Quantifying the Role of Firms in Intergenerational Mobility*

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June 30, 2025

Abstract

We quantify the role of firms in intergenerational mobility using administrative data from Israel. We decompose the intergenerational elasticity of earnings (IGE) into an individual-IGE and a firm-IGE using an AKM framework. The firm-IGE—reflecting the sorting of children from higher-income families into better-paying firms—accounts for 23 percent of the IGE. We then explore underlying mechanisms. While skill transmission explains part of the firm-IGE, roughly half cannot be accounted for by skill differences. Moreover, sector-level sorting explains a large share of the firm-IGE, indicating that structural barriers across sectors—rather than firm-level discrimination—are a key driver of intergenerational sorting.

*We thank Jan Stuhler, Nathan Wilmers, Per Engzell, Matthew Staiger, Jason Sockin, Jaime Arellano-Bover, Lorenzo Lagos, Ran Abramitzky, Manuel Arellano, Raj Chetty, Simon Jager, Pat Kline, Liran Einav, Martin Nybom, Nina Roussille, Isaac Sorkin, and Muly San for helpful comments. We gratefully acknowledge financial support from the Shultz Fellowship, Stanford Center for Computational Social Science, Proyectos de Generacion de Conocimiento 2021, and Stanford Graduate Research Opportunity Grant for this work. All views and any errors are our own.

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1 Introduction

Why do children of high-earning families tend to have high earnings themselves? A potential explanation is their privileged access to certain employers: There is growing evidence that parental social networks influence the allocation of workers to firms (Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2022; Staiger, 2023; Eliason et al., 2023). However, we still do not know whether firms play a *quantitatively* important role in the intergenerational persistence of earnings.

In this paper, we quantify the role of firms in intergenerational mobility. First, we decompose the intergenerational elasticity of earnings (IGE) into a firm-IGE and an individual-IGE using a two-way fixed effects framework in the spirit of Abowd et al. (1999) (AKM). The firm-IGE reflects the extent to which individuals from higher-income families sort into better-paying firms; we find that it accounts for 23% of the IGE in Israel. We then explore potential mechanisms and show that the individual-IGE is strongly related to education, suggesting that it is, in large part, explained by skill differences. In contrast, our results indicate that both skill-related and non-skill-related factors play equally important roles in shaping the firm-IGE.

To implement this decomposition, we construct a population-wide earnings dataset from the Israeli National Insurance administrative records. We decompose each worker's earnings into two components, following Card et al.'s (2013) implementation of the AKM model: an *Individual Component* that captures earnings differences across workers within the same firm (reflecting skill and other person-specific factors), and a *Firm Pay Premium* that captures earnings differences across firms. We then estimate how each of these components relates to parental income through the following regressions:

$$\text{Individual Component}_i = \text{constant} + \beta^{\text{Ind-IGE}} \times \log \text{Parental Income}_i + \text{error},$$
$$\text{Firm Pay Premium}_i = \text{constant} + \beta^{\text{Firm-IGE}} \times \log \text{Parental Income}_i + \text{error}.$$

These components add up exactly to the overall intergenerational elasticity of earnings:

$$\beta^{\text{IGE}} = \beta^{\text{Ind-IGE}} + \beta^{\text{Firm-IGE}}. \tag{1}$$

That is, the *Individual-IGE* ($\beta^{\text{Ind-IGE}}$) measures the extent to which individuals from richer families earn more than their coworkers in the same firm, while the *Firm-IGE* ($\beta^{\text{Firm-IGE}}$) measures the extent to which they sort into better-paying firms.[1] Using the decomposition in Equation (1), we conclude that the firm component is responsible for 23% of the IGE in Israel.

In the second part of the paper, we explore mechanisms using a descriptive analysis of the correlates of the individual- and firm-IGE. We proceed in two steps. First, we investigate which aspects of an individual's background are most predictive of future sorting to high-paying firms, focusing on education, demographic group, and father's sector of employment. Second, we examine the margins along which this sorting occurs once individuals are active in the labor market, namely sector of employment and residential location.

In the socioeconomic-background analysis, we find that education explains 40% of the individual-IGE, roughly five times as much as demographics and father's sector combined. This suggests that differences in skill play a dominant role in the individual-IGE. In contrast, for the firm-IGE, demographics and father's sector together explain 33%, a contribution comparable to that of education. This pattern implies that both skill differences and non-skill factors—such as social networks, preferences, and discrimination—play an important role in sorting high-SES individuals into high-paying firms.

In the sorting analysis, we find that sector of employment accounts for 49% of the firm-IGE, while residential neighborhood explains 19% (Panel (c) of Figure 4). In other words, sorting across sectors plays the dominant role in shaping the firm-IGE. Nonetheless, approximately one-third of the firm-IGE remains unexplained by these observed factors.

In the third part of the paper, we further explore mechanisms, focusing on assortative matching—that is, the tendency of more skilled workers to sort into firms that pay higher wage premia. Prior research shows that children from higher-income families tend to be more skilled (e.g., Mogstad and Torsvik, 2022), and that higher-skilled workers are more likely to sort into higher-paying firms (e.g., Card et al., 2013). A key question, therefore, is whether individuals from higher-SES backgrounds tend to work at better-paying firms even relative to equally skilled individuals from lower-SES backgrounds.

[1] See Section 3.3, Equation (5), for the formal version of these regressions.

The fact that differences in education account for 33% of the firm-IGE suggests that skill-based sorting plays an important role, but does not fully explain the firm-IGE. One limitation of this interpretation is that skill is not directly observed, and education may not capture all relevant dimensions of skill. A common approach in the literature to address this issue is to proxy skill using persistent within-firm earnings differences, estimated via AKM individual effects (Gerard et al., 2021; Engzell and Wilmers, 2024). Following this approach, we find that roughly half of the firm-IGE can be attributed to assortative matching. This suggests that high-SES individuals are employed at firms that pay substantially higher wage premia, even relative to equally skilled low-SES workers.

We then formally derive the assumptions required for this interpretation and show that they are strong. Most importantly, one must assume that the individual component of earnings reflects only variation in skill. However, social networks likely influence not only the sorting of workers across firms but also their outcomes within firms. Stinson and Wignall (2018) and Staiger (2023) show that having a parent employed at the same firm is associated with sizable earnings gains—most of which stem from sorting into higher-paying firms, though some also result from higher within-firm earnings. Similarly, San (2022) finds that in Israel, 84 percent of the wage gains associated with weak social connections arise through job mobility. While this evidence suggests that social networks affect labor market outcomes primarily through firm sorting, the assumption that the individual component is determined *exclusively* by skill is not empirically supported. Therefore, our results regarding the role of assortative matching in the firm-IGE should be viewed as suggestive.

Several mechanisms could explain the sorting of high-SES individuals into higher-paying firms beyond assortative matching. One possibility is discrimination. If firms engage in discriminatory employment practices, they may prefer to hire workers from certain socioeconomic backgrounds (Bertrand and Mullainathan, 2004; Rubinstein and Brenner, 2014; Ariel et al., 2015; Rivera and Tilcsik, 2016; Kline et al., 2022). The fact that a substantial share of the firm-IGE is explained by demographics is consistent with this mechanism. However, the finding that half of the firm-IGE is driven by sorting across sectors suggests that firm-specific discrimination is unlikely to be the primary driver. For discrimination to play a central role, it would require widespread discrimination across entire high-paying sectors. Investigating this possibility is an important avenue for future research.

Another mechanism involves imperfect information, which creates frictions on both the demand and supply sides of the labor market. On the demand side, firms do not perfectly observe worker skill (Sousa-Poza and Ziegler, 2003; Faccini, 2014). On the supply side, workers are not aware of all job opportunities (Calvó-Armengol and Jackson, 2004; Jäger et al., 2021; Sockin and Sojourner, 2022). In both cases, high-SES individuals may benefit from social networks that alleviate information frictions and provide access to better jobs (Magruder, 2010; Corak and Piraino, 2011; Kramarz and Skans, 2014; San, 2022; Staiger, 2023). The observed relationship between residential neighborhood and the firm-IGE provides suggestive evidence that social networks may play an important role. Notably, we find that neighborhood explains substantially more of the firm-IGE than commuting zone. This pattern supports an interpretation based on local informational networks rather than spatial labor market segmentation—in contrast to explanations focused on residential segregation across regional labor markets as emphasized by Sprung-Keyser and Porter (2023) and Card et al. (2025).

This paper contributes to an extensive literature investigating the determinants of intergenerational mobility. Several mechanisms have been studied, including human capital (Becker and Tomes, 1979, 1986; Restuccia and Urrutia, 2004; Heckman and Mosso, 2014; Bell et al., 2019; Lee and Seshadri, 2019; Barrios-Fernandez et al., 2021); nature versus nurture (Black et al., 2020); location (Chetty et al., 2016); and social networks (Putnam, 2015; Chetty et al., 2022b,a). Most closely related to our work, several papers have shown a relationship between family social networks and being employed by specific firms (Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; Staiger, 2023; Eliason et al., 2023). We are the first to *quantify* firms' contribution to the observed correlation between parents' and children's earnings.

Three contemporaneous papers are especially related to our work. Engzell and Wilmers (2024) employs a similar empirical strategy and concludes that "an imperfectly competitive labor market provides an opening for skill-based rewards in one generation to become class-based advantages in the next." Our main distinction is that we explicitly examine the role of assortative matching in generating these patterns. San (2022) uses the same Israeli administrative data to study the role of parental professional connections. His structural approach allows for a more detailed analysis of mechanisms but relies on stronger identifying assumptions. Staiger (2023) studies jobs obtained through parents' employers in the United States, while we examine how family background affects access to high-paying firms more broadly. Finally, in slightly more recent work, Forsberg et al. (2024) build on our approach to estimating assortative matching and augment it with direct measures of cognitive and non-cognitive skills from military enlistment records from Sweden.

Despite differences in context and methodology, results across these papers are remarkably consistent. We find that access to better-paying firms explains 23 percent of the IGE in Israel—identical to the estimate in Sweden reported by Engzell and Wilmers (2024). We also find that roughly half of the firm-IGE (about 12 percent of the total IGE) cannot be explained by skill differences. Similarly, San (2022) estimates that equalizing social connections, while holding skills constant, would reduce the Arab-Jew wage gap by 12 percent. In the United States, Staiger (2023) shows that the IGE would be 7.2 percent lower if no one gained employment through parental connections. Finally, Forsberg et al. (2024) conclude that approximately half of the firm-IGE can be attributed to skill differences—matching our estimates using a different empirical setting.

Our work also relates to the literature that uses a two-way fixed effects framework to quantify the importance of firms to wage inequality. This approach was initially proposed by Abowd et al. (1999) and applied in many contexts (e.g., Card et al., 2013; Sorkin, 2018; Song et al., 2019; Bonhomme et al., 2019, 2022; Kline et al., 2020), including Israel (Arellano-Bover and San, 2023). Most closely related to our work, Gerard et al. (2021) measure the effects of firm policies on racial pay differences. They find that non-Whites are less likely to be hired by high-paying firms, which explains about 20% of the racial wage gap in Brazil. We contribute to this literature by formalizing the assumptions required to use worker fixed effects as a proxy for skill, which is a common practice in previous studies.

The rest of the paper is organized as follows. Section 2 describes the data and setting. Section 3 quantifies the contribution of firms to the IGE. Sections 4 and 5 explore mechanisms; the former examines a broad set of channels, while the latter focuses specifically on assortative matching. Section 6 concludes.

2 Data and setting

2.1 Setting: Israel

Israel is a high-income economy, with a GDP per capita of 54,690 USD and over 80% of the labor force in the service sector. Israel is also highly educated: 46% of 25- to 64-year-olds are college educated—the second highest share in the world—and 83% of its population has completed high school, which is higher than the OECD average (75%).

Despite its economic and educational success, Israel is one of the most unequal countries in the OECD,[2] second only to the United States. Approximately 21% of Israelis live below the poverty line, compared with an average of 11% in the OECD. Previous research commonly attributes such high inequality to the socioeconomic disadvantages experienced by two communities: Israeli-Arabs and Ultra-Orthodox Jews (David and Bleikh, 2014; Sarel et al., 2016). In 2011, 70% of Ultra-Orthodox and 57% of Arabs were living below the poverty line (David and Bleikh, 2014). These numbers are partially explained by cultural and educational differences. For example, Ultra-Orthodox schools are exempt from the core curriculum and focus instead on religious studies. Also, Ultra-Orthodox Jewish men and Arab women traditionally do not participate in the labor force: Non-employment rates among non-college-educated Ultra-Orthodox men and Arab women are 50% and 74%, respectively, compared with 13% for the non-college-educated, non-orthodox Jewish population (Sarel et al., 2016). Moreover, parental networks play an important role in the Israeli labor market: 11% of individuals find their first job in a firm where one of their parents had worked (San, 2022).

2.2 Data

Decomposing the IGE into individual and firm components requires a panel of individual earnings with employer identifiers, parent-child links, and individ-

[2]The disposable income Gini coefficient is 41.4.

ual covariates, such as age and education. We built such a dataset by combining three sources: the Israeli Civil Registry, Israeli Social Security, and the Israeli Council for Higher Education. The civil registry reports the year of birth and parents of every Israeli citizen. Social Security data cover the universe of the formal labor market. These data are at employer-employee-year level, and report total yearly earnings and number of months worked in that year. The education data cover all individuals with a college degree.

We build measures of ethnicity, religiosity, place of residence, and education as follows. Ethnicity (Jewish or Israeli-Arab) is reported when citizens are issued their identification card at birth and is recorded in the civil registry data. We take the definition of "Ultra-Orthodox" from the Israeli Central Bureau of Statistics, which labels "Ultra-Orthodox" individuals of Jewish ethnicity who attended an orthodox school.[3] Social Security records report the place of residence at two levels of aggregation: "Ezor Statisti" and "Semel Yeshuv," which we refer to as commuting zones and neighborhoods, respectively. Finally, the data inform what type of higher education institution (if any) each individual graduated from. Table A.1 reports descriptive statistics for each type of institution. We see high variation across school types. For example, university graduates earn 50% more than individuals who graduate from a teaching college.

We construct our study sample as follows. First, we collect all Israeli citizens—both male and female—born between 1965 and 1980 from the civil registry and link them to their fathers.[4] We then match those individuals and their fathers to the social security and education data. We observe fathers' earnings from 1986 to 1991 and children's from 2010 to 2015—i.e., when both groups are between 30 and 50 years old. This is commonly done in the intergenerational mobility literature to capture the period in which earnings are less affected by transitory fluctuations (Mazumder, 2016).

Our empirical analysis estimates firm earnings premiums based on individuals with stable jobs, as opposed to temporary or part-time (Card et al., 2013; Song et al., 2019). Hence, in the children's generation, we only keep stable jobs. A job is defined as stable if, in a given calendar year, the employee worked in it

[3]"School" here refers to elementary, middle, or high school. Note that we do not observe which school each individual attended; the Bureau of Statistics only reports whether it was an orthodox school.

[4]Appendix B explains why we use the father's earnings rather than the mother's or household earnings.

Table 1—Summary statistics

	Full Sample	IGM Sample	IGM-AKM Sample
Number of individuals			
	1,282,243	775,241	684,847
Demographic Groups (%)			
Arab	20.1	14.9	14.5
Ashkenaz	21.2	22.3	22.9
Ethiopian	0.3	0.3	0.3
Sepharadic	35.9	39.9	39.7
Ultra-Orthodox Jew	5.0	3.3	3.2
USSR	4.7	4.9	5.3
Missing	12.7	14.4	14.2
College Educated (%)			
	39.3	49.6	50.1
Earnings			
Mean of log-earnings		11.59	11.63
Mean of father's log-earnings		10.70	10.72

Notes: This table reports summary statistics of our data. "Full Sample" includes all Israeli citizens born between 1986 and 1991. The "IGM Sample " restricts the sample to individuals with stable jobs and whose fathers have nonzero reported income. The "IGM-AKM Sample" further restricts the sample to individuals employed at firms with at least 10 workers. Demographic groups are defined as follows. We take the official definition of "Arab" and "Ultra-Orthodox Jew" from the Israeli Civil Registry. The remaining individuals are broadly classified as "Secular Jews" and are subdivided depending on the country of origin of their parents and grandparents. Families from countries that were in the Soviet Union are classified as "USSR" and those from Ethiopia as "Ethiopian." The remaining are classified as "Ashkenaz" or "Sephardic" based on which is the major Jewish community in their family's origin country.

for at least 5 months and earned at least $3,000 that year.[5] If a worker has more than one stable job in a given year, we keep the one with higher total earnings. In the parents' generation, we do not estimate firm earnings premiums, and income data are used as a measure of SES status. Hence, we calculate their total income by summing over all jobs in a given year.

Table 1 reports summary statistics for the 1.3 million Israeli citizens born between 1965 and 1980. Restricting the sample to individuals with stable jobs and whose fathers have nonzero reported income excludes 40% of the sample, resulting in 775 thousand individuals. We will call this the intergenerational mobility sample (*IGM sample*). To reduce noise in the estimation of firm pay premiums, we restrict the sample to individuals employed at firms with at least 10 workers, which reduces the sample size by an additional 12% and yields

[5]Average monthly earnings in Israel are $2,934, and the minimum monthly earnings for full-time employment (by law) is $1,486.

685 thousand individuals. We call this the *IGM-AKM* sample and it is our main sample.

It is common to focus on the formal labor market in studies of intergenerational mobility. This limitation is not particularly problematic in our setting: Only 6.6% of the Israeli economy is informal (Gyomai and van de Ven, 2014), and tax evasion is equally common across demographic groups (Arlozorov, 2012). However, we impose an additional restriction: We include only workers in firms with at least 10 workers. This additional restriction is potentially concerning, since it might make it hard to compare our results with previous literature. Reassuringly, Table 1 shows that the IGM-AKM sample is similar to the IGM sample in terms of earnings, father earnings, demographics, and education. In particular, note that father earnings are only 0.02 log points higher in the IGM-AKM sample. As a comparison, the standard deviation of father earnings is 0.64 log points. Hence, sample selection is not likely to play a major role in our results. Also, in Section 3.4, we show how to extend our results to the IGM sample, under certain assumptions, and the findings are unchanged.

3 Firms and intergenerational mobility

3.1 AKM: The role of firms in cross-sectional inequality

In this section, we discuss the determinants of the cross-sectional distribution of earnings. Our goal is to decompose earnings into individual and firm components, as well as age and time trends. For this purpose, we follow Card et al.'s (2013) implementation of the AKM model and estimate the regression:

$$\log Y_{i,t} = \overbrace{\alpha_i}^{\text{individual component}} + \underbrace{\psi_{J(i,t)}}_{\text{firm component}} + \overbrace{x'_{it}\beta^x}^{\text{covariates}} + \underbrace{r_{i,t}}_{\text{error term}} , \quad (2)$$

where $logY_{i,t}$ is the log-earnings of individual i in year t, α_i is an individual fixed effect, $J(i,t)$ is the firm in which individual i works in year t, and $\psi_{J(i,t)}$ is a firm fixed effect. Following the standard specification in the AKM literature, we control for time-varying covariates $x'_{it}\beta^x$: year fixed effects, age,[6] and age squared.

[6] Following Gerard et al. (2021), we normalize $x'_{it}\beta^x = 0$ in the baseline year for 40-year-old males and 35-year-old females, which correspond to the approximate peaks of their earnings

$r_{i,t}$ is an error term. The individual component (α_i) represents worker characteristics that are equally rewarded across firms.[7] The firm component (ψ_j) is called the *firm earnings premium* and captures persistent earnings differences related to firm j.

The AKM model has been shown to successfully summarize key empirical patterns in several labor markets (e.g., Card et al., 2013; Sorkin, 2018; Song et al., 2019; Gerard et al., 2021). In Appendix C.1, we show that this framework also fits our data well. In particular, we test the restrictions imposed in Regression (2), such as the log-linear functional form and that the error term $(r_{i,t})$ is independent of the probability of moving. We find no evidence of violations of these assumptions.

The fixed effects in Regression (2) are estimated with measurement error and, as a consequence, the correlation between individual and firm components is underestimated (Bonhomme et al., 2019, 2022; Kline et al., 2020). We address this issue in two ways. First, to minimize bias, we estimate Regression (2) using all workers in the Israeli labor market from 2010 to 2015 (AKM sample) and not only those in the IGM-AKM sample.[8] Second, we follow Bonhomme et al. (2019) and group firms into 100 clusters using a k-means algorithm, estimating the AKM model with cluster fixed effects rather than firm fixed effects. We then assign the estimated cluster effects as the earnings premium for all firms within each cluster.

As is usual in the AKM literature, we present the estimates of Regression 2

profiles.

[7]Equation (2) does not account for the fact that high-SES individuals tend to have steeper income growth (Mello et al., 2022). Hence, the estimated individual fixed effects might be biased, resulting in biased mobility estimates. To minimize this issue, we follow the intergenerational mobility literature and use only individuals between 30 and 50 years old in our mobility estimates (details in Setion 3.2). Figure A.12 in Engzell and Wilmers (2024) shows that the relationship between parental income and AKM fixed effects stabilizes after the age of 30.

[8]A potential concern is that firm premiums estimated with the AKM sample are not representative for the IGM-AKM sample. Appendix C.2 shows that firm premiums estimated with the AKM sample are highly correlated with the ones estimated with the IGM-AKM sample. Moreover, Appendix C.2 also shows that premiums estimated only with workers from low- or high-income families are highly correlated with full-sample estimates. Previous research has found similar patterns for workers of different ethinicities (Gerard et al., 2021) and gender (Sorkin, 2017).

in the form of the following variance decomposition:

$$
\begin{aligned}
Var\big(\log Y_{it}\big) = \quad & \overbrace{Var\big(\alpha_i\big)}^{\text{individual comp.}} \quad + \overbrace{Var\big(\psi_{J(i,t)}\big)}^{\text{firm comp.}} + \overbrace{2 \cdot Cov\big(\alpha_i, \psi_{J(i,t)}\big)}^{\text{sorting}} \\
& + \underbrace{Var\big(x_{it}'\beta^x\big) + 2 \cdot Cov\big(x_{it}'\beta^x, \alpha_i + \psi_{J(i,t)}\big) + Var\big(r_{i,t}\big)}_{\text{covariates and error term}}
\end{aligned} \tag{3}
$$

Results are reported in Table 2. In the AKM sample, the individual component is responsible for 78% of the variation in earnings and the firm component for 11%. The sorting of high-earners into high-paying firms is responsible for 16% of the variation.[9] We find similar results within the IGM-AKM sample; the main difference is a somewhat less important individual component (70%). These patterns align qualitatively with findings in other contexts: the individual component predominantly explains the variation in earnings, but firm and sorting components also play important roles. However, it is noteworthy that previous research in other countries has typically found the firm component to account for at least 15% of earnings variance (Card et al., 2018), which is higher than what we observe in Israel. Therefore, caution is advised when generalizing our findings to different contexts.

Table 2—Earnings variance decomposition

	AKM Sample	IGM-AKM Sample
Variance components:		
Individual component (α)	0.79	0.69
Firm component (ψ)	0.08	0.08
Sorting $(Cov(\alpha, \psi))$	0.21	0.19
Covariates and residual	-0.08	0.04

Notes: This table decomposes the total variation in earnings into several components, as defined in Equation (3). The included covariates are age, age-squared, and year fixed effects. The "AKM sample" includes all individuals in the largest connected set between 2010 and 2015. The "IGM-AKM sample" restricts the AKM sample to individuals born between 1965 and 1980 and whose fathers have nonzero reported income.

3.2 IGE: Measuring intergenerational mobility

We use a canonical measure of mobility: the elasticity of child earnings to parent earnings (Solon, 1992), which is commonly called the intergenerational elas-

[9] Covariates and the error term are responsible for the remaining *negative* part of the variation (-5%).

ticity of earnings (IGE).[10] Following the literature, we construct measures of earnings net of age and time effects. For the children's generation, we build net log earnings using the AKM framework (2): $\log \widetilde{Y}_{it} \equiv \alpha_i + \psi_{J(i,t)} + r_{i,t}$.

For the parents' generation, a natural approach would be to estimate Regression (2) and analogously define net earnings. However, in their generation firms were smaller, there were fewer job movers, and the informal market was bigger. The combination of these factors renders the connected set very small (<50% of the sample) and not representative. Hence, for parents, we follow the standard approach and define net log-earnings as the residuals of a regression of log earnings on age, age squared, and year fixed effects.

Finally, we estimate the IGE with the following regression:

$$\overline{logY_i} = \beta_0^{IGE} + \beta^{IGE} \cdot \overline{logY_{f(i)}} + \epsilon_i^{IGE}, \tag{4}$$

where $\overline{logY_i}$ is individual i's average net-log earnings between 2010 and 2015, $\overline{logY_{f(i)}}$ is her father's[11] net-log earnings between 1986 and 1991, β^{IGE} is the IGE, our parameter of interest, and ϵ_i^{IGE} is a residual.

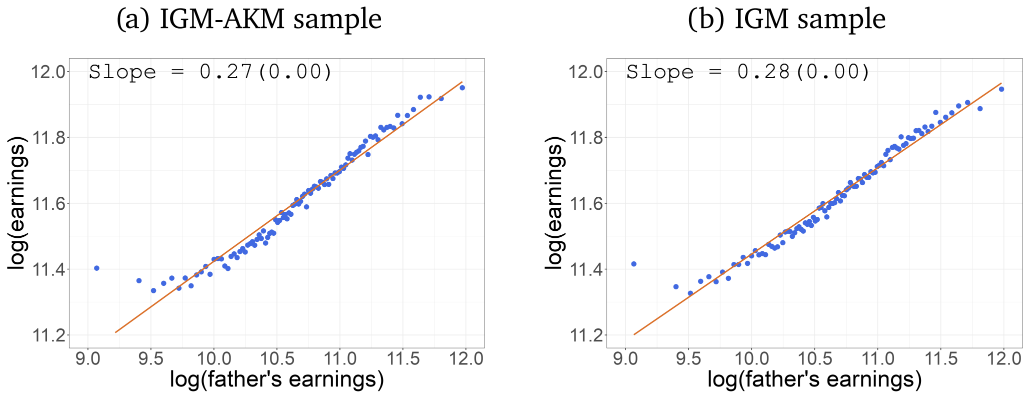
Figure 1, Panel (a) shows OLS estimates of Regression (4) and plots the underlying data. We find that the IGE in Israel is 0.25. That is, a 10% increase in a child's father's earnings is correlated with a 2.5% increase in her earnings in adulthood. Note that this estimate is restricted to individuals in the connected set—i.e., the IGM-AKM sample, as defined in Section 2.2. Panel (b) shows that the IGE for the IGM sample is similar (0.28). Reassuringly, Heler (2017) estimates an identical IGE using the same data. These estimates are larger than the IGE in Scandinavian countries, such as Norway (0.19) and Sweden (0.23), and smaller than other OECD countries, such as the United States (0.43) and Germany (0.31) (Bratberg et al., 2017).[12] We conclude that the in-

[10] Other commonly used statistics include the correlation between parent and child earnings ranks and transition probabilities between parent and child occupations. However, these measures are independent of the cross-sectional distribution of earnings (**?**). Hence, in this paper, we use the IGE as our measure of intergenerational mobility, because firms' earnings premium affect both the correlation between parent and child earnings *and* cross-sectional earnings inequality.

[11] We focus on fathers because female labor market participation was substantially smaller in the parents' generation. Hence, the father's income is more representative of a family's socioeconomic status. More details in Appendix B.

[12] Cross-country comparisons of IGE estimates require caution, because studies often differ in several respects, such as parent's vs. father's earnings, different age ranges, and number of years used. For a detailed discussion of the sensitivity of IGE estimates, see Mazumder (2016).

Figure 1—The intergenerational elasticity of earnings (IGE)



Notes: This figure plots log children's earnings against log fathers' earnings. Panel (a) presents estimates for the IGM-AKM sample, and Panel (b) presents estimates for the IGM sample (see Section 2.2). The slope of the fitted line is the intergenerational elasticity of earnings (IGE). Earnings are calculated as the average yearly earnings in 2010-2015 for children and 1986-1991 for fathers and are the residuals from a regression of log earnings on age, age-squared and year fixed effects.

tergenerational persistence of earnings in Israel is comparable to that of other high-income countries.

3.3 Firm-IGE: The role of firms in intergenerational mobility

We now turn to our main objective: estimating the role of firms in intergenerational mobility. To this end, we define measures of persistence for the firm and individual components, analogous to the IGE:

$$\begin{aligned} \widehat{\alpha}_i &= \beta_0^{\alpha|Y_f} + \beta^{\alpha|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\alpha|Y_f}, \\ \widehat{\psi}_i &= \beta_0^{\psi|Y_f} + \beta^{\psi|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\psi|Y_f}, \end{aligned} \tag{5}$$

where $\beta^{\alpha|Y_f}$ is the individual-IGE, $\beta^{\psi|Y_f}$ is the firm-IGE, and $\widehat{\alpha}_i$ and $\widehat{\psi}_i$ are, respectively, the estimated individual component and the average firm component of earnings of worker i (See Equation 2).

The framework in Regression 5 is useful because it provides an exact decomposition of the IGE into individual and firm components (proof in Appendix D):

$$\overbrace{\beta^{IGE}}^{\text{IGE}} = \overbrace{\beta^{\alpha|Y_f}}^{\text{individual-IGE}} + \overbrace{\beta^{\psi|Y_f}}^{\text{firm-IGE}} . \tag{6}$$

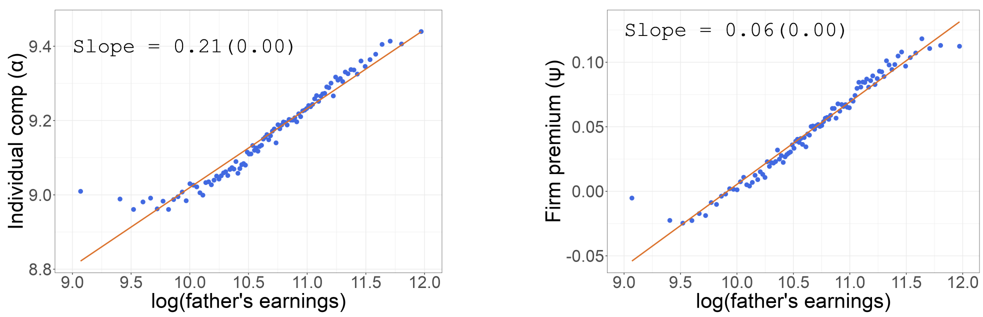
Equation 6 highlights that the intergenerational correlation in earnings operates through two distinct channels. First, individuals from higher-income families tend to earn more than their coworkers within the same firm—a pattern captured by the individual-IGE. Second, they are more likely to be employed at firms that pay higher wage premia, as reflected in the firm-IGE.

We estimate Regression (5) by OLS. Note that OLS delivers unbiased estimates even though $\widehat{\alpha}_i$ and $\widehat{\psi}_i$ have measurement error, because they are left-hand-side variables.[13] Estimated coefficients are reported in Table 3 and Figure 2 shows the underlying data. We find that the individual-IGE is 0.208 (Column 2) and the firm-IGE is 0.061 (Column 3). Using the decomposition in Regression (6), we conclude that the firm component is responsible for 23% of the intergenerational persistence in earnings, whereas the individual component is responsible for 77%.

The firm-IGE share can be interpreted through the following counterfactual exercise: How much lower would the IGE be if individuals were randomly assigned to firms—regardless of parental income—while holding all else constant? For this interpretation to be valid, we must assume that earnings follow the AKM framework, as specified in Equation (2), and that the individual and firm components remain invariant under this counterfactual reassignment.

Figure 2—Decomposing intergenerational mobility

(a) Individual-IGE (b) Firm-IGE



Notes: Panel (a) plots children's individual components against their father's log earnings. Panel (b) plots children's average firm component against their father's log earnings. The slopes of the fitted lines in Panels (a) and (b) are, respectively, the individual-IGE and the firm-IGE. Earnings are calculated as average yearly earnings in 2010-2015 for children and 1986-1991 for fathers and are the residuals from a regression of log earnings on age, age-squared, and year fixed effects.

A natural concern is whether these patterns are unique to Israel. Indeed, the social dynamics between Secular Jews, Ultra-Orthodox Jews, and Israeli-Arabs are unique in many dimensions. However, following a methodology sim-

[13] Under the assumption of classical measurement error.

ilar to ours in Sweden, a much more ethnically homogenous country, Engzell and Wilmers (2024) estimate that the firm-IGE accounts for 23.2% of the IGE, remarkably close to the number we find for Israel.

Table 3—Decomposing the IGE into individual and firm components

	(1)		(2)		(3)
Dependent variable:	$\overline{\log Y}_i$		$\widehat{\alpha}_i$		$\widehat{\psi}_i$
	$\overbrace{\beta^{IGE}}^{\text{IGE}}$	$=$	$\overbrace{\beta^{\alpha \mid Y_f}}^{\text{individual-IGE}}$	$+$	$\overbrace{\beta^{\psi \mid Y_f}}^{\text{firm-IGE}}$
$\overline{logY_{f(i)}}$	0.269		0.208		0.061
	(0.002)		(0.002)		(0.001)
Share of IGE	1.00		0.77		0.23
	.		(0.009)		(0.003)
Observations	684,847		684,847		684,847

Notes: This table reports the results of the decomposition of the intergenerational earnings elasticity (IGE) into individual and firm components, as described in Equation (6). Column (1) shows the IGE (Equation 4). Column (2) shows the elasticity of children's individual component of earnings $(\widehat{\alpha}_i)$ to their father's earnings, which we call individual-IGE (Equation 5). Column (3) shows the elasticity of children's firm component of earnings $\left(\widehat{\psi}_i\right)$ to their father's earnings, which we call firm-IGE (Equation 5). The bottom panel reports the share of the IGE explained by each component. Standard errors are in parentheses. Standard errors for shares are calculated using the delta method. Fathers' earnings are calculated as average yearly earnings between 1986 and 1991 and are the residuals from a regression of log earnings on age, age-squared, and year fixed effects.

3.4 Firm-IGE: Robustness to sample selection

We now assess the robustness of our baseline results from Table 3 by extending the sample along four key dimensions: birth cohort range, job stability, father employment, and child employment. These exercises help clarify whether our estimate of the firm's role in the IGE is sensitive to sample selection criteria.

We begin by relaxing the age restrictions implicit in our cohort selection. The baseline includes individuals born between 1965 and 1980, observed in the labor market between 2010 and 2015 (ages 30 to 50). To evaluate whether firm effects persist outside this range, we expand the sample to birth cohorts from 1955 to 1990, increasing the age range to 20-60. As shown in Panel A of Table A.2, the results remain nearly unchanged: the firm-IGE accounts for 22% of the overall IGE, compared to 23% in the baseline. This suggests that the contribution of firms is not driven by lifecycle effects specific to mid-career workers.

Next, we examine the role of labor force attachment. Our main analysis, following standard AKM practice (e.g., Card et al., 2013), includes only individuals with stable jobs. As a robustness check, we include all individuals who ever worked in a firm that is part of the AKM sample, even if only for a single month. While these individuals are not used to estimate firm effects, we assign them the firm premium estimated using stable workers in the same firm. We impute person effects (α_i) for temporary workers as the difference between their earnings, residualized for age, and their imputed firm premium. Results are shown in Panel B of Table A.2: the firm share of the IGE increases from 22% to 27%. These results indicate that socioeconomic background plays an even larger role in determining firm placement for individuals with weaker labor market attachment compared to those in more stable jobs.

We also explore the implications of excluding individuals whose fathers reported zero earnings, a standard restriction in IGE estimation due to the undefined log of zero. To include these observations, we impute the log earnings of fathers with zero income using the log of the first percentile of positive father earnings. As shown in Panel C of Table A.2, including these cases increases the firm share of the IGE slightly, from 22% to 26%. A likely explanation is that Ultra-Orthodox Jews and Israeli Arabs are disproportionately represented among non-employed fathers, and these groups tend to be employed in firms with lower pay premiums.

Finally, we examine the role of child non-employment. Figure E.1 shows that individuals from high-income families are more likely to be employed. To incorporate this extensive-margin selection, we extend our decomposition in Appendix E to include a participation component alongside the firm and individual terms. We find that participation explains 25% of the IGE, with firms and individuals accounting for 17% and 58%, respectively. Whether this strengthens or weakens the role of firms depends on the source of non-employment: if low-SES individuals are non-employed due to barriers in firm access, our baseline may understate firm effects; if the driver is skill or preference heterogeneity, the opposite may be true. In this paper, we focus on firm effects among employed individuals and leave a full analysis of extensive-margin mechanisms for future research.

4 Behind the firm-IGE

In this section, we examine which observable factors help explain the firm-IGE—that is, why individuals from high-SES backgrounds are more likely to sort into high-paying firms. We proceed in three steps. Section 4.1 outlines our empirical strategy for quantifying the contribution of each factor to the firm-IGE. Section 4.2 investigates which aspects of an individual's background are most predictive of later employment in high-paying firms, with a focus on education, demographic group, and father's sector. Section 4.3 then turns to the margins along which this sorting occurs once individuals are active in the labor market, namely sector of employment and residential location.

4.1 Empirical Strategy

In this subsection, we describe how we estimate the share of the individual- and firm-IGE that can be explained by a given covariate—such as education or location. We present two approaches: one that evaluates each covariate separately, and another that allows for multiple covariates to be considered jointly.

To quantify the role of a single covariate X, we adopt a straightforward approach: we measure how much the individual- and firm-IGE coefficients decline when X is added as a control. Specifically, we estimate:

$$\begin{aligned}
\widehat{\alpha}_i &= \beta^{\alpha|Y_f,X} \cdot \overline{\log Y}_{f(i)} + \beta^{\alpha|X} X_i + \epsilon_i^{\alpha|X}, \\
\widehat{\psi}_i &= \beta^{\psi|Y_f,X} \cdot \overline{\log Y}_{f(i)} + \beta^{\psi|X} X_i + \epsilon_i^{\psi|X},
\end{aligned}$$

where $\widehat{\alpha}_i$ and $\widehat{\psi}_i$ are the estimated person and firm effects from the AKM model described in Section 3.1, and $\overline{\log Y}_{f(i)}$ denotes average log father earnings.

We define the share of each IGE component explained by X as the proportional reduction in the corresponding coefficient:

$$\begin{aligned}
\text{Share of individual-IGE explained by } X &= 1 - \frac{\beta^{\alpha|Y_f,X}}{\beta^{\alpha|Y_f}}, \\
\text{Share of firm-IGE explained by } X &= 1 - \frac{\beta^{\psi|Y_f,X}}{\beta^{\psi|Y_f}},
\end{aligned} \tag{7}$$

where $\beta^{\alpha|Y_f}$ and $\beta^{\psi|Y_f}$ are the coefficients from Regression (5) estimated without controlling for X, and represent the baseline measures of the individual- and firm-IGE, respectively.

where $\beta^{\alpha|Y_f}$ and $\beta^{\psi|Y_f}$ are the estimated coefficients from Regression (5), where X is excluded, and represent, respectively, the individual- and firm-IGE.

To evaluate the marginal explanatory power of each covariate when multiple controls are included simultaneously, we apply the decomposition proposed by Gelbach (2016). Let $\vec{X} = \{X^1, X^2, \ldots\}$ be a vector of covariates, and let the outcome be either $\widehat{\alpha}_i$ or $\widehat{\psi}_i$. We estimate:

$$\text{Outcome}_i = \beta^{\text{Outcome}|Y_f,\vec{X}} \cdot \overline{\log Y}_{f(i)} + \vec{\beta}^{\text{Outcome}|\vec{X}} \cdot \vec{X}_i + \epsilon_i.$$

Following Gelbach (2016), the change in the coefficient on parental income between the restricted model shown in Equation (5)—which includes no controls—and the full model—which includes all controls—can be linearly decomposed into the contribution of each covariate. Specifically, the portion attributable to covariate X^k is:

$$\pi_k \cdot \beta_k^{\text{Outcome}|\vec{X}},$$

where $\beta_k^{\text{Outcome}|\vec{X}}$ is the k-th element of $\vec{\beta}^{\text{Outcome}|\vec{X}}$, and π_k is the slope from a regression of X^k on $\overline{\log Y}_{f(i)}$.

We then calculate the marginal share of the IGE explained by each covariate X^k as:

$$\begin{aligned} \text{Marginal share of individual-IGE explained by } X^k &= \frac{\pi_k \cdot \beta_k^{\alpha|\vec{X}}}{\beta^{\alpha|Y_f} - \beta^{\alpha|Y_f,\vec{X}}}, \\ \text{Marginal share of firm-IGE explained by } X^k &= \frac{\pi_k \cdot \beta_k^{\psi|\vec{X}}}{\beta^{\psi|Y_f} - \beta^{\psi|Y_f,\vec{X}}}. \end{aligned} \tag{8}$$

4.2 Pre-Labor Market: Education and Family Background

In this section, we investigate which aspects of an individual's background are the main drivers of the individual- and firm-IGE. We focus on factors highlighted by prior research as central to inequality and mobility: children's educational attainment (e.g., Restuccia and Urrutia, 2004; Pekkarinen et al., 2009; Zimmerman, 2019) and demographic group (e.g., Chetty et al., 2020; Gerard et al., 2021). In addition, given our focus on how family background shapes labor market sorting, we also include the father's sector of employment in the analysis.

Figure 3 presents the share of the firm- and individual-IGE explained by education, demographics, and father's sector. Panels (a) and (b) report total explanatory power, based on Equation (7), when each variable is included separately.[14] Panels (c) and (d) show the marginal explanatory power of each variable when all are included jointly, using Equation (8).[15] For brevity, we focus the discussion below on the marginal contributions; the total effects yield similar conclusions.

We find that education explains a substantial share of both the individual- and firm-IGE: 40.2% and 33.3%, respectively. The strong link between education and the individual-IGE is consistent with the interpretation that person effects reflect skill. The fact that education also explains a large share of the firm-IGE suggests an important role for assortative matching, whereby high-skill individuals sort into high-paying firms. We return to this mechanism in Section 5.

In contrast, demographic group plays a substantially larger role in the firm-IGE than in the individual-IGE: 25.5% versus 8.1%. This strong association between firm sorting and demographics may reflect labor market segregation. Indeed, as we show in Appendix G, individuals are substantially more likely to work alongside others from the same demographic group.

Father's sector explains virtually none of the individual-IGE and only a small share of the firm-IGE (7.7%). While individuals are more likely than chance to work in the same sector as their father, such cases account for only 0.5% of total employment, limiting the explanatory power of sectoral persistence. This low overlap is likely due to our focus on individuals aged 30 to 50—well beyond labor market entry. In contrast, prior research focusing on first jobs shows that individuals are often employed not only in the same sector as their parents, but

[14] "Education" refers to the type of higher education institution attended (if any); see Table A.1 for details. "Demographics" is defined as Arab, Ashkenazi, Ethiopian, Sephardic, Ultra-Orthodox Jew, USSR origin, or Missing. "Father's sector" refers to the 2-digit sector of the father's main employer during the observed period.

[15] Gelbach (2016) focuses on continuous covariates. To apply the decomposition, we convert our categorical variables into continuous measures by replacing group indicators with the average log father earnings for each group.

in the same firm.[16]

Taken together, these results highlight that the individual- and firm-IGE capture distinct pathways through which socioeconomic background shapes labor market outcomes. Education is the dominant channel for the individual-IGE, explaining roughly five times as much as demographics and father's sector combined. This suggests a proeminent role for skill in the individual-IGE. In contrast, for the firm-IGE, demographics and father's sector together explain as much as education. This suggests that both skill and non-skill factors—such as social networks, preferences, and discrimination—play an important role in sorting high-SES individuals into high-paying firms. Indeed, prior research in Israel has shown that Israeli Arabs are less likely to receive callbacks for job interviews in a randomized audit study (Ariel et al., 2015).

4.3 Labor Market Sorting: Location and Sector

In the last section, we have established that socioeconomic background strongly influences labor market sorting. In this section, we investigate along which margins this influence manifests. High-paying firms tend to be concentrated in particular sectors and locations. We therefore ask whether the sorting of high-SES individuals into high-paying firms occurs across sectors and locations, or within them. We examine location at two levels: commuting zone and neighborhood.[17]

Figure 4 presents the share of the individual- and firm-IGE that can be explained by sector and location. Panels (a) and (b) report total explanatory power, based on Equation (7), while Panels (c) and (d) present marginal contributions, computed using Equation (8).[18]

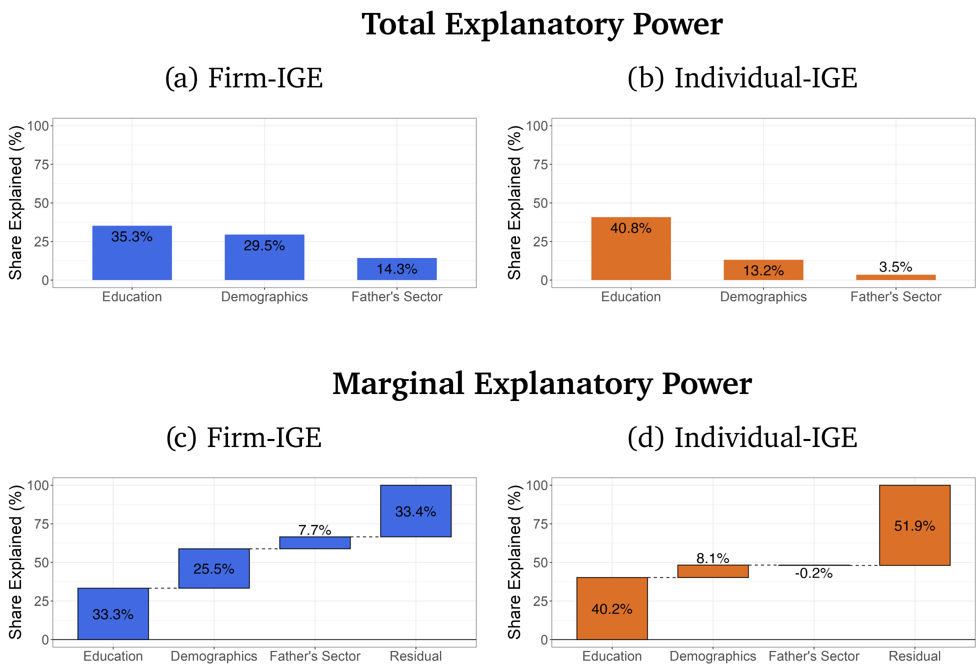
Note that commuting zones and neighborhoods cannot be jointly included in the marginal analysis, as they are perfectly collinear. We therefore begin by

[16] Using U.S. data, Staiger (2023) finds that 5.5% of individuals begin their first stable job at the same firm as a parent. Similarly, San (2022), using Israeli data, finds that 11% of individuals obtain their first stable job at a firm where a parent had what he terms "a strong social connection."

[17] Throughout this section, "location" refers to the individual's residential neighborhood during the period they are observed in the labor market. "Sector" refers to the two-digit industry code corresponding to the sector in which the individual earns the highest total income over the same period.

[18] As in Section 4.2, all covariates are included as categorical fixed effects when computing total explanatory power, and as continuous variables when computing marginal effects. Categorical variables are transformed into continuous measures by replacing group indicators with the average log father earnings of individuals in each group.

Figure 3—The role of education and family background



Notes: This figure shows how much of the firm- and individual-IGE can be explained by observed characteristics. Panels (a) and (b) display total explanatory power, calculated using Equation (7). Panels (c) and (d) show marginal explanatory power, which attributes the reduction in the IGE coefficient to each covariate when all controls are included jointly, following Equation (8). Parental income is measured as the average of log father earnings over 1986–1991, residualized of age and year effects. The individual ($\hat{\alpha}_i$) and firm ($\hat{\psi}_i$) components are estimated from an AKM model. "Education" refers to the type of higher education institution attended by the child, as defined in Table A.1. "Demographics" includes indicators for Arab, Ashkenazi, Ethiopian, Sephardic, Ultra-Orthodox, USSR origin, or missing. "Father's sector" is the two-digit industry code of the father's main employer during the observation period. The "Residual" category reflects the portion of the IGE not accounted for by the included covariates.

considering which unit of location is more informative in our setting. Panels (a) and (b) show that commuting zone explains only 6.3% of the firm-IGE and 3.0% of the individual-IGE. This contrasts with findings from Sprung-Keyser and Porter (2023) and Card et al. (2025), who show that commuting zones play a central role in access to high-paying firms and human capital formation. The likely reason for this discrepancy is the difference in context: while those papers use U.S. data—from a geographically vast country—we study Israel, where labor markets are more spatially integrated. Given the limited explanatory power of commuting zones in our setting, we focus the rest of the discussion on neighborhoods. Moreover, we concentrate below on marginal contributions; the total effects are qualitatively similar.[19]

[19] We focus the discussion on the firm-IGE results, shown in Panel (c), as this section centers on labor market sorting. The individual-IGE results, reported in Panel (d), are included for

Panel (c) of Figure 4 shows that neighborhood sorting accounts for 19% of the firm-IGE, while sector of employment explains 49%. In other words, sorting along the sector margin plays the dominant role in explaining why individuals from high-SES backgrounds are more likely to work at high-paying firms, raising the question of why high-SES individuals disproportionately sort into high-paying sectors.

One potential explanation is sectoral persistence: individuals may be more likely to work in the same sector as their father. We explore this possibility in Appendix F, where we estimate an AKM-style decomposition (Regression 5) using sector-level earnings premiums rather than firm-level premiums. We find that children of high-earning fathers are more likely to work in high-premium sectors—what we refer to as the *sector-IGE*. However, only 9% of the sector-IGE is explained by the father's own sector, implying that high-SES children sort into high-paying sectors even when their fathers did not. This finding echoes the results in Section 4.2, which showed that father's sector explains only a small fraction of the firm-IGE.

Another explanation is that sectoral sorting reflects demographic segregation. Our data supports this interpretation, particularly for more disadvantaged groups: Ethiopian Jews, Ultra-Orthodox Jews, and Israeli Arabs are 101%, 224%, and 43% more likely than chance, respectively, to be employed in the same sector as others from their own demographic group.

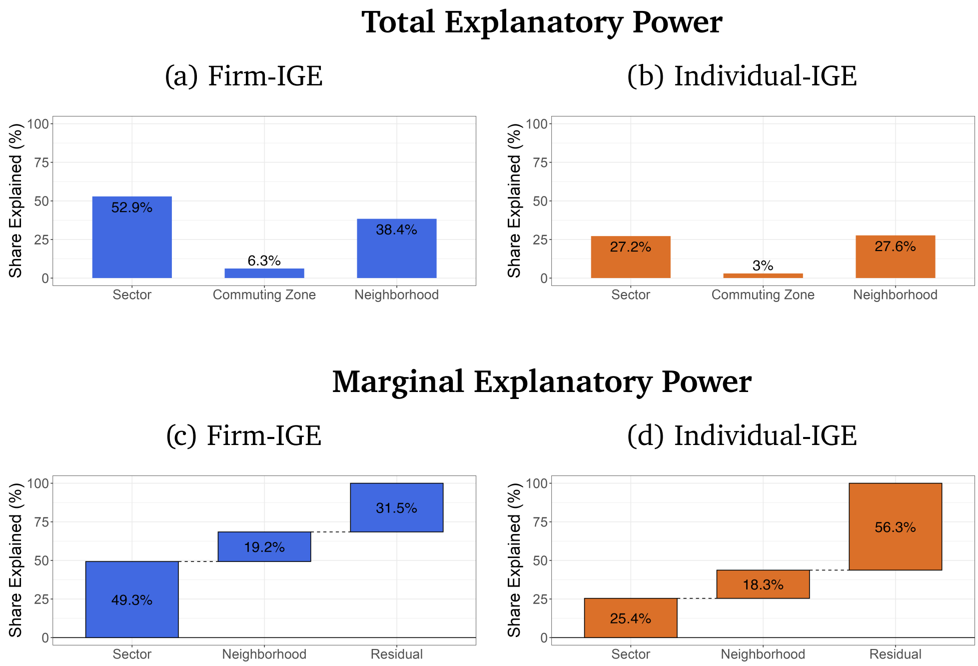
In sum, the results in this section suggest that the sorting of high-SES individuals into high-paying firms occurs largely through sectoral channels, and that demographic segregation is a key driver of this sorting. This finding has important implications. For instance, it may suggest less emphasis on firm-level discrimination in hiring, and greater attention to understanding why individuals from certain backgrounds are less likely to enter high-paying sectors.

5 Can assortative matching explain the firm-IGE?

Prior research shows that children from higher-income families tend to be more skilled (e.g., Mogstad and Torsvik, 2022), and that more skilled workers sort into higher-paying firms (e.g., Card et al., 2013). This implies that the firm-IGE may be partly explained by assortative matching of high-skill workers into high-

completeness.

Figure 4—Labor Market Sorting: Location and Sector



Notes: This figure shows how much of the firm- and individual-IGE can be explained by sorting along different margins. Panels (a) and (b) report total explanatory power, computed using Equation (7). Panels (c) and (d) report marginal explanatory power, which attributes the reduction in the IGE coefficient to each covariate when all controls are included jointly, as in Equation (8). Parental income is measured as the average of log father earnings over 1986–1991, residualized for age and year effects. The individual ($\hat{\alpha}_i$) and firm ($\hat{\psi}_i$) components are estimated using the AKM framework. "Sector" refers to the childs 2-digit industry of employment. "Commuting zone" and "Neighborhood" refer to the modal residential commuting zone and neighborhood of the child during 2010–2015, respectively. The "Residual" category captures the share of the IGE not explained by the included covariates.

paying firms. A central question, however, is whether non-skill-based sorting also contributes to the firm-IGE. In other words, do individuals from higher-SES backgrounds work at better-paying firms even when compared to equally skilled individuals from lower-SES backgrounds?

The results in Section 4 shed light on this question. Figure 3d shows that differences in education account for 31.3% of the firm-IGE. This suggests that skill-based sorting plays an important role, but does not fully explain the firm-IGE. One limitation of this interpretation is that skill is not directly observed, and education may not capture all relevant dimensions of worker skill. A common approach in the literature to solve this issue is to measure skill as persistent within-firm earnings differences, estimated using AKM worker fixed effects (Gerard et al., 2021; Engzell and Wilmers, 2024). We implement this approach in Section 5.1.

However, firms may reward worker characteristics unrelated to skill not only in hiring but also through promotions and pay raises. This introduces potential bias when using AKM worker effects as proxies for skill. In Section 5.2, we formalize this concern and lay out the identifying assumptions required to draw valid conclusions about the role of assortative matching in the firm-IGE.

5.1 Estimating assortative matching

This section examines how to estimate the role of assortative matching in the firm-IGE using the worker component of earnings, $\widehat{\alpha}_i$, as a proxy for skill (Gerard et al., 2021; Engzell and Wilmers, 2024). Following this approach, we test whether high-SES individuals are more likely to work in better-paying firms compared to low-SES individuals with similar $\widehat{\alpha}_i$. Consistent with our empirical strategy in Section 4, we implement this by estimating the firm-IGE while controlling for $\widehat{\alpha}_i$ in the following OLS regression:

$$\widehat{\psi}_i = \beta_0^{\psi|\alpha,Y_f} + \beta_\alpha^{\psi|\alpha,Y_f} \cdot \widehat{\alpha}_i + \beta_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{\psi|\alpha,Y_f}, \tag{9}$$

where $\beta_{Y_f}^{\psi|\alpha,Y_f}$ is the parameter of interest. Controlling for $\widehat{\alpha}_i$ absorbs the portion of the firm-IGE explained by skill-based sorting, while any remaining variation reflects other factors, such as social networks or discrimination. If the inclusion of $\widehat{\alpha}_i$ substantially reduces the firm-IGE estimate, this suggests that assortative matching on skills accounts for a large share of the observed relationship.

Table 4, Column (1), reports OLS estimates of the baseline firm-IGE, following Regression (5), while Column (2) adds $\widehat{\alpha}_i$ as a control, as in Regression (9). The firm-IGE declines from 0.061 to 0.029 after controlling for $\widehat{\alpha}_i$, implying that assortative matching explains roughly half of the firm-IGE. Our findings closely align with Forsberg et al. (2024), who use a similar strategy but also include direct measures of cognitive and non-cognitive skills from military enlistment tests. Using Swedish data, they likewise conclude that approximately 50 percent of the firm-IGE can be attributed to differences in skill.

In the next section, we formally discuss the assumptions required to interpret the results in Table 4 as a measure of the contribution of assortative matching to the firm-IGE.

Table 4—Firm-IGE controlling for the individual component of earnings

Dependent variable:	Firm earnings premium $(\widehat{\psi}_i)$	
	(1)	(2)
$\overline{logY_{f(i)}}$	0.061	0.029
	(0.001)	(0.001)
Control		$\widehat{\alpha}$
Observations	295,912	295,912

Notes: This table shows estimates of the firm-IGE controlling for the individual component of earnings. Standard errors are in parentheses. The firm-IGE is the elasticity of children's firm component of earnings to their father's earnings $\left(\overline{\log Y_{f(i)}}\right)$. Individual (α_i) and firm $(\overline{\psi}_i)$ components are AKM fixed effects (see Section 3.3). Column (1) presents the firm-IGE without controls. Column (2) control for children's individual component of earnings (α_i). Fathers' earnings are calculated as the average yearly earnings between 1986 and 1991 and are the residuals from a regression of log earnings on age, age-squared, and year fixed effects.

5.2 When can we use worker AKM effects as a proxy for skill?

Econometric Model

We now present a simple econometric framework that formally defines assortative matching and its contribution to the firm-IGE. Let workers be characterized by *human capital* H_i, which measures their skill. Earnings, Y_i, are composed of within-firm differences , α and firm pay premia, ψ:

$$Y_i = \alpha_i + \psi_i, \tag{10}$$

and both components are influenced by human capital:

$$\begin{aligned} \psi_i &= \theta^{\psi} \cdot H_i + \xi_i^{\psi}, \\ \alpha_i &= \theta^{\alpha} \cdot H_i + \xi_i^{\alpha}, \end{aligned} \tag{11}$$

where θ^{ψ} and θ^{α} capture the causal effect of skill on each earnings component. Structural residuals ξ_i^{ψ} and ξ_i^{α} capture remaining variation in earnings due to factors beyond skill, such as social networks, cultural fit, or discrimination.

Under this framework, the firm-IGE can be decomposed as follows (see Appendix H.1 for derivation):

$$\underbrace{\beta^{\psi|Y_f}}_{\text{firm-IGE}} = \underbrace{\theta^{\psi} \cdot \beta^{H|Y_f}}_{\text{assortative matching}} + \underbrace{\beta^{\xi^{\psi}|Y_f}}_{\text{residual SES effect}}, \tag{12}$$

where $\beta^{H|Y_f}$ and $\beta^{\xi^\psi|Y_f}$ are coefficients from the following OLS regressions:

$$
\begin{aligned}
H_i &= \beta^{H|Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{H|Y_f}, \\
\xi_i^\psi &= \beta^{\xi^\psi|Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{\xi^\psi|Y_f}.
\end{aligned}
\tag{13}
$$

Equation (12) highlights two distinct channels. First, high-SES individuals might have higher skills, which gives them access to better firms (assortative matching). Second, they may work at better firms even conditional on skill, due to other advantages (residual SES effect). We define the *AM-share* as the proportion of the firm-IGE explained by assortative matching:

$$
\overline{AM} \equiv \frac{\text{assortative matching}}{\text{firm-IGE}} = \frac{\theta^\psi \cdot \beta^{H|Y_f}}{\theta^\psi \cdot \beta^{H|Y_f} + \beta^{\xi^\psi|Y_f}}. \tag{14}
$$

In practice, computing $\overline{AM}$ is challenging. As shown in Equation (14), estimating $\overline{AM}$ requires knowledge of the parameters in Equations (11) and (13), both of which depend on H_i. Since H_i is not observed, these equations cannot be directly estimated from the data. Below, we discuss the assumptions under which $\overline{AM}$ can be identified using observable variables.

Estimating $\overline{AM}$: Necessary Assumptions

Recovering $\overline{AM}$ from observable data requires three key assumptions.

First, since $\widehat{\alpha}_i$ enters as a regressor in Equation (9), any measurement error in $\widehat{\alpha}_i$ would lead to attenuation bias. We therefore must assume no measurement error, that is, $\widehat{\alpha}_i = \alpha_i$.

Second, we must assume that α_i is a valid proxy for skill. It is not enough to assume that the residual component of α_i, ξ_i^α, is independent of father's income. Because $\widehat{\alpha}_i$ is included as a control in Equation (9), we would also need ξ_i^α to be uncorrelated with $\widehat{\alpha}_i$. But this is inconsistent with the model: by construction, $\widehat{\alpha}_i$ mechanically reflects ξ_i^α. In effect, including $\widehat{\alpha}_i$ as a covariate creates a "bad control" problem unless we impose the stronger condition that α_i is fully determined by skill. For this reason, we assume $\xi_i^\alpha = 0$.

Third, identifying the causal effect of H_i on ψ_i, denoted θ^ψ, is complicated by the potential correlation between H_i and other determinants of ψ_i, such as social networks or discrimination. This correlation would induce omitted variable bias. To address this concern, we assume that, conditional on parental income, H_i is independent of all other factors affecting ψ_i. Formally, we assume that the residuals $\epsilon_i^{H|Y_f}$ and $\epsilon_i^{\xi^\psi|Y_f}$ from regressions (13) are independent.

Under these assumptions, $\overline{AM}$ can be estimated by comparing the firm-IGE from two regressions: a baseline model with no controls (Equation (5)) and a model that includes $\widehat{\alpha}_i$ as a control (Equation (9)). The following proposition formalizes this result.

Proposition 1 *Assume: (i) $\widehat{\alpha}_i$ is estimated without error; (ii) $\xi_i^\alpha = 0$; and (iii) $\epsilon^{H|Y_f}$ and $\epsilon^{\xi^\psi|Y_f}$ are independent. Then:*

$$\overline{AM} = 1 - \frac{\beta_{Y_f}^{\psi|\alpha,Y_f}}{\beta^{\psi|Y_f}},$$

where $\beta^{\psi|Y_f}$ is the firm-IGE from Regression (5) and $\beta_{Y_f}^{\psi|\alpha,Y_f}$ is the firm-IGE controlling for $\widehat{\alpha}_i$ from Regression (9).

Proof: *See Appendix H.2.*

Results and discussion

Using Proposition 1 and the results in Table 4, we estimate $\overline{AM} = 52\%$, implying that roughly half of the firm-IGE can be attributed to assortative matching. This suggests that high-SES individuals are employed at firms that pay substantially higher wage premia, even relative to equally skilled low-SES workers. Nevertheless, the assumptions required for identification are strong.

First, measurement error is a well-documented concern in AKM estimates (Bonhomme et al., 2019, 2022; Kline et al., 2020). Following Bonhomme et al. (2019), we group firms using a k-means algorithm to reduce noise; however, some measurement error likely remains. Thus, the assumption of no measurement error does not hold exactly.

Second, social networks influence not only the sorting of workers across firms but also their outcomes within firms. Stinson and Wignall (2018) and Staiger (2023) show that having a parent employed at the same firm is associated with sizable earnings gains—most of which stem from sorting into higher-paying firms, though some also result from higher within-firm earnings. Similarly, San (2022) finds that in Israel, 84 percent of the wage gains associated with weak social connections arise through job mobility. While this evidence suggests that social networks affect labor market outcomes primarily through firm sorting (ψ_i), the assumption that α_i is determined *exclusively* by skill is not empirically supported.

Third, it is unlikely that skills are uncorrelated with other factors that affect ψ_i, particularly social networks. Education, for example, is a key determinant of skill and also shapes social networks in ways that have important labor market implications (Zimmerman, 2019; Chetty et al., 2022b; Michelman et al., 2022).

The main takeaway is that assessing the contribution of assortative matching to the firm-IGE is empirically challenging without invoking strong assumptions to address unobserved skill variation. All three assumptions underlying Proposition 1 are inconsistent with the empirical evidence if taken literally, though they may still provide a useful first-order approximation.

6 Conclusion

This paper quantifies the role of firms in intergenerational mobility using administrative data from Israel. We decompose the intergenerational elasticity of earnings into firm and individual components, showing that firm sorting accounts for 23 percent of the IGE. This implies that the allocation of workers across firms is an important channel through which parental background shapes labor market outcomes.

Our results suggest that both skill-based and non-skill-based factors contribute to this sorting. While differences in education explain a substantial share of the firm-IGE, other factors less directly related to skill—such as demographic background and residential location—also play an important role. Specifically, we find suggestive evidence that roughly half of the firm-IGE cannot be explained by skill differences alone.

We further show that sectoral sorting is the dominant margin through which firm sorting operates: nearly half of the firm-IGE is explained by differences in sector of employment. This highlights the importance of understanding how access to high-paying sectors is shaped by family background, an issue that merits further research. In particular, future work should investigate what barriers—whether institutional, informational, or network-based—prevent equally skilled individuals from different family backgrounds from accessing the same sectors.

References

Abowd, John, Francis Kramarz, and David Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Arellano-Bover, Jaime and Shmuel San, "The Role of Firms in the Assimilation of Immigrants," *SSRN Electronic Journal*, 2023.

Ariel, Barak, Ilanit Tobby-Alimi, Irit Cohen, Mazal Ben Ezra, Yafa Cohen, and Gabriela Sosinski, "Ethnic and Racial Employment Discrimination in Low-Wage and High-Wage Markets: Randomized Controlled Trials Using Correspondence Tests in Israel," *The Law & Ethics of Human Rights*, May 2015, *9* (1), 113–139.

Arlozorov, Merav, "The Proportion of Arab Businesses That Do Not Report to the Income Tax Is the Same as the Proportion of Jewish Businesses," *TheMarker*, May 2012.

Barrios-Fernandez, Andres, Christopher Neilson, and Seth Zimmerman, "Elite Universities and the Intergenerational Transmission of Human and Social Capital," 2021, p. 96.

Becker, Gary S. and Nigel Tomes, "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *Journal of Political Economy*, December 1979, *87* (6), 1153–1189.

_ and _ , "Human Capital and the Rise and Fall of Families," *Journal of Labor Economics*, 1986, *4* (3), S1–S39.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "Who Becomes an Inventor in America? The Importance of Exposure to Innovation*," *The Quarterly Journal of Economics*, May 2019, *134* (2), 647–713.

Bertrand, Marianne and Sendhil Mullainathan, "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination," *American Economic Review*, September 2004, *94* (4), 991–1013.

Black, Sandra and Paul Devereux, "Recent Developments in Intergenerational Mobility," in "Handbook of Labor Economics," Vol. Volume 4b, Elsevier, 2011, pp. 1487–1541.

Black, Sandra E., Paul J. Devereux, Petter Lundborg, and Kaveh Majlesi, "Poor Little Rich Kids? The Role of Nature versus Nurture in Wealth and Other Economic Outcomes and Behaviours," *The Review of Economic Studies*, July 2020, *87* (4), 1683–1725.

Bonhomme, Stephane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler, "How Much Should We Trust Estimates of Firm Effects and Worker Sorting?," *Journal of Labor Economics*, March 2022.

_ , Thibaut Lamadon, and Elena Manresa, "A Distributional Framework for Matched Employer Employee Data," *Econometrica*, 2019, *87* (3), 699–739.

Bratberg, Espen, Jonathan Davis, Bhashkar Mazumder, Martin Nybom, Daniel D. Schnitzlein, and Kjell Vaage, "A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the US," *The Scandinavian Journal of Economics*, 2017, *119* (1), 72–101.

Calvó-Armengol, Antoni and Matthew O. Jackson, "The Effects of Social Networks on Employment and Inequality," *American Economic Review*, June 2004, *94* (3), 426–454.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, January 2018, *36* (S1), S13–S70.

_ , **Jesse Rothstein, and Moises Yi**, "Location, Location, Location," *American Economic Journal: Applied Economics*, January 2025, *17* (1), 297–336.

_ , **Jörg Heining, and Patrick Kline**, "Workplace Heterogeneity and the Rise of West German Wage Inequality*," *The Quarterly Journal of Economics*, August 2013, *128* (3), 967–1015.

Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt, "Social Capital I: Measurement and Associations with Economic Mobility," *Nature*, August 2022, *608* (7921), 108–121.

_ , **and** _ , "Social Capital II: Determinants of Economic Connectedness," *Nature*, August 2022, pp. 1–13.

_ , **Nathaniel Hendren, and Lawrence F. Katz**, "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment," *American Economic Review*, 2016, *106* (4), 855–902.

_ , _ , **Maggie R. Jones, and Sonya R. Porter**, "Race and Economic Opportunity in the United States: An Intergenerational Perspective," *The Quarterly Journal of Economics*, May 2020, *135* (2), 711–783.

Corak, Miles and Patrizio Piraino, "The Intergenerational Transmission of Employers," *Journal of Labor Economics*, 2011, *29* (1), 37–68.

David, Dan-Ben and Haim Bleikh, "Gaping Gaps: Income Inequality in Israel," September 2014.

Eliason, Marcus, Lena Hensvik, Francis Kramarz, and Oskar Nordström Skans, "Social Connections and the Sorting of Workers to Firms," *Journal of Econometrics*, April 2023, *233* (2), 468–506.

Engzell, Per and Nathan Wilmers, "Firms and the Intergenerational Transmission of Labor Market Advantage," Working Paper, SocArXiv 2024.

Faccini, Renato, "Reassessing Labour Market Reforms: Temporary Contracts as a Screening Device," *The Economic Journal*, March 2014, *124* (575), 167–200.

Forsberg, Erika, Martin Nybom, and Jan Stuhler, "Labor-Market Drivers of Intergenerational Earnings Persistence," *Working Papers*, 2024.

Gelbach, Jonah B., "When Do Covariates Matter? And Which Ones, and How Much?," *Journal of Labor Economics*, April 2016, *34* (2), 509–543.

Gerard, François, Lorenzo Lagos, Edson Severnini, and David Card, "Assortative Matching or Exclusionary Hiring? The Impact of Employment and Pay Policies on Racial Wage Differences in Brazil," *The American Economic Review*, 2021, *111* (10), 40.

Gyomai, György and Peter van de Ven, "The Non-Observed Economy in the System of National Accounts," Technical Report, OECD June 2014.

Heckman, James J. and Stefano Mosso, "The Economics of Human Development and Social Mobility," *Annual Review of Economics*, August 2014, *6* (1), 689–733.

Heler, Oren, "Intergenerational Mobility in Israel." PhD dissertation, Hebrew University, Jerusalem 2017.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer, "Worker Beliefs About Outside Options," Working Paper 29623, National Bureau of Economic Research December 2021.

Kline, Patrick, Evan K Rose, and Christopher R Walters, "Systemic Discrimination Among Large U.S. Employers*," *The Quarterly Journal of Economics*,

November 2022, *137* (4), 1963–2036.
—, **Raffaele Saggio, and Mikkel Sølvsten**, "Leave Out Estimation of Variance Components," *Econometrica*, 2020, *88* (5), 1859–1898.
Kramarz, Francis and Oskar Nordström Skans, "When Strong Ties Are Strong: Networks and Youth Labour Market Entry," *The Review of Economic Studies*, July 2014, *81* (3), 1164–1200.
Lee, Sang Yoon (Tim) and Ananth Seshadri, "On the Intergenerational Transmission of Economic Status," *Journal of Political Economy*, April 2019, *127* (2), 855–921.
Magruder, Jeremy R., "Intergenerational Networks, Unemployment, and Persistent Inequality in South Africa," *American Economic Journal: Applied Economics*, January 2010, *2* (1), 62–85.
Mazumder, Bhashkar, "Estimating the Intergenerational Elasticity and Rank Association in the United States: Overcoming the Current Limitations of Tax Data," in "Inequality: Causes and Consequences," Vol. 43 of *Research in Labor Economics*, Emerald Group Publishing Limited, January 2016, pp. 83–129.
Mello, Ursula, Martin Nybom, and Jan Stuhler, "A Lifecycle Estimator of Intergenerational Income Mobility," 2022, p. 59.
Michelman, Valerie, Joseph Price, and Seth D Zimmerman, "Old Boys' Clubs and Upward Mobility Among the Educational Elite*," *The Quarterly Journal of Economics*, May 2022, *137* (2), 845–909.
Mogstad, Magne and Gaute Torsvik, "Family Background, Neighborhoods and Intergenerational Mobility," in "Handbook of Family Economics" 2022, p. 74.
Pekkarinen, Tuomas, Roope Uusitalo, and Sari Pekkala Kerr, "School Tracking and Intergenerational Income Mobility: Evidence from the Finnish Comprehensive School Reform," *Journal of Public Economics*, 2009, *93* (7-8), 965–973.
Putnam, Robert D., *Our Kids: The American Dream in Crisis*, reprint edition ed., Simon & Schuster, March 2015.
Restuccia, Diego and Carlos Urrutia, "Intergenerational Persistence of Earnings: The Role of Early and College Education," *American Economic Review*, December 2004, *94* (5), 1354–1378.
Rivera, Lauren A. and András Tilcsik, "Class Advantage, Commitment Penalty: The Gendered Effect of Social Class Signals in an Elite Labor Market," *American Sociological Review*, December 2016, *81* (6), 1097–1131.
Roy, A. D., "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 1951, *3* (2), 135–146.
Rubinstein, Yona and Dror Brenner, "Pride and Prejudice: Using Ethnic-Sounding Names and Inter-Ethnic Marriages to Identify Labour Market Discrimination," *The Review of Economic Studies*, 2014, *81* (1 (286)), 389–425.
San, Shmuel, "Who Works Where and Why: The Role of Social Connections in the Labor Market," 2022.
Sarel, Michael, Itamar Yakir, Asher Meir, Itzik Pinhas, and Amir Feder, "Israel's Path to Economic and Social Prosperity," Technical Report, Kohelet Economic Forum, Israel November 2016.
Sockin, Jason and Aaron Sojourner, "What's the Inside Scoop? Challenges in the Supply and Demand for Information on Employers," *Journal of Labor Economics*, July 2022.
Solon, Gary, "Intergenrational Income Mobility in the United States," *American Economic Review*, 1992.
Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *The Quarterly Journal of Economics*, February 2019, *134* (1), 1–50.

Sorkin, Isaac, "The Role of Firms in Gender Earnings Inequality: Evidence from the United States," *American Economic Review*, May 2017, *107* (5), 384–387.

_ , "Ranking Firms Using Revealed Preference," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1331–1393.

Sousa-Poza, Alfonso and Alexandre Ziegler, "Asymmetric Information about Workers' Productivity as a Cause for Inefficient Long Working Hours," *Labour Economics*, December 2003, *10* (6), 727–747.

Sprung-Keyser, Ben and Sonya Porter, "The Economic Geography of Lifecycle Human Capital Accumulation: The Competing Effects of Labor Markets and Childhood Environments," *Working Papers*, November 2023, (23-54).

Staiger, Matthew, "The Intergenerational Transmission of Employers and the Earnings of Young Workers," 2023.

Stinson, Martha and Christopher Wignall, "Fathers, Children, and the Intergenerational Transmission of Employers," Working Paper, U.S. Census Bureau, Center for Economic Studies March 2018.

Zimmerman, Seth D., "Elite Colleges and Upward Mobility to Top Jobs and Top Incomes," *American Economic Review*, January 2019, *109* (1), 1–47.

Supplemental Appendix

A Appendix Figures and Tables

Table A.1—Types of Higher Education Institution

	% Pop.	% Grads	Father Log Inc	Log Inc	% Stable Job
Type of Higher Ed					
University	15	38	10.99	12.00	81
College	9	23	10.85	11.82	84
Teaching College	4	11	10.76	11.50	86
Engineering School	5	12	10.73	11.76	82
Practical Training	3	7	10.66	11.48	76
Diploma	1	1	10.63	11.58	79
Other	3	8	10.77	11.76	85
None	61		10.49	11.29	57

Notes: This table shows descriptive statistics of each higher education institution type. The first column shows the share of our sample with a degree from each type of institution. The second column shows the same shares, but only among the ones with a degree. The third column shows the average log earnings of the graduates' fathers between 1986 and 1991. The fourth column shows the average log earnings of the graduates themselves between 2010 and 2015. The fifth column shows the share of the graduates that held a stable job—as defined in Section 2.2—at least once between 2010 and 2015.

Table A.2—– Individual and firm components of the IGE: Robustness

Panel A: Expanded birth cohorts			
$\overline{logY_{f(i)}}$	0.227	0.177	0.050
	(0.001)	(0.001)	(0.000)
Share of IGE	1.00	0.78	0.22
	.	(0.007)	(0.002)
Observations	1,351,577	1,351,577	1,351,577
Panel B: Temporary jobs			
$\overline{logY_{f(i)}}$	0.260	0.191	0.069
	(0.002)	(0.002)	(0.001)
Share of IGE	1.00	0.73	0.27
	.	(0.009)	(0.003)
Observations	737,038	737,038	737,038
Panel C: Non-employed fathers			
$\overline{logY_{f(i)}}$	0.190	0.140	0.050
	(0.001)	(0.001)	(0.000)
Share of IGE	1.00	0.74	0.26
	.	(0.006)	(0.002)
Observations	1,045,819	1,045,819	1,045,819

Notes: This table reports robustness checks for the decomposition of the intergenerational earnings elasticity (IGE) into individual and firm components, as described in Equation (6). Baseline estimates are presented in Table 3. Panel A expands the analysis to include birth cohorts from 1955 to 1990. Panel B includes all individuals who were ever employed at a firm in the AKM sample, even if only for a single month. Panel C includes individuals whose fathers reported zero earnings during the observed period. See Section 3.4 for further details on each specification.

B Why Father Earnings?

In this project, we use parental earnings as a proxy for children's socioeconomic background (SES). In the setting we study, fathers' earnings is a better proxy than mothers' or household earnings. Female labor force participation in the 1980s in Israel—when we measure parental earnings—was below 50%. In this context, having a household with two earners is often a sign of low SES. Indeed, Appendix Table B.1 shows that fathers' earnings are more correlated with children's earnings than mothers' or household earnings.

Note that using fathers' earnings as a proxy for SES is a common practice in the literature. For a review, see Black and Devereux (2011).

Table B.1—Parental earnings rank vs child earnings rank

	Family earnings Measure		
	Household	Father	Mother
Coefficient	.23	.246	.093
	(.003)	(.003)	(.003)
Obs	156555	156555	156555
R^2	.049	.055	.008

Notes: This table presents the rank correlation between children's earnings rank and their household, fathers' and mothers' earning ranks. Both parents' and childrens' earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

C Validating the AKM decomposition

C.1 Specification test

In this appendix, we test the restrictions imposed by the AKM framework. In particular, the restriction that the log-linear structure of earnings and that the job moving probability is uncorrelated with the error term. We test this restrictions with the approach proposed by Sorkin (2018).

From Equation (2), we have:

$$\log Y_{i,t} = \alpha_i + \psi_{J[i,t]} + x'_{i,t}\beta^x + r_{i,t} \ ,$$
$$\log Y_{i,t+1} = \alpha_i + \psi_{J[i,t+1]} + x'_{i,t+1}\beta^x + r_{i,t+1} \ , \ .$$

Taking first differences:

$$\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta^x = \Delta\psi_{J[i,t]} + \Delta r_{i,t}$$

We now take expectations, conditional on moving:

$$\mathbb{E}\big[\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta^x | M_{i,t} = 1\big] = \Delta\mathbb{E}\big[\psi_{J[i,t]} | M_{i,t} = 1\big] + \mathbb{E}\big[\Delta r_{i,t} | M_{i,t} = 1\big]$$

where $M_{i,t}$ indicates whether worker i changed firms in year t:

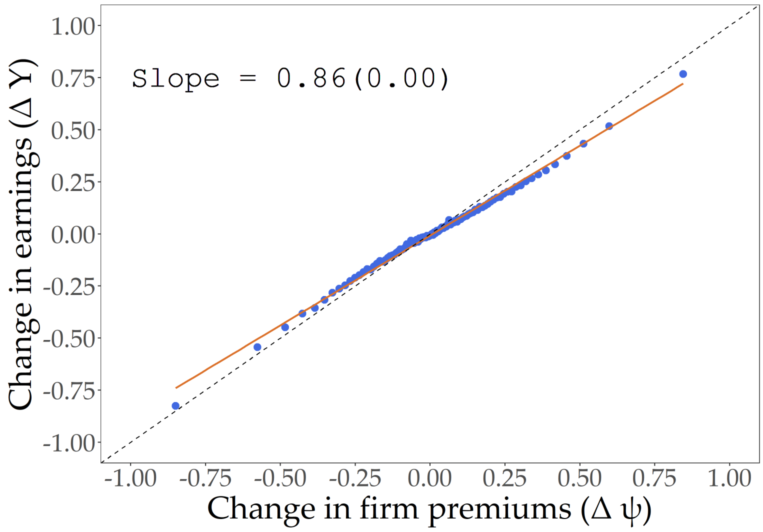
$$M_{i,t} \equiv \mathbb{1}\big\{J(i,t) \neq J(i,t+1) \ \& \ J(i,t) \neq Non\ Emp \ \& \ J(i,t+1) \neq Non\ Emp\big\}.$$

The key assumption to estimate Equation (2) by OLS is that the probability of moving is uncorrelated with the error term, that is $\mathbb{E}\big[\Delta r_{i,t} | M_{i,t} = 1\big] = 0$. Under this assumption:

$$\mathbb{E}\big[\Delta \log Y_{i,t} - \Delta x'_{i,t}\beta^x | M_{i,t} = 1\big] = \Delta\mathbb{E}\big[\psi_{J[i,t]} | M_{i,t} = 1\big]$$

We take this restriction to the data by focusing on job switchers and comparing their residualized earnings change against their firm-effect change. The results are in Figure C.1. The solid blue line plots the best-fitting line. The dashed line plots the 45 degree line. We find that earnings changes closely follow changes in firm premiums, showing that the AKM framework fits the data well.

Figure C.1—Earnings Change Corresponds to Firm Fixed Effect Change



Notes: This figure shows how the magnitude of earnings changes relate to the change in firm-level pay for employer-to-employer transitions who switch annual stable jobs. The earnings are the residualized annualized earnings in the last year at the previous job and in the first year at the new job. We bin the job changers into equally sized bins on the basis of the change in the firm effects. The circles plot the bin means. The solid line plots the best-fitting line estimated based on the micro-data. The dashed line plots the 45 degree line.

C.2 Firm premium estimates by socioeconomic background

In our main analysis, we use firm premiums estimated using all workers, not only the ones in IGM sample. A potential concern is that firm premiums estimated with the full sample are not representative for the IGM sample. In this Appendix, we show the correlation between firm premiums estimated in different sub-samples. The results are in Table C.1.

We see that the correlation between premiums estimated with the full sample and the IGM sample is 0.88. This is very similar to the correlation between premiums estimated with the full sample and with a sample with the same number of observations as the IGM sample (0.90). This indicates that the underlying premiums are the same in the full and the IGM sample, and the observed differences are due to measurement error.

A related concern is that, within the IGM sample, premiums are different for high- and low-SES workers. Table C.1 reports the correlations between premiums estimated with each of these samples and the ones estimated with the full sample. As a comparison, we also show results for premiums estimated with a 50% random sample of the IGM sample. We see that these three correlations are very similar to each other. Once again, this indicates that the underlying premiums faced by this groups are the same, and the observed differences are due to measurement error.

Table C.1—Correlation between firm premiums in different samples

	Full	IGM	Random (Full)	Random (IGM)	Low-SES	High-SES
Full	1.00					
IGM	0.88	1.00				
Random (Full)	0.90	0.77	1.00			
Random (IGM)	0.83	0.92	0.75	1.00		
Low-SES	0.78	0.90	0.72	0.81	1.00	
High-SES	0.84	0.95	0.77	0.88	0.71	1.00

Notes: This table shows the correlations between firm premiums (ψ) estimated in different samples. Firm premiums are defined in Equation (2). "Full" includes all workers with a stable job in the Israeli labor market in 2010-2015. "IGM" only includes the ones that have fathers with positive earnings. "Random (Full)" is a random sub-sample of the full sample with the same size as the IGM sample. "Random (IGM)" is a 50% random sample of the IGM sample. "High-SES" and "Low-SES" are, respectively, workers above and below the median father earnings in the IGM sample.

D Proof of Equation (6):

From the definition of $\overline{\log Y}_i$, we have:

$$\overline{\log Y}_i \equiv \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\log\widetilde{Y}_{it} = \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\left\{\widehat{\alpha}_i + \psi_{J(i,t)} + r_{i,t}\right\} = \widehat{\alpha}_i + \widehat{\psi}_i. \tag{D.1}$$

Above, we used that $\sum_{t\in\mathcal{T}_i} r_{i,t} = 0$ because $r_{i,t}$ is the residual of an OLS regression with individual fixed effects. Moreover, by definition, $\beta^{IGE} \equiv \frac{Cov\left(\overline{logY_i},\overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)}$.

Replacing Equation (D.1) into this definition:

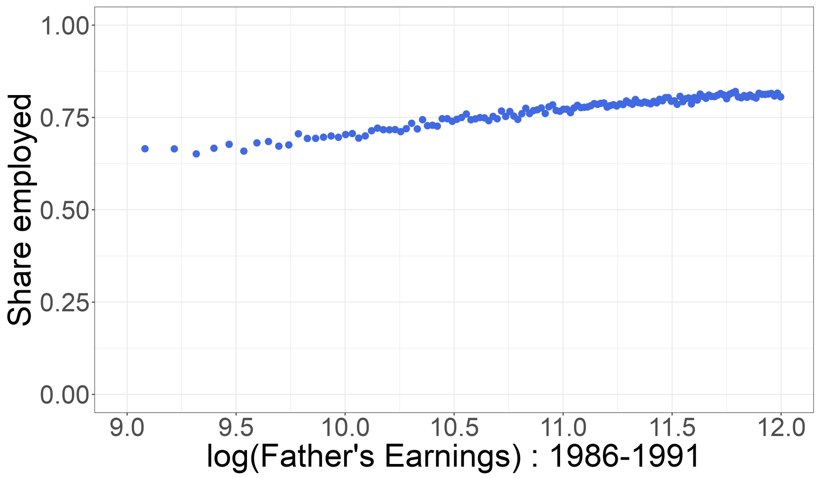
$$\beta^{IGE} = \frac{Cov\left(\widehat{\alpha}_i + \widehat{\psi}_i, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} = \frac{Cov\left(\widehat{\alpha}_i, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} + \frac{Cov\left(\widehat{\psi}_i, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} = \beta^{\alpha|Y_f} + \beta^{\psi|Y_f}$$

$\square$

E Non-employment

A common limitation in research estimating intergenerational elasticities—including the IGE—is the exclusion of non-employed individuals, since $\log(0)$ is undefined. This exclusion is potentially problematic because non-employment is not randomly distributed: as shown in Figure E.1, individuals from lower-SES backgrounds are more likely to be non-employed.

Figure E.1—Employment Rates by Father's earnings



Notes: The figure plots the share of employed children by father's log earnings. "Employed" is defined as holding a stable job for at least one year during the sample period.

To address this issue, we extend the IGE framework to incorporate non-employment. Let $\overline{Y}_i = \mathbb{E}[Y_{it} \mid i]$ denote the average earnings of individual i over the observation window, and $\overline{Y}_{f(i)}$ the analogous measure for their father. Rather than modeling $\mathbb{E}[\log \overline{Y}_i \mid \overline{Y}_{f(i)}]$, which is undefined when $\overline{Y}_i = 0$, we consider the log of expected earnings: $\log \mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}]$. Since the expectation of earnings is strictly positive once we average over a given father earnings level, this formulation includes all individuals, regardless of employment status.

We define the extended IGE as:

$$\log \mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}] = \beta^{\widetilde{IGE}} \cdot \overline{\log Y}_{f(i)} + \text{residual}.$$

E.1 Decomposing Expected Earnings

We can decompose expected earnings into employment probability times expected earnings conditional on employment:

$$\mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}] = P(\text{employed}_i \mid \overline{Y}_{f(i)}) \cdot \mathbb{E}\left[\overline{Y}_i \mid \overline{Y}_{f(i)}, \text{employed}_i = 1\right],$$

where "employed" indicates whether the individual holds a stable job for at least one year within our sample period.

For employed individuals, residualized earnings follow the AKM decomposition:[20]

$$\log Y_{it} = \alpha_i + \psi_{J(i,t)} + r_{it}.$$

Therefore, using the law of iterated expectations, we write:

$$\begin{aligned}
\mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}] &= P(\text{employed}_i \mid \overline{Y}_{f(i)}) \cdot \mathbb{E}\left[\mathbb{E}[Y_{it} \mid i] \mid \overline{Y}_{f(i)}, \text{employed}_i = 1\right] \\
&= P(\text{employed}_i \mid \overline{Y}_{f(i)}) \cdot \mathbb{E}\left[\mathbb{E}[e^{\alpha_i + \psi_{J(i,t)} + r_{it}} \mid i] \mid \overline{Y}_{f(i)}, \text{employed}_i = 1\right] \\
&= P(\text{employed}_i \mid \overline{Y}_{f(i)}) \cdot \mathbb{E}[e^{\alpha_i + \psi_{J(i,t)} + r_{it}} \mid \overline{Y}_{f(i)}, \text{employed}_i = 1].
\end{aligned}$$

Taking logs:

$$\log \mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}] = \log P(\text{employed}_i \mid \overline{Y}_{f(i)}) + \log \mathbb{E}[e^{\alpha_i + \psi_{J(i,t)} + r_{it}} \mid \overline{Y}_{f(i)}, \text{employed}_i = 1].$$

We approximate the second term using a log-linear expansion:

$$\log \mathbb{E}[e^{\alpha_i + \psi_{J(i,t)} + r_{it}} \mid \overline{Y}_{f(i)}] \approx \mathbb{E}[\alpha_i \mid \overline{Y}_{f(i)}] + \mathbb{E}[\psi_{J(i,t)} \mid \overline{Y}_{f(i)}] + \mathbb{E}[r_{it} \mid \overline{Y}_{f(i)}].$$

This approximation becomes more accurate as the conditional variance of earnings components decreases. Conditioning on $\overline{Y}_{f(i)}$ reduces the dispersion of α_i, $\psi_{J(i,t)}$, and r_{it}, making the linearization more reliable. Still, some approximation error remains.

Additionally, using the law of iterated expectations, we have that:

$$\mathbb{E}[\psi_J(i,t) \mid \overline{Y}_{f(i)}] = \mathbb{E}[\mathbb{E}[\psi_J(i,t) | i] \mid \overline{Y}_{f(i)}] = \mathbb{E}[\overline{\psi}_i \mid \overline{Y}_{f(i)}],$$

[20] The full AKM model includes covariates, $x'_{it}\beta^x$, which we omit here because we are interested in residualized earnings, after removing age effects.

and that:

$$\mathbb{E}[r_{it} \mid \overline{Y}_{f(i)}] = \mathbb{E}[\mathbb{E}[r_{it}|i] \mid \overline{Y}_{f(i)}] = \mathbb{E}[0 \mid \overline{Y}_{f(i)}] = 0.$$

Combining terms yields the decomposition:

$$\log \mathbb{E}[\overline{Y}_i \mid \overline{Y}_{f(i)}] \approx \log P(\text{employed}_i \mid \overline{Y}_{f(i)}) + \mathbb{E}[\alpha_i \mid \overline{Y}_{f(i)}] + \mathbb{E}[\overline{\psi}_i \mid \overline{Y}_{f(i)}]. \tag{E.1}$$

E.2 Decomposing the Extended IGE

We estimate the following regressions:

$$\begin{aligned} \log P(\text{employed}_i \mid \overline{Y}_{f(i)}) &= \beta^W \cdot \overline{\log Y}_{f(i)} + \text{residual}, \\ \mathbb{E}[\alpha_i \mid \overline{Y}_{f(i)}] &= \beta^\alpha \cdot \overline{\log Y}_{f(i)} + \text{residual}, \\ \mathbb{E}[\overline{\psi}_i \mid \overline{Y}_{f(i)}] &= \beta^\psi \cdot \overline{\log Y}_{f(i)} + \text{residual}. \end{aligned}$$

Using Equation E.1 and following the same steps as in Appendix D, we can show that the extended intergenerational elasticity can be expressed as:

$$\beta^{\widetilde{IGE}} \approx \beta^W + \beta^\alpha + \beta^\psi. \tag{E.2}$$

Using Equation (E.2), we find that employment (β^W) accounts for 25% of the IGE, while the firm (β^ψ) and individual (β^α) components account for 17% and 58%, respectively. The interpretation of the participation margin depends on its underlying drivers. If low-SES individuals are less likely to work due to limited access to certain firms, then firm effects may be larger than our baseline estimates suggest. Conversely, if non-employment reflects skill deficits or preferences, the role of firms may be overstated. In this paper, we focus on employed individuals and leave the extensive-margin interpretation for future research.

F Sector Persistence

A potential mechanism behind the firm-IGE is sector persistence. Indeed, individuals are 27% more likely than chance to work in the same sector as their fathers. To further investigate this pattern, we perform an AKM decomposition of earnings using sector fixed effect, instead of firm fixed effects:

$$\log Y_{i,t} = \alpha_i^S + \psi_{J(i,t)}^S + x_{it}'\beta^x + r_{i,t}^S \ ,$$

where ψ_i^S are sector-level earnings premium. We estimate this regression separately for fathers and children. Since there are much fewer sector than firms, the connected set in this specification includes virtually all workers in the IGM sample (defined in Table 1) in both generations.

We then calculate the average earnings premium of each worker $\left(\widehat{\psi}^S\right)$ regress it against their father log earnings. We find an elasticty of 0.028, which we name sector-IGE. Note that the sector-IGE is half of the firm-IGE, indicating that the firm-IGE is, to a large extend, driven high-SES children work in high-paying sectors.

Finally, we investigate the role of fathers' sectors in the sector-IGE. We perform the decomposition:

$$\overbrace{\frac{Cov(\overline{logY_{f(i)}}, \widehat{\psi}_i^S)}{Var(\overline{logY_{f(i)}})}}^{\text{Sector-IGE}} = \overbrace{\frac{Cov(\widehat{\alpha}_{f(i)}^S, \widehat{\psi}_i^S)}{Var(\overline{logY_{f(i)}})}}^{\text{individual-to-sector}} + \overbrace{\frac{Cov(\widehat{\psi}_{f(i)}^S, \widehat{\psi}_i^S)}{Var(\overline{logY_{f(i)}})}}^{\text{sector-to-sector}} + \overbrace{\frac{Cov(\widehat{r}_{f(i)}^S, \widehat{\psi}_i^S)}{Var(\overline{logY_{f(i)}})}}^{\text{residual-to-sector}}$$

We find that the sector-to-sector component accounts for only 9% of the sector-IGE. That is, children of high-earnings parents tend to work in high-earnings- premium sectors, even if the father himself does not.

G Labor market and residential segregation

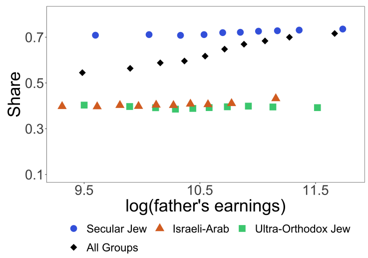
In this appendix, we examine the relationship between parental income and the ethnicity of coworkers and neighbors. We focus on the share of Secular Jews as they represent the group with the highest earnings.

Figure G.1 presents the results of this analysis. We find a strong positive correlation between parental income and a higher share of Secular Jews among coworkers (Panel (a)). However, this correlation disappears within demographic groups. In other words, Secular Jews are more likely than Arabs to work with other Secular Jews, while high-SES Arabs are not more likely than low-SES Arabs to work with Secular Jews. Similar patterns are observed for residential segregation at neighborhood level (Panel (c)). Moreover, we see much less segregation at commuting zone level (Panel (d)) than at neighborhood level, consistent with the results discussed above.

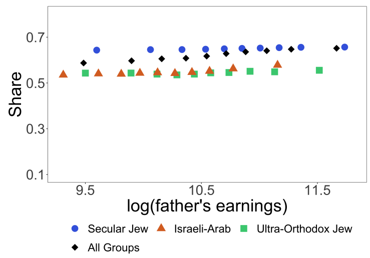
Figure G.1—Labor-Market and Residential Segregation

Labor Market

(a) Share Sec. Jews in Firm

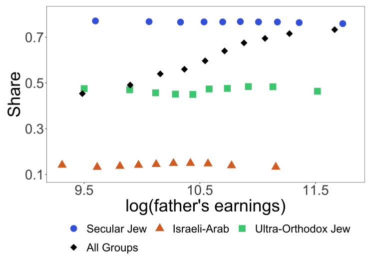


(b) Share Sec. Jews in Sector

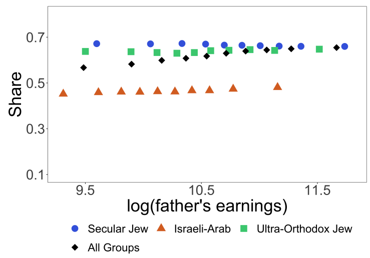


Residence

(c) Share Sec. Jews in Neighborhood



(d) Share Sec. Jews in Comm. Zone



Notes: Panel (a) shows the share of Secular Jewish coworkers in one's firm as a function of her father's earnings. Panel (b) shows the share of Secular Jewish workers in one's sector as a function of her father's earnings. "Sector" is a 3-digit sector and there are 420 unique sectors. Panel (c) shows the share of Secular Jewish neighbors as a function of the individual's father's earnings. Panel (d) shows the share of individuals in one's commuting zone who are Secular Jewish as a function of their father's earnings. In all panels, father's earnings the average yearly earnings between 1986 and 1991 and are residuals from a regression of log earnings on age, age-squared, and year fixed effects.

One potential explanation for this phenomenon is assortative matching, whereby Secular Jews tend to work together and reside nearby because they posses higher skills, and therefore are richer, on average. However, the data do not support this explanation. If segregation were driven solely by assortative matching, we would expect the demographic composition of neighbors and coworkers to be correlated with parental income even after accounting for the worker's own demographic group, which is not what we see in Figure G.1. Moreover, differences in education do not explain segregation. Israeli-Arabs and Ultra-Orthodox Jews have, respectivelly, 35% and 37% fewer Secular Jew coworkers than Secular Jews do. Controlling for education[21] reduces these differences only modestly, to 33% and 34%. These results indicate that demographic groups are not segregated based on vertically differentiated skills, but horizontal differentiation could still play an important role. If this is the case, we should see these horizontally differentiate workers self-selecting into different sectors (Roy, 1951). However, this is not consistent with the modest segregation we find at sector level (see Panel (b)).

In sum, these patterns suggest that factors other than skill are pivotal in determining the allocation of workers to firms.

[21]We use here the most granular measure of education available, which includes a dummy for each type of higher education institution, as described in Appendix Table A.1.

H Assortative matching model: Proofs

H.1 Proof of Equation (12)

We start from the model in Equation (11):

$$\psi_i = \theta^\psi \cdot H_i + \xi_i^\psi.$$

Therefore:

$$\text{Cov}(\psi_i, \overline{\log Y_{f(i)}}) = \theta^\psi \cdot \text{Cov}(H_i, \overline{\log Y_{f(i)}}) + \text{Cov}(\xi_i^\psi, \overline{\log Y_{f(i)}}).$$

Dividing both sides by $\text{Var}(\overline{\log Y_{f(i)}})$ yields Equation (12):

$$\beta^{\psi|Y_f} = \theta^\psi \cdot \beta^{H|Y_f} + \beta^{\xi^\psi|Y_f}.$$

H.2 Proof of Proposition 1

We prove that, under assumptions (i)–(iii), the AM-share can be identified as:

$$\overline{AM} = 1 - \frac{\beta_{Y_f}^{\psi|\alpha,Y_f}}{\beta^{\psi|Y_f}},$$

where $\beta^{\psi|Y_f}$ is the firm-IGE from a regression of ψ_i on $\overline{\log Y_{f(i)}}$, and $\beta_{Y_f}^{\psi|\alpha,Y_f}$ is the coefficient on $\overline{\log Y_{f(i)}}$ from a regression of ψ_i on both $\widehat{\alpha}_i$ and $\overline{\log Y_{f(i)}}$.

Step 1: Express ψ_i as a function of α_i.
Under assumption (ii), $\xi_i^\alpha = 0$, so equation (11) implies $\alpha_i = \theta^\alpha H_i$. Substituting this into the equation for ψ_i yields:

$$\psi_i = \frac{\theta^\psi}{\theta^\alpha}\alpha_i + \xi_i^\psi.$$

Step 2: Substitute the residual decomposition of ξ_i^ψ.
By definition of $\beta^{\xi^\psi|Y_f}$, we can write:

$$\xi_i^\psi = \beta^{\xi^\psi|Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{\xi^\psi|Y_f},$$

where $\epsilon_i^{\xi^\psi|Y_f}$ is the residual from regressing ξ_i^ψ on $\overline{\log Y_{f(i)}}$. Substituting into the expression for ψ_i gives:

$$\psi_i = \frac{\theta^\psi}{\theta^\alpha}\alpha_i + \beta^{\xi^\psi|Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{\xi^\psi|Y_f}. \tag{H.1}$$

Step 3: Identify the coefficient on $\overline{\log Y_{f(i)}}$.

Consider the regression of ψ_i on α_i and $\overline{\log Y_{f(i)}}$. From equation (H.1), the coefficient on $\overline{\log Y_{f(i)}}$ will be equal to $\beta^{\xi^\psi|Y_f}$ if the following two conditions hold:

(a) Cov($\overline{\log Y_{f(i)}}, \epsilon_i^{\xi^\psi|Y_f}$) $= 0$, which holds by construction of the regression residual;

(b) α_i is independent of $\epsilon_i^{\xi^\psi|Y_f}$ conditional on $\overline{\log Y_{f(i)}}$.

To verify (b), note that under assumption (ii), $\alpha_i = \theta^\alpha H_i$. From equation (13), $H_i = \beta^{H|Y_f} \cdot \overline{\log Y_{f(i)}} + \epsilon_i^{H|Y_f}$, so:

$$\alpha_i = \theta^\alpha \beta^{H|Y_f} \cdot \overline{\log Y_{f(i)}} + \theta^\alpha \epsilon_i^{H|Y_f}.$$

Assumption (iii) states that $\epsilon_i^{H|Y_f}$ and $\epsilon_i^{\xi^\psi|Y_f}$ are independent, implying that α_i is conditionally independent of $\epsilon_i^{\xi^\psi|Y_f}$ given $\overline{\log Y_{f(i)}}$. Therefore, condition (b) holds, and we conclude that:

$$\beta_{Y_f}^{\psi|\alpha,Y_f} = \beta^{\xi^\psi|Y_f}.$$

Step 4: Complete the proof.

From equation (12):

$$\beta^{\psi|Y_f} = \theta^\psi \cdot \beta^{H|Y_f} + \beta^{\xi^\psi|Y_f}.$$

Solving for the assortative matching component:

$$\theta^\psi \cdot \beta^{H|Y_f} = \beta^{\psi|Y_f} - \beta^{\xi^\psi|Y_f} = \beta^{\psi|Y_f} - \beta_{Y_f}^{\psi|\alpha,Y_f}.$$

Substituting into equation (14) gives:

$$\overline{AM} = \frac{\theta^\psi \cdot \beta^{H|Y_f}}{\beta^{\psi|Y_f}} = 1 - \frac{\beta_{Y_f}^{\psi|\alpha,Y_f}}{\beta^{\psi|Y_f}}.$$