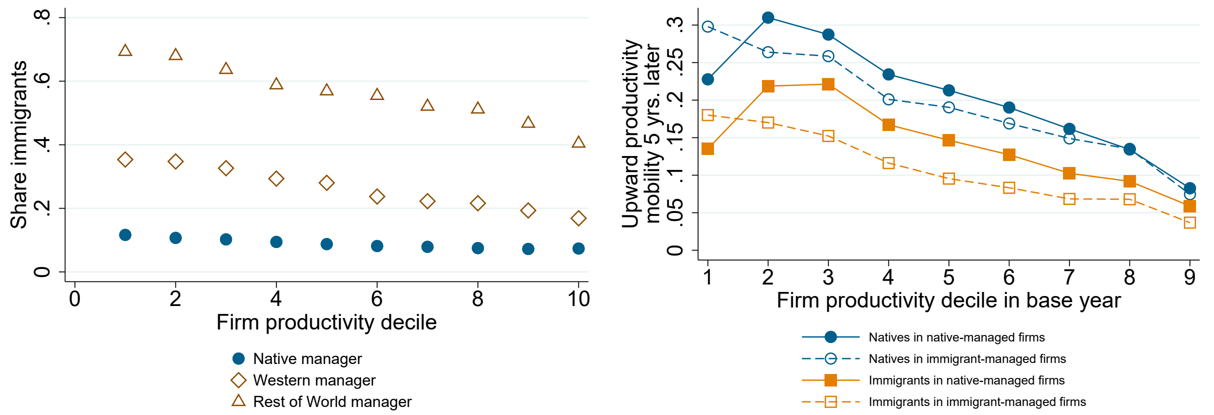
Panel A of Table 3 indeed shows that the share of immigrant managers declines with firm productivity, with most immigrant managers clustered in the bottom four deciles of the productivity distribution. This pattern is driven by Rest of World managers, and is thus similar to the worker sorting patterns. In addition, the share of immigrant workers at immigrant-managed firms vastly exceeds the share at native-managed firms throughout the firm productivity distribution, even though the gap does decrease with productivity (Figure 3a). Immigrant density is greater at workplaces managed by people born outside Western countries, but higher also at firms under Western compared to native management. Figure A.11 additionally shows that across the productivity distribution, the share of Western (Rest of World) workers is much higher under Western (Rest of World) management than in firms with another manager origin. Thus, even a crude classification such as the one we use for immigrants from different parts of the world is able to capture sorting along origin lines.

For the purpose of understanding how managers contribute to worker sorting, we take the allocation of managers across the firm productivity distribution as given. However, we may wonder whether the concentration of immigrant managers in low - productive firms (and poorer worker prospects) is simply due to immigrant managers being “poor managers". To shed light on this possibility, we estimate manager contributions to firm value added (see, e.g., Graham et al., 2012).[14] We find that the average quality of native and immigrant managers is very similar (A.10a). Moreover, the share of immigrants working in immigrant-managed firms is higher than the share in native-managed firms, regardless of manager quality (A.10b). Hence, differences in manager quality by origin are unlikely to drive sorting.

Immigrants sort into immigrant-managed firms, and immigrant managers are concentrated in the bottom of the productivity distribution. These two patterns may reinforce each other and affect immigrants' ability to climb the productivity ladder. To shed light on whether worker-manager similarity relates to upward mobility, Figure 3b shows mobility rates by worker and manager origin, across the productivity distribution of the initial firm. Both immigrant and native workers are less likely to move to a more productive firm under initial immigrant management. The gap between immigrant and native workers is similar across manager types, and the subgroups of immigrants fare similarly in this case (Figure A.12). Thus, there is no clear indication that worker-manager similarity affects mobility prospects directly.

occupational classification (Åslund et al., 2014).

[14]We estimate the following equation on the largest connected set of firms linked by manager mobility: $\ln(VA/N)_{ft} = \alpha_t + \gamma_f + \lambda_{manager} + \beta X_{ft} + \varepsilon_{ft}$, 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) and $\lambda_{manager}$ are manager fixed effects.



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

(b) Upward mobility, by manager type and firm productivity

Figure 3: Firm productivity and managers

Notes: Panel (a) shows the leave-out-manager share of immigrants in each firm productivity decile, by manager type. Panel (b) shows the probability of working in a firm of higher productivity five years later relative to the first year an individual is observed in the data, by immigrant status and manager type.

5 Discussion and conclusion

In this paper, we use population-wide matched employer-employee data from Sweden to document how working in firms of different levels of productivity contributes to the immigrant-native earnings gap. We group firms into productivity deciles based on a method that accounts for business cycle fluctuations and productivity shocks and allows for including fully-segregated firms in the analysis. We show that the gains from working in more productive firms are substantial for all workers, but are larger for immigrants and particularly so for those born outside Western countries.

Our decomposition analysis reveals that the productivity decile premiums reduce the earnings gap by 6 percent and that sorting and pay-setting work in opposite directions. While the over-representation of immigrants in less productive firms widens the gap by 21 percent, the relatively higher premiums that immigrants earn reduces the gap by 27 percent. Moreover, skill differences between immigrants and natives explain a minor share of the sorting component of the premium gap, particularly for non-Western immigrants. Instead, we find manager hiring practices along ethnic lines to be a relevant sorting channel: immigrant managers are strongly concentrated in low-productive firms, and there is a striking segregation of workers into firms under same-origin management.

The presence of earnings gains associated with working in more productive firms is consistent with imperfectly competitive labor markets, where firms rather than markets set wages (Card, 2022; Manning, 2020). The fact that immigrants gain more from entering better firms but do so less frequently possibly points to a combination of two factors that go beyond a bargaining story as in e.g. Card et al. (2016): immigrants face barriers to climbing the ladder, and firms of different productivity exert varying degrees of monopsony power over different groups of workers. If on the one hand low-productive employers were relatively more likely to push down wages for immigrant workers, we would indeed expect to observe the greater earnings returns to working in more productive firms among immigrants. This is in line with Bassier et al. (2022) who find that the degree of monopsony power is higher for low-wage workers and in low-wage sectors like retail and restaurants.[15] On the other hand, given that we estimate the earnings returns from movers, it is possible that many migrants are stuck in low-productive firms and those that manage to move have a better bargaining position relative to working in the least productive firms (compared to natives making the same transition).

The existence of firm productivity premiums may not only be about bargaining between firms and workers, but also about institutions and norms. Conditional on accessing a high-productive firm, immigrants with poor outside options could for instance gain more from firm policies that benefit all employees in similar ways (e.g. due to high union density and general egalitarian social norms).

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.

[15] The empirical evidence on whether monopsony power is likely to be greater over immigrants than natives is sparse. Hirsch and Jahn (2015) conjecture that search costs may be greater for immigrants than natives and find that immigrants supply labor to the firm less elastically than natives. Seegmiller (2023) instead finds that wage markdowns are greater for more skilled workers.

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A Appendix

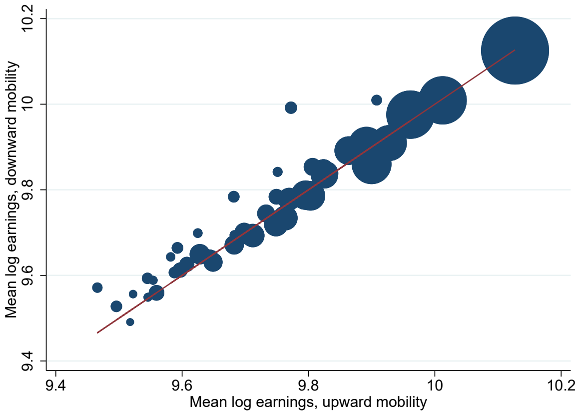
A.1 Exogenous mobility

To estimate our main regression (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.

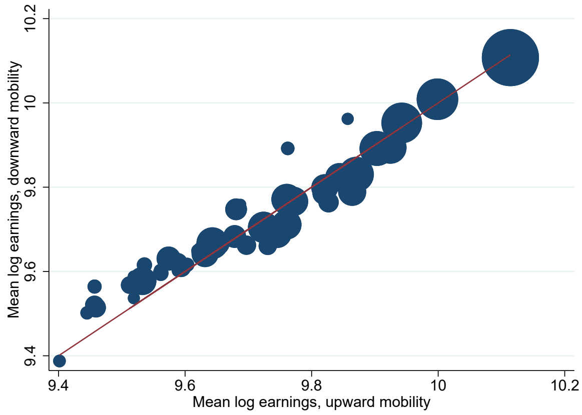
To test this assumption, we restrict our attention to workers who move across firms at least once in 2000–2016 and who are employed for at least four consecutive years at firms with non-missing productivity ranking: two years at their pre-move employer and two years at the new employer. We then apply the same sampling restrictions adopted in the main analyses.[16] Figure A.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 upwards and downwards mobility across firm productivity deciles is approximately symmetric across the decile transitions. We find qualitatively similar results when plotting raw, unadjusted log-earnings, although in that case for immigrants the average log-earnings of the upward movers appear slightly larger than those of downward movers (Figure A.2). Results are also qualitatively 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 setting.

[16]Figure A.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 there is little movement from both extremes (bottom and top deciles) but a non-trivial amount of movement across deciles otherwise. The patterns are similar between immigrants and natives.



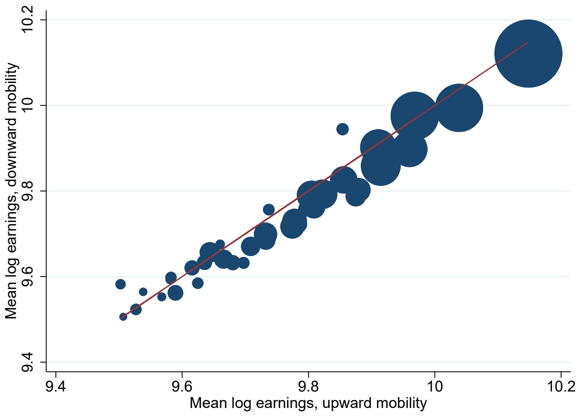
(a) Natives



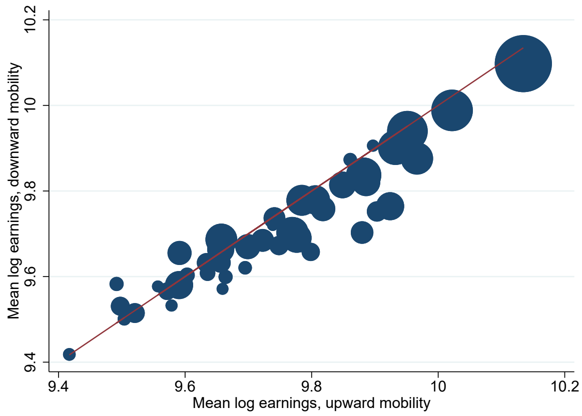
(b) Immigrants

Figure A.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.



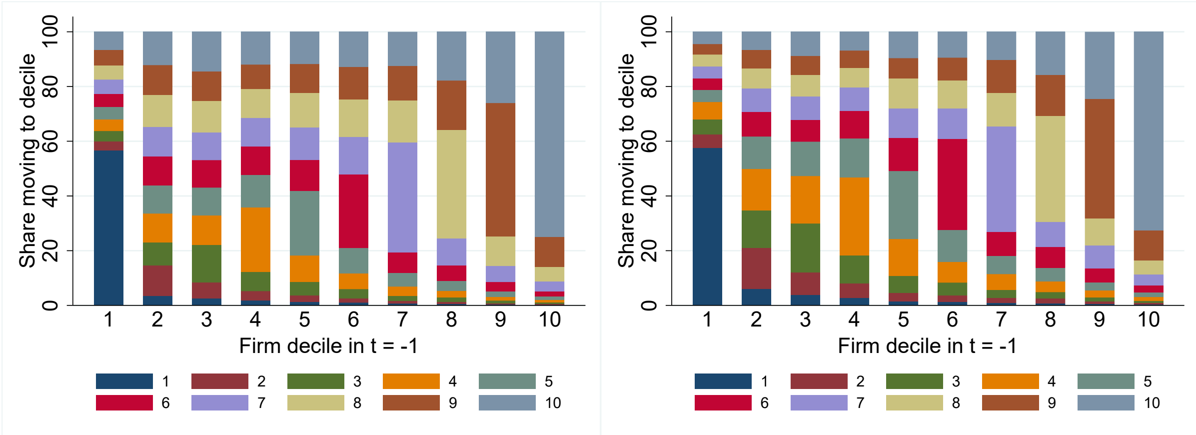
(a) Natives



(b) Immigrants

Figure A.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 A.3: Mobility across firm productivity deciles

A.2 Additional figures

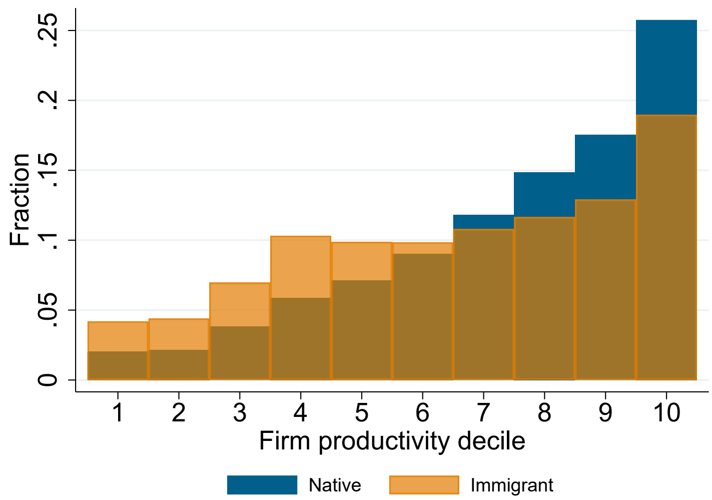


Figure A.4: Distribution of immigrants and natives across productivity deciles

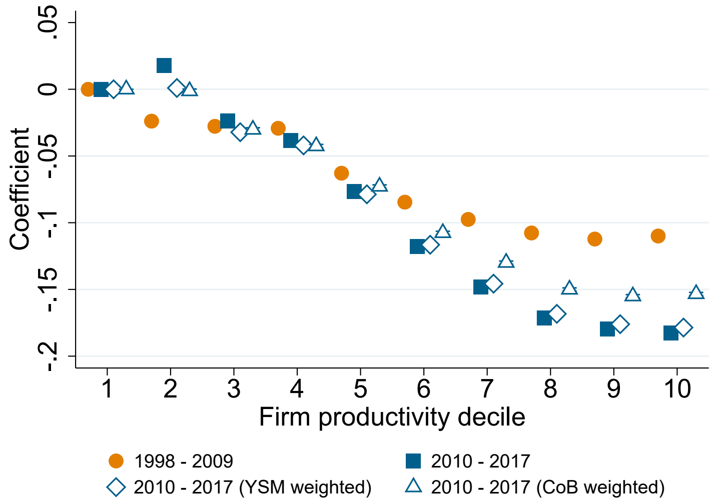


Figure A.5: Sorting of immigrants across productivity deciles

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.

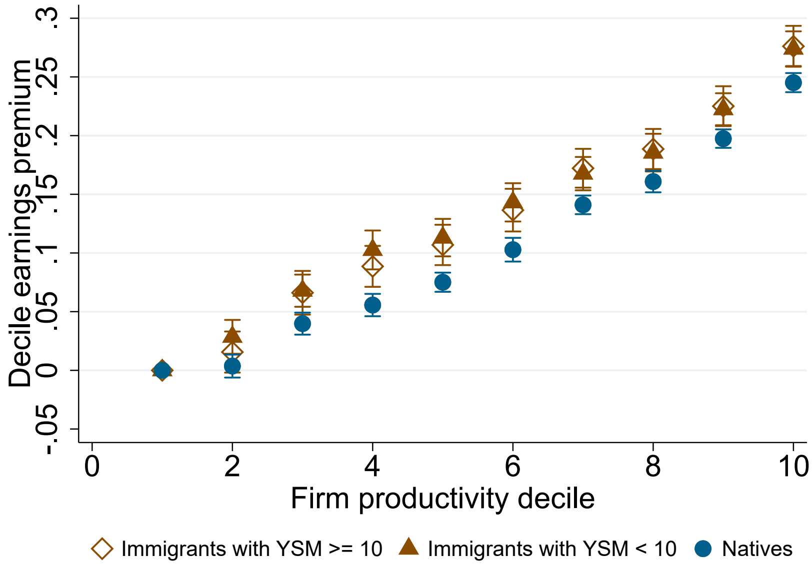
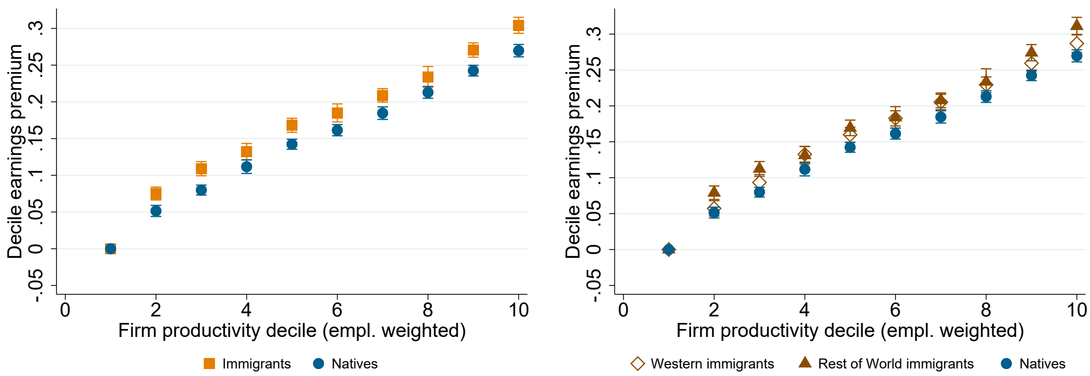


Figure A.6: Earnings returns to working in more productive firms – YSM

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) All immigrants

(b) By immigrant group

Figure A.7: 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.

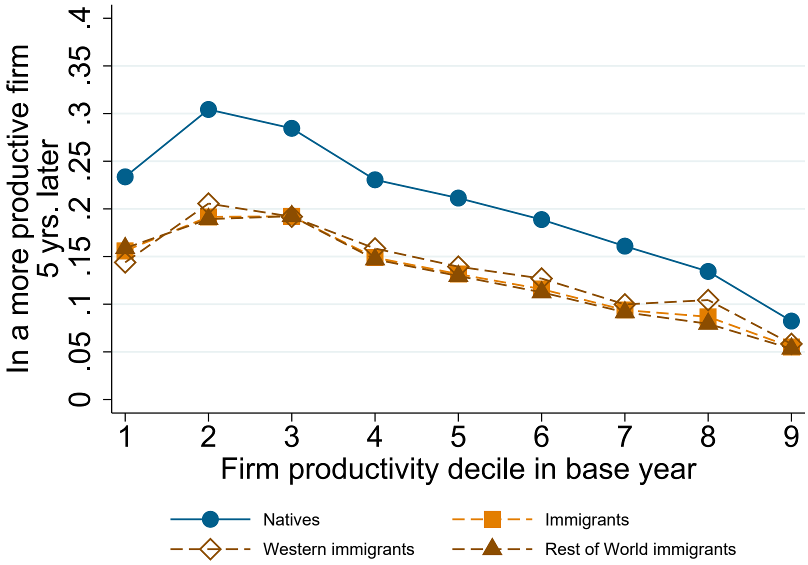
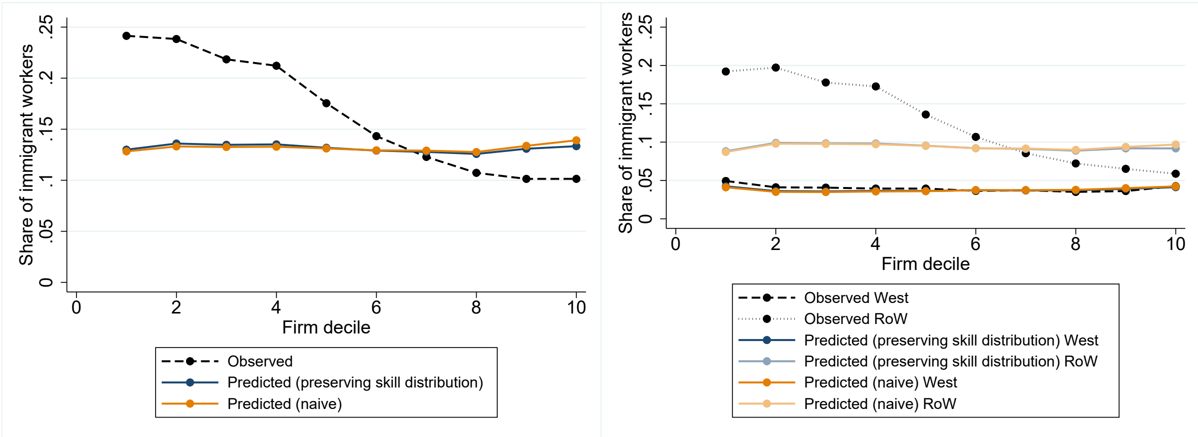


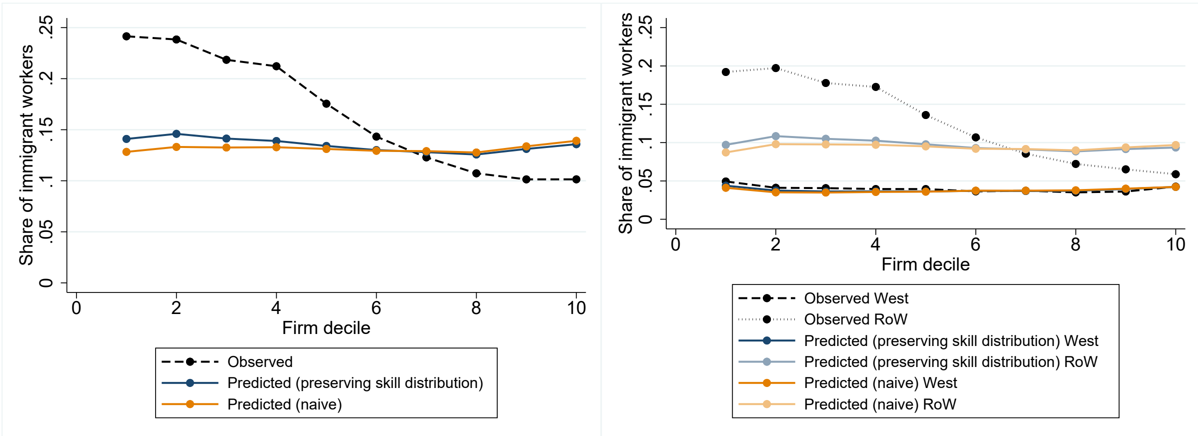
Figure A.8: Upward mobility between productivity deciles

Notes: Share who move up the productivity ranking, conditional on where they start. We define upward mobility as working in a higher productivity decile five years later compared to when the individual is first observed. The outcome variable takes the value 1 if the productivity decile five years later is strictly higher than in the initial year, and 0 otherwise. Since by construction the outcome does not vary for those that start off in the highest decile, we disregard these individuals.



(a) All immigrants, deciles of person fixed effects

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



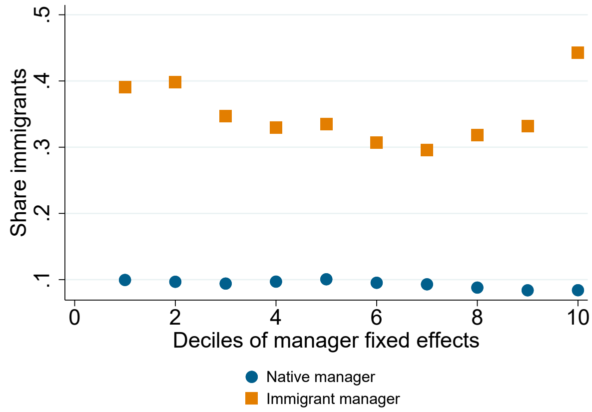
(c) All immigrants, education groups

(d) By immigrant group, education groups

Figure A.9: 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.

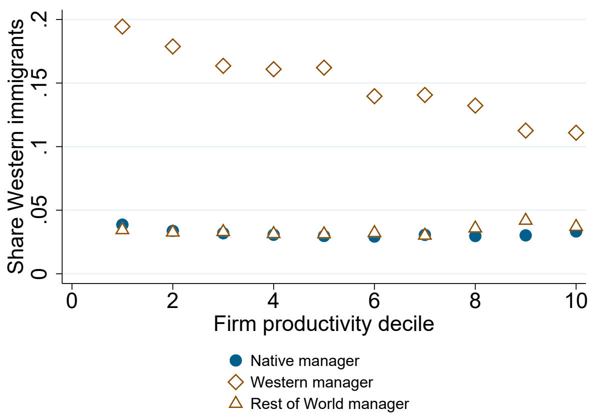
(a) Manager fixed effects distribution, by immigrant status



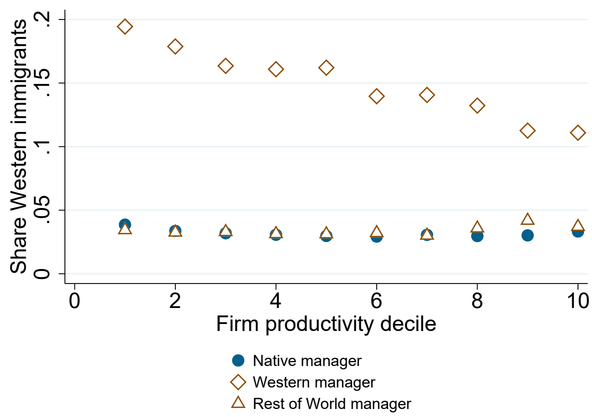
(b) Share immigrants, by manager quality

Figure A.10: 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: $\ln(VA/N)_{ft} = \alpha_t + \gamma_f + \lambda_{manager} + \beta X_{ft} + \varepsilon_{ft}$, 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.



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



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

Figure A.11: 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.

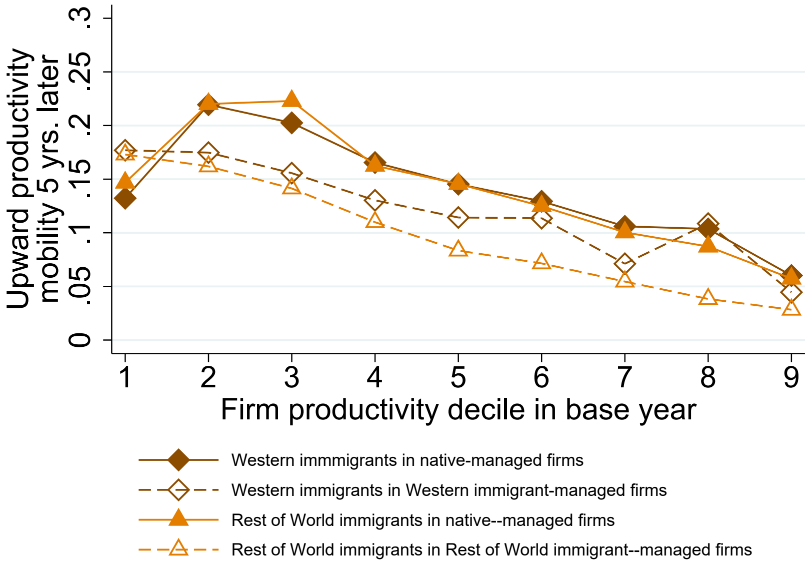


Figure A.12: Upward mobility by worker and manager origin

Notes: The figure shows the probability of working in a firm of higher productivity five years later relative to the first year an individual is observed in the data, by immigrant group and manager type.

A.3 Additional tables

Table A.1: Earnings returns to working in more productive firms

Decile	Natives	All immigrants	Western immigrants	Rest of World immigrants
	(1)	(2)	(3)	(4)
2	0.004 (0.005)	0.017 (0.008)	0.003 (0.009)	0.021 (0.009)
3	0.040 (0.005)	0.065 (0.009)	0.043 (0.009)	0.070 (0.009)
4	0.056 (0.005)	0.095 (0.009)	0.070 (0.009)	0.101 (0.009)
5	0.075 (0.004)	0.111 (0.009)	0.091 (0.009)	0.117 (0.009)
6	0.103 (0.005)	0.141 (0.009)	0.128 (0.008)	0.145 (0.010)
7	0.141 (0.004)	0.175 (0.008)	0.159 (0.008)	0.180 (0.009)
8	0.161 (0.005)	0.192 (0.009)	0.187 (0.008)	0.192 (0.009)
9	0.197 (0.004)	0.231 (0.008)	0.216 (0.008)	0.235 (0.009)
10	0.245 (0.004)	0.284 (0.008)	0.265 (0.008)	0.290 (0.009)

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.2: Variance decomposition

	Natives	Immigrants	Western immigrants	Rest of World immigrants
	(1)	(2)	(3)	(4)
Person effects	0.389	0.465	0.523	0.436
Firm decile effects	0.015	0.021	0.020	0.021
Cov. person and firm decile effects	0.044	0.066	0.069	0.058
Xb and associated covariances	0.222	0.097	0.080	0.100
Residual	0.330	0.352	0.308	0.385
Corr. person/firm decile effects	0.285	0.335	0.337	0.299

Notes: Results from two-way fixed effects models estimated separately for natives (column 1), immigrants (column 2) Western immigrants (column 3) and Rest of World immigrants (column 4). Models include year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies.