Quantifying the Role of Firms in Intergenerational Mobility*

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Abstract

We investigate the role of firms in intergenerational mobility by decomposing the intergenerational elasticity of earnings (IGE) into firm-IGE and individual-IGE components using a two-way fixed effect framework. Using data from Israel, we find that the firm component is responsible for 22% of the overall IGE. We then explore potential mechanisms and find that education differences explain a large share of the individual-IGE, while place of residence and demographics are more important for the firm-IGE. Guided by these empirical patterns, we develop a novel method to estimate the role of skill-based sorting and find that it accounts for approximately half of the firm-IGE. Our results provide evidence that the intergenerational transmission of earnings encompasses more than just human capital and highlight the importance of promoting equal access to high-paying firms and reducing labor market segregation in efforts to enhance equality of opportunity.

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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. Indeed, 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, 2020; Staiger, 2021). 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 firm-IGE and individual-IGE components using a two-way fixed effect framework, in the spirit of Abowd et al. (1999) (AKM). The firm-IGE is a result of individuals from higher-income families sorting into better-paying firms, and we find that it is responsible for 22% of the IGE in Israel. We then explore potential mechanisms and show that the individual-IGE is strongly related to education, whereas the firm-IGE can be attributed to demographic segregation in both the labor market and neighborhoods. Finally, we investigate the role of skill-based sorting and find that it accounts for approximately half of the firm-IGE.

In the first part of the paper, we quantify how much firms contribute to the IGE. We construct a population-wide earnings dataset from Israeli National Insurance administrative records. We first use this data to decompose cross-sectional inequality into individual and firm components following Card et al.'s (2013) implementation of the AKM model. We find that both components strongly correlate with parental earnings. Then, we show that the IGE equals the sum of two elasticities: the individual component of earnings to parental earnings (individual-IGE) and the firm component of earnings to parental earnings (firm-IGE). Using this decomposition, we conclude that the firm component is responsible for 22% of the IGE.

In the second part, we delve into the mechanisms underlying the person-IGE and firm-IGE by exploring the relationship between the person- and firm-IGE and various worker characteristics. We focus on factors that have been empirically shown to influence inequality and mobility, namely education (e.g., Restuccia and Urrutia, 2004; Pekkarinen et al., 2009; Zimmerman, 2019), location (e.g., Chetty et al., 2014a, 2016), and demographics (e.g., Chetty et al., 2020; Gerard et al., 2021). We employ a simple method: measuring how much the person- and firm-IGE are reduced when these characteristics are included as controls. We find that education explains a larger proportion of the person-IGE, whereas demographics[1] and location account for a greater share of the firm-IGE. The differences

[1]In our context, demographic group refers to *Secular Jew*, *Ultra-Orthodox Jew*, and *Israeli Arab*. Details in Section 2.1.

are stark: For example, demographics explain 43% of the firm-IGE and only 16% of the person-IGE.

These results suggests that the person- and firm-IGE represent different forms of intergenerational transmission of earnings. On the one hand, the person-IGE, being mostly associated with education, is likely to be driven by differences in skill and human capital. On the other hand, the firm-IGE, being mostly associated with demographics and location, is likely to be driven by other factors, such as social networks, preferences, and discrimination.

To further investigate the role of demography and location, we examine the relationship between parental income and the ethnicity of co-workers and neighbors. We find a strong positive correlation between parental income and a higher share of secular Jews among both neighbors and co-workers. 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[2] Arabs are not more likely than low-SES Arabs to work with secular Jews. Similar patterns are observed for residential segregation.

One potential explanation for this phenomenon is assortative matching, whereby secular Jews tend to work together and reside in close proximity because they are more educated and possess higher skills. However, this explanation is not consistent with the data. If segregation was driven by assortative matching, we would expect the demographic composition of neighbors and co-workers to be correlated with parental income even after controlling for the worker's own demographic group. The absence of such correlation suggests that factors other than skill are pivotal in determining the allocation of workers to firms.

In the third part, we further explore the role of assortative matching and investigate whether high-SES individuals overrepresented in better-paying firms only because they are more skilled. Such a fact, while perhaps speaking to inequities in early life—e.g., higher-earning parents invest more during childhood—would not be ex post inefficient. The main empirical challenge is that skill is not directly observed. A common solution is to attribute persistent within-firm earnings differences, as measured by worker fixed effects, to skill (Gerard et al., 2021; Engzell and Wilmers, 2021). However, other worker characteristics that are not related to skill are also rewarded within firms. For example, labor-market nepotism influences not only who gets hired but also who gets promoted.

To address this issue, we propose an econometric model that yields a formal definition of assortative matching. We then use this model to estimate the role of assortative matching with two approaches. The first, which we refer to as *controlled-firm-IGE*, follows the

[2]SES stands for socioeconomic status. In this paper, high- and low-SES refer to individuals from high- and low-earning families, respectively.

literature and uses worker fixed effects as a proxy for skill. The second approach, which we name *observable proxies*, uses education and demographic group as proxies for skill and social networks, respectively.

The controlled-firm-IGE approach estimates that assortative matching accounts for 51% of the firm-IGE, and the observable-proxies approach estimates that it accounts for 46%. While the assumptions required by each of these two strategies are strong, it is noteworthy that they are distinct from one another. Hence, the similarity of the estimates obtained under these different assumptions lends credibility to the validity of the results. Furthermore, we propose three alternative methods to bound the contribution of assortative matching under less stringent assumptions. Two of these methods suggest that skill-based sorting explains at most 53% of the firm-IGE, and the third method at most 74%.

Taken together, these findings strongly suggest that factors other than assortative matching play a significant role in the firm-IGE, with high-SES individuals occupying better firms, even when compared with low-SES individuals of equal skill. These findings are in line with the patterns documented in part two, which also indicate that the firm-IGE is unlikely to be explained by differences in skill.

Several mechanisms could explain the sorting of high-SES workers to better-paying firms beyond assortative matching. In the presence of discriminatory employment policies, firms prefer to hire workers from certain socioeconomic backgrounds (Bertrand and Mullainathan, 2004; Rubinstein and Brenner, 2014; Gaddis, 2015; Rivera and Tilcsik, 2016; Kline et al., 2022). The fact that the firm-IGE is to a large extent explained by demographics is consistent with this mechanism.

Additionally, imperfect information creates frictions on both labor demand and supply. On the demand side, firms do not perfectly observe workers' skill (Sousa-Poza and Ziegler, 2003; Faccini, 2014). On the supply side, workers are not aware of all job openings (Calvó-Armengol and Jackson, 2004; Jäger et al., 2021). In both cases, high-SES individuals have social networks that alleviate the information problem and give them access to better jobs (Magruder, 2010; Corak and Piraino, 2011; Kramarz and Skans, 2014; San, 2020; Staiger, 2021). The strong relationship between neighborhoods and the firm-IGE provides suggestive evidence that social networks play an important role.

Finally, compensating differentials might contribue to the firm IGE (Taber and Vejlin, 2020). If low-SES workers value non-monetary amenities more, they might self-select into lower-paying firms. To shed light on this issue, we estimate firm values from job flows, following the revealed preference approach proposed by Sorkin (2018). We estimate firm values separately for high- and low-SES individuals and find that correlation between earnings premium (ψ) and firm values is 0.58 for low-SES workers, compared with 0.46 for high-SES. That is, the low-SES value non-monetary amenities more, not less, suggesting that compensating differentials cannot explain the firm-IGE.

This paper contributes to an extensive literature that investigates 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; Chetty et al., 2017; Bell et al., 2019; Lee and Seshadri, 2019; Acemoglu, 2022; Barrios-Fernandez et al., 2021; Hermo et al., 2021); nature versus nurture (Black et al., 2020); location (Chetty et al., 2016, 2018); and social networks (Putnam, 2015; Chetty et al., 2022a,b). Most closely related to our work, several papers have shown a relationship between family social networks and being employed at specific firms (Corak and Piraino, 2011; Kramarz and Skans, 2014; Stinson and Wignall, 2018; San, 2020; Staiger, 2021). We are the first to *quantify* the contribution of firms to the observed correlation between parents' and children's earnings. A contemporaneous paper in Sociology uses an approach similar to ours 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" (Engzell and Wilmers, 2021). Our main distinction relative to their work is that we investigate the role of assortative matching.

Our work also relates to the literature that uses a two-way fixed effect 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, 2016; Sorkin, 2018; Card et al., 2018; Bloom et al., 2018; Song et al., 2019; Bonhomme et al., 2019, 2022; Kline et al., 2020). 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, a common practice in previous studies. We also propose strategies to estimate assortative matching under alternative assumptions.

The rest of the article is organized as follows. Section 2 presents the data and the setting. Section 3 estimates how much firms contribute to the IGE. Sections 4 and 5 discuss mechanisms; the first focusing on education, location, and demographics; and the second 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, which is the second highest share in the world, and 83% of its population has completed high school, which is higher than the OECD average (75%) (Schleicher, 2013).

Despite its economic and educational success, Israel is one of the most unequal countries in the OECD[3], second only to the United States. Approximately 21% of Israelis live below the poverty line, compared with an 11% average in the OECD (OECD, 2016). 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 income poverty line (David and Bleikh, 2014). Furthermore, 36 out of the 40 towns in Israel with the highest unemployment rates were Arab towns. 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 is 50% and 74%, respectively, compared with 13% for non-college-educated, non-orthodox Jewish population (Sarel et al., 2016).

2.2 Data

Decomposing the IGE into individual and firm components requires a panel of individual earnings with employer identifiers, parent-child links, and individual covariates, such as age and education. We built such a dataset by combining three sources: the Israeli Civil Registry, Israeli Social Security, and Israeli Council for Higher Education. The civil registry reports year of birth and parents of every Israeli citizen. The social security data cover the universe of the formal labor market. These data are at the 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.

Our data allow us to observe ethnicity, religiosity, and place of residence. Ethnicity (Jewish or Israeli Arab) is reported when citizens are issued their identification card at birth and is recorded in the civil registry data. Following the definition of the Israeli Central Bureau of Statistics, we define individuals as religious based on schooling. That is, we label "Ultra-Orthodox" individuals of Jewish ethnicity who attended an orthodox school. Finally, we observe place of residence from the social security records in two levels of aggregation: statistical zones which are loosely related to the common definition of commuting zones; and 'Semel Yeshuv', which are more percise geographic units, slightly larger from

[3]The disposable income Gini coefficient is 41.4

neighborhoods.

Our data also inform what type of higher education institution (if any) each individual graduated from. Appendix Table G.1 shows descriptive statistics of 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 take all Israeli citizens 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, 2015).

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 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 summing over all jobs in a given year.

Table I 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*). Further restricting to individuals in the largest connected set[6] drops another 23%, resulting in 595 thousand individuals. We will call this the *IGM-AKM* sample and it will be 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 make an additional restriction: including only workers in the largest connected set. This additional restriction is particularly concerning as it might make it hard to compare our results with the previous literature. Reassuringly, Table I shows that the IGM-AKM sample is similar to the IGM sample in terms

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

[5]Average monthly earnings in Israel are $2,934, and the minimum monthly earnings for full-time employment (by law) is $1,486 (IMF, 2018).

[6]The "largest connected set" is the largest set of firms that are connected by worker flows. It is necessary to restrict the sample to the largest connected set to estimate an earnings model with worker and firm fixed effects (Abowd et al., 1999).

of father earnings, demographics, and education. In particular, note that father earnings are only 0.04 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. Additionally, in Section 3.4, we show how to extend our results to the IGM sample, under certain assumptions, and the findings are unchanged.

Table I

Summary statistics

	Full Sample	IGM Sample	IGM-AKM Sample
Number of individuals			
	1,282,243	775,241	595,493
Demographic Groups (%)			
Arab	20.1	14.9	13.8
Ashkenaz	21.2	22.3	22.7
Ethiopian	0.3	0.3	0.5
Sepharadic	35.9	39.9	39.8
Ultra-Orthodox Jew	5.0	3.3	3.6
USSR	4.7	4.9	5.3
Missing	12.7	14.4	14.3
College Educated (%)			
	39.3	49.6	52.5
Earnings			
Mean of log-earnings		11.59	11.67
Mean of father's log-earnings		10.70	10.74

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 non-zero reported income. The "IGM-AKM Sample" further restricts the sample to individuals in the largest connected set (see Section 2.2). The 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 coming from countries that were in the Soviet Union are classified as "USSR" and those coming 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.

3 Firms and intergenerational mobility

In this section, we estimate the role of firms in intergenerational mobility, using the following steps. First, Section 3.1 investigates the role of firms in cross-sectional earnings inequality. Second, Section 3.2 discusses how to measure intergenerational mobility. Section 3.3 presents our main contribution: It builds on the previous results and demonstrates how the IGE can be decomposed into individual and firm components. Finally, Section 3.4 discusses the robustness of our results.

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:

$$\log Y_{i,t} = \overbrace{\alpha_i}^{\text{individual component}} + \underbrace{\psi_{J(i,t)}}_{\text{firm component}} + \overbrace{x_{it}'\beta^x}^{\text{covariates}} + \underbrace{r_{i,t}}_{\text{error term}}, \tag{1}$$

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, and age squared. $r_{i,t}$ 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 E.1, we show that this framework also fits our data well. In particular, we test the restrictions imposed in Regression (1), 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 (1) 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 (1) 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,

[7] Equation (1) 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 (2021) 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 E.2 shows that firm premiums estimated with the AKM sample are highly

in Section 5.2, we propose an instrumental variable strategy to correct the small-sample bias that results from measurement error in the fixed-effect estimates.

As usual in the AKM literature, we present the estimates of Regression 1 in the form of the following variance decomposition:

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

The results are reported in Table II. 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%). Overall, the patterns are in line with those documented in other contexts: Most of the variation is explained by the individual component, but firm and sorting components also play important roles.

Table II

Earnings variance decomposition

	AKM Sample	IGM-AKM Sample
Variance components:		
Individual component $(Var(\alpha))$	0.78	0.70
Firm component $(Var(\psi))$	0.11	0.10
Sorting $(Cov(\alpha, \psi))$	0.16	0.19
Covariates and residual	-0.05	0.01

Notes: This table decomposes the total variation in earnings into several components, as defined in Equation (2). 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 non-zero reported income.

3.2 IGE: Measuring intergenerational mobility

Studies of intergenerational mobility aim to measure the degree to which an individual's opportunities depend on her family's socioeconomic status. For practical purposes, re-

correlated with the ones estimated with the IGM-AKM sample. Moreover, Appendix E.2 also shows that premiums estimated only with workers from low- or high-income families are highly correlated with full-sample estimates. Previous research found similar patterns for workers of different ethinicities (Gerard et al., 2021) and gender (Sorkin, 2017).

[9] Covariates and the error term are responsible for the remaining *negative* part of the variation (-4%).

searchers often focus on the relationship between the earnings of parents and their children (Solon, 1999; Black and Devereux, 2011b). Following this tradition, we use a canonical measure of mobility: the elasticity of child earnings to parent earnings, which is commonly called the intergenerational elasticity of earnings (IGE).[10]

Individuals are observed at different ages and years, and their earnings are subject to life-cycle and business-cycle fluctuations. Hence, for comparability, we need a measure of earnings net of age and time effects (Solon, 1992). For the children's generation, we build net log earnings $\left(\log \widetilde{Y}_{it}\right)$ using Regression (1). That is, we define:

$$\log \widetilde{Y}_{it} \equiv \alpha_i + \psi_{J(i,t)} + r_{i,t}.$$

For the parents' generation, a natural approach would be to estimate Regression (1) 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 for each year between 1986 and 1991 as the residual of the following regression:

$$\log Y_{it} = \overbrace{x_{it}'\beta^x}^{\text{covariates}} + \underbrace{\log \widetilde{Y}_{it}}_{\text{residual}}, \tag{3}$$

where the included covariates are age, age squared, and year fixed effects.

We then calculate the average net earnings of each individual:

$$\overline{\log Y}_i \equiv \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \log \widetilde{Y}_{it}, \tag{4}$$

where $\mathcal{T}_i$ is the set of years in which individual i is observed in our labor market data and N_i is the size of $\mathcal{T}_i$.

Finally, we estimate the IGE with the following regression:

$$\overline{logY_i} = \beta_0^{IGE} + \beta^{IGE} \cdot \overline{logY_{f(i)}} + \epsilon_i^{IGE}, \tag{5}$$

where $f(i)$ is the father[11] of individual i, and therefore $\overline{logY_{f(i)}}$ is the average log-earnings

[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 (Chetty et al., 2014b). 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'

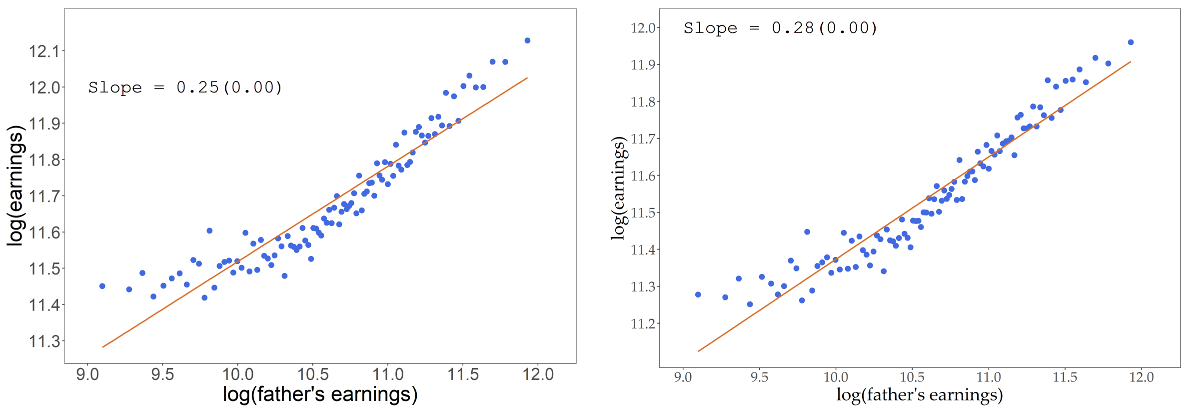
of the father of individual i between 1986 and 1991; β^{IGE} is the IGE, our parameter of interest; and ϵ_i^{IGE} is a residual.

Figure I

The intergenerational elasticity of earnings (IGE)

(a) IGM-AKM sample

(b) IGM sample



Notes: This figure plots log children's earnings against log fathers' earnings. Panel (b) presents the estimates for the full IGM sample, and Panel (a) presents the estimates for the IGM-AKM 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.

Table III, Column (1), shows OLS estimates of Regression (5) and Appendix Figure Ia plots the underlying data. We find that the IGE in Israel is 0.23. That is, a 10% increase in a child's father's earnings is correlated with a 2.3% 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. Appendix Figure Ib shows that the IGE for the IGM sample is larger (0.28). Heler (2017) estimates an almost identical IGE using the same data, but with a slightly different sample definition. 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 intergenerational persistence of earnings in Israel is comparable to that of other high-income countries.

generation. Hence, the father's income is more representative of a family's socioeconomic status. More details in Appendix D.

[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).

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

In Section 3.2, we showed that individuals from richer families have higher earnings, on average. Moreover, in Section 3.1, we found that variation in firms' earnings premium substantially contributes to cross-sectional earnings inequality. Motivated by these results, in this section we study the role firms play in the intergenerational persistence of earnings.

We begin by investigating how the individual and firm components of earnings, as defined in the AKM decomposition (Regression 1), correlate with father's earnings. For this purpose, we rank individuals by each of these components and study the relationship between their and their fathers' ranks. The results are reported in Figures IIa and IIb, which show that both components of earnings are highly correlated with father's earnings. Individuals from families in the bottom percentile of the distribution rank around the 40th percentile in both components, whereas those in the top percentile rank around the 70th percentile.

As with all rank-rank measures of mobility, the results in Figures IIa and IIb do not consider the magnitude of cross-sectional inequality. That is, they ignore the fact that the individual and firm components are not equally important in explaining the cross-sectional variation in earnings. To take this into account, we define a measure of persistence for the firm and individual components analogous to the IGE:

$$\begin{aligned} \alpha_i &= \beta_0^{\alpha|Y_f} + \beta^{\alpha|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\alpha|Y_f}, \\ \overline{\psi}_i &= \beta_0^{\psi|Y_f} + \beta^{\psi|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\psi|Y_f}, \end{aligned} \tag{6}$$

where $\beta^{\alpha|Y_f}$ is the individual-IGE, $\beta^{\psi|Y_f}$ is the firm-IGE, and $\overline{\psi}_i$ is the average firm premium of each worker:

$$\overline{\psi}_i \equiv \frac{1}{N_i} \sum_{t \in \mathcal{T}_i} \psi_{J(i,t)}.$$

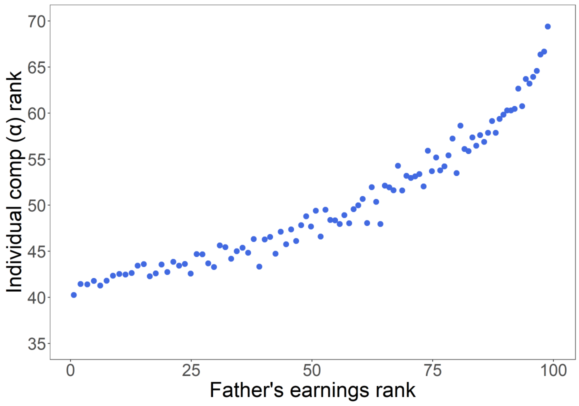
The framework in Regression 6 is useful because it provides an exact decomposition of the IGE into individual and firm components (proof in Appendix A):

$$\overbrace{\beta^{IGE}}^{\text{IGE}} = \overbrace{\beta^{\alpha|Y_f}}^{\text{individual-IGE}} + \overbrace{\beta^{\psi|Y_f}}^{\text{firm-IGE}} . \tag{7}$$

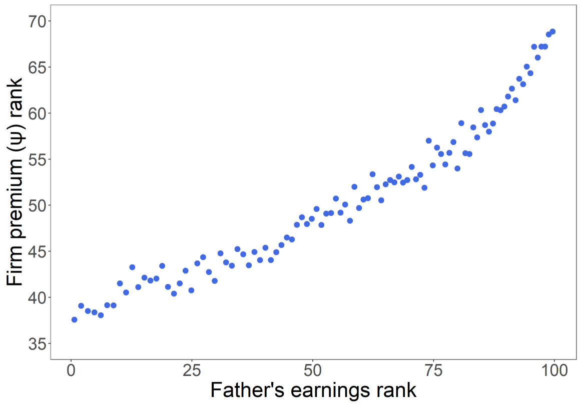
We estimate Regression (6) by OLS. Note that OLS delivers unbiased estimates even though α_i and ψ_i have measurement error, because they are left-hand-side variables. The estimated coefficients are reported in Table III, and Figures IIc and IId show the underlying data. We find that the individual-IGE is 0.20 (Column (2)) and the firm-IGE is 0.035

Figure II
Decomposing intergenerational mobility

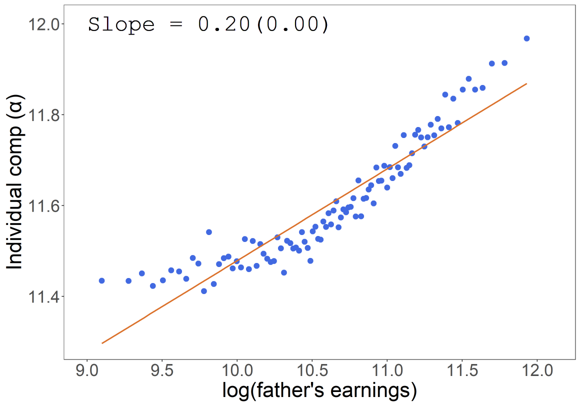
(a) Individual-IGM (ranks)



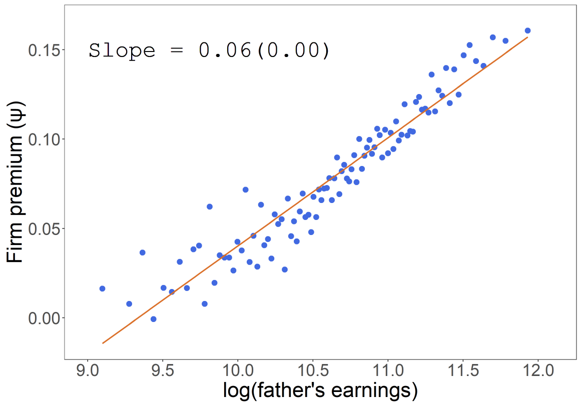
(b) Firm-IGM (ranks)



(c) Individual-IGE



(d) Firm-IGE



Notes: Panel (a) plots children's individual component (α) rank against their father's earnings rank. Panel (b) plots children's firm component (ψ) rank against their father's earnings rank. Individual and firm components are AKM fixed effects (Section 3.3). Panel (c) plots children's individual components against their father's log earnings. Panel (d) plots children's average firm component against their father's log earnings. The slopes of the fitted lines in Panels (c) and (d) are, respectively, the individual-IGE and the firm-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.

(Column (3)). Using the decomposition in Regression (7), we conclude that the firm component is responsible for 15.3% of the intergenerational persistence in earnings, whereas the individual component is responsible for 84.7%. Similarly, Engzell and Wilmers (2021) estimate that the firm-IGE accounts for 23.2% of the IGE in Sweden. The difference in these estimates might be due to the time frame: six years here and thirty in Engzell and Wilmers (2021). On the one hand, a longer time frame helps increase the precision of the estimates. On the other hand, it requires the stronger assumption that firm earnings premium are fixed over a 30-year period.

These findings, which indicate that access to better firms is a critical driver of the intergenerational persistence in earnings, yield important implications for our understanding of why individuals face different opportunities in the labor market. Next, in Section 4, we begin to explore the mechanisms behind this pattern.

Table III

Decomposing the IGE into individual and firm components

	(1)		(2)		(3)
Dependent variable:	$\overline{\log Y}_i$		α_i		$\overline{\psi}_i$
	$\overbrace{\beta^{IGE}}^{\text{IGE}}$	$=$	$\overbrace{\beta^{\alpha\vert Y_f}}^{\text{individual-IGE}}$	$+$	$\overbrace{\beta^{\psi\vert Y_f}}^{\text{firm-IGE}}$
$\overline{logY_{f(i)}}$	0.253		0.197		0.056
	(0.000)		(0.000)		(0.000)
Share of IGE	1.00		0.78		0.22
	.		(0.000)		(0.000)
Observations	595,493		595,493		595,493

Notes: This table reports the results of the decomposition of the intergenerational earnings elasticity (IGE) into individual and firm components, as described in Equation (7). Column (1) shows the IGE (Equation 5). Column (2) shows the elasticity of children's individual component of earnings (α_i) to their father's earnings, which we call individual-IGE (Equation 6). Column (3) shows the elasticity of children's firm component of earnings $(\overline{\psi}_i)$ to their father's earnings, which we call firm-IGE (Equation 6). The bottom panel reports the share of the IGE explained by each component. Standard errors are in parentheses. Standard errors for the shares are calculated using the delta method. 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.

3.4 Firm-IGE: Robustness to sample selection

A limitation of the decomposition in Equation (7) is that we can only estimate it for individuals in the largest connect set. Since high-SES workers are more likely to be in the largest connected set, endogenous sample selection might bias our results. In this section, we perform two robustness exercise to address this issue.

First, we restrict the analysis to a population that is less affected by differential selection into the connected set: college-educated workers. Only 13% of these workers are not in the connected set. Moreover, when focusing on college-educated workers, father earnings are only 0.006 log points higher in the IGM-AKM sample compared to the IGM sample. Appendix Table C.1 presents estimates of Equation (7) for this group and the results are very similar to the baseline: The firm-IGE is responsible for 21% of the IGE, compared to 22% in the baseline.

Second, we propose a method to extend the analysis to all workers with stable jobs (the IGM sample). For this, we impute α_i and $\overline{\psi}_i$ for workers not in the largest-connected. We divide workers into bins given their education, demographic group, and gender. We then calculate the average estimated α_i and $\overline{\psi}_i$ of each bin and input these values for workers not in the largest connected set. Appendix Table C.2 presents estimates of Equation (7) using the imputted values and results are almost identical to the baseline: The firm-IGE is responsible for 22% of the IGE.

To sum up, given both our robustness exercises above result in similar results as our baseline estimation, we conclude that endogenous sample selection does not substantially affect our results.

4 Behind the firm-IGE: The role of education, demography, and location

In this section, we delve into the mechanisms underlying the person-IGE and firm-IGE by exploring the relationship between the person- and firm-IGE and various worker characteristics. We focus on factors that have been empirically shown to influence inequality and mobility, namely education (e.g., Restuccia and Urrutia, 2004; Pekkarinen et al., 2009; Zimmerman, 2019), location (e.g., Chetty et al., 2014a, 2016), and demographics (e.g., Chetty et al., 2020; Gerard et al., 2021).

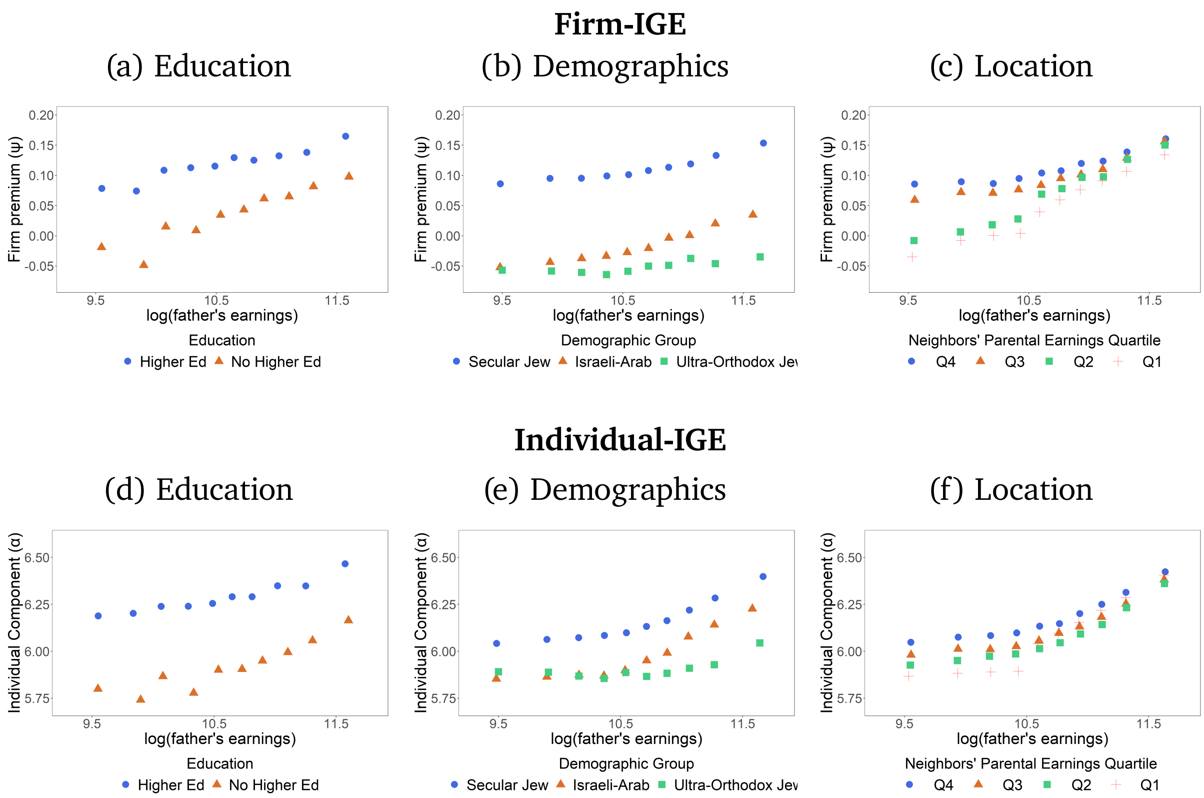
Figure III presents the relationship between the individual (α) and firm (ψ) components of earnings and parental income, by education, demographic group, and residential location. Notably, the same qualitative patterns hold across all three dimensions. Regarding education, college-educated workers exhibit higher values for both components at any given parental income level. We see the same patterns for Secular Jews, compared to other demographics groups, and workers residing in high-SES neighborhoods compared to those in low-SES neighborhoods. In spite of these qualitatively similar results, comparing the magnitudes of the effects reveals important differences. Education is more strongly related to the individual component, while demographics and location to the firm component.

To quantify the role such differences play in the IGE, we employ a simple method: measuring how much the person- and firm-IGE are reduced when education, demographic group, or location are included as controls. Formally, we run the regressions:

$$\log \alpha_i = \beta^{\alpha|Y_f|X} \cdot \overline{logY_{f(i)}} + \gamma_X + \epsilon_i^{\alpha|X}$$
$$\log \psi_i = \beta^{\psi|Y_f|X} \cdot \overline{logY_{f(i)}} + \gamma_X + \epsilon_i^{\psi|X}$$

Figure III

Firm- and individual-IGE by demographics, education, and location



Notes: This figure plots the firm and individual IGE by demographics and education. Panels (a), (b), and (c) plot children's firm component (ψ) against their father's earnings by education level, demographic group, and location, respectively. Similarly, panels (d), (e), and (f) plot children's individual component (α) against their father's earnings by education level, demographic group, and location, respectively. Individual and firm components are AKM fixed effects (Section 3.3). 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. In panels c and f individuals are divided into four groups based on the average parental income of their neighbors.

where X is education, demographic group, or location; γ_X are fixed effects; and ϵ are residuals. Then we measure the share of the person- and firm-IGE explained by each of these variables as:

$$\text{Share of person-IGE explained by } X = 1 - \frac{\beta^{\alpha|Y_f|X}}{\beta^{\alpha|Y_f}}$$

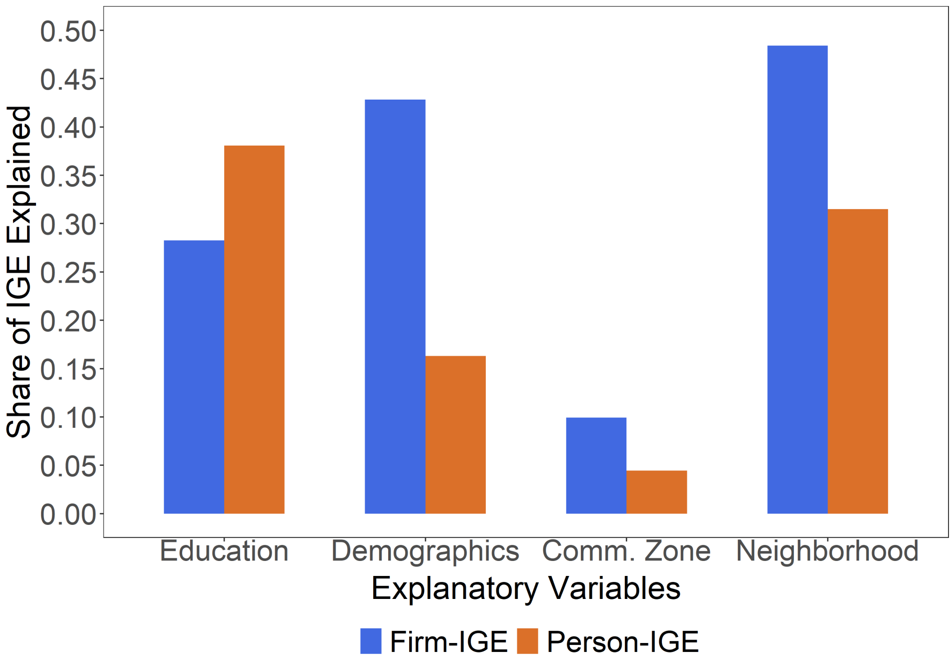
$$\text{Share of firm-IGE explained by } X = 1 - \frac{\beta^{\psi|Y_f|X}}{\beta^{\psi|Y_f}}$$

Figure IV presents the estimated shares, and the underlying regressions are in Table IV. In our baseline analysis, we use two education levels (college and no college) and three demographic groups (Secular Jew, Ultra-Orthodox Jew, and Israeli-Arab). Appendix Figure C.2 presents results using more granular definitions of education and demographic group, and the results are similar. Regarding location, we present results at both the neighborhood and commuting zone level since they are substantially different as we discuss below.

The results in Figure IV confirm the patterns observed in Figure III: Education explains a larger proportion of the person-IGE, whereas demographics and location account for a greater share of the firm-IGE. The differences are stark: For example, demographics explain 43% of the firm-IGE and only 16% of the person-IGE.

Figure IV

Share of firm- and individual-IGE explained by different covariates



Notes: This figure shows the share of the firm- and individual-IGE that is explained by different covariates. The firm- and individual-IGE are, respectively, the elasticity of children's firm and individual components 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). "Share Explained" is how much the estimated elasticity is reduced with the inclusion of each control, compared with the specification without controls. Fathers' earnings are 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. "Education" is defined as having college education or not, and "Demographic group" is defined as Secular Jew, Ultra-Orthodox Jew, or Israeli Arab. "Comm. Zone" and "Neighborhood" are, respectively, commuting zone and neighborhood of residence.

These results suggests that the person- and firm-IGE represent different forms of intergenerational transmission of earnings. On the one hand, the person-IGE, being mostly associated with education, is likely to be driven by differences in skill and human capital. On the other hand, the firm-IGE, being mostly associated with demographics and location, is likely to be driven by other factors, such as social networks, preferences, and discrimination.

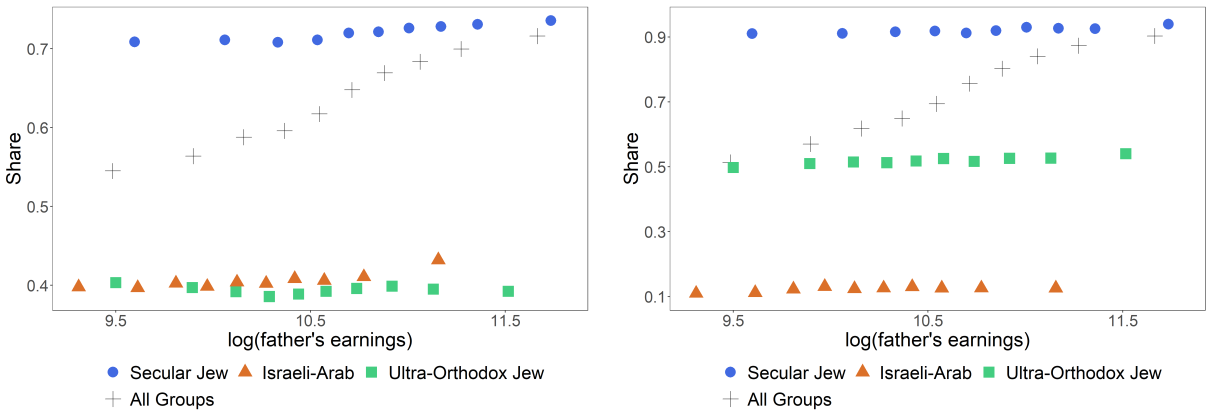
Figure IV also shows that location only matters at the neighborhood level, not at the commuting zone level. That is, the firm-IGE stems from a more granular form of segregation rather than workers being in different labor markets. To further investigate the nature of this segregation, we examine the relationship between parental income and the ethnicity of co-workers and neighbors. We focus on the share of secular Jews as they represent the group with the highest earnings, as shown in Figure III.

Figure V presents the results of this analysis. We find a strong positive correlation between parental income and a higher share of secular Jews among both neighbors and co-workers. 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.

One potential explanation for this phenomenon is assortative matching, whereby secular Jews tend to work together and reside in close proximity because they are more educated and possess higher skills. However, this explanation is not consistent with the data. If segregation was driven by assortative matching, we would expect the demographic composition of neighbors and co-workers to be correlated with parental income even after controlling for the worker's own demographic group. The absence of such correlation suggests that factors other than skill are pivotal in determining the allocation of workers to firms. Motivated by these findings, the next section proposes an econometric framework to estimate the share of the firm-IGE that cannot be attributed to differences in skills.

Figure V
Labor-Market and Residential Segregation

(a) Share of Secular Jewish Co-workers (b) Share of Secular Jewish Neighbors



Notes: Panel (a) shows that shares of an individual's co-workers that is Secular Jewish as a function or her father's earnings. Panel (b) shows that shares of an individual's neighbors that is Secular Jewish as a function or her father's earnings. In both panels, fathers' earnings are 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.

Table IV

Firm- and individual-IGE controlling for demographics and education

Dependent variable:	Firm earnings premium $(\overline{\psi}_i)$				Individual component (α_i)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{logY_{f(i)}}$	0.032	0.040	0.050	0.029	0.165	0.122	0.188	0.135
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control	Dem Group	Educ	CZ	NBH	Dem Group	Educ	CZ	NBH
Share Explained	0.43	0.28	0.10	0.48	0.16	0.38	0.04	0.32
	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.004)	(0.005)
Observations	595,493	595,493	595,493	595,493	595,493	595,493	595,493	595,493

Notes: This table shows estimates of the firm- and individual-IGE in different specifications. Standard errors are in parentheses. The firm- and individual-IGE are, respectively, the elasticity of children's firm and individual components of earnings to their father's earnings $(\overline{\log Y_{f(i)}})$. Individual (α_i) and firm $(\overline{\psi}_i)$ components are AKM fixed effects (see Section 3.3). "Share Explained" is how much the estimated elasticity is reduced with the inclusion of each control, compared with the specification without controls. Fathers' earnings are 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. "Education" is defined as having college education or not, and "Demographic group" is defined as Secular Jew, Ultra-Orthodox Jew, or Israeli Arab.

5 Can assortative matching explain the firm-IGE?

Existing research shows that children born to higher-income parents grow up to be more skilled (e.g., Mogstad and Torsvik, 2022), and more skilled workers tend to sort into higher-paying firms (e.g., Card et al., 2013). Thus, the finding that sorting into higher-paying firms is responsible for some portion (22%) of the IGE in Israel, although novel, is not surprising. The main question is whether non-skill-based sorting plays a role. If skill-based sorting is primarily responsible, then future research on intergenerational mobility should continue to focus on human capital. If non-skill-based sorting plays an important role, then future research ought to investigate why individuals born to high-SES parents are more likely to find jobs at high-paying firms. Hence, in this section, we investigate why individuals from higher socioeconomic backgrounds tend to work in better-paying firms, with an emphasis on assortative matching.

The main empirical challenge is that skill is not directly observed. A common solution is to attribute persistent within-firm earnings differences, as measured by α, to skill (Gerard et al., 2021; Engzell and Wilmers, 2021). However, other worker characteristics that are not related to skill are also rewarded within firms. For example, labor-market nepotism influences not only who gets hired but also who gets promoted.

To address this issue, we proceed as follows. First, Section 5.1 presents a formal definition of assortative matching. Then, Section 5.2 describes the necessary assumptions to use α as a proxy for skill and presents the corresponding results. Section 5.3 presents an alternative approach that explores the relationship between parental income, education, and demographic groups. It is worth noting that the assumptions required in Section 5.3 are distinct from the ones in Section 5.2, and thus comparing the resulting estimates will help in evaluating the robustness of our results. Also, both Sections 5.2 and 5.3 show how to obtain bounds, instead of a point estimate, under weaker assumptions. Finally, Section 5.4 discusses implications.

5.1 Econometric model

We now present a simple econometric model that provides a formal definition of assortative matching and its role in the firm-IGE. Let workers be characterized by *human capital* H_i and *social capital* S_i. Human capital represents all worker characteristics related to productivity, including training and skills. Social capital represents social networks, cultural matching, discrimination, and other reasons high-SES workers obtain high-paying jobs, beyond what can be explained by human capital.

We allow both types of capital to affect within-firm earnings differences (α), as well as access to high-earnings-premium firms (ψ):

$$\begin{aligned}\overline{\psi}_i &= \theta_H^{\psi} \cdot H_i + \theta_S^{\psi} \cdot S_i + \eta_i^{\psi}, \\ \alpha_i &= \theta_H^{\alpha} \cdot H_i + \theta_S^{\alpha} \cdot S_i + \eta_i^{\alpha},\end{aligned} \tag{8}$$

where θ_H^{ψ},θ_S^{ψ}, θ_H^{α}, and θ_S^{α} are parameters assumed to be positive. The residuals η_i^{ψ} and η_i^{α} represent luck and measurement error, and are assumed to be idiosyncratic.

Under this framework, the firm-IGE can be decomposed as (proof in Appendix B):

$$\overbrace{\beta^{\psi|Y_f}}^{\text{firm-IGE}} = \underbrace{\theta_H^{\psi} \cdot \beta^{H|Y_f}}_{\text{assortative matching}} + \underbrace{\theta_S^{\psi} \cdot \beta^{S|Y_f}}_{\text{SES-effect}}, \tag{9}$$

where $\beta^{H|Y_f}$ and $\beta^{S|Y_f}$ are the slopes in the following OLS regressions:

$$\begin{aligned}H_i &= \beta^{H|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{H|Y_f}, \\ S_i &= \beta^{S|Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{S|Y_f}.\end{aligned}$$

Equation (9) decomposes the firm-IGE into two channels. First, high-SES individuals are more productive and hence have access to better firms (assortative matching). Second, high-SES individuals work in better firms, even compared with equally productive low-SES workers, because of their higher social capital (SES-effect). Our object of interest is the share of the firm-IGE that can be explained by assortative matching (henceforth *AM-share*):

$$\overline{AM} \equiv \frac{\theta_H^{\psi} \cdot \beta^{H|Y_f}}{\theta_H^{\psi} \cdot \beta^{H|Y_f} + \theta_S^{\psi} \cdot \beta^{S|Y_f}}. \tag{10}$$

5.2 Estimating $\overline{AM}$: The controlled firm-IGE approach

Empirical strategy

This section discusses how to estimate AM-share using the individual component of earnings (α_i) as a proxy for productivity (Gerard et al., 2021; Engzell and Wilmers, 2021). Following this approach, we investigate whether high-SES individuals work in better-paying firms compared with low-SES individuals with the same α_i. We implement this by estimating the firm-IGE with α_i as a control in the following OLS regression:

$$\overline{\psi_i} = \beta_0^{\psi|\alpha,Y_f} + \beta_{\alpha}^{\psi|\alpha,Y_f} \cdot \alpha_i + \beta_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\psi|\alpha,Y_f}, \tag{11}$$

where $\beta_{Y_f}^{\psi|\alpha,Y_f}$ is the *controlled firm-IGE*. Controlling for α_i absorbs the part of the firm-IGE that operates through human capital (assortative matching), and the remaining variation comes from social capital (SES-effect). Hence, if including α_i as a control substantially reduces the firm-IGE, then assortative matching plays an important role; that is, the AM-share is large. However, this interpretation requires three strong assumptions. We will now state these assumptions, and then propose an alternative approach that relaxes them.

First, note that α_i measures persistent within-firm differences in earnings. Hence, using α_i as a proxy for human capital requires assuming that persistent within-firm earnings differences are only due to differences in productivity. That is, we need to assume that social capital might help workers get a job in a better firm, but not to grow within the firm $\left(\theta_S^\alpha = 0\right)$.

Second, α_i is a right-hand-side variable in Regression (11). Hence, measurement error in α_i causes bias in the estimated coefficients. Hence, we must assume that α_i is estimated without any measurement error.

Third, human and social capital might be correlated. Since human capital affects α_i and social capital affects $\psi_{J(i,t)}$, this creates a correlation between α_i and $\epsilon_i^{\psi|\alpha,Y_f}$. As a result, estimating Regression (11) by OLS would yield biased coefficients. Hence, we must assume that there is no correlation between human and social capital once we control for fathers' earnings $\left(\epsilon_i^{H|Y_f} \perp\!\!\!\perp \epsilon_i^{S|Y_f}\right)$.

Under these three (strong) assumptions, we can estimate AM-share by comparing the baseline firm-IGE (Regression (6)) with the controlled firm-IGE (Regression (11)). The following proposition formalizes this result.

Proposition 1 *Assume that (i) α_i is not affected by social capital $\left(\theta_S^\alpha = 0\right)$; (ii) α_i is estimated without measurement error $\left(\eta_i^\alpha = 0\right)$; and (iii) human and social capital are uncorrelated, conditional on father's earnings $\left(\epsilon_i^{H|Y_f} \perp\!\!\!\perp \epsilon_i^{S|Y_f}\right)$. 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, as defined in Regression (6), and $\beta_{Y_f}^{\psi|\alpha,Y_f}$ is the controlled firm-IGE, as defined in Regression (11).

Proof: *Appendix B.*

The assumptions in Proposition 1 are arguably too restrictive. Hence, we now show how we can bound AM-share under more flexible assumptions.

First, we relax the assumption that persistent within-firm earnings differences are only due to differences in productivity. Instead, we assume that social capital is *relatively* more important during job search than for explaining within-firm earnings differences $\left(\frac{\theta_S^\psi}{\theta_H^\psi} \geq \frac{\theta_S^\alpha}{\theta_H^\alpha}\right)$.

In line with this assumption, both Stinson and Wignall (2018) and Staiger (2021) find that sharing a firm with a parent is associated with substantial earnings gains, and most of these gains come from working at a high-wage firm rather than from having relatively high earnings within the firm. Similarly, San (2020) finds that 84% of the wage gains of weak social connections in Israel are realized through job changes. Under this weaker assumption, α_i reflects not only differences in human capital, but also differences in social capital. Therefore, adding α_i as a control in Regression (11) reduces the IGE *more* than it would if we directly controlled for human capital and yields an *upper bound* to AM-share.

Second, we relax the assumptions of no measurement error and no correlation between social and human capital. As a consequence, OLS estimates of Regression (11) are biased, as discussed above. A common solution in the literature is to use a split-sample-based instrument (Goldschmidt and Schmieder, 2017; Drenik et al., 2022). However, in our case, the instrumented covariate is α, whereas in those studies it is ψ. Appendix F shows that the split-sample approach delivers valid instruments for ψ but not for α. Hence, we follow a different strategy and instrument α with workers' education level. That is, we estimate the following 2SLS regression:

$$\begin{aligned}&\text{Second stage:}\\&\overline{\psi_i} = \widetilde{\beta}_0^{\psi|\alpha,Y_f} + \widetilde{\beta}_\alpha^{\psi|\alpha,Y_f} \cdot \alpha_i + \widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{logY_{f(i)}} + \widetilde{\epsilon}_i^{\psi|\alpha,Y_f}\\&\text{First stage:}\\&\alpha_i = \beta_0^{\alpha|Z,Y_f} + \beta_Z^{\alpha|Z,Y_f} \cdot Z_i + \beta_{Y_f}^{\alpha|Z,Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\alpha|Z,Y_f},\end{aligned} \tag{12}$$

where Z_i is a measure of individual i's education. As usual with instrumental variables, this approach requires both inclusion and exclusion assumptions, which we discuss below.

The inclusion assumption is that education is positively correlated with human capital. This would be violated if education had no impact on productivity or skill. In line with our assumption, several papers have shown that education is associated with skill formation (e.g., Cunha et al., 2010; Jackson et al., 2020).

The standard exclusion assumption would be that social capital is uncorrelated with education. However, previous research has shown that relationships built during college are valuable in the labor market (Zimmerman, 2019; Michelman et al., 2022). Moreover, Chetty et al. (2022a) demonstrate that differences in college attendance are one reason why high-SES individuals are more likely to befriend other high-SES individuals, with subsequent important consequences for economic mobility. Hence, assuming that social capital is uncorrelated with education would go against the empirical evidence. Therefore, we adopt a weaker assumption that allows us to bound AM-share instead of getting a point estimate: We assume that education is *not* negatively correlated with social capital. This assumption would be violated, for example, if individuals had *worse* social capital as a result of going to college, which would contradict the empirical evidence (e.g., Zimmerman, 2019; Michelman et al., 2022; Chetty et al., 2022a). Our assumption could also be violated if individuals who pursue more education are more likely to choose career paths based on non-pecuniary benefits. If that is the case, the assumption requires that the positive effect of education on social networks outweighs its effect on preferences.

We then follow the same approach as before: comparing the baseline firm-IGE (Regression (6)) with the controlled firm-IGE, now instrumenting α_i with education (Regression (12)). However, we cannot attribute all of the difference between the baseline and controled firm-IGEs to assortative matching, because we allow both α_i and education to be correlated with social capital. Therefore, controlling for (instrumented) α_i absorbs a part of the effect of social capital and, as a result, the controlled firm-IGE is smaller than it would be if we directly controlled for human capital. Hence, this procedure gives us an upper bound to AM-share instead of a point estimate. The following proposition formalizes this intuition.

Proposition 2 *Let Z_i be a measure of individual i's education level. Assume that (i) social capital is relatively more important in explaining the allocation of workers to firms than within-firm earnings variation $\left(\frac{\theta_S^\psi}{\theta_H^\psi} \geq \frac{\theta_S^\alpha}{\theta_H^\alpha}\right)$ and (ii) $\beta_Z^{H|Y_f,Z} > 0$ and $\beta_Z^{S|Y_f,Z} \geq 0$, where these parameters are defined by the OLS regressions:*

$$H_i = \beta_0^{H|Y_f,Z} + \beta_{Y_f}^{H|Y_f,Z}\overline{logY_{f(i)}} + \beta_Z^{H|Y_f,Z} Z_i + \epsilon^{H|Y_f,Z},$$
$$S_i = \beta_0^{S|Y_f,Z} + \beta_{Y_f}^{S|Y_f,Z}\overline{logY_{f(i)}} + \beta_Z^{S|Y_f,Z} Z_i + \epsilon^{S|Y_f,Z}.$$

Then

$$\overline{AM} \leq 1 - \frac{\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f}}{\beta^{\psi|Y_f}},$$

where $\beta^{\psi|Y_f}$ is the firm-IGE, as defined in Regression (6), and $\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f}$ is the instrumented controlled firm-IGE, as defined in Regression (12).

Proof: *Appendix B.*

Results

Table V, Column (1) reports OLS estimates of Regression (6) and Column (2) of Regression (11). We see that the firm-IGE goes down from 0.035 to 0.017 when we add α as a control. Proposition 1 shows how to estimate $\overline{AM}$ from these coefficients (controlled-firm-IGE method). The resulting estimate is that $\overline{AM}$ is 51%. Figure VI summarizes the estimates

Table V

Firm-IGE controlling for the individual component of earnings

	Dependent variable: Firm earnings premium $(\overline{\psi}_i)$		
	(1)	(2)	(3)
$\overline{logY_{f(i)}}$	0.056 (0.000)	0.017 (0.000)	0.014 (0.000)
Control		α	α
Instrument			Has Higher Ed
F-stat			775,977
Observations	595,493	595,493	595,493

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. Columns (2)-(3) control for children's individual component of earnings (α_i). Column (2) is estimated by OLS and Column (3) by 2SLS using an indicator for having a college degree as an instrument for the individual component. 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.

of $\overline{AM}$ obtained under different approaches.

Column (3) of Table V reports the 2SLS estimates of Regression (12), using an indicator of having a college degree as the instrument.[13] The firm-IGE is now reduced to 0.09. Under the assumptions in Proposition 2, this implies that the $\overline{AM}$ is at most 74%. That is, *at least* 26% of the firm-IGE cannot be explained by skill-based sorting. As a robustness exercise, Appendix G.1 presents estimates using alternative instruments that take into account education quality, and the results are similar.

5.3 Estimating $\overline{AM}$: The observable proxies approach

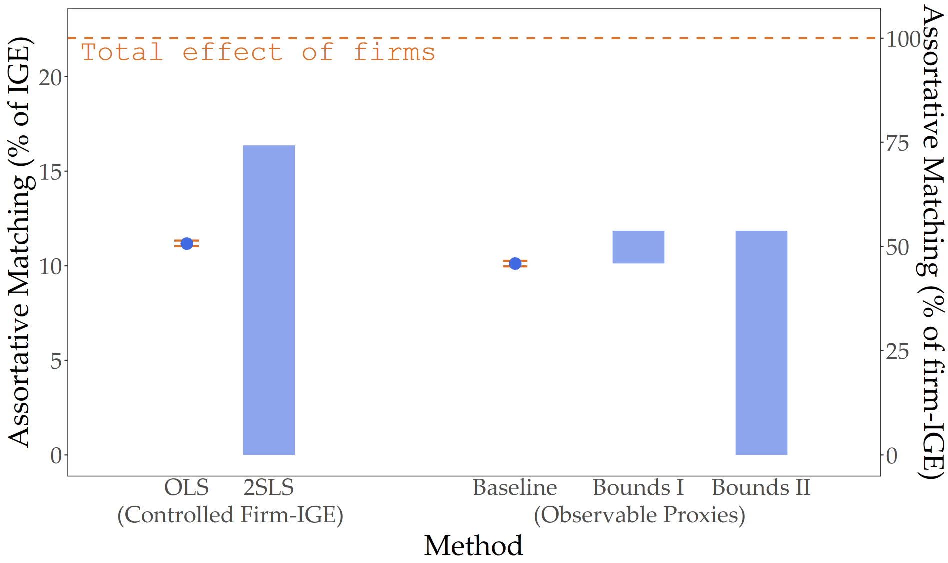
Empirical strategy

The assumptions behind the controlled-IGE estimate, presented in Section 5.2, are arguably too restrictive. Hence, we now estimate the role of assortative matching using an alternative approach that relies on a different set of assumptions. Comparing the estimates obtained under these distinct assumptions will allow us to evaluate the validity of our results.

In the alternative approach, we build on the insights from Section 4 and use education

[13] 46% of 25- to 64-year-olds in Israel have a higher education degree, and 50% in our sample.

Figure VI
The role of assortative matching in the firm-IGE



Notes: This figure presents the share of the IGE (left axis) and firm-IGE (right axis) that is due to the assortative-matching channel, according to different methods. Dots represent point estimates and bars represent bounds. Section 5 describes how this decomposition is calculated. Error bars represent 99% confidence intervals, computed using the delta method.

and demographics as proxies for human and social capital. Formally, consider the regressions:

$$\begin{aligned} H_i &= \beta_{Y_f}^{H|Y_fED} \cdot \overline{logY_{f(i)}} + \beta_E^{H|Y_fED} \cdot E_i + \beta_D^{H|Y_fED} \cdot D_i + \epsilon_i^{H|Y_fED}, \\ S_i &= \beta_{Y_f}^{S|Y_fED} \cdot \overline{logY_{f(i)}} + \beta_E^{S|Y_fED} \cdot E + \beta_D^{S|Y_fED} \cdot D + \epsilon_i^{S|Y_fED}, \end{aligned} \tag{13}$$

where E_i and D_i are the expected log income of individual i given, respectively, her education and demographic group.

If we knew the parameters of Regression (13), we could construct measures of predicted human and social capital. Then, we could obtain an unbiased estimate by calculating $\overline{AM}$, as defined in Equation 10, using these predictions instead of actual human and social capital.[14] However, since H_i and S_i are unobserved, it is not feasible to estimate Regression (13) directly. Instead, we estimate the following:

$$\begin{aligned} \alpha_i &= \beta_{Y_f}^{\alpha|Y_fED}\overline{logY_{f(i)}} + \beta_E^{\alpha|Y_fED} E_i + \beta_D^{\alpha|Y_fED} D_i + \epsilon_i^{\alpha|Y_fED}, \\ \overline{\psi}_i &= \beta_{Y_f}^{\psi|Y_fED}\overline{logY_{f(i)}} + \beta_E^{\psi|Y_fED} E_i + \beta_D^{\psi|Y_fED} D_i + \epsilon_i^{\psi|Y_fED}. \end{aligned} \tag{14}$$

[14] Proof in Appendix B.

The coefficients of Regression (14) are functions of the parameters in Regression (13) and the econometric model (8). Hence, we can invert this system to recover our parameters of interest. However, the system has more unknown parameters than identifying moments and we need to impose restrictions that reduce the model's degrees of freedom. To address this, we assume that education and demographics are, respectively, perfect proxies for human and social capital. That is, when comparing individuals with the same parental earnings and education, demographic group is uncorrelated with human capital; when comparing individuals with the same parental earnings and demographic background, education is uncorrelated with social capital. With these assumptions in place, it is possible to recover $\overline{AM}$ and the coefficients of Regression (13) from those of Regression (14). This result is formalized in the following proposition:

Proposition 3 *Assume that* $\beta_D^{H|Y_f ED} = \beta_E^{S|Y_f ED} = 0$. *Then*

$$\overline{AM} = 1 - \frac{\beta_{Y_f}^{S|Y_f ED} + \beta_D^{S|Y_f ED} \cdot \frac{\mathit{Cov}\left(D_i, \overline{logY_{f(i)}}\right)}{\mathit{Var}\left(\overline{logY_{f(i)}}\right)}}{\beta^{\psi|Y_f}},$$

where $\beta^{\psi|Y_f}$ *is the firm-IGE, as defined in Regression (6), and* $\beta_{Y_f}^{S|Y_f ED}$ *and* $\beta_D^{S|Y_f ED}$ *can be written as functions of the coefficients in Regression (14). Formulas in Appendix B.*

Proof: *Appendix B.*

Proposition 3 shows how we can obtain a point estimate for $\overline{AM}$ under the assumption that education and demographics are perfect proxies for human and social capital, respectively. By relaxing these assumptions, we can impose bounds on $\overline{AM}$.

First, we relax the assumption that demographic group is a perfect proxy for social capital (*Bounds I*). Instead, we assume that, controlling for education and parental income, demographics affect earnings more through social capital than human capital. Providing support for this assumption, there is substantial geographic segregation between demographic groups in Israel[15] and there is ample evidence that certain groups are discriminated against in the labor market in Israel and other contexts (e.g., Bertrand and Mullainathan, 2004; Rubinstein and Brenner, 2014; Gaddis, 2015; Rivera and Tilcsik, 2016).

Second, we also relax the assumption that education is a perfect proxy for human capital (*Bounds II*). As discussed in Section 5.2, the evidence is at odds with this assumption. We then follow the same approach as in Section 5.2 and assume that education is *not* negatively correlated with social capital, instead of assuming that this correlation is zero.

These assumptions are formalized below.

[15] See Appendix **??**.

<u>**Assumptions**</u>

Bounds I: $\left(\beta_S^\alpha + \beta_S^\psi\right) \cdot \beta_D^{S|Y_f ED} \geq \left(\beta_H^\alpha + \beta_H^\psi\right) \cdot \beta_D^{H|Y_f ED}$ and $\beta_E^{S|Y_f ED} = 0$

Bounds II: $\left(\beta_S^\alpha + \beta_S^\psi\right) \cdot \beta_D^{S|Y_f ED} \geq \left(\beta_H^\alpha + \beta_H^\psi\right) \cdot \beta_D^{H|Y_f ED}$ and $\beta_E^{S|Y_f ED} \geq 0$

The bounds are obtained numerically. We take each $\beta_D^{H|Y_f ED}, \beta_E^{S|Y_f ED}$ that satisfy the above assumptions and compute $\overline{AM}$ following a procedure similar to Proposition 3. Then, we take the upper and lower bounds of these estimates. Appendix B.5 describes the step-by-step procedure.

Results

OLS estimates of Regression 14 are presented in Table VI. They provide further support for the conclusions drawn in Section 4: Education is more strongly associated with the worker component of earnings, while demographic group is more strongly associated with the firm component.[16] Proposition 3 outlines the methodology for calculating $\overline{AM}$ from these coefficients. The resulting estimates, depicted in Figure VI, indicate that $\overline{AM}$ accounts for 46% of the firm-IGE, according to the observable-proxies approach.

These results use broad groupings for the covariates: Education is defined as having college education or not, and demographic group is defined as Secular Jew, Ultra-Orthodox Jew, or Israeli Arab. To assess the robustness of our findings, we examine alternative ways of defining these covariates. Individuals with college education are divided based on the type of institution attended.[17] Moreover, Secular Jews, which represent over 70% of the sample, are divided into Ashkenaz, Sephardic, ex-USSR, and Ethiopians based on the country of origin of individuals' families. In the alternative specification, we estimate that $\overline{AM}$ is 56%.

Figure VI also shows the bounds obtained with the observable-proxies approach under more flexible assumptions. First, relaxing the assumption that demography is a perfect proxy for social capital, we find that $\overline{AM}$ is between 46% and 53% (*Bounds I*). Second, when we also relax the assumption that education is a perfect proxy for human capital, we find that $\overline{AM}$ is at most 53% (*Bounds II*).

5.4 Discussion

This section presented an examination of the role of assortative matching in the firm-IGE, using two distinct approaches. The controlled-firm-IGE approach estimates that assortative matching accounts for 51% of the firm-IGE, while the observable-proxies approach estimates that it accounts for 46%. Whereas the assumptions required by each approach

[16] That is, Appendix Table VI shows that $\frac{\beta_E^{\alpha|Y_f ED}/\beta_D^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED}/\beta_D^{\psi|Y_f ED}} >> 1$.

[17] The different types of higher education institutions in Israel are described in Appendix G.1.

Table VI

Estimating assortative matching: The observable proxies approach

Dependent variable:	Firm earnings premium $(\overline{\psi}_i)$	Individual component (α_i)
	(1)	(2)
$\overline{logY_{f(i)}}$	0.020	0.103
	(0.000)	(0.000)
E_i	0.114	0.633
	(0.000)	(0.001)
D_i	0.251	0.242
	(0.000)	(0.001)
Observations	595,493	595,493

Notes: This table presents OLS estimates of Regression (14). E_i and D_i are the expected log income of individual i given, respectively, her education and demographic group. Individual (α_i) and firm $(\overline{\psi}_i)$ components are AKM fixed effects (see Section 3.3). Fathers' earnings $(\overline{\log Y_{f(i)}})$ is the average log yearly earnings between 1986 and 1991 and are residuals from a regression of log earnings on age, age-squared, and year fixed effects. Standard errors are in parentheses.

are strong, they are also distinct from one another. On the one hand, the key assumption behind the controlled-firm-IGE estimate is that within-firm earnings variation is solely a result of differences in human capital. On the other hand, the observable-proxies estimation assumes that when controlling for education and parental income, demographic group is independent of human capital and that when controlling for parental income and demographic group, education is independent of social capital. The similarity of the estimates obtained under these different assumptions lends credibility to the results.

We also construct bounds for $\overline{AM}$ that are valid under weaker assumptions. One of the bounds, which is associated with the controlled-firm-IGE method, establishes that at least 26% of the firm-IGE cannot be attributed to assortative matching. The other two bounds, which are associated with the observable-proxies approach, establish that at least 47% of the firm-IGE cannot be attributed to assortative matching.

Taken together, these findings strongly suggest that factors other than assortative matching play a significant role in the firm-IGE, with high-SES individuals occupying better firms, even when compared with low-SES individuals of equal skill. These findings are in line with the patterns documented in Section 4, which also indicate that the firm-IGE is unlikely to be explained by differences in skill.

Several mechanisms could explain the sorting of high-SES workers to better-paying firms beyond assortative matching. In the presence of discriminatory employment policies, firms prefer to hire workers from certain socioeconomic backgrounds (Bertrand and Mullainathan, 2004; Rubinstein and Brenner, 2014; Gaddis, 2015; Rivera and Tilcsik, 2016; Kline et al., 2022). The fact that the firm-IGE is to a large extent explained by demographics is consistent with this mechanism.

Additionally, imperfect information creates frictions on both labor demand and supply. On the demand side, firms do not perfectly observe workers' skill (Sousa-Poza and Ziegler, 2003; Faccini, 2014). On the supply side, workers are not aware of all job openings (Calvó-Armengol and Jackson, 2004; Jäger et al., 2021). In both cases, high-SES individuals have social networks that alleviate the information problem and give them access to better jobs (Magruder, 2010; Corak and Piraino, 2011; Kramarz and Skans, 2014; San, 2020; Staiger, 2021). The strong relationship between neighborhoods and the firm-IGE provides suggestive evidence that social networks play an important role.

Finally, compensating differentials might contribue to the firm IGE (Taber and Vejlin, 2020). If low-SES workers value non-monetary amenities more, they might self-select into lower-paying firms. To shed light on this issue, we estimate firm values from job flows, following the revealed preference approach proposed by Sorkin (2018). We estimate firm values separately for high- and low-SES individuals and find that correlation between earnings premium (ψ) and firm values is 0.58 for low-SES workers, compared with 0.46 for high-SES. That is, the low-SES value non-monetary amenities more, not less, suggesting that compensating differentials cannot explain the firm-IGE.

6 Conclusion

In this paper, we examine the role of firms in intergenerational mobility by decomposing the intergenerational elasticity of earnings (IGE) into firm-IGE and individual-IGE components. Our analysis, based on population-wide earnings data from Israel, reveals that the firm component is responsible for 22% of the IGE. We then explore potential mechanisms and show that the individual-IGE is strongly related to education, whereas the firm-IGE can be attributed to demographic segregation in both the labor market and neighborhoods. Finally, we investigate the role of skill-based sorting and find that it accounts for approximately half of the firm-IGE.

Our results provide new insights into the role of firms in intergenerational mobility and highlight the fact that the transmission of social status goes beyond productivity and skills. These results have important policy implications; they suggest that efforts to improve intergenerational mobility should not be limited to human capital and that policies that enhance low-SES workers' access to high-paying firms are necessary.

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Proofs

A Decomposing the IGE: Proof

In this Section, we proof the decomposition in Equation (7). From Equation (4), we have that:

$$\begin{aligned}\overline{\log Y}_i &\equiv \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\log\widetilde{Y}_{it} = \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\left\{\alpha_i + \psi_{J(i,t)} + r_{i,t}\right\} \\ &= \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\alpha_i + \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}\psi_{J(i,t)} + \frac{1}{N_i}\sum_{t\in\mathcal{T}_i}r_{i,t} = \alpha_i + \overline{\psi}_i.\end{aligned} \tag{A.1}$$

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. Now note that the IGE, by definition, is given by $\beta^{IGE} \equiv \frac{Cov\left(\overline{logY_i}, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)}$. Replacing Equation (A.1) into this definition:

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

$\square$

B Measuring Assortative Matching: Proofs

B.1 Proof of Equation (9)

Consider the following best linear projection (henceforth, BLP):

$$\begin{aligned} H_i &= \beta^{H|Y_f}\overline{logY_{f(i)}} + \epsilon_i^{H|Y_f}, \\ S_i &= \beta^{S|Y_f}\overline{logY_{f(i)}} + \epsilon_i^{S|Y_f}. \end{aligned} \tag{B.1}$$

Replacing (B.1) into (8), we have:

$$\overline{\psi}_i = \left[\theta_H^{\psi} \cdot \beta^{H|Y_f} + \theta_S^{\psi} \cdot \beta^{S|Y_f}\right]\overline{logY_{f(i)}} + \left[\eta_i^{\psi} + \theta_H^{\psi}\epsilon_i^{H|Y_f}. + \theta_S^{\psi}\epsilon_i^{S|Y_f}\right]. \tag{B.2}$$

Note that $\epsilon_i^{H|Y_f}$ and $\epsilon_i^{S|Y_f}$ are BLP residuals, so, by definition, $\mathbb{E}\left[\epsilon_i^{H|Y_f}.\middle|\overline{logY_{f(i)}}\right] = 0$ and $\mathbb{E}\left[\epsilon_i^{S|Y_f}.\middle|\overline{logY_{f(i)}}\right] = 0$. Moreover, η_i^{ψ} is assumed to be independent, then $\mathbb{E}\left[\epsilon_i^{\psi}\middle|\overline{logY_{f(i)}}\right] = 0$. That is, the residual of Equation (B.2) is uncorrelated with the covariate. Therefore, the coefficient on $\overline{logY_{f(i)}}$ in an OLS estimate of Equation (B.2) delivers the an unbiased estimate of the following parameter:

$$\beta^{\psi|Y_f} = \theta_H^{\psi} \cdot \beta^{H|Y_f} + \theta_S^{\psi} \cdot \beta^{S|Y_f}.$$

□

B.2 Proof of Proposition 1

Consider the following OLS regression:

$$\overline{\psi_i} = \beta_0^{\psi|\alpha,Y_f} + \beta_{\alpha}^{\psi|\alpha,Y_f} \cdot \alpha_i + \beta_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\psi|\alpha,Y_f}. \tag{B.3}$$

Using Equations (8) and (B.3) to write $\overline{\psi}_i$ in terms of α_i and $\overline{logY_{f(i)}}$:

$$\overline{\psi}_i = \left[\theta_S^{\psi} - \frac{\theta_H^{\psi}\theta_S^{\alpha}}{\theta_H^{\alpha}}\right]\beta^{S|Y_f}\overline{logY_{f(i)}} + \frac{\theta_H^{\psi}}{\theta_H^{\alpha}}\alpha_i + \left[\eta_i^{\psi} - \frac{\theta_H^{\psi}}{\theta_H^{\alpha}}\eta_i^{\alpha} + \left(\theta_S^{\psi} - \frac{\theta_H^{\psi}\theta_S^{\alpha}}{\theta_H^{\alpha}}\right)\epsilon_i^{S|Y_f}\right] \tag{B.4}$$

If there is no measurement error in α $\left(\eta_i^{\alpha} = 0\right)$ and social capital does not affect α

$\left(\theta_S^{\alpha} = 0\right)$, then:

$$\overline{\psi}_i = \theta_S^{\psi} \cdot \beta^{S|Y_f} \cdot \overline{logY_{f(i)}} + \frac{\theta_H^{\psi}}{\theta_H^{\alpha}} \cdot \alpha_i + \left[\eta_i^{\psi} + \theta_S^{\psi}\epsilon_i^{S|Y_f}\right]. \tag{B.5}$$

Notice that η_i^{ψ} is assumed to be independent, then $\mathbb{E}\left[\epsilon_i^{\psi}\middle|\overline{logY_{f(i)}}, \alpha_i\right] = 0$. Moreover: (a.) $\epsilon_i^{S|Y_f}$ is the OLS residual of Regression (B.1). Hence by definition, it is uncorrelated with $\overline{logY_{f(i)}}$. (b.) By assumption, social capital does not impact α_i, and $\epsilon_i^{H|Y_f}$ and $\epsilon_i^{S|Y_f}$ are uncorrelated. Therefore, α_i and $\epsilon_i^{S|Y_f}$ are uncorrelated. That is, the residual of Equation (B.5) is uncorrelated with the covariates. Therefore, the coefficient on $\overline{logY_{f(i)}}$ in an OLS estimate of Equation (B.5) delivers the an unbiased estimate of the following parameter:

$$\beta_{Y_f}^{\psi|\alpha,Y_f} = \theta_S^{\psi} \cdot \beta^{S|Y_f}.$$

Finally, this implies that:

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

□

B.3 Proof of Proposition 2

Define the BLP of H_i and S_i on $\overline{logY_{f(i)}}$ and Z_i:

$$\begin{aligned} H_i &= \beta_0^{H|Y_f,Z} + \beta_{Y_f}^{H|Y_f,Z}\overline{logY_{f(i)}} + \beta_Z^{H|Y_f,Z} Z_i + \epsilon^{H|Y_f,Z}, \\ S_i &= \beta_0^{S|Y_f,Z} + \beta_{Y_f}^{S|Y_f,Z}\overline{logY_{f(i)}} + \beta_Z^{S|Y_f,Z} Z_i + \epsilon^{S|Y_f,Z}. \end{aligned} \tag{B.6}$$

Note that we see in that data that $\overline{logY_{f(i)}}$ and Z_i are positively correlated, and we assume that $\beta_Z^{S|Y_f,Z} \geq 0$. Then, using the omitted-variable-bias formular, we have that:

$$\beta_{Y_f}^{S|Y_f,Z} \leq \beta^{S|Y_f} \tag{B.7}$$

First stage

Replacing (B.6) in (8) to write α_i in terms of $\overline{logY_{f(i)}}$ and Z_i:

$$\begin{aligned}
&\alpha_i = \widehat{\alpha}_i + \left[\eta_i^\alpha + \theta_H^\alpha \epsilon_i^{H|Y_f,Z} + \theta_S^\alpha \epsilon_i^{S|Y_f,Z}\right] \\
&\text{where} \\
&\widehat{\alpha}_i \equiv \beta_{Y_f}^{\alpha|Y_f,Z} \cdot \overline{logY_{f(i)}} + \beta_Z^{\alpha|Y_f,Z} \cdot Z_i \\
&\beta_{Y_f}^{\alpha|Y_f,Z} \equiv \theta_H^\alpha \beta_{Y_f}^{H|Y_f,Z} + \theta_S^\alpha \beta_{Y_f}^{S|Y_f,Z} \\
&\beta_Z^{\alpha|Y_f,Z} \equiv \theta_H^\alpha \beta_Z^{H|Y_f,Z} + \theta_S^\alpha \beta_Z^{S|Y_f,Z}
\end{aligned} \tag{B.8}$$

By assumption, η_i^α is uncorrelated with $\overline{logY_{f(i)}}, Z_i$. Moreover, $\epsilon^{H|Y_f,Z}, \epsilon^{S|Y_f,Z}$ are BLP residuals, so, by definition, they are uncorrelated with $\overline{logY_{f(i)}}, Z_i$. Therefore, an OLS regression yields unbiased estimates of Equation $(B.8)$.

It will be useful later to have S_i as a function of $\widehat{\alpha}_i$ and $\overline{logY_{f(i)}}$. For this, we isolate Z_i in Equation (B.8) and then replace it in Equation (B.6). This gives us:

$$S_i = \frac{\beta_Z^{S|Y_f,Z}}{\beta_Z^{\alpha|Y_f,Z}} \cdot \widehat{\alpha}_i + \left\{\beta_{Y_f}^{S|Y_f,Z} - \beta_Z^{S|Y_f,Z} \frac{\beta_{Y_f}^{\alpha|Y_f,Z}}{\beta_Z^{\alpha|Y_f,Z}}\right\} \cdot \overline{logY_{f(i)}} + \epsilon_i^{S|Y_f,Z} \tag{B.9}$$

Second stage

Using (B.12) to write $\overline{\psi}_i$ in terms of α_i and S_i, we get:

$$\overline{\psi}_i = \frac{\theta_H^\psi}{\theta_H^\alpha}\alpha_i + \left[\theta_S^\psi - \theta_H^\psi \frac{\theta_S^\alpha}{\theta_H^\alpha}\right] \cdot S + \left[\epsilon_i^\psi - \frac{\theta_H^\psi}{\theta_H^\alpha}\epsilon_i^\psi\right] \tag{B.10}$$

Now let's write $\overline{\psi}_i$ in terms of $\widehat{\alpha}_i$ and $\overline{logY_{f(i)}}$. For this, we replace Equations (B.8) and (B.9) into (B.10). We get:

$$\begin{aligned}
&\overline{\psi}_i = \widetilde{\beta}_0^{\psi|\alpha,Y_f} + \widetilde{\beta}_\alpha^{\psi|\alpha,Y_f} \cdot \widehat{\alpha}_i + \widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{logY_{f(i)}} + \widetilde{\epsilon}_i^{\psi|\alpha,Y_f} \\
&\text{where} \\
&\widetilde{\beta}_\alpha^{\psi|\alpha,Y_f} \equiv \frac{\theta_H^\psi}{\theta_H^\alpha} + \left[\theta_S^\psi - \theta_H^\psi \frac{\beta_S^\alpha}{\theta_H^\alpha}\right] \cdot \frac{\beta_Z^{S|Y_f,Z}}{\beta_Z^{\alpha|Y_f,Z}} \\
&\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \equiv \theta_S^\psi \left[1 - \frac{\theta_H^\psi}{\theta_S^\psi}\frac{\beta_S^\alpha}{\theta_H^\alpha}\right]\left[\beta_{Y_f}^{S|Y_f,Z} - \beta_Z^{S|Y_f,Z}\frac{\beta_{Y_f}^{\alpha|Y_f,Z}}{\beta_Z^{\alpha|Y_f,Z}}\right] \\
&\widetilde{\epsilon}_i^{\psi|\alpha,Y_f} \equiv \eta_i^\psi + \theta_H^\alpha \frac{\theta_H^\psi}{\theta_H^\alpha} \cdot \epsilon_i^{H|Y_f,Z} + \theta_S^\psi \cdot \epsilon_i^{S|Y_f,Z}
\end{aligned} \tag{B.11}$$

Note that $\widetilde{\epsilon}_i^{\psi|\alpha,Y_f}$ is uncorrelated with $\overline{logY_{f(i)}}$ and Z_i. Hence, it is also uncorrelated with $\widehat{\alpha}_i$. Therefore, an OLS regression of $\overline{\psi}_i$ on $\overline{logY_{f(i)}}$ and $\widehat{\alpha}_i$ gives unbiased estimates of the coefficients in Equation (B.11). Consequently, 2SLS estimates of $\overline{\psi}_i$ on $\overline{logY_{f(i)}}$ and α_i, using $\widehat{\alpha}_i$ as an instrument for α_i, gives consistent estimates of the coefficients in Equation (B.11).

Using (B.11), we can bound $\overline{AM}$ the following way. First, note that $\beta_Z^{S|Y_f,Z}\frac{\beta_{Y_f}^{\alpha|Y_f,Z}}{\beta_Z^{\alpha|Y_f,Z}} \geq 0$ because: (I) We see in the data that $\beta_{Y_f}^{\alpha|Y_f,Z}, \beta_Z^{\alpha|Y_f,Z} > 0$, (II) By assumption, $\beta_Z^{S|Y_f,Z} \geq 0$. Therefore:

$$\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \leq \theta_S^{\psi}\left[1 - \frac{\theta_H^{\psi}}{\theta_S^{\psi}}\frac{\beta_S^{\alpha}}{\theta_H^{\alpha}}\right]\beta_{Y_f}^{S|Y_f,Z}.$$

Moreover, we know that $0 \leq \left[1 - \frac{\theta_H^{\psi}}{\theta_S^{\psi}}\frac{\beta_S^{\alpha}}{\theta_H^{\alpha}}\right] \leq 1$ because: (1) By assumption, $\frac{\theta_H^{\psi}}{\theta_S^{\psi}}\frac{\beta_S^{\alpha}}{\theta_H^{\alpha}} < 1$, (2) By definition, $\theta_H^{\psi}, \theta_S^{\psi}, \beta_S^{\alpha}, \theta_H^{\alpha} \geq 0$. Therefore:

$$\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \leq \theta_S^{\psi}\beta_{Y_f}^{S|Y_f,Z}.$$

Moreover, from Equation (B.7), $\beta_{Y_f}^{S|Y_f,Z} \leq \beta^{S|Y_f}$. Therefore:

$$\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \leq \theta_S^{\psi}\beta^{S|Y_f}.$$

Finally:

$$1 - \frac{\widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f}}{\beta^{\psi|Y_f}} \geq 1 - \frac{\theta_S^{\psi}\beta^{S|Y_f}}{\beta^{\psi|Y_f}} = 1 - \frac{\theta_S^{\psi}\beta^{S|Y_f}}{\theta_S^{\psi}\beta^{S|Y_f} + \theta_H^{\psi}\beta^{H|Y_f}} = \frac{\theta_H^{\psi}\beta^{H|Y_f}}{\theta_S^{\psi}\beta^{S|Y_f} + \theta_H^{\psi}\beta^{H|Y_f}} = \overline{AM}$$

$\square$

B.4 Proof of Proposition 3

Note that human and social capital are unobserved latent variables. Hence, they can be redefined such that θ_S^{ψ} and θ_H^{ψ} are normalized to 1. The model becomes:

$$\begin{aligned} \overline{\psi}_i &= H_i + S_i + \eta_i^{\psi}, \\ \alpha_i &= \theta_H^{\alpha} \cdot H_i + \theta_S^{\alpha} \cdot S_i + \eta_i^{\alpha}, \end{aligned} \tag{B.12}$$

Equation 10 becomes:

$$\overline{AM} = 1 - \frac{\beta^{S|Y_f}}{\beta^{\psi|Y_f}}. \tag{B.13}$$

By definition, the regression coefficient $\beta^{S|Y_f}$ is:

$$\begin{aligned}\beta^{S|Y_f} &\equiv \frac{Cov\left(S_i, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} \\ &= \beta_{Y_f}^{S|Y_f ED} \frac{Cov\left(\overline{logY_{f(i)}}, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} + \beta_E^{S|Y_f ED} \frac{Cov\left(E, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} \\ &+ \beta_D^{S|Y_f ED} \frac{Cov\left(D, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} + \frac{Cov\left(\epsilon_i^{S|Y_f ED}, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)}\end{aligned}$$

Note that $\epsilon_i^{S|Y_f ED}$ is the residual of a regression that includes $\overline{logY_{f(i)}}$. Hence, $Cov\left(\epsilon_i^{S|Y_f ED}, \overline{logY_{f(i)}}\right)$ $= 0$. Therefore:

$$\beta^{S|Y_f} = \beta_{Y_f}^{S|Y_f ED} + \beta_E^{S|Y_f ED} \frac{Cov\left(E, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} + \beta_D^{S|Y_f ED} \frac{Cov\left(D, \overline{logY_{f(i)}}\right)}{Var\left(\overline{logY_{f(i)}}\right)} \tag{B.14}$$

Now let us show how to write $\beta_{Y_f}^{S|Y_f ED}$, $\beta_E^{S|Y_f ED}$, and $\beta_D^{S|Y_f ED}$ as functions of the coefficients in Regression (14). Plugging the Equations in (13) into (B.12), we have that:

$$\begin{aligned}\beta_q^{\alpha|Y_f ED} &= \beta_{Y_f}^{H|Y_f ED} \cdot \beta_H^\alpha + \beta_{Y_f}^{S|Y_f ED} \cdot \beta_S^\alpha \\ \beta_E^{\alpha|Y_f ED} &= \beta_E^{H|Y_f ED} \cdot \beta_H^\alpha + \beta_E^{S|Y_f ED} \cdot \beta_S^\alpha \\ \beta_D^{\alpha|Y_f ED} &= \beta_D^{H|Y_f ED} \cdot \beta_H^\alpha + \beta_D^{S|Y_f ED} \cdot \beta_S^\alpha \\ \beta_{Y_f}^{\psi|Y_f ED} &= \beta_{Y_f}^{H|Y_f ED} + \beta_{Y_f}^{S|Y_f ED} \\ \beta_E^{\psi|Y_f ED} &= \beta_E^{H|Y_f ED} + \beta_E^{S|Y_f ED} \\ \beta_D^{\psi|Y_f ED} &= \beta_D^{H|Y_f ED} + \beta_D^{S|Y_f ED}\end{aligned} \tag{B.15}$$

Define $\kappa^H = \frac{\beta_D^{H|Y_f ED}}{\beta_E^{H|Y_f ED}}$ and $\kappa^S \equiv \frac{\beta_E^{S|Y_f ED}}{\beta_D^{S|Y_f ED}}$. Solving the system of equations in (B.15):

$$\begin{aligned}\beta_H^\alpha &= \frac{\beta_E^{\alpha|Y_f ED} - \kappa^S \beta_D^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED} - \kappa^S \beta_D^{\psi|Y_f ED}} \\ \beta_S^\alpha &= \frac{\beta_D^{\alpha|Y_f ED} - \kappa^H \beta_E^{\alpha|Y_f ED}}{\beta_D^{\psi|Y_f ED} - \kappa^H \beta_E^{\psi|Y_f ED}}\end{aligned} \tag{B.16}$$

$$
\begin{aligned}
\beta_{Y_f}^{S|Y_f ED} &= \frac{\beta_H^{\alpha}\beta_{Y_f}^{\psi|Y_f ED} - \beta_{Y_f}^{\alpha|Y_f ED}}{\beta_H^{\alpha} - \beta_S^{\alpha}} \\
\beta_E^{S|Y_f ED} &= \frac{\beta_H^{\alpha}\beta_E^{\psi|Y_f ED} - \beta_E^{\alpha|Y_f ED}}{\beta_H^{\alpha} - \beta_S^{\alpha}} \\
\beta_D^{S|Y_f ED} &= \frac{\beta_H^{\alpha}\beta_D^{\psi|Y_f ED} - \beta_D^{\alpha|Y_f ED}}{\beta_H^{\alpha} - \beta_S^{\alpha}}
\end{aligned}
\tag{B.17}
$$

Now, let us use the assumption that when controlling for education and parental income, demographic group is uncorrelated with human capital and that, when controlling for parental income and demographic group, education is uncorrelated with social capital. This implies $\kappa^H = \kappa^S = 0$. Replacing $\kappa^H = \kappa^S = 0$ into (B.16), we find β_H^{α} and β_S^{α}. Finally, replacing β_H^{α} and β_S^{α} into (B.17), we can write $\beta_{Y_f}^{S|Y_f ED}$ and $\beta_D^{S|Y_f ED}$ as functions of the coefficients in Regression (14):

$$
\beta_{Y_f}^{S|Y_f ED} = \frac{\frac{\beta_E^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED}} \cdot \beta_{Y_f}^{\psi|Y_f ED} - \beta_{Y_f}^{\alpha|Y_f ED}}{\frac{\beta_E^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED}} - \frac{\beta_D^{\alpha|Y_f ED}}{\beta_D^{\psi|Y_f ED}}} \; ; \quad \beta_D^{S|Y_f ED} = \frac{\frac{\beta_E^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED}} \cdot \beta_D^{\psi|Y_f ED} - \beta_D^{\alpha|Y_f ED}}{\frac{\beta_E^{\alpha|Y_f ED}}{\beta_E^{\psi|Y_f ED}} - \frac{\beta_D^{\alpha|Y_f ED}}{\beta_D^{\psi|Y_f ED}}}
$$

$\square$

B.5 Observable proxies: Bounds

From Equation (B.15), we have that:

$$
\begin{aligned}
\beta_{Y_f}^{H|Y_f ED} &= \beta_{Y_f}^{\psi|Y_f ED} - \beta_{Y_f}^{S|Y_f ED}, \\
\beta_E^{H|Y_f ED} &= \beta_E^{\psi|Y_f ED} - \beta_E^{S|Y_f ED}, \\
\beta_D^{H|Y_f ED} &= \beta_D^{\psi|Y_f ED} - \beta_D^{S|Y_f ED}.
\end{aligned}
\tag{B.18}
$$

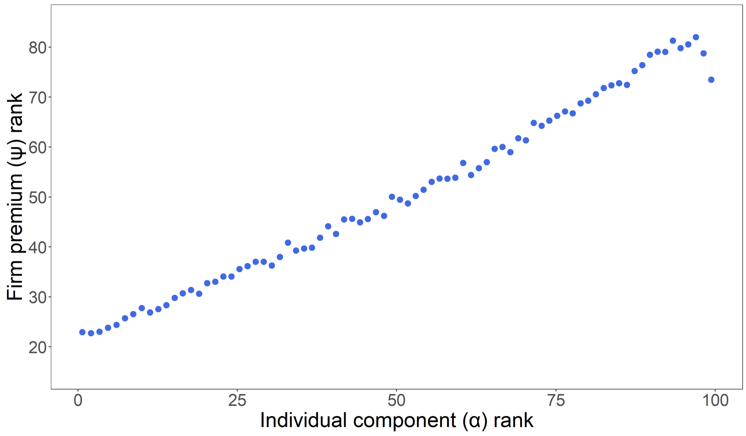
We construct bounds to $\overline{AM}$ under a given set of assumptions $\mathcal{A}$ as follows. (I) Take a large grid of possible values of κ^S and κ^H. (II) For each κ^S and κ^H, use Equation (B.16) to calculate β_H^{α} and β_S^{α}. (III) Given β_H^{α} and β_S^{α}, use Equations (B.17) and (B.18) to calculate $\beta_{Y_f}^{S|Y_f ED}$, $\beta_D^{H|Y_f ED}$, $\beta_E^{H|Y_f ED}$, $\beta_{Y_f}^{H|Y_f ED}$, $\beta_D^{H|Y_f ED}$, and $\beta_E^{H|Y_f ED}$. (IV) Use Equation (B.13) to calculate $\overline{AM}'$. If the corresponding parameters $\left(\beta_H^{\alpha}, \beta_S^{\alpha}, \beta_{Y_f}^{S|Y_f ED}, \beta_D^{H|Y_f ED}, \beta_E^{H|Y_f ED}, \beta_{Y_f}^{H|Y_f ED}, \beta_D^{H|Y_f ED}, \text{and } \beta_E^{H|Y_f ED}\right)$ are consistent with the stated assumptions $\mathcal{A}$, add $\overline{AM}'$ to the set of possible values of $\overline{AM}$.

Online Appendices

C Appendix Figures and Tables

Figure C.1

Cross-sectional assortative matching



Notes: This plots the relationship between children's individual (α) and firm (ψ) components of earnings. Individual and firm components are AKM fixed effects (see Section 3.3).

Table C.1

Decomposing the IGE – Robustness: Only college educated workers

	(1)		(2)		(3)
Dependent variable:	$\overline{\log Y}_i$		α_i		$\overline{\psi}_i$
	$\overbrace{\beta^{IGE}}^{\text{IGE}}$	$=$	$\overbrace{\beta^{\alpha\|Y_f}}^{\text{individual-IGE}}$	$+$	$\overbrace{\beta^{\psi\|Y_f}}^{\text{firm-IGE}}$
$\overline{logY_{f(i)}}$	0.161		0.127		0.034
	(0.001)		(0.001)		(0.000)
Share of IGE	1.00		0.79		0.21
	.		(0.001)		(0.001)
Observations	312,594		312,594		312,594

Notes: This table reports the results of the decomposition of the intergenerational earnings elasticity (IGE) into individual and firm components, as described in Equation (7). Only college-educated workers are included in the sample. Column (1) shows the IGE (Equation 5). Column (2) shows the elasticity of children's individual component of earnings (α_i) to their father's earnings, which we call individual-IGE (Equation 6). Column (3) shows the elasticity of children's firm component of earnings $(\overline{\psi}_i)$ to their father's earnings, which we call firm-IGE (Equation 6). The bottom panel reports the share of the IGE explained by each component. Standard errors are in parentheses. Standard errors for the shares are calculated using the delta method. 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.

Table C.2

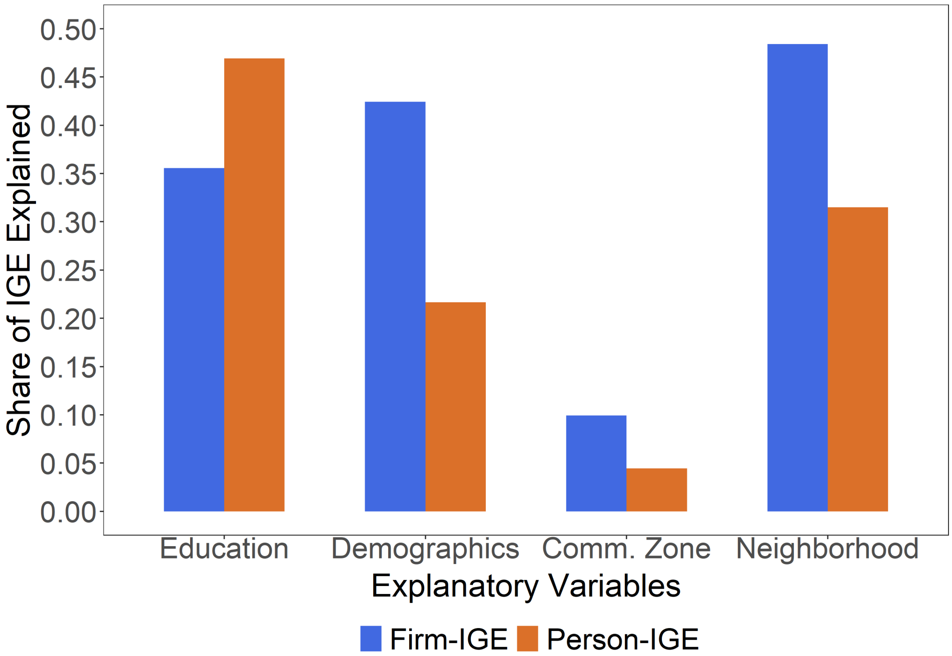
Decomposing the IGE – Robustness: Inputting α and ψ

	(1)		(2)		(3)
Dependent variable:	$\overline{\log Y}_i$		α_i		$\overline{\psi}_i$
	$\overbrace{\beta^{IGE}}^{\text{IGE}}$	$=$	$\overbrace{\beta^{\alpha\|Y_f}}^{\text{individual-IGE}}$	$+$	$\overbrace{\beta^{\psi\|Y_f}}^{\text{firm-IGE}}$
$\overline{logY_{f(i)}}$	0.280		0.217		0.062
	(0.000)		(0.000)		(0.000)
Share of IGE	1.00		0.78		0.22
	.		(0.000)		(0.000)
Observations	775,232		775,232		775,232

Notes: This table reports the results of the decomposition of the intergenerational earnings elasticity (IGE) into individual and firm components, as described in Equation (7). All individuals with stable jobs and whose fathers have nonzero reported income are included in the sample (IGM sample, as defined in Section 2.2). For individuals not in the connected set, we use predicted α_i and $\overline{\psi}_i$ as outcomes in columns (2) and (3), respectively. The prediction is fully non-parametric based on their gender, demographic group, and education. Column (1) shows the IGE (Equation 5). Column (2) shows the elasticity of children's individual component of earnings (α_i) to their father's earnings, which we call individual-IGE (Equation 6). Column (3) shows the elasticity of children's firm component of earnings $(\overline{\psi}_i)$ to their father's earnings, which we call firm-IGE (Equation 6). The bottom panel reports the share of the IGE explained by each component. Standard errors are in parentheses. Standard errors for the shares are calculated using the delta method. 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.

Figure C.2

Share of firm- and individual-IGE explained by different covariates



Notes: This figure shows the share of the firm- and individual-IGE that is explained by different covariates. The firm- and individual-IGE are, respectively, the elasticity of children's firm and individual components of earnings to their father's earnings $(\overline{\log Y_{f(i)}})$. Individual (α_i) and firm $(\overline{\psi}_i)$ components are AKM fixed effects (see Section 3.3). "Share Explained" is how much the estimated elasticity is reduced with the inclusion of each control, compared with the specification without controls. Fathers' earnings are 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. "Education" is a categorical variable indicating the type of higher education institutions attended, if any (see Appendix G.1). "Demographic group" is defined as Secular Jew (Ashkenaz), Secular Jew (Sephardic), Secular Jew (Ethiopian), Secular Jew (USSR), Ultra-Orthodox Jew, or Israeli Arab. "Comm. Zone" and "Neighborhood" are, respectively, commuting zone and neighborhood of residence.

D 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 D.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 (2011a).

Table D.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.

E Validating the AKM decomposition

E.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 (1), 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:

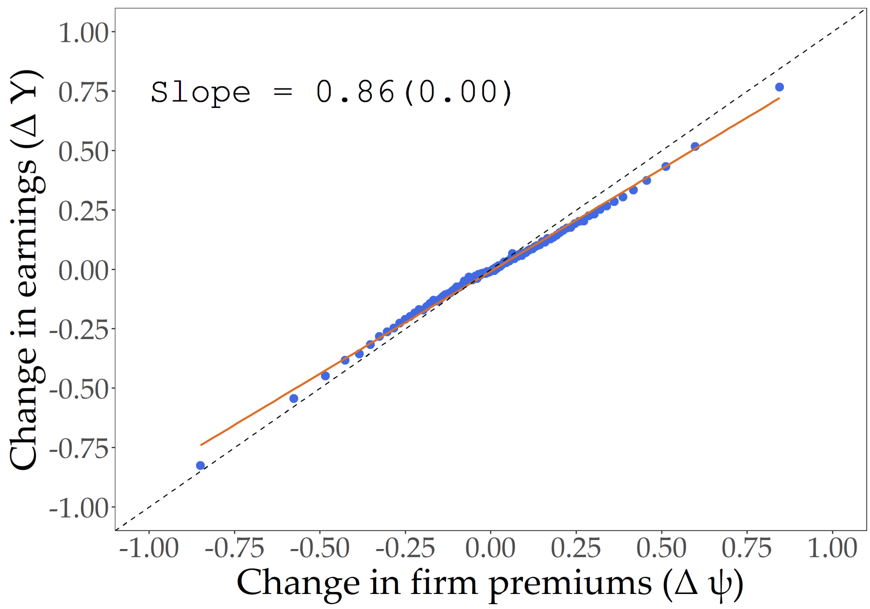
$$M_{i,t} \equiv \mathbb{1}\big\{J(i,t) \neq J(i,t+1) \ \& \ J(i,t) \neq Non\ Emp \ \& \ J(i,t+1) \neq Non\ Emp\big\}.$$

The key assumption to estimate Equation (1) 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 E.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 E.1 Earnings Change Corresponds to Firm Fixed Effect Change



Notes: These figures show 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 red line plots the 45 degree line.

E.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 E.1.

We see that the correlation between premiums estimated with the full sample and the IGM sample is 0.86. 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 (0.89). 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 E.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 E.1 Correlation between firm premiums in different samples

	Full	IGM	Random (Full)	Random (IGM)	Low-SES	High-SES
Full	1.00					
IGM	0.86	1.00				
Random (Full)	0.89	0.76	1.00			
Random (IGM)	0.80	0.91	0.74	1.00		
Low-SES	0.77	0.89	0.71	0.80	1.00	
High-SES	0.82	0.93	0.77	0.86	0.70	1.00

Notes: This table shows the correlations between firm premiums (ψ) estimated in different samples. Firm premiums are defined in Equation (1). "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. "High-SES" and "Low-SES" are, respectively, workers above and below the median father earnings in the IGM sample. "Random (IGM)" is a 50% random sample of the IGM sample.

F Split-sample Instruments

In this appendix, we demonstrate that we can use a split-sample technique to build an instrument for $\psi_{J(i,t)}$, as in Goldschmidt and Schmieder (2017) and Drenik et al. (2022), but not to build an instrument for α_i.

Consider the AKM decomposition of earnings:

$$\log Y_{i,t} = \overbrace{\alpha_i}^{\text{individual component}} + \underbrace{\psi_{J(i,t)}}_{\text{firm component}} + \overbrace{x_{it}'\beta^x}^{\text{covariates}} + \underbrace{r_{i,t}}_{\text{error term}} . \tag{F.1}$$

Since Card et al. (2013), the AKM literature usually assumes the error term can be decomposed into three terms. The exact assumptions about each term differ from paper to paper. Here we present a strong version of these assumptions and show that, even under these strong assumptions, split-sample techniques cannot be used to build an instrument for α_i. Consider the following decomposition:

$$r_{i,t} = \eta^M_{iJ(i,t)} + \zeta^P_{it} + \eta^T_{it}. \tag{F.2}$$

η^M_{ij} represents a matching component between worker i and firm j, that is, worker i is a particularly good (or bad) fit for firm j. η^M_{ij} is constant across time and we assume it is idiosyncratic and has mean zero across workers $\left(\mathbb{E}\left[\eta^M_{ij}|i\right]\right) = 0$ and across firms $\left(\mathbb{E}\left[\eta^M_{ij}|j\right]\right) = 0$. η^T_{it} is an idiosyncratic shock. ζ^P_{it} is a permanent worker-level shock follows a unit-root process:

$$\zeta^P_{it} = \zeta^P_{i,t-1} + \eta^P_{it},$$

where η^P_{it} is an idiosyncratic shock.

Let us first show that, under these assumptions, we *can* use a split-sample technique to build an instrument for $\psi_{J(i,t)}$ (Goldschmidt and Schmieder, 2017; Drenik et al., 2022). Say we want to estimate the following regression:

$$B_{it} = \beta_0^{B|\psi} + \beta^{B|\psi} \cdot \psi_{J(i,t)} + \epsilon_{it}^{B|\psi}, \tag{F.3}$$

where B_{it} is an outcome of interest and the parameter of interest is $\beta^{B|\psi}$.

Firm premiums $\left(\psi_j\right)$ are not directly observed, so we have to use estimated firm premiums instead, leading to an attenuation bias. As a solution, we can randomly split the workers into two equal-sized samples $\mathcal{I}_1$ and $\mathcal{I}_2$. Then we estimate Equation (F.1) separately with each of these samples, which results in two different firm-premiums estimates:

$\widehat{\psi}_j^{I_1}$ and $\widehat{\psi}_j^{I_2}$, respectively. Then we can estimate the coefficients in Equation (F.3) with the following 2SLS regression:

$$\begin{aligned}&\text{Second stage:}\\&B_{it} = \beta_0^{B|\psi} + \beta^{B|\psi} \cdot \widehat{\psi}_{J(i,t)}^{I_1} + \epsilon_{it}^{B|\psi^1}\\&\text{First stage:}\\&\widehat{\psi}_{J(i,t)}^{I_1} = \beta_0^{\psi^1|\psi^2} + \beta^{\psi^1|\psi^2} \cdot \widehat{\psi}_{J(i,t)}^{I_2} + \epsilon_{it}^{\psi^1|\psi^2}\end{aligned} \tag{F.4}$$

That is, we use $\widehat{\psi}_j^{I_2}$ as an instrument for $\widehat{\psi}_j^{I_1}$. This gives us a consistent estimate of $\beta^{B|\psi}$ because the measurement error in $\widehat{\psi}_j^{I_2}$ and $\widehat{\psi}_j^{I_1}$ are uncorrelated. The reason is that all the elements on the error term (Equation (F.2)) are uncorrelated across workers, and $\widehat{\psi}_j^{I_2}$ and $\widehat{\psi}_j^{I_1}$ are estimated using different workers.

Now let us show that we *can not* use a split-sample technique to build an instrument for α_i. Say we want to estimate the following regression:

$$B_i = \beta_0^{B|\alpha} + \beta^{B|\alpha} \cdot \alpha_i + \epsilon_i^{B|\alpha}, \tag{F.5}$$

where B_i is an outcome of interest and the parameter of interest is $\beta^{B|\alpha}$. Analogously to the previous case, α_i is not directly observed, so we have to use estimated version instead, leading to an attenuation bias.

How could we solve this with a split-sample approach? We cannot split the sample by worker because $\mathcal{I}_1$ just gives estimates of α_i for workers in $\mathcal{I}_1$, and vice-versa for $\mathcal{I}_2$. That is, there are no α's estimated in both samples.

One alternative is to split the sample randomly by years: $\mathcal{T}_1$ and $\mathcal{T}_2$. Then we estimate Equation (F.1) separately with each of these samples, which results in two different worker-component estimates: $\widehat{\alpha}_i^{T_1}$ and $\widehat{\alpha}_i^{T_2}$, respectively. However, the measurement errors in $\widehat{\alpha}_i^{T_1}$ and $\widehat{\alpha}_i^{T_2}$ are correlated for two reasons. First, we have same workers and firms in the two samples, so the match component of the error term $\left(\eta_{iJ(i,t)}^M\right)$ is correlated across the samples. Second, we have the same workers in the two samples and the permanent shock $\left(\zeta_{it}^P\right)$ is correlated accross time.

Another alternative is to split the sample randomly by firm: $\mathcal{J}_1$ and $\mathcal{J}_2$. Then we estimate Equation (F.1) separately with each of these samples, which results in two different worker-component estimates: $\widehat{\alpha}_i^{J_1}$ and $\widehat{\alpha}_i^{J_2}$, respectively. Now the match component is not correlated anymore across samples. However, the permanent component of the error term still is because we have the same workers in the two samples. Therefore, the measurement error in $\widehat{\alpha}_i^{J_1}$ and $\widehat{\alpha}_i^{J_2}$ are correlated.

In conclusion, we could only use a split-sample approach to build an instrument for

α_i under very strong assumptions. For example, if we assumed that the error term in the earnings process (Equation (F.1)) is fully idiosyncratic.

G Measuring Assortative Matching: Robustness

G.1 Instrumental Variable

In this appendix, we assess the robustness of the results in Section 5.2 to different ways of constructing the instrumental variable. In Section 5.2, we estimate an upper bound to AM-share using the coefficients from the following 2SLS regression:

$$\begin{aligned}
&\text{Second stage:}\\
&\overline{\psi_i} = \widetilde{\beta}_0^{\psi|\alpha,Y_f} + \widetilde{\beta}_\alpha^{\psi|\alpha,Y_f} \cdot \alpha_i + \widetilde{\beta}_{Y_f}^{\psi|\alpha,Y_f} \cdot \overline{logY_{f(i)}} + \widetilde{\epsilon}_i^{\psi|\alpha,Y_f}\\
&\text{First stage:}\\
&\alpha_i = \beta_0^{\alpha|Z,Y_f} + \beta_Z^{\alpha|Z,Y_f} \cdot Z_i + \beta_{Y_f}^{\alpha|Z,Y_f} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\alpha|Z,Y_f},
\end{aligned} \tag{G.1}$$

where the instrumental variable Z_i is a measure of individual i's education. In Section 5.2, we use an indicator of having a college degree as the instrument. Now, we present alternative specifications that take into account education quality.

We measure education quality the following way. Our data indicates what type of higher education institutions (if any) each individual graduated from.[18] Table G.1 shows descriptive statistics of each type of institution. Indeed, we see a high variation across education types. For example, university graduates earn 50% more than individuals graduating from a teaching college.

We create proxies of the education quality of each of these types of institutions based on the labor market outcomes of their former students. We build three different proxies: average log earnings of the students' fathers, average log earnings of the students themselves, and share of the students with stable jobs. We can also calculate these averages for the individuals without any higher education degree. We build our instrument by defining Z_i as the quality of the higher institution that individual i attended, for each of the three proxies of quality. Finally, we build one more alternative instrument making Z_i equal to a vector of dummies of institution type—"None" being the baseline category.

The results are in Table G.2. It shows estimates of Regression (G.1) using different

[18]The education types can broadly be classified into non-academic and academic (i.e. approved by the council of higher education). When entering high school (10th grade), students choose whether to enroll in the academic or non-academic track. The students on the academic track will take nation-wide standardized tests and receive a high-school diploma ('bagrut'). This diploma will allow them to attend an academic institution (university, academic college, or teachers' college). Academic colleges in Israel are similar to liberal arts college in the U.S. and, generally speaking, are perceived as less prestigious then universities (that can provide a doctorate degree as well). The students that chose a non-academic track may continue until the 14th grade, receiving more practical training (non-academic school). They can instead signup post high-school to a specific diploma studies (e.g. barber) or a non-academic 2-year practical engineering school ('handesay').

instruments, and the corresponding AM-share upper bounds are in Figure G.1. Using different measures of education as the instrument might change the resulting AM-share upper bound for at least two reasons. First, the more Z_i is correlated with social capital, the larger the resulting upper bound will be. Therefore, we will get different upper bounds if different measures of education are differentially associated with social capital. Second, differences between the estimates might also reflect misspecification in our model. In particular, Equation (8) assumes the effects of human and social capital are homogeneous and linear. If the true underlying model is nonlinear, the different estimates might be reflecting differences in the compliers affected by each instrument.

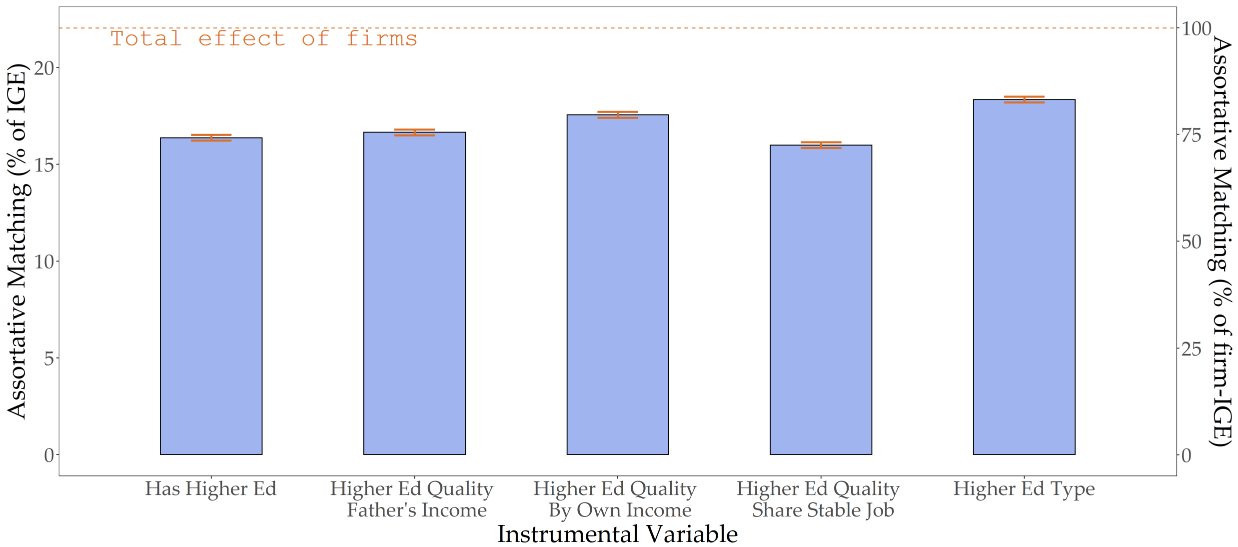
The second bar in Figure G.1 shows our baseline result (presented in the main text): at most 76% of the firm-IGE is due to assortative matching. The third to seventh bar present estimates with alternative instruments. We see that the estimates are stable across different instruments, indicating model misspecification is not driving the results.

Table G.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 institutions. 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 forth 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.

Figure G.1 The role of assortative matching in the firm-IGE - Robustness



Notes: This figure presents the share of the IGE (left axis) and firm-IGE (right axis) that is due to the assortative-matching channel, in different specifications. In all columns, but the first, the labels in the x-axis describe the instrumental variable used in the estimation. Section 5.2 describes how this decomposition is calculated. The error bars represent 95% confidence intervals, computed using the delta method.

Table G.2 Firm earnings premium and father's earnings - Robustness

	Dependent variable: Firm earnings premium $(\overline{\psi}_i)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{logY_{f(i)}}$	0.056	0.017	0.014	0.014	0.011	0.015	0.009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control		α	α	α	α	α	α
Instrument			Has Higher Ed	Higher Ed Quality	Higher Ed Quality	Higher Ed Quality	Higher Ed Type
Quality Measure				Father Inc	Own Inc	Share Stable Job	
F-stat			775,977	1,098,853	1,109,100	700,612	174,159
Observations	595,493	595,493	595,493	595,493	595,493	595,493	595,493

Notes: This table shows estimates of the firm-IGE in different specifications. The firm-IGE is the elasticity of children's firm component of earnings $(\overline{\psi}_i)$ to their fathers' earnings $\left(\overline{\log Y_{f(i)}}\right)$. Individual and firm components are AKM fixed effects (see Section 3.3). Column (1) presents the firm-IGE without controls. Columns (2)-(7) control for children's individual component of earnings (α_i). Column (2) is estimated by OLS and Columns (3)-(7) by 2SLS. In Column (3), the instrumental variable is an indicator for having a college degree. In Columns (4)-(6), the instrumental variables are measures of education quality. In Column (7), the instrumental variable is dummies indicating the type of higher education institutions attended. 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.