Quantifying the Role of Firms in Intergenerational Mobility*

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May 26, 2021

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Abstract

It has been widely documented that there is a strong relationship between parents and children's earnings. A separate strand of the inequality literature has shown that differences in firm pay premiums contribute substantially to the distribution of earnings. In this paper, we quantify the role of access to better-paying firms on intergenerational mobility in Israel. Using job switchers to identify firm wage premiums, we find that differences in access to better-paying firms are responsible for 17% of the intergenerational earnings elasticity. About half of this pattern is due to the fact that firms amplify the effect of worker's productivity. Another quarter is due to sorting of certain ethnicities to better paying firms.

*We thank Ran Abramitzky, Nano Barahona, Raj Chetty, Liran Einav, Caroline Hoxby, Petra Persson, and Isaac Sorkin for helpful comments. We gratefully acknowledge financial support from the Shultz Fellowship, Stanford Center for Computational Social Science, and the Stanford Graduate Research Opportunity Grant for this work. All views and errors are our own.

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1 Introduction

Equality of opportunity, the notion that everyone, regardless of family background, should have the chance to pursue any life goal, is widely seen as one of the cornerstones of a fair society. This has inspired much research in Economics and Sociology, and it has been widely documented that children of higher-income families tend to earn a higher income themselves (Solon, 1992; Morgan et al., 2006; Chetty et al., 2014b; Bratberg et al., 2017).

What explain this relationship between parents' and children's earnings? Previous literature has emphasized the importance of early life conditions in shaping essential life skills (Heckman and Mosso, 2014; Lee and Seshadri, 2019). A separate strand of the inequality literature has shown that some firms pay workers with similar skills more than others, and these differences in firm pay premiums contribute substantially to the distribution of earnings (Abowd et al., 1999; Sorkin, 2018; Card et al., 2018; Song et al., 2019). In an imperfect labor market, richer children might end up in firms with higher pay premiums. Indeed, it has been shown that children get access to better paying firms through their parents San (2020); Staiger (2021), but how much does that matter for the intergenerational persistence in earnings?

In this paper, we quantify the role of access to better paying firms on intergenerational mobility (IGM) in Israel. For this purpose, we decompose the observed elasticity between father's and children's earnings into firm-specific pay premium and individual-specific productivity. We find that differences in access to better-paying firms are responsible for 17% of the intergenerational earnings elasticity.

For this purpose we construct a population-wide income data from the Israeli National Insurance and parent-children links from the administrative records of the Israeli

Civil Registry. Our sample consists of all Israeli citizens born between 1965-1980. We observe these individuals in the labor market from 2010 to 2015 and their fathers from 1986 to 1991, when both groups are in their early 40's (and their earnings stabilize).

We focus our analysis on a common measure of intergenerational mobility – the intergenerational elasticity of earnings (IGE). We find an IGE of 0.41 in Israel, well within the range of other OECD countries. In other words – a 10% increase in a child's father earnings is correlated with a 4.1% increase in her earnings in adulthood.

How much of the IGE can be explained by access of richer children to higher paying firms? After equalizing firm earnings premiums, the IGE coefficient shrinks from 0.41 to 0.34. This result implies a marginal contribution of 17% of the IGE is due to the firms where they work.

What might explain the access of richer children to better-paying firms? one possibility will be assortative matching – high-paying firms might hire children of wealthier families because of their higher human capital. Indeed, we find that about a half of the correlation between child's firm pay-premiums and father's earnings is because firms amplify the effect of ability (i.e. assortative matching). Furthermore, about a quarter of the variation can be explained by the fact that people of certain ethnicities go to better paying firms, suggesting a substative role of ethnic segregation or discrimination in the labor-market.

The remainder of this paper goes as follows. Sections 2 describe the data and the Israeli context. Section 3 discuss the estimation of firm pay premiums, and quantifies their contribution to the intergenerational elasticity of earnings in Israel. Section 4 proposes an empirical framework to quantitatively evaluate the importance of the different channels that might explain the importance of firms in intergenerational mobility. Section 5 apply our decomposition method to quantify the importance of child's ethnic background on inequality in opportunities in the labor-market. Section 6 concludes and discuss some policy implications.

2 Data and Setting

2.1 Data

We rely on two data sources to perform our analysis: the Israeli civil registry and income records from the Israeli Social Security (ISS). The Israeli civil registry covers the entire population of Israel. For every Israeli citizen, the registry informs her unique id, her parents' id, year of birth, year of death, and months in which the individual was abroad. The ISS administrative database consists of yearly-level income reports, divided into the following categories: (1) employer-employee matches; (2) self-employed workers who report and submit payments to the ISS; (3) individuals who receive unemployment benefits from the ISS.[1]

Note that a worker can be reported multiple times in the same year, one for each employer and another one/two if she has received income from unemployment insurance or/and self-employment in the same year. For each report, we see the total earnings received from the corresponding source each year and in which months this income was received. The benefits of this structure are twofold. First, we can calculate average monthly earnings. Second, we can identify in which months a worker did not receive any labor earnings.

For the remainder of this paper, we will refer to both individuals receiving unemployment insurance and the ones with zero (or unreported) earnings as *non-employed*.

[1]Individuals are eligible for unemployment benefit in Israel only if they were employed in 12 out of the last 18 months. The benefits are given as a percentage of the average monthly earnings in the past six months.

As discussed above, the data structure allows us to identify in which months an individual was neither employed, self-employed, receiving unemployment insurance, abroad, or deceased.[2] We impute zero earnings for these months. While we acknowledge this is an understatement (due to transfers and informal jobs), their earnings are unlikely to be substantial. Moreover, they do not have access to social benefits, such as vacations, parental leave, retirement, and unemployment insurance. Hence we believe this zero income imputation is a reasonable approximation.

Finally, our empirical strategy is estimating pay premiums based on individuals switching stable jobs. The focus on stable jobs is to capture moves that are more related to a job switch rather than a short "gig". Therefore, we classify each employer-employee match as stable or temporary. A job is defined as stable if, in a given calendar year, the employee worked in it for at least five months and earned at least $3,000 that year.[3] Finally, a job is defined as temporary if it is not stable. Our definition of temporary job is trying to capture individuals that were doing a side "gig" job and weren't deriving their main source of income from that job. Hence the choice of working less than half of the year in a job, or alternatively, were working for several months but earning less than the equivalent of two months of minimum wage.

We constructed our study sample the following way. We first take all Israeli citizens born between 1965-1980 from the civil registry and link them to their fathers.[4] We link approximately 95% of the sample. We then match those individuals and their fathers to tax returns and unemployment insurance records. We observe fathers' labor market outcomes from 1986 to 1991 and children's from 2010 to 2015, i.e., when both groups

[2]We use the border control records to identify citizens abroad for more than 90 days in a given year (and the number of days abroad) and impute the missing months that correspond to the time abroad.

[3]The average monthly earnings in Israel is $2,934, while the minimum monthly earnings (by law, for full-time employment) are $1,486.

[4]see Appendix E for a discussion of the choice of father's rather than mother's or household income

are between their 30-50, as commonly used in the intergenerational mobility literature to capture the period in which their earnings profile stabilize and thus less affected by transitory fluctuations (Mazumder, 2015). Finally, we drop fathers who have zero earnings.[5]

2.2 Setting: Israeli Context

Israel is a developed economy, with relatively high employment and education levels. In 1948, when the State of Israel was established, the region was already populated by three demographic groups: Ashkenazi Jews, Sephardic Jews, and Arabs (Lewin-Epstein and Semyonov, 1986). Since then, the newly formed State was mostly populated by Jewish migration and the Jewish population in Israel grew from 650 thousands in 1948 to over 2 million in by 1964 (Hodge, 1973). Today, the economy of Israel is a small service oriented economy (81.6% of labor force), focused on the high-tech sector. It's GDP per capita is $37,670. There are 8.48 million citizens (75% Jewish), labor force participation rate is 63.9% and employment rate is 61.6%. The average monthly earnings is 10,465 NIS ($2,934) and the monthly minimum wage is 5,300 NIS ($1,486) (IMF, 2018). Israel is also a highly educated country: according to the OECD, it ranks second in the world in terms of tertiary education rate among 25-64-year-olds (46%), significantly higher than the OECD average (32%) (Schleicher, 2013).

Despite its economic success, Israel is one of the most unequal countries in the OECD, with a Gini coefficient of 41.4, second only to the United States in terms of disposable income inequality (David and Bleikh, 2014). Approximately 21% of Israelis

[5] From 1986 to 1991, we do not have self-employment records. Hence a large share of the unreported fathers might be due to measurement error.

were found to be living under the poverty line (compared to an OECD average of 11%)(OECD, 2016).

This high inequality is commonly attributed to the socioeconomic disadvantages and high unemployment rates experienced by two segregated communities: the Israeli-Arab and Ultra-Orthodox Jewish populations. In 2011, 70% of Orthodox and 57% of Arabs were living bellow the market income poverty line (David and Bleikh, 2014). Furthermore, of the 40 towns in Israel with the highest unemployment rates, 36 were Arab towns. These numbers are partially explained by cultural values, since Ultra-Orthodox Jewish men and Arab women stay out of the labor force. Indeed, non-employment rates among the non-college educated Orthodox men and Arab women is 50% and 74% respectively, compared to 13% for the non-college educated, non-orthodox Jewish population (Sarel et al., 2016). Moreover, there are substantial human capital disparities due to Ultra-Orthodox schools being exempt from the core curriculum, focusing instead on religious studies.

3 Intergenerational Mobility and Access to Better Paying Firms

Two measures of inequality had gathered increasing attention in the past couple of decades: (1) inequality of *opportunities*, measured by the intergenerational elasticity of earnings (IGE) between parents and children; and (2) the role of firms' play in inequality in *outcomes*, measured by the firm's wage premiums. This section merges these two measures to understand whether inequality of opportunities is related to access to better-paying firms. We begin by measuring the IGE in Israel in Section 3.1.

We then continue by measuring the correlation between father's earnings and firms' wage premiums of the child in Section 3.2. We conclude the Section by taking stock of the role of access to better paying firms on the IGE in Section 3.3.

3.1 Measuring Intergenerational Mobility in Israel

One way to study intergenerational mobility is to ask, "What are the outcomes of children from low-income families relative to those of children from high-income families?". This question, which focuses on the relative outcomes of children from different parental backgrounds, has been the subject of most prior research on intergenerational mobility (Solon, 1999; Black and Devereux, 2011; Chetty et al., 2014a). Figure 1a plots a bin scatter of log child's earnings against log father's earnings. We see that kids of the poorest parents in Israel make 120% less than kids from the richest parents. The raw data shows a striking linear pattern which simplifies our following analysis.

In order to provide a parsimonious summary of the degree of mobility, it is useful to characterize the joint earnings distribution using a small set of statistics. A common statistic which we will focus on is the intergenerational elasticity of earnings (IGE).[6] The IGE is the coefficient from the regression of average log child earnings ($\overline{logY_i}$) on log parent earnings ($\overline{logY_{f(i)}}$). Formally:

$$\overline{logY_i} = \beta^{IGE} \cdot \overline{logY_{f(i)}} + \epsilon_i^{IGE} \tag{1}$$

[6]There are two common parsimonious measures of *relative* intergenerational mobility: the correlation between child's and parent's earnings ranks (rank-rank) and the intergenerational elasticity of earnings (IGE). Throughout the analysis, both father's and child's earnings are the residuals from a regression of log earnings on age, age-squared and year fixed effects. This procedure controls for life-cycle and business-cycle fluctuations on earnings (see Solon (1992)). For the rest of the paper we will focus on the IGE rather then the rank-rank measure, since unlike the rank-rank measure, the IGE have additively separable properties that allows us to do the decomposition exercise this paper is set to perform. For further discussion on the conceptual differences between the two measures see Section 2 in Chetty et al. (2014a).

We find an IGE of 0.415 in Israel (first row of Table 1). In other words – a 10% increase in a child's father earnings is correlated with a 4.15% increase in her earnings in adulthood.[7]

3.2 Father's Earnings and Firms' Wage Premiums

It has been documented that some firms pay workers with similar skills more than others, and that these differences in firm pay premiums contribute substantially to the distribution of earnings (Abowd et al., 1999; Card et al., 2013; Gerard et al., 2018). In the context of intergenerational mobility, these policies are likely to play an even larger role, given the importance of labor-market frictions. Previous work have shown that workers are more likely to find jobs in companies where their parents have worked (Magruder, 2010; Corak and Piraino, 2011; Kramarz and Skans, 2014; San, 2020; Staiger, 2021). In this section we investigate whether workers from higher socioeconomic backgrounds tend to work in firms that pay higher wages to workers of all backgrounds.

For this purpose we will present the correlation between father's earnings and children's firm earnings premium. We will first estimate firm's wage premiums in the spirit of Abowd et al. (1999) (henceforth 'AKM estimation').[8] That is, we assume earnings follow a log-linear functional form:

[7]To have some relative understanding of these numbers, consider the following: IGE in Israel is comparable to other OECD countries. Our estimate of the IGE in Israel, is between analogous estimates for United States (0.432) and Germany (0.314) (Bratberg et al., 2017).

[8]Note that these firm's wage premiums can only be estimated for individuals that are part of the labor-force and in a stable job. For this reason we explore in Appendix B how the probability of participation in the labor-force and having a stable job varies by parental earnings. Indeed we find that parental earnings is highly correlated with the probability the child is in the labor force and that this fact explains 28% of the IGE.

$$logY_{i,t} = \alpha_i + \psi_{J(i,t)} + \gamma_{a(i,t)} + r_{i,t} \ , \tag{2}$$

where $logY_{i,t}$ is log-earnings of individual i at time t, α_i is the *individual component of earnings*, $J(i,t)$ is firm the firm in which individual i works in at time t, $\psi_{J(i,t)}$ the *firm component of earnings*, $\gamma_{a(i,t)}$ are age fixed-effects, and $r_{i,t}$ an error term. In appendix C, we show that the firm effects capture the magnitude of the earnings declines. In this specification, the *individual component* captures the earnings dispersion within the firm, while the *firm component* (firm earnings premium) captures the earnings dispersion across firms.

Note that Equation 2 is estimated from 2010-2015, resulting with different *estimated* $\hat{\psi}$ for child i across years (if she changed firms). Therefore, for the rest of this paper we will use the average firm pay premium of individual i in our sample, formally:

$$\overline{\hat{\psi}_i} = \frac{\sum_{t \in T} \hat{\psi}_{J(i,t)}}{|T|}$$

where $|T|$ is the total number of years we observe earnings for the children.

Figure 1b shows that children of higher earning fathers earn a higher average firm pay premium. More precisely, workers coming from a median family enjoy a 21% premium relative to those on the bottom of the income distribution due to the firms where they work. This is in addition to differences in the individual component of earnings, which is portable across firms.[9]

[9]Appendix D discusses the importance of the individual component.

3.3 Taking Stock

In the previous subsections we have shown that individuals coming from poorer families:

1. earn less in adulthood;

2. are more often employed in firms that offer a lower earnings premium.

After establishing the relationship between father earnings and a child's firm wage premium, we move on to understand how much of the inequality of opportunities can be explained by access to better-paying firms.

By taking means across Equation 2 we get the following decomposition:

$$\overline{logY_i} = \hat{\alpha}_i + \overline{\hat{\psi}_i} \tag{3}$$

Then, we use the decomposition in Equation 3 on the left hand-side of Equation 1 and so we can seperatly estimate:

$$\hat{\alpha}_i = \beta^{\alpha} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\alpha} \tag{4}$$

$$\overline{\hat{\psi}_i} = \beta^{\psi} \cdot \overline{logY_{f(i)}} + \epsilon_i^{\psi} \tag{5}$$

Therefore, we get the following decomposition of the IGE[10]:

$$\beta^{IGE} = \beta^{\alpha} + \beta^{\psi}$$

[10] Note that we don't need to decompose r_{it} since $E[r_{it}|i] = 0$ mechanically, by construction of the AKM regression. Since parental earnings in childhood is fixed for child i, so we get: $E[r_{it}|logY_{f(i)}] = 0$ and so the regression will not run.

After shuting down the firm pay premiums channel, the IGE coefficient shrinks from 0.415 to 0.344, implying firms are responsible of $\frac{\beta^{\psi}}{\beta^{IGE}}$ share of the IGE, which we estimate to be 17% (first two lines of Table 1). This shows that a substantial part of the difference in earnings between individuals from different socio-economic backgrounds is due to the firms where they work.[11]

4 Intergenerational Mobility and Assortative Matching

4.1 Assortative Matching

One potential explanation of the role of firms in IGE is assortative matching – children of wealthier families could be employed in high-paying firms *because of* their better human capital. First, to establish the existence of assortative matching in the data, we plot in Figure 2a the relationship between child's average wage preimum and her worker fixed-effect. We can see a strong relationship between the two, consistent with earlier studies in other countries (Card et al., 2013; Gerard et al., 2018).

Second, to tie this finding to intergenerational mobility, we plot the relationship between the worker fixed-effect component from Equation 2 against father's earnings in Figure 2b. As you can see there is a strong and linear relationship between worker's fixed-effect and father's earning. The combination of Figures 1b, 2a and 2b suggests that the portion of the IGE explained by firms (i.e. 17%) is partially explained by assortative matching.

[11]Note that the individual fixed-effect (our measure of ability) is still responsible for 83% of the IGE. This finding is consistent with numerouse studies emphasizing the intergenerational transmition of human capital. See Heckman and Mosso (2014) and Mogstad (2017) for a review of the literature

4.2 Decomposing the Role of Assortative Matching

Next, we quantify the importance of the assortative matching channel using a simple decomposition exercise. We will focus our attention on β^{ψ} and use these cross-elasticities to decompose the role of firms in the following way:

$$\beta^{\psi} = \underbrace{\beta_{\alpha}^{\psi} \cdot \beta^{\alpha}}_{\text{Assortative Matching Component}} + \underbrace{\beta_{Y_f}^{\psi}}_{\text{Remaining Parental Earnings Component}} \tag{6}$$

Where β^{α} is estimated from regression 4 and the cross-elasticities $\beta_{Y_f}^{\psi}$ and β_{α}^{ψ} are estimated from the following regressions:

$$\overline{\hat{\psi}_i} = \beta_{\alpha}^{\psi} \cdot \alpha_i + \beta_{Y_f}^{\psi} \cdot \overline{logY_{f(i)}} + \eta_i^{\psi}$$

The results of this cross-elasticities (presented in Table 2) suggests that family background plays an important role in determining labor-market outcomes. The elasticity of the firm earnings premium to father's income is 7.1%. After controlling for child's productivity (proxied by the individual's fixed effect), it falls to 2.2%, but remains strongly significant. These results point to the fact that productivity can explain a large share of the variation in access to better paying firms, but there's some room for alternative mechanisms in play. Note that this elasticity could be downward biased, since social networks can help individuals to achieve superior positions inside a firm, hence the individual component of earnings (α) does not reflect only human capital differentials. At the same time, since α is a noisy estimate for productivity (due to finite sample problems, see Lentz et al. (2018); Bonhomme et al. (2019)), it will create an upward bias of our estimates.[12]

With those cross-elasticities we can now return to Equation 6 and quantify the importance of each one of those components. The results of this decomposition are reported in Table 1. We can see that the worker component of earnings explain 45% of the variation. These findings suggest that about half of the association between access to better paying firms and family's resources is due to assortative matching in the labor-market. In Section 4.3 and 5 we explore other potential channels that can explain the remaining 55%.

4.3 Other Potential Drivers

What else can explain the access of richer children to better-paying firms? In this subsection we discuss two other potential drivers: (1) search time – richer children have an informal safety net that allows them to search longer and find a better-paying firm; (2) social networks – richer families are part of social networks that facilitate access to high paying firms.

The search time explanation will suggest that richer kids can search for longer and end in 'better' firm (a la Chetty 2009) since their family's resources serves as an informal safety net. To explore that channel we plot the probability of finding a stable job against father's earnings in Figure B4. However, we find no evidence for this channel in the data.

[12]To see this compare the coefficient estimates in multiple regression with (a) an accurately measured productivity control variable (α), (b) instead only productivity measured with error ($\hat{\alpha}$) and (c) without controlling for productivity at all. Then all coefficient estimates with $\hat{\alpha}$ (b) will be a weighted average of (a) the coefficient estimates with α and (c) excluding productivity. The weight showing how far inclusion of the error-ridden statistical control variable moves the results toward what they would be with an accurate measure of that variable is equal to the fraction of signal in (signal + noise), where "signal" is the variance of α that is not explained by variables that were already in the regression, and "noise" is the variance of the measurement error. For further discussion see this post.

The social networks explanation will argue that richer children are better connected to higher paying firms through their parent's social networks. San (2020) asks this question using exactly the same data in the Israeli National Insurance Institute, and the timing of job movements of parents' coworkers as identifying variation.

San (2020) finds that workers are three to four times more likely to find employment in firms where their parents have professional connections than in otherwise similar firms. He then use the same variation to structurally estimate a matching model of the labor market with search frictions, and find that connections double the probability of meeting and increase by 35% the likelihood of being hired after meeting. The estimated value of one additional meeting with a connected firm is 3.7% of the average wage, with around 2/5 of the increase coming from the direct value of a connection.

Finally, connections matter for inequality across ethnicities; San (2020) find that the wage gap between Arabs and Jews decreases by 12% when equalizing the groups' connections, but increases by 56% when prohibiting the hiring of connected workers. These seemingly opposing results are explained by the fact that Arabs have connections to lower-paying firms but use their connections more extensively.

5 Applications

5.1 Ethnicity

San (2020) findings that some ethnicities in Israel are better connected to higher-paying firms suggest another important avenue of inquiry – ethnic segregation and discrimination. In this Section we apply our decomposition method to quantify the importance of child's ethnic background on inequality in opportunities in the labor-market. In Section 2.2 we discussed the high inequality in Israel that is commonly attributed to the socioeconomic disadvantages and high unemployment rates experienced by two segregated communities: the Israeli-Arab and Ultra-Orthodox Jewish populations.

Indeed, we find that both the Arab and the Orthodox-Jewish children work in firms with lower-wage premiums for any given level of parental earnings (see Figure 3). Furthermore, we can see that both Arabs and Orthodox-Jews are more likely to come from lower income families (there are more density of them on the left end of the distribution).

We interpret these results, coupled with the specific Israeli context, as a suggestive evidence that these two communities are segregated from higher-paying firms in the labor market. However, one should note that we cannot disentangle between segregation and discrimination, and so for the rest of this paper we will loosely use the phrasing 'segregation' to mean 'segregation or discrimination'.[13]

5.2 Decomposing the Role of Ethnicity

Applying our method to understand the role of ethnicity we extend our framework in the following way:

$$\beta^{\psi} = \underbrace{\beta^{\psi}_{\alpha} \cdot \beta^{\alpha}_{w_f}}_{\text{Worker FE Component}} + \underbrace{\beta^{\psi}_{eth} \cdot \beta^{eth}_{w_f}}_{\text{Ethnicity Component}} + \underbrace{\beta^{\psi}_{w_f}}_{\text{Remaining Parental Earnings Component}} \tag{7}$$

[13]For example – it could be that Arabs don't segregate, they apply to firms with higher pay premium but are not hired due to discrimination.

Where the cross-elasticities are estimated from the following regressions:

$$\overline{\hat{\psi}_i} = \beta^{\psi}_{\alpha} \cdot \alpha_i + \beta^{\psi}_{eth} + \beta^{\psi}_{Y_f} \cdot \overline{logY_{f(i)}} + \zeta^{\psi}_i$$

$$eth_i = \beta^{eth}_{w_f} \cdot \overline{logY_{f(i)}} + \zeta^{eth}_i$$

With those cross-elasticities (presented in Table 2) we can now return to Equation 7 and quantify the importance of each one of those components. The results of this decomposition are reported in Table 1. We can see that ethnicity explains 22% of the variation. These findings suggest that two thirds of the association between access to better paying firms and family's resources is due to assortative matching and segregation in the labor-market.

The remaining 31% should be investigated further. One potential explanation for it is the social network mechanism discussed in Section 4.3, however we don't have a direct way to quantify it's share of the variation. Furthermore, social networks can simultaneously play a role through the ethnicity channel (kids from different ethnicities have different social networks) and through the worker component (individuals take their family's social networks with them when moving between firms).

6 Conclusion

In this article, we use population-wide labor-income data from the administrative records of the Israeli Social Security to quantify the importance of firms in the intergenerational mobility. We find that wealthier children work in better-paying firms and that this differential access to better-paying firms explains 17% of the IGE. We then show that assortative matching explain about a half of the role of firms in IGE, implying that firms exacerbate the role of individual's productivity. Finally, we show that this disadvantage seems to be bigger among specific communities in Israel – the Israeli-Arab and Ultra-Orthodox Jews.[14]

The policy debate around equality of opportunities usually focus on human capital (Chetty et al., 2020). Our results show that workers from a lower socioeconomic background have worse labor market outcomes even controlling for skill, suggesting that these advantage propagates into the labor market, beyond just human capital. This indicates that policies promoting equality of opportunity should not be restricted to childhood and better access to education, but include interventions in the labor market such as income-based affirmative action, to help mitigate this source of inequality.

[14]Nevertheless, our results should be taken with caution until we apply a correction to the AKM estimation as suggested in Bonhomme et al. (2019).

Table 1: Intergenerational Elasticities of Earnings

Counter-factual	Interpertation	Coefficient	Share
IGE (Wages)		0.415	
Firm Effects Removed		0.344	17%
Baseline (Firm Effects)		0.071	
Worker FE Component	Assortative Matching	0.032	45%
Ethnicity Component	Segregation/discrimination	0.015	22%
Parental Earnings Component		0.022	31%

Notes: This table presents the results from the counterfactual exercise described in section 3.3. All coefficients were estimated using a Poisson regression, as described in equation 11, but for the second row, which was estimated with an OLS, as described in equation 9. The third row presents the counterfactual exercise of equalizing the number of months spent in each job type. The fifth row presents the counterfactual exercise of equalizing the firm earnings premiums. This can be done only for the subsample of workers for which we can estimate AKM effects, i.e., workers employed, at least for a period, in a firm belonging to the largest connected set. Hence we begin by estimating the benchmark IGE restricting the sample to the connected set (fourth row). The marginal contribution (second column) is defined as the marginal change in the IGE implied by each counterfactual exercise (see equation 10 for a formal definition).

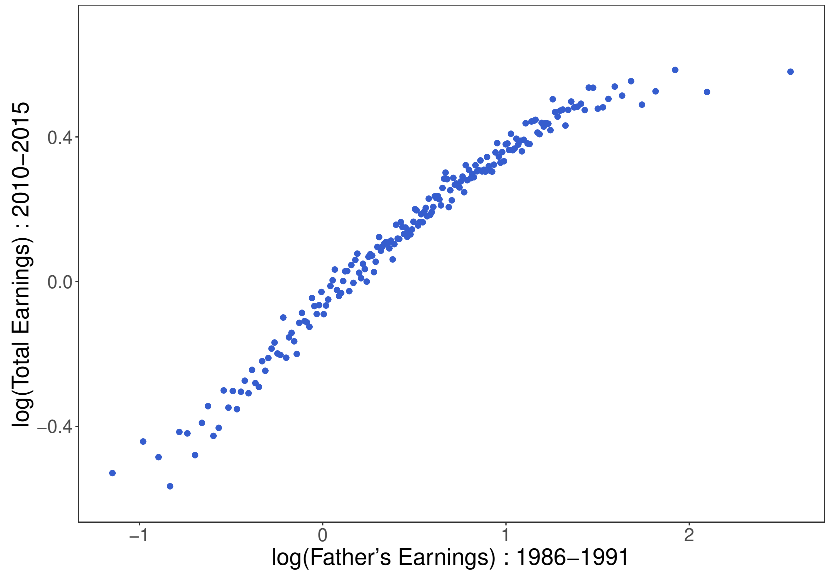
Table 2: Firm Earnings Premium and Fathers' Earnings

	Dependent variable:		
	Child's Firm FE		
	(1)	(2)	(3)
log(Father's Earnings)	0.071***	0.048***	0.022***
	(0.0002)	(0.0002)	(0.0002)
Worker's FE			0.084***
			(0.0001)
Ethnicity FE	No	Yes	Yes
Observations	2,017,304	2,017,304	2,017,304
R^2	0.067	0.140	0.371

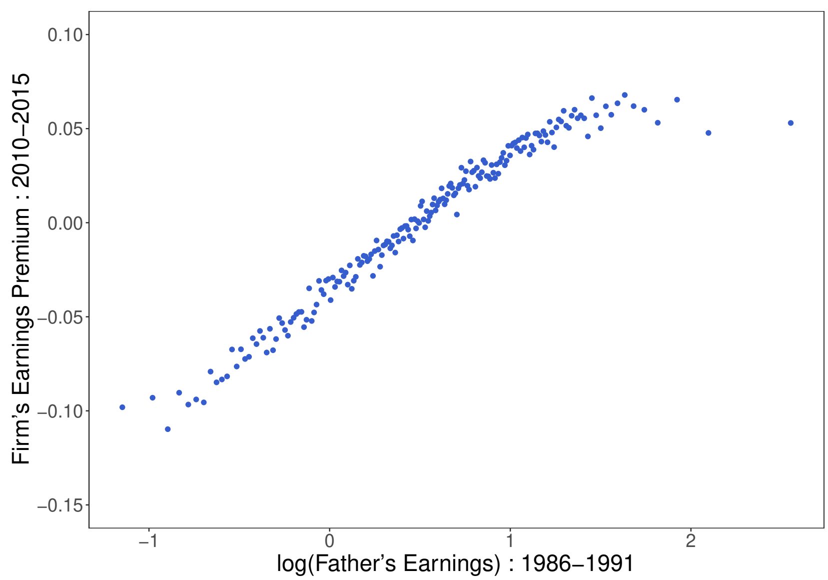
Note: robust SE in paranthesis *p<0.1; **p<0.05; ***p<0.01

Notes: This table presents the results from regressing log father's earnings and child's earnings fixed effect on child's average earnings premium. Child's earnings premium is calculated as the AKM firm fixed effect, where Child's earnings fixed effect is calculated as the AKM individual fixed effect (see section 3.2 for a formal definition). Father's earnings is the average yearly earnings between 1986-1991. Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

Figure 1: Intergenerational Mobility and Access to Better Paying Firms



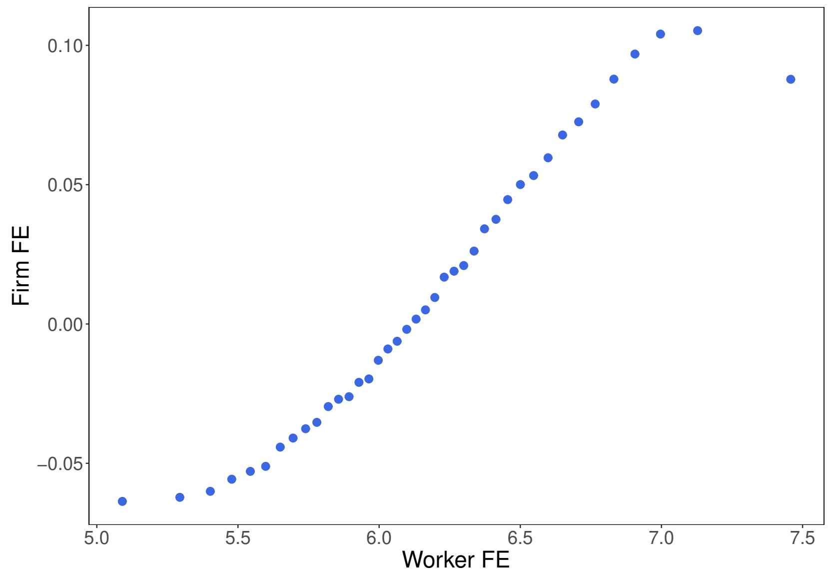
(a) Intergenerational Elasticity of Earnings (IGE)



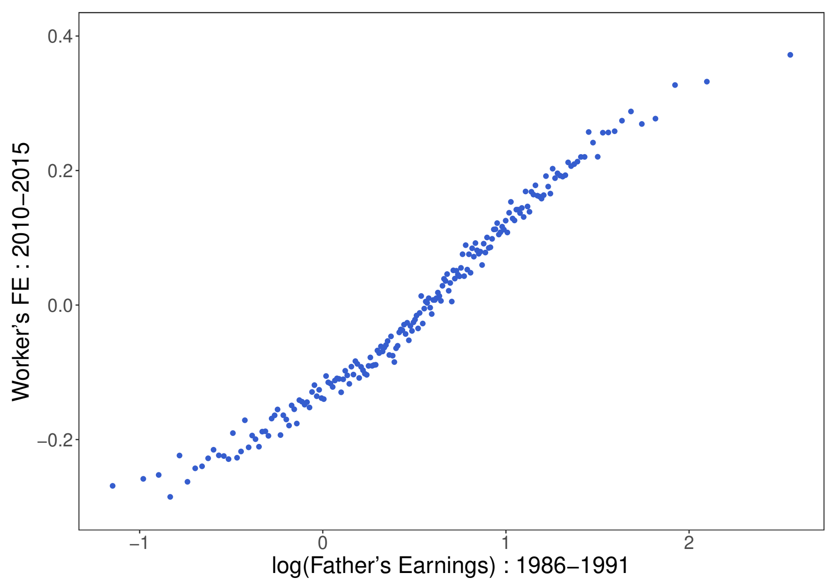
(b) Firm's Earnings Premium vs. Log Father's Earnings

Notes: panel (a) plots log child's earnings against log father's earnings. Earnings is calculated as the average yearly earnings earned during sample's years (2010-2015 for children, 1986-1991 for fathers). Panel (b) plots child's average earnings premium against log father's earnings. Child's earnings premium is calculated as the AKM firm fixed effect (see section 3.2 for a formal definition). Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

Figure 2: Assortative Matching: Worker FE are correlated with parental earnings & firm wage premiums



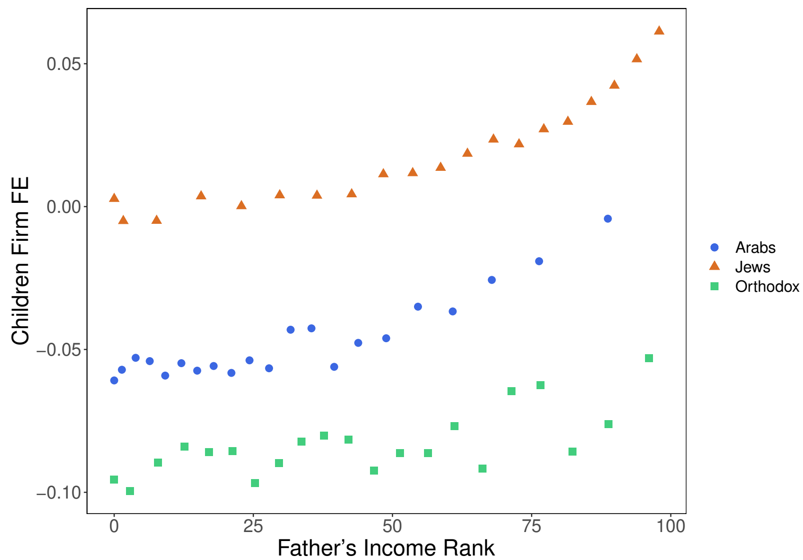
(a) Firm's Earnings Premium vs. Worker's Fixed Effect



(b) Worker's Fixed Effect vs. Log Father's Earnings

Notes: Panel (a) plots the child's average earnings premium against child's worker's fixed effect, both estimated from an AKM regression (see section 3.2 for a formal definition). Panel (b) plots child's worker's fixed effect against log father's earnings. Worker's fixed effect is calculated as the AKM worker fixed effect (see section 3.2 for a formal definition). Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings. Earnings is observed at 2010-2015 for children and 1986-1991 for fathers.

Figure 3: Child's Firm Earnings Premium vs. Father's Earnings Rank (by Ethnicity)



Notes: This figure plots child's average earnings premium (between 2010-2015) against father's earnings rank by ethnic groups. Child's earnings premium is calculated as the AKM firm fixed effect (see section 3.2 for a formal definition). Father's earnings is the average yearly earnings between 1986-1991. Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

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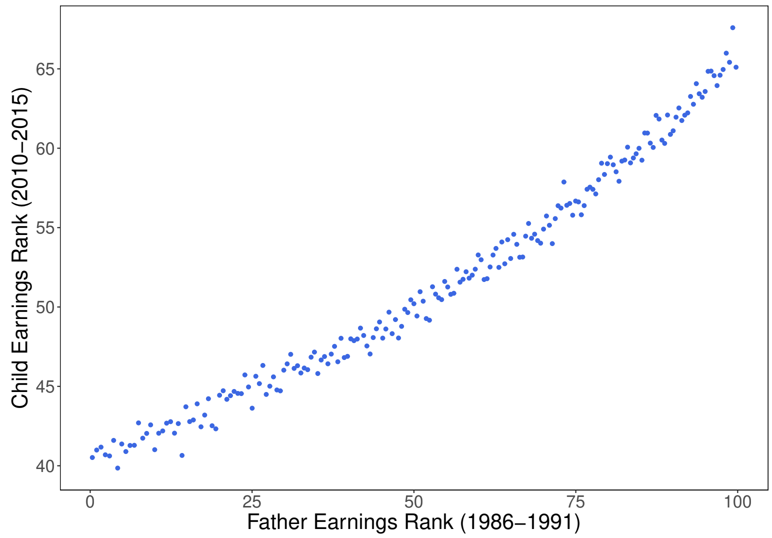
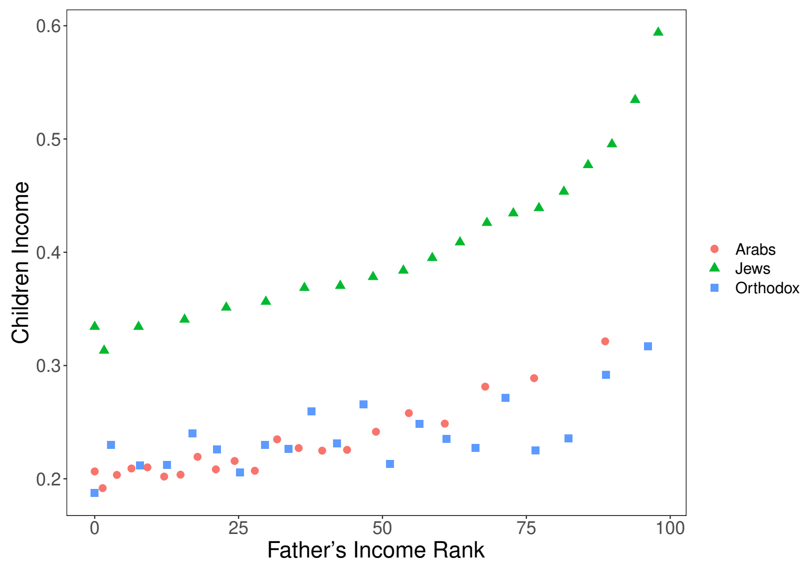
A Appendix

Figure A1: Child's Earnings Rank vs. Father's Earnings Rank



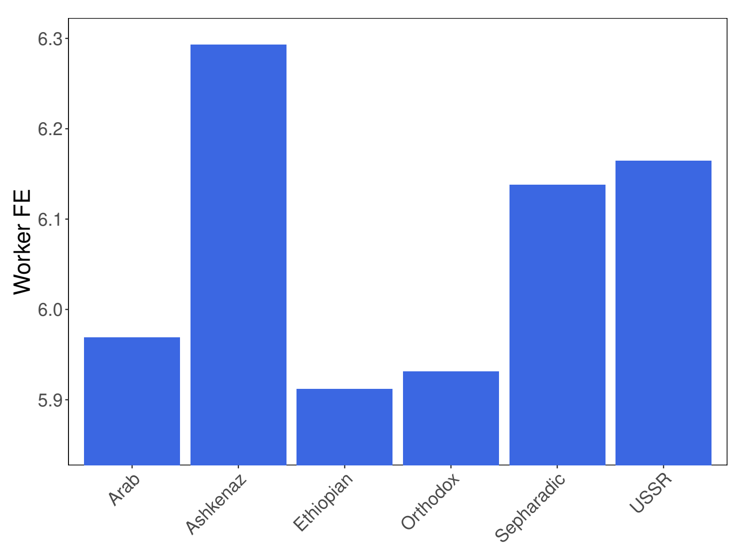
Notes: This figure plots child's earnings rank against father's earnings rank. Earnings is calculated as the average yearly earnings earned during sample's years (2010-2015 for children, 1986-1991 for fathers). Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

Figure A2: Log Child's Earnings vs. Father's Earnings Rank (by Ethnicity)



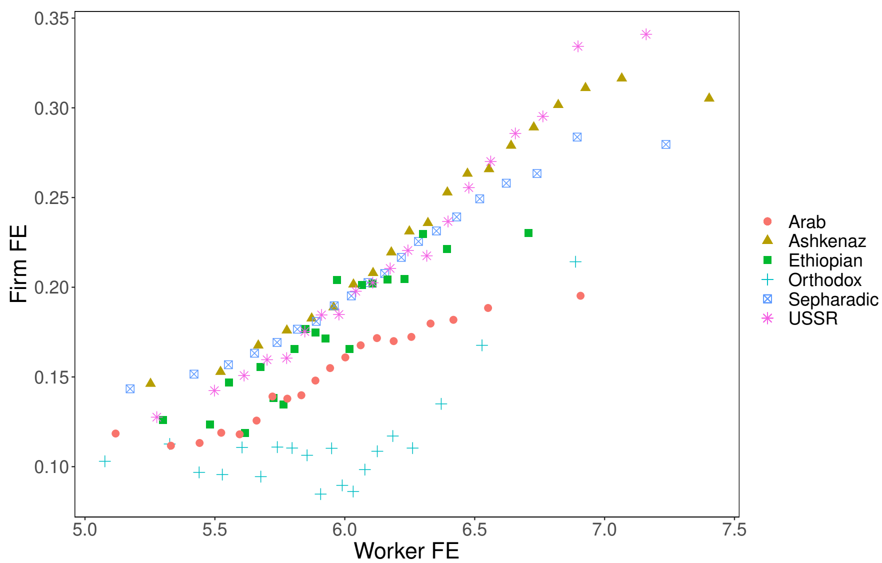
Notes: This figure plots log child's earnings against father's earnings rank across ethnic groups. Child's earnings is calculated as the yearly average earnings the child earned in that category between 2010-2015. Father's earnings is the average yearly earnings between 1986-1991. Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

Figure A3: Worker's Fixed Effect by Ethnicity



Notes: This figure presents worker's fixed effect by ethnic groups. Worker's fixed effect is calculated as the AKM worker fixed effects (see section 3.2 for a formal definition).

Figure A4: Worker's Fixed Effect vs. Firm Earnings Premium (by Ethnicity)



Notes: This figure plots worker's fixed effect against earnings premium by ethnic groups. Worker's and firm's fixed effect is calculated as the AKM fixed effects (see section 3.2 for a formal definition).

B Intergenerational Mobility and Employment Status

B.1 Father's Earnings and Non-Employment Rates

In this section, we focus on the participation (extensive) margin as our first step to decompose income persistence. We will show that non-employment plays an important role in the intergenerational transmission of income in Israel. We then brake it down further into disparities in labor force participation and separation rates.

As described in Section 2.1, workers can be in four different states: stable job, temporary job, self-employed, and non-employed. Total yearly earnings will depend on the monthly wages of these states and on the number of months workers spend on each of them. The availability of the Israeli monthly level employment data allows us to perform such an exercise which was not feasible with other datasets used in the intergenerational mobility literature.

Figure B1 presents the relationship between child's monthly wage and father's earnings across the three employment categories. We see that stable-job wages are higher for any given father's earnings level. Moreover, stable-job wages are the most strongly correlated with father's earnings. This suggests that job stability play an important part in explaining the observed mobility patterns.

We now calculate, for each individual, the share of months she spends in each of the four status we defined (stable job, temporary job, self-employed, and non-employed) during the time span covered in our sample (2010-2015).[15] Figure B2 shows how these shares vary with father's earnings. The most striking pattern is that individuals from low-income families are more likely to be non-employed and less likely to be in

[15] Individuals can hold multiple status in a month, e.g. employed by a firm and self-employed. Hence these shares can sum to more than one. Non-employment, however, is mutually exclusive with respect to all other status.

a stable job. However, for above-median father earnings, this relationship is substantially weaker, that is, past a certain level, father's earnings does not contribute to the probability of stable employment. This could be explained by children living out of their family's bequest or owning a business.

Note that both self-employment and temporary jobs comprise a substantial share of months, but there is little correlation with parental income. Ex-ante, we expected low-income individuals to be employed in unstable jobs more often. However, the data shows that the most relevant margin is the differential rates of non-employment. Given this stark disparities in non-employment, we devote the remainder of this section to understanding this phenomenon.

The observed differences in employment levels arises from the combination of three margins: some individuals are never-employed (extensive margin), length of non-employment conditional on labor force participation (job-finding probability) and length of employment (separation probability). Figures B3, B4 and B5 describe how each of these three margins vary with father's earning. Figure B3 plots the share of individuals who were never employed (i.e 'always non-employed') against their father's earnings. Again, the pattern is striking: workers coming from the bottom of the income distribution have a 20% chance of being permanently excluded from the labor force, while the same statistic is 8% for the median worker. The figure also shows the share of individuals who never had a stable job, and the results are very similar: workers coming from the bottom of the income distribution have a 39% chance of never having a stable job, while the same statistic is 25% for the median worker. These results indicate that labor force participation is likely to play a central role in income persistence. In particular, the similarity between the two plots in Figure B3 show that the correlation between father's earnings and the probability of holding a stable job is driven by the differences in labor force participation.

Second, we shift our focus to the job-finding probability and find no evidence for it's importance. Figure B4 presents the probability an individual finds a stable job as a function of her father's earnings.[16] We find that higher parental earnings is correlated with higher probability of finding a job (blue dots). However this result might be driven by individuals who are permanently excluded from the labor force. In order to isolate a purely intensive margin channel, we remove these individuals from the sample. This completely eliminates the correlation between job-finding rates and father's earning. This shows that labor force participation disparities are the main driver of the differences in job-finding rates and that there is no significant intensive-margin variation, consistent with the patterns in Figure B3.

Finally, we focus on the job-separation probability and find some correlation between the job separation probability and father's earnings. Figure B5 plots the probability of keeping a stable job against father's earnings. This probability is defined as: conditional on being in a stable-job in a given month, what is the share of individuals who have a stable job the following month. The results show that children of wealthier families have a higher chance of keeping a job – i.e., a lower separation probability. More specifically, the monthly job-destruction rate is 2.2% for the children of low-income families, compared to a median of 1.5%.

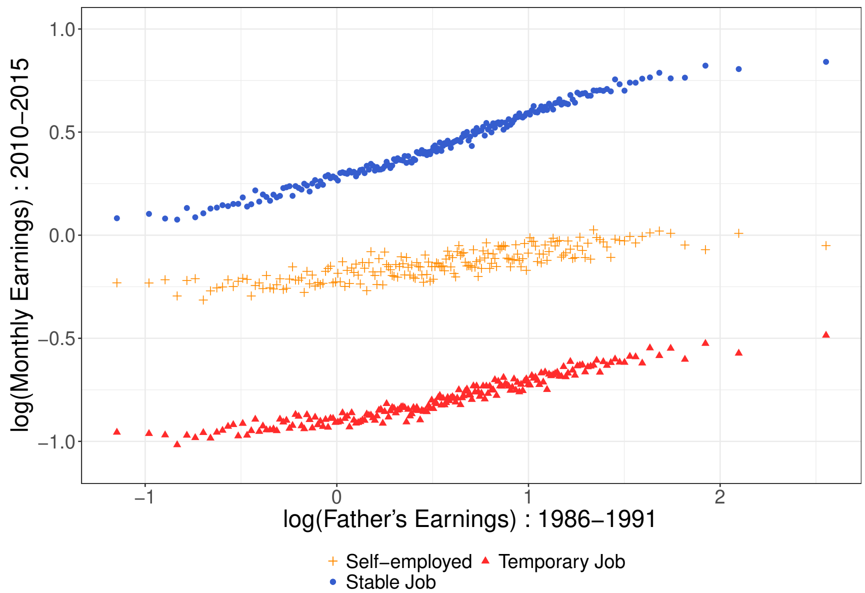
B.2 Taking Stock

In the previous sections we have shown that individuals coming from poorer families:

1. are more likely to be non-employed;

[16] We define the probability an individual finds a stable job as the share of individuals who find a stable job in a given month, conditional on not being in a stable-job in the previous month.

Figure B1: Log Child's Monthly Earnings vs. Log Father's Earnings (by Employment Type)



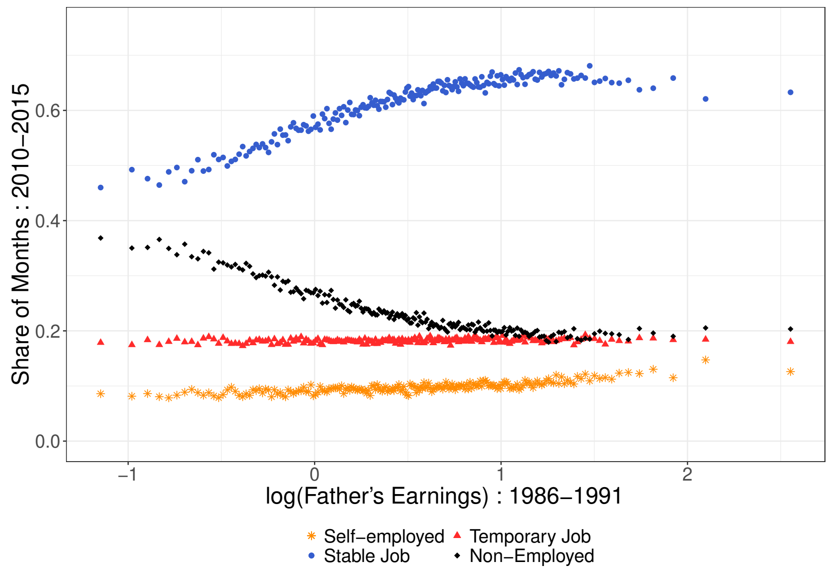
Notes: This figure plots log child's monthly earnings against log father's earnings across three employment categories: stable-job, temporary-job and self-employment (see section 2.1 for classification). Child's monthly earnings in a given category is calculated as the total earnings the child earned in that category between 2010-2015 divided by the number of months she worked in that category. Father's earnings is the average yearly earnings between 1986-1991. Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

2. are more often employed in firms that offer a lower earnings premium.

We now propose an empirical framework to quantitatively evaluate the importance of these mechanisms to the persistence of income across generations. Our strategy is to derive counterfactual scenarios in which each of these channels is shut down and measure the change in the intergenerational elasticity of income (IGE) implied by this exercise. The larger the decrease in this elasticity, the more important the channel that was shut down is.

As described in section 2.1, in each month a worker can be in one or more of the following status: *stable job*, *temporary job*, *non-employed* or *self-employed*. Under this

Figure B2: Share of Months Employed vs. Log Father's Earnings (by Employment Type)



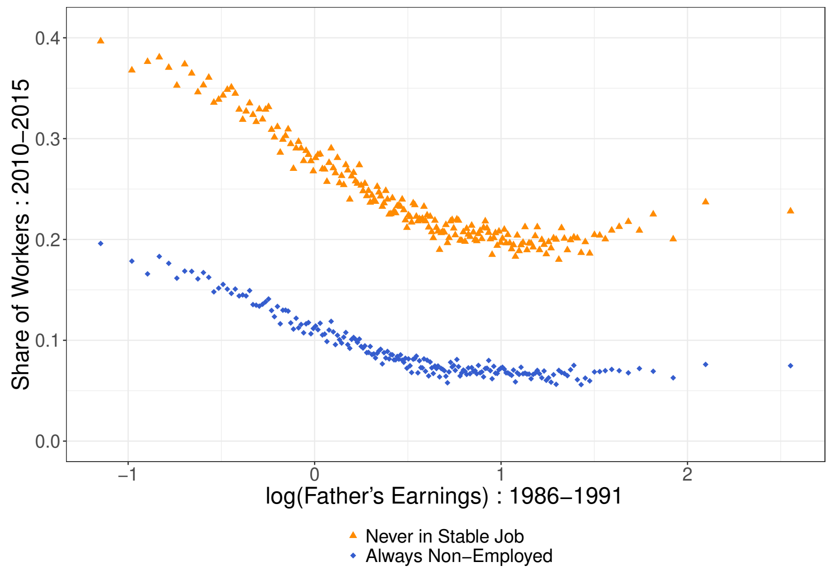
Notes: This figure plots the share of months in a year an individual spent in a given employment status (between 2010-2015) against log father's earnings, across four employment categories: stable-job, temporary-job, self-employment and non-employment (see section 2.1 for classification). Note that an individual might have more than one employment status (e.g. both had an employer and was self-employed in a given month). Thus, summing the share of months for a given person across all employment status, might not sum up to one. Father's earnings is the average yearly earnings between 1986-1991. Father's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

division, the total earnings of a given worker i is equal to the number of months she spends in each status k – which we denote m_{ki} – times her average monthly earnings in this status – which we denote w_{ki}. Formally:

$$\text{earnings}_i = \sum_k w_{ki} \cdot m_{ki} \ . \tag{8}$$

Using this identity, we perform a series of counterfactual exercises in which we assume alternative earnings ($\tilde{w}_{ik}$) and/or months ($\tilde{m}_{ik}$) distributions, implying an al-

Figure B3: Share of Workers Non-Employed vs. Log Father's Earnings



Notes: This figure plots the share of individuals who are either never in a stable job or always non-employed (between 2010-2015) against log father's earnings. Note that 'always non-employed' (out of the labor force) are a subset of the individuals that are 'never in a stable job'. Father's earnings is the average yearly earnings between 1986-1991. Father's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

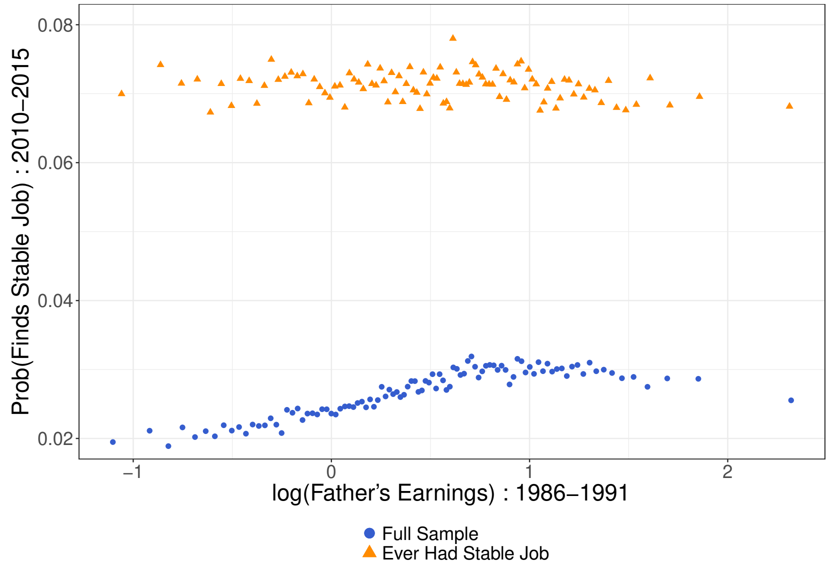
ternative earnings distribution:

$$\widetilde{\text{earnings}}_i = \sum_k \tilde{w}_{ik} \cdot \tilde{m}_{ik} \ .$$

The next step is to compare the earnings mobility in the actual and in the counterfactual scenarios. More specifically, we estimate the IGE using the benchmark and the alternative earnings distributions, always keeping the father's earnings distribution unchanged. That is, we estimate the elasticities π and $\tilde{\pi}$ in the following regressions:

$$\begin{aligned} \log(\text{child's earnings}) &= \pi_0 + \pi \log(\text{father's earnings}) \ ; \\ \log(\text{child's } \widetilde{\text{earnings}}) &= \tilde{\pi}_0 + \tilde{\pi} \log(\text{father's earnings}) \ . \end{aligned} \tag{9}$$

Figure B4: Job Finding Probability vs. Log Father's Earnings



Notes: This figure plots the probability an individual finds a stable job against log father's earnings. The probability an individual finds a stable job is defined as: conditional on not being in a stable-job in a given month, what is the share of individuals who find a stable job next month (between 2010-2015). Father's earnings is the average yearly earnings between 1986-1991. Father's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings. We repeat the exercise twice, once for the full sample and once restricting only to children that ever had a stable job.

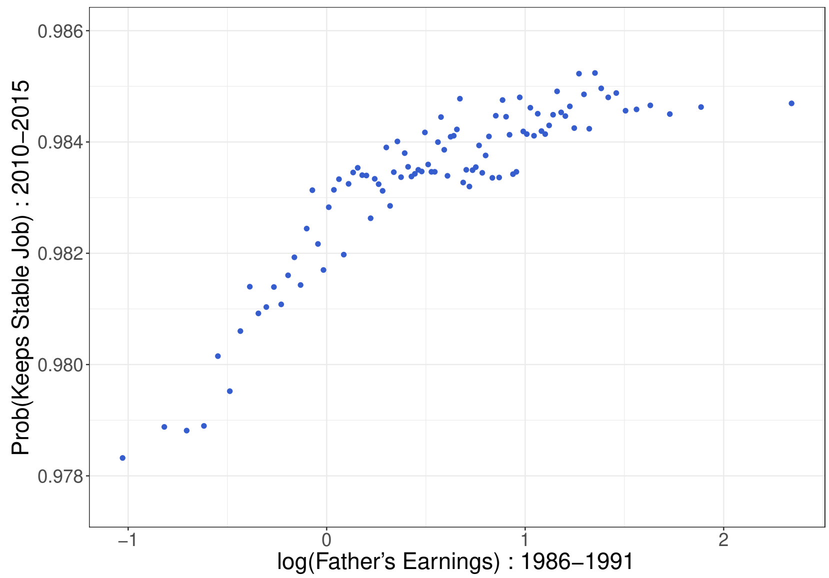
Finally, we compute the marginal change in the IGE implied by each counterfactual exercise:

$$\text{Marginal Contribution} = \frac{\pi - \tilde{\pi}}{\tilde{\pi}} \tag{10}$$

A limitation of this approach is that never-employed individuals, having zero earnings, will be dropped in the benchmark specification, and will be included in counterfactuals in which we assume they are working. We address this issue by estimating the elasticity by non-linear least squares, more specifically, a Poisson regression (PPML).[17]

[17]See Silva and Tenreyro (2006) for a discussion of the additional benefits of PPML over OLS for estimating elasticities.

Figure B5: Job Destruction Probability vs. Log Father's Earnings



Notes: This figure plots the probability an individual keeps a stable job against log father's earnings. The probability an individual keeps a stable job is defined as: conditional on being in a stable-job in a given month, what is the share of individuals who keep a stable job next month (between 2010-2015). Father's earnings is the average yearly earnings between 1986-1991. Father's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

Formally, our estimating equations are:

$$\begin{aligned} \mathbb{E}\left[\text{child's earnings} \,|\, \text{father's earnings}\right] &= \exp\left[\pi_0 + \pi \log(\text{father's earnings})\right] \ ; \\ \mathbb{E}\left[\widetilde{\text{child's earnings}} \,\middle|\, \text{father's earnings}\right] &= \exp\left[\tilde{\pi}_0 + \tilde{\pi} \log(\text{father's earnings})\right] \ . \end{aligned} \tag{11}$$

A second limitation is that we do not observe earnings for everyone under all status. For example, if a given worker was never self-employed, we have to estimate how much her earnings would have been in order to perform couterfactuals in which she is self-employed. On these occasions, we predict earnings using other workers coming from a similar family background. Formally, we define:

$$w_{ik} \equiv \mathbb{E}_{i'}[w_{i'k} \,|\, m_{i'k} > 0 \ , \ fi' = fi] \ , \forall i, k \text{ s.t. } m_{ik} = 0 \ .$$

In the remainder of this section, we describe each of the counterfactual exercises we have performed.

<u>Counterfactual #1</u> – *Equalizing participation in each job type*

In this exercise, our goal is to measure the quantitative importance of the variance in the number of months each worker spends in different job status. For this purpose, we keep earnings at their benchmark values and equalize months worked across all individuals. Formally:

$$\tilde{w}_{ik} = w_{ik} \; , \forall i, k \; ;$$

$$\tilde{m}_{ik} = \mathbb{E}_{i'}[m_{i'k}] \; , \forall i, k \; .$$

Our main results are in Table 1. The first two rows compare the baseline IGE estimated by OLS (11) with a Poisson regression (11). The estimates are similar (0.379 vs 0.397), indicating that the use of a non-linear estimator is not driving our results. For the reminder of this section, all coefficients are estimated with a Poisson regression.

In our first counterfactual, we equalize the number of months spent in each job type which reduces the IGE to 0.311, implying a marginal contribution of 28%. Moreover, in section B.3, we have shown that the differences in the allocation of months between workers coming from poor and rich families are driven almost entirely by an extensive participation margin. That is, among children of poorer families there is a substantial share of individuals permanently out of the labor force.

Taken together these results indicate that the participation margin is a main driver of the persistence of income inequality across generations, which can be due to either a labor supply or a labor demand explanation. The labor supply explanation is that individuals from poorer families have a relatively higher reservation wage, maybe due to higher costs of searching for work. This could be related to cultural reasons: the non-employment rate among the non-college educated orthodox men and Arab women is 50% and 74% respectively, compared to 13% for the non-college-educated, non-orthodox Jewish population (Sarel et al., 2016). The labor demand explanation is that the drop in participation is just a consequence of a lower offered wage. In other words, individuals from poorer families have lower potential earnings, hence they are less likely to look for jobs, even keeping search costs constant. In future work, we wish to provide further evidence to help telling apart these two channels.

In our second counterfactual, we equalize firm earnings premiums. This can be done only for the subsample of workers for which we can estimate AKM effects, i.e., workers employed, at least for a period, in a firm belonging to the largest connected set.[18] Hence we begin by estimating the benchmark IGE restricting the sample to the connected set. The resulting estimate is 0.332, representing a reduction almost as large as the one we obtained when equalizing the allocation of months. The reason is that the AKM sample mechanically excludes individuals that were never employed, shutting down the participation margin.

B.3 Decomposing the Non-employment Differentials

We have shown that three factors could contribute to the employment gap between individuals coming from high- versus low-income families: labor force participation and, conditional on participation, the length of employment and non-employment spells. It is challenging to compare the magnitudes of this margins, since the first is a stock and

[18] The identification result in Abowd et al. (2002) show that the employer fixed effect in Abowd et al. (1999) can only be estimated in the connected set of employers. To be in the connected set, an employer has to either hire a worker from or have a worker hired by an employer in the connected set.

the second, a flow, which can lead to complicated compound effects. In this section we introduce a simple model of job search that incorporates these three elements and will allow us to evaluate the quantitative importance of each factor.

Our model consists in a discrete-time, infinite-horizon economy, populated by a large number of workers characterized by different paternal-income levels fi. Each worker is *never-employed* with probability S_{fi}^{Never}. These individuals will always be non-employed with probability one. For the rest of the working force, the dynamics is as follows. In the first period, they are employed with probability P_{fi}^{find}. In each subsequent period, individuals currently employed keep their status with probability P_{fi}^{keep}, and the ones currently non-employed find a job with probability P_{fi}^{find}.

In steady state, the number of workers moving into employment must be equal to the number of workers moving out of employment, which implies:

$$J_{fi} \cdot (1 - P_{fi}^{keep}) = (1 - J_{fi} - S_{fi}^{Never}) \cdot P_{fi}^{find} ,$$

where J_{fi} is the steady-state employment rate among individuals with parental income fi. Isolating J_{fi}:

$$J_{fi} = \left(\frac{1}{1 + \frac{1 - P_{fi}^{keeps}}{P_{fi}^{finds}}} \right) \cdot \left(1 - S_{fi}^{Never}\right) \ . \tag{12}$$

We now calibrate the parameters to match the flows we observe in the data. For the purpose of this exercise, we combine all status other than *Stable Job* into *Non-Employment*. Each period in our model correspond to a month. The share of *never-working* agents (S_{fi}^{Never}) is taken from Figure B3. The probability of job creation (P_{fi}^{find}) is taken from Figure B4, using the sample of workers that are employed in a stable job at least once. The probability of continuing employment (P_{fi}^{keep}) is taken from Figure B5. Given these parameters we calculate the steady state of our model as shown in Figure B6 (blue dots). The fit with the data (gray dots) is quite precise, showing that our steady-state assumption is a good representation of the data.

Finally, we use the model to evaluate the quantitative importance of each of the three factors described above. For this purpose, we perform a series of counterfactual exercises. In each of these exercises, one parameter is kept constant across the population, whereas the remaining follow their benchmark distribution. The constant parameter is calibrated at the mean of its benchmark distribution. The results presented in Figure B6 show a very clear pattern. The extensive margin is the most important driver of the employment gap between individuals coming from different family backgrounds. Differential rates of job destruction are relatively less important, however they also play a significant role.

C Validating the AKM decomposition

In this section test the restriction that the log-linear structure of earnings imposes on the data. For equation 2, we have:

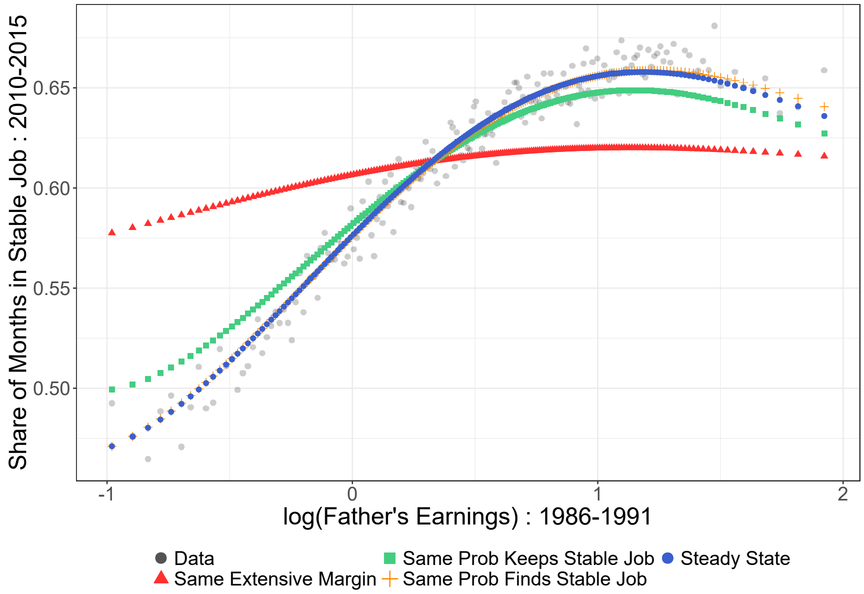
$$w_{i,t} = \alpha_i + \psi_{J[i,t]} + \mathbf{X}_{i,t} \cdot \boldsymbol{\beta} + \epsilon^y_{i,t} \; ,$$

$$w_{i,t+1} = \alpha_i + \psi_{J[i,t+1]} + \mathbf{X}_{i,t+1} \cdot \boldsymbol{\beta} + \epsilon^y_{i,t+1} \; .$$

Taking first differences:

$$\Delta w_{i,t} - \Delta \mathbf{X}_{i,t} \cdot \boldsymbol{\beta} = \Delta \psi_{J[i,t]} + \Delta \epsilon^y_{i,t} \; .$$

Figure B6: Counterfactuals Exercise: Month in Stable Employment



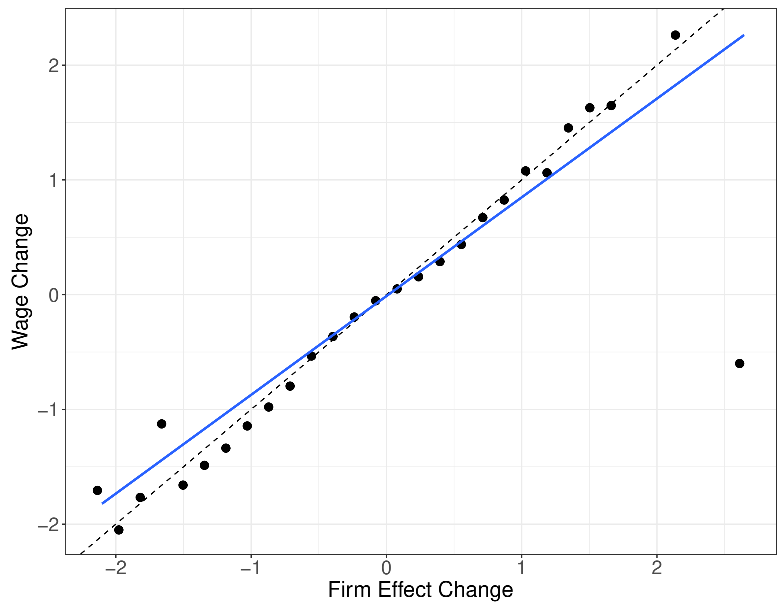
Notes: This figure plots the share of months an individual is employed in a stable job against log father's earnings. The share of months in a stable job (between 2010-2015) are plotted against the steady state prediction of our model, and three other counterfactuals. In each of these exercises, one parameter is kept constant across the population, whereas the remaining follow their benchmark distribution. The constant parameter is calibrated at the mean of its benchmark distribution (see Section B.3 for a formal definition). Father's earnings is first residualzed from a regression of age, age-squared and year fixed effects on log earnings, then averaged between 1986-1991.

In expectation:

$$\mathbb{E}\left[\Delta w_{i,t} - \Delta \mathbf{X}_{i,t} \cdot \boldsymbol{\beta}\right] = \mathbb{E}\left[\Delta \psi_{J[i,t]}\right] \ .$$

We take this restriction to the data by focusing on job switchers and comparing their earnings change against their firm-effect change. The results are in Figure C1. The solid blue line plots the best-fitting line estimated based on the micro-data. The dashed line plots the 45 degree line. Indeed, a percentage change in earnings is corresponds to a percentage change in wage premiums, as implied by the log-linear structure we use.

Figure C1: Earnings Change Corresponds to Firm Fixed Effect Change

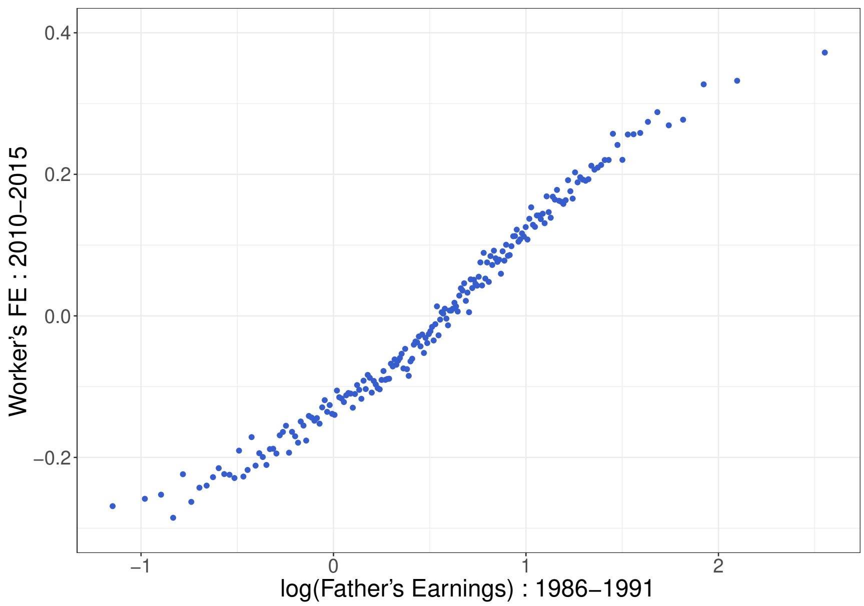


D The Role of the Individual Component of Earnings

In section 3.2 we used the AKM framework in order to decompose the *individual* vs. *firm* component of the child's earnings. We showed the firm component is correlated with father's earnings as an indicator for the importance of family's social networks in intergenerational mobility. For the sake of completeness, we will perform below the equivalent exercise with the individual component as a proxy of the child's abilities.

Figure D1 plots child's earnings individual component against father's earnings. The strong relationship between the two suggests ability plays an important role in intergenerational-mobility patterns, supporting the common human capital story. Note however, that we cannot give this ability measure a mere interpretation of human capital, since the child's genetic "endowment" are also constant within a person across time, and thus, also captured in the individual fixed effect.

Figure D1: Constant Earning Component vs. Log Father's Earnings



Notes: This figure plots child's earnings fixed effect (between 2010-2015) against log father's earnings. Child's earnings fixed effect is calculated as the AKM individual fixed effect (see section 3.2 for a formal definition). Father's earnings is the average yearly earnings between 1986-1991. Both father's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.

E Why Father Earnings?

In this section we explain our choice of focusing merely on father's, rather than mother's or household earnings.

The study of intergenerational mobility is trying to pin down a measure of equality of opportunities in the society. Thus, we would want a proxy for the child's socio-economic (SES) environment she was raised in (this is why sociologist traditionally use occupations). The choice of earnings (for both the parent and the child) serves as a parsimonious measure of SES. But who's earnings should we choose? Table 3 below presents the rank correlation between child's earnings rank and household, father's and mother's earning ranks. The estimates from the household and father's regressions are very close at 0.23 and 0.246 respectively, while the estimates from the mother's regression is as low as 0.093. This suggests that father's earnings are a good proxy for household earnings in total.

So why not to use household earnings? a household with a second earner could also be correlated with a lower SES families, rather than higher. This trend is of course changing over time but our period of study of the parents goes back three decades ago. For example, Israel's female labor force participation had been rising in the last couple of decades, reaching a high of 60% in 2017. Nevertheless, in the late 1980's it was as low as 40%-45%.[19]

Thus, even though factoring in the income of the second earner will give us a better picture of the *earned* resources in the household, it will also be convoluted with a family from a lower wealth and SES background. In fact, focusing on the R^2 we see using father's earnings has a higher explanatory power than household earnings, and much

[19] International Labour Organization, ILOSTAT database. Early release of the 2017 ILO Labour Force Estimates and Projections, retrieved in November 2017.

higher than mother's earnings. Furthermore, aggregating the household earnings introduce a question of whether we should normalize it so single parent families will be comparable as well? some economist suggest to divide by the square root of two as to correct for increasing return to scale. In an effort to try and reduce the noise involved, these two reasons lead us to choose father's earnings as a single parsimonious measure that captures SES background.

Table 3: Family 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 results from the the rank correlation between child's earnings rank and household, father's and mother's earning ranks. Both parent's and child's earnings are the residuals from a regression of age, age-squared and year fixed effects on log earnings.