Intergenerational Income Mobility in Turkey*

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Abstract

We examine the extent of intergenerational income mobility in Turkey and offer comparable intergenerational income elasticity estimates using the Turkish Statistical Institute's Survey of Income and Living Conditions datasets and *TS2SLS* methodology. First, we document that the intergenerational earnings elasticity between fathers and sons is around one-half, indicating a similar level of mobility in the United States. Second, we report a considerably larger elasticity of one between fathers and daughters. We show that this result stems from the historically low labor force participation and self-selection of females into employment in Turkey. We demonstrate that the household income elasticity estimates for sons and daughters are accordingly similar, around four-fifths. Third, we show that descendants residing in Turkey's more affluent regions are more likely to have experienced upward mobility. Fourth, we report a decline in intergenerational mobility for more recent birth cohorts, as seen in other countries. Fifth, we complement our regression analyses with alternative mobility measures such as the rank-rank slope and transition matrices. These measures indicate more pronounced intergenerational persistence at the two ends of the income distribution. Our robust findings align with the previous literature on Turkey's intergenerational educational mobility.

Keywords: Social Mobility; Income Persistence; Labor Earnings; Household Income; Income Inequality
JEL Classification: J62; D1; D3

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1 Introduction

Rapidly growing intergenerational mobility literature recently focuses on how existing economic inequalities persist across generations.[1] While the extent of intergenerational mobility — the transmission of economic outcomes across generations — has been measured for various countries, Turkey remains an exception. This study investigates intergenerational mobility in Turkey and offers cross-country comparable estimates to fill this gap in the literature.

Previous studies often estimate *intergenerational elasticities* (*IGE*) to measure the association between the economic outcomes of parents and descendants. The most commonly used summary measure is the intergenerational *earnings* elasticity, i.e., the coefficient from the log-log regression of descendants' lifetime labor earnings on that of their parents. While the earlier mobility literature focuses almost exclusively on developed countries, estimates of intergenerational earnings elasticity in developing countries have proliferated recently.[2] Meanwhile, the literature on Turkey has been limited to intergenerational *educational* mobility mainly due to data limitations. Accordingly, Turkey lacks a detailed analysis of intergenerational income mobility despite its sizable economic activity, high degree of economic inequality, and distinct labor market structure. This paper offers novel estimates for Turkey's intergenerational income elasticities, as well as for its other (e.g., rank-rank slope, transition matrix) intergenerational mobility measures.

We rely on the Turkish Statistical Institute's (*TurkStat*) Survey of Income and Living Conditions (*SILC*) micro datasets covering 2005 to 2017. We estimate Turkey's intergenerational income elasticities using the two-sample two-stage least-squares (*TS2SLS*) methodology (Björklund and Jäntti, 1997) under the presence of Turkey's data limitations. We also examine the extent of heterogeneity in Turkey's intergenerational mobility estimates over gender, time, geography, and income distribution.

To estimate intergenerational elasticities consistently, we predict parents' earnings and income using retrospective information on parental characteristics. We first estimate returns to education and occupations using pooled *SILC* cross-sectional datasets. We then use children's reports of their parents' educational attainment and occupation, which are available in *TurkStat*'s Intergenerational Transmission of Disadvantages Module provided with *SILC* cross-section in 2010. We combine these predictions and children's reports of their income to estimate our intergenerational mobility measures.

[1] See Mogstad and Torsvik (2021) for a comprehensive discussion on the advances in the related literature.

[2] See Narayan et al. (2018) for a broad set of estimates for developed and developing countries.

Our *TS2SLS* estimate for Turkey's intergenerational earnings elasticity is 0.51 for father-son pairs. Cross-country comparison indicates that Turkey exhibits an intergenerational earnings elasticity similar to the least mobile developed countries such as the United States and the United Kingdom. Several additional novel findings emerge from our analysis.

We first document that the estimated intergenerational earnings elasticity between fathers and daughters is twice as large as that of father-son pairs. This result practically suggests that daughters inherit the same degree of inequality as their fathers. We show that this striking result stems from Turkey's historically low female labor force participation. In particular, parental effects on daughters' outcomes are overestimated due to the self-selection of females into employment. Accordingly, our estimations suggest comparable intergenerational equivalized household income elasticities for sons and daughters, both close to four-fifths. We report that parental earnings are correlated with both their children's and their spouses' earnings similarly; thus, assortative mating plays a crucial role in the intergenerational persistence of household income.

We next complement our analysis by estimating rank-based mobility measures. Contrary to *IGE*, our rank-rank slope estimates indicate slightly weaker intergenerational mobility in Turkey than in the US. In addition, we show using rank-based measures that descendants residing in more affluent regions of Turkey are more likely to have experienced upward mobility. Further, we present quintile group transition matrices to illustrate heterogeneous patterns across the income distribution. In line with the previous literature, intergenerational persistence emerges strongest in the top and bottom quintiles.

We also investigate the evolution of intergenerational income mobility. Our findings imply a decline in intergenerational mobility over birth cohorts (except for sons in the youngest cohorts). We observe a similar trend via the rank-rank slope, which is robust to changes in inequality over cohorts. We also report that younger cohorts are less likely to have experienced upward mobility, as seen in the US and several other countries.

Finally, we provide a set of alternative estimations and verify that our estimates are not sensitive to specification differences.

The rest of the paper is organized as follows: In Section 2, we review the related literature; in Section 3, we discuss the theoretical background; in Section 4, we describe the data we use; in Section 5, we present our estimation methodology and report our results, and in Section 6, we conclude.

2 Related Literature

The number of studies investigating the empirics of intergenerational economic mobility has increased rapidly in recent decades. In his seminal paper, Solon (1992) points out the sources of biases in early empirical studies and offers a standard methodology to estimate intergenerational income persistence.[3] Since then, comparable and robust estimates have emerged for different countries, albeit confined mainly to developed ones.[4] As a result of better data availability and methodological advances, comparable estimates for numerous developing countries have also become available recently (Narayan et al., 2018). Our study is motivated primarily by the lack of estimates for Turkey.

As one of the more unequal members of the *OECD*, Turkey's economic inequalities are well-studied in the literature. Among the more recent studies, Tansel et al. (2018) focus on Turkey's wage inequality and report 90/10 and 90/50 percentile ratios for different gender, age, sector, and education groups using the Turkish Statistical Institute's (*TurkStat*) Survey of Income and Living Conditions (*SILC*) for the 2005-2011 period. Filiztekin (2015) decomposes income inequality over various population subgroups while also studying regional idiosyncrasies for the 1994-2011 period using *TurkStat*'s Household Budget Survey (*HBS*). The most recent study by Tamkoç and Torul (2020) provides cross-country comparable estimates of Turkey's economic inequalities following the guidelines by Krueger et al. (2010). They use both *HBS* and *SILC* to show a recent downward trend in wage, income, and consumption inequality between 2002 and 2016, which accords well with the rapid minimum wage growth during this period.[5] Overall, while the key patterns in Turkey's cross-sectional inequalities across subgroups and over time are well-documented, no previous study accurately investigated Turkey's intergenerational income mobility and how it relates to the evolution of Turkey's income inequality.

The main reason behind the lack of studies addressing Turkey's intergenerational income mobility is the shortage of long-running longitudinal datasets. Ideally, an analysis of intergenerational income mobility relies on data from both parents' and descendants' working life. Datasets with such information (e.g., the Panel Study of Income Dynamics (*PSID*) for the US and longitudinal income tax records for Sweden and Canada) allowed researchers (e.g., Solon 2002, Corak and Heisz 1999, and Österberg 2000) to measure inter-

[3] For instance, Becker and Tomes (1986) report intergenerational earnings elasticity estimates ranging between 0.15 and 0.28 for the US, which later turned out to be considerably smaller than the actual value.

[4] Among many others, see Österbacka (2001) for Finland, Bratberg et al. (2005) for Norway and Corak and Heisz (1999) for the US and Canada.

[5] See also Torul and Öztunalı (2018) for Turkey's *wealth* inequality.

generational income mobility consistently for numerous countries.[6] Unfortunately, the only available panel dataset in Turkey — *SILC* panel dataset — follows individuals for at most four years. Further, *SILC* provides data on parents *only if* subjects were living with their parents at the time of the survey. As *SILC* does not provide data for descendants who do not live with their parents, it fails to represent Turkish parent-descendant pairs correctly. Thus, results via *SILC* panel dataset would offer biased estimates.[7] We believe our paper offers credible estimates by relying on nationally representative datasets and appropriate methodology.

There are a few studies on Turkey's intergenerational *educational* mobility. Since educational attainment is usually constant throughout adulthood and many surveys include questions on parental education, data requirements for measuring educational mobility are relatively easier to meet.[8] Using *TurkStat*'s Adult Education Survey (*AES*) in 2007, Tansel (2015) documents that mothers' educational background has a more pivotal role than fathers', and intergenerational associations are stronger when the parental educational background is short of a primary school degree. Öztunalı and Torul (2022) examine both ordinal and cardinal measures of intergenerational educational mobility using the Intergenerational Transmission of Disadvantages Module of *SILC* in 2010. They document that Turkey has a relatively low degree of mobility compared to the developed countries in the literature, and the primary measures of intergenerational educational mobility (the regression and correlation coefficients and the rank-rank slope via years of schooling) evolved in a U-shaped pattern. That is, the relative intergenerational educational mobility prospects of the descendants born to low-educated parents improved for the cohorts born between 1951 and 1964 and worsened for those born after. They also show that intergenerational educational mobility exhibits immense heterogeneity over socio-economic factors. Aydemir and Yazıcı (2019) concentrate on the cross-regional variation in intergenerational educational mobility in Turkey. Using their own survey data, they find a positive relationship between intergenerational educational mobility and regional development. Our paper complements these studies by offering the first insights into the empirics of intergenerational transmission of *income*, thereby contributing to a better understanding of Turkey's intergenerational mobility.

The *Fair Progress* report by Narayan et al. (2018) offers the most comprehensive picture of intergenerational mobility worldwide. Unfortunately, Turkey is not among the 75 countries for which intergenerational

[6] Mazumder (2018) reviews the contributions of *PSID* for unveiling various aspects of intergenerational mobility in the US.

[7] All previous studies that attempted to measure intergenerational income mobility in Turkey (Mercan, 2012; Mercan and Barlin, 2016; Duman, 2021) use these co-residing father-son pairs in their analysis. Therefore, their estimates not only suffer from measurement error but also from an unrepresentative dataset.

[8] Despite the widespread availability of data, the cardinal specification of education is not straightforward and poses various challenges for econometric analysis. For an extended discussion see Öztunalı and Torul (2022) and Torul and Öztunalı (2017).

income elasticities are reported.[9]

Recently a growing number of studies unveiled intergenerational income mobility for developing countries by relying on the two-sample methods (*TSIV* and *TS2SLS*), which have less strict data requirements. Among them, Dunn (2007) estimates intergenerational earnings elasticity for Brazil and reports results in the range of 0.69–0.85 for father-son pairs. In another study with the same methodology, Nunez and Miranda (2010) report results for Chile in the range of 0.57–0.74.[10]

In this paper, we similarly use the *TS2SLS* method to offer comparable estimates for Turkey. The *TS2SLS* estimator was first introduced by Angrist and Krueger (1992) and later popularized in the intergenerational mobility literature by Björklund and Jäntti (1997). This method allows for estimating intergenerational earnings elasticity in the absence of longitudinal data when children's and fathers' earnings are available in two different datasets. Specifically, available parental characteristics are used first to predict parental income, which is next used in the intergenerational regression of interest.[11] We benefit from the *SILC* cross-sectional datasets to predict parental income. We combine these results with the *SILC* Intergenerational Transmission of Disadvantages Module in 2010 to estimate intergenerational elasticities. Our numerous sensitivity checks confirm the robustness of our findings.[12,13]

[9] Another comprehensive study by Hertz et al. (2008) documents 50-year trends of intergenerational educational mobility for 42 developed and developing countries while also excluding Turkey.

[10] See also Ng (2013) for Singapore, Kan et al. (2015) for Taiwan, and Grawe (2004) for Ecuador, Nepal, Pakistan, and Peru.

[11] Fathers' educational attainment and social class are often used to predict their income (Dearden et al., 1997; Lefranc and Trannoy, 2005). Nevertheless, other instruments such as sector and geographical dummies as in Piraino (2007) for Italy and firm size as in Lefranc et al. (2014) might also be included in predicting parental income. Previous work by Checchi et al. (1999) on intergenerational mobility in Italy relies on a relatively crude measure: the mean earnings of each occupation.

[12] While the earlier literature focuses solely on father-son pairs, recent studies also report estimates for father-daughter, mother-son, and mother-daughter pairs. Among the first attempts, Chadwick and Solon (2002) show that intergenerational elasticity of earnings is lower for daughters than sons in the US. Similar patterns are reported by Jäntti et al. (2014) in Nordic countries and by Lefranc et al. (2014) in Japan. Dearden et al. (1997), however, report the opposite in Great Britain, as we report in Turkey.

[13] Another strand of the literature focuses on the variations in intergenerational mobility over income distribution and documents that mobility varies immensely over income within the same economy. Österberg (2000) and Dearden et al. (1997) complement their estimates with transition matrices, both revealing stronger persistence at the two tails of the income distribution. Also, Jäntti et al. (2014) use transition matrices to compare intergenerational mobility across countries over the whole income distribution. See also Chetty et al. (2014) for the state-of-the-art use of transition matrices for a comprehensive analysis of intergenerational mobility in the US. Further, see Bratberg et al. (2007) and Palomino et al. (2018) for the use of quantile regressions.

3 Theoretical Background

3.1 Issues in *IGE* Estimation

In estimating intergenerational elasticities (*IGE*), the baseline relationship between parents' and children's income can be summarized by the following equation (Becker and Tomes, 1986):

$$y_c = \alpha + \beta y_p + \epsilon \tag{1}$$

where y_c and y_p denote the natural logarithm of children's and parents' lifetime earnings, respectively. If both are directly observed for a *random* sample of families, one could estimate $\hat{\beta}$ via an ordinary least squares (*OLS*) regression. However, lifetime earnings are not directly observable in most datasets, and often the only available source of information is annual earnings. Therefore, annual earnings of children in year t and parents in year s serve as a proxy for lifetime earnings:

$$y_{ct} = y_c + \nu_{ct} \tag{2}$$

$$y_{ps} = y_p + \nu_{ps} \tag{3}$$

where ν denotes transitory earning shocks. The conventional method in the literature is to average over multiple years of observed earnings to proxy for lifetime earnings. In that case, assuming transitory shocks are independently and identically distributed (i.i.d.) with a mean of zero, the probability limit of the *OLS* estimate using averaged earnings is as follows:

$$\text{plim}\hat{\beta} = \beta \frac{\sigma^2_{yp}}{\sigma^2_{yp} + \sigma^2_{\nu p}/T} \tag{4}$$

The attenuation factor increases with the variance of transitory errors $\sigma^2_{\nu p}$ and decreases with the number of years used for averaging T. Ideally, as many years as possible should be used in averaging parental income to acquire consistent estimates of β.[14] While the convention is to average over at least five years of earnings (Solon, 1992), Mazumder (2005) shows that taking longer multiyear averages progressively improves *IGE*

[14]Note that $\sigma^2_{\nu c}$ does not appear in equation (4), indicating that under the assumption of purely transitory and homoskedastic errors, *IGE* can be consistently estimated even when a single year of children's earnings is used. However, averaging over children's earnings alters the precision of the *IGE* estimate. The variance of transitory earning shocks experienced by the children $\sigma^2_{\nu c}$ appears in the probability limit of *R* statistic: $\text{plim}\hat{R} = \frac{\beta\sigma^2_{yp}}{\sqrt{(\sigma^2_{yp}+\sigma^2_{\nu p})(\sigma^2_{yp}+\sigma^2_{\nu c})}}$. Contrary to the convention, we keep single-year income measures for children in our estimations in Appendix D. Otherwise, our sample sizes become overly small and yield uninformative results.

estimates.[15] As a result, even when multiple years of observations are available, *OLS* estimates of *IGE* might well be downward-inconsistent.[16]

Another potential source of bias is life-cycle variations of income, which do not show up in the equations above. While both generations' *adult earnings* are necessary for an accurate estimation of *IGE*, surveys systematically report descendants relatively early and parents late in their life cycles. Empirically, the relationship between current and lifetime income varies over the life cycle. Therefore, instead of equations (2) and (3), a more accurate formulation of earnings would take the form:

$$y_t = \lambda_t y + \nu_t \tag{5}$$

for both generations, where λ_t denotes how strongly the lifetime component y affects annual earnings y_t. As the subscript indicates, λ_t varies over age and needs not equal one. Correspondingly, even when transitory errors are assumed to be homoskedastic and i.i.d., an individual's age at the time of measurement might generate bias in *IGE* estimates. Hence, equation (4) can be rewritten as follows:

$$\text{plim}\hat{\beta} = \beta \overline{\lambda}_{ct} \overline{\lambda}_{pt} \frac{\sigma^2_{yp}}{\overline{\lambda}^2_{pt} \sigma^2_{yp} + \sigma^2_{\upsilon p}/T} \tag{6}$$

where $\overline{\lambda}_{pt}$ and $\overline{\lambda}_{ct}$ denote the multiyear averages of λ_t for parents and children, respectively. Using data on complete earnings histories of individuals in the United States, Haider and Solon (2006) report that their estimates for λ_t start as low as 0.2 at the age of 20, monotonically increase over age until 40 (and reach 1 around this peak), and then decrease to 0.6–0.8 later in life.[17] Hence, the life-cycle variation of earnings is likely to bias *IGE* estimates further downward. The main implication of this result is that individuals with higher lifetime earnings tend to have steeper initial earnings growth, and differences in earnings observed at earlier ages understate differences in lifetime earnings.[18]

Equation (6) also assumes that the variance of transitory earning shocks σ^2_υ is constant over the life cycle. However, Baker and Solon (2003) and Grawe (2006) provide empirical evidence that $\sigma^2_{\upsilon t}$ too depends on age and reaches its minimum around the age of 40. In addition, Nybom and Stuhler (2016) show that the path

[15] More precisely, *IGE* estimate for the US increases from 0.25 when T=2 to 0.45 when T=7, and to 0.61 when T=16.

[16] Moreover, the bias would be aggravated under persistent earning shocks. See Mazumder (2005) and Muller (2010) for further discussion.

[17] Measuring children's earnings further from the age of 40 would bias *IGE* estimates downward, whereas the effect would be in the opposite direction for the case of fathers.

[18] Böhlmark and Lindquist (2006) reach similar conclusions using Swedish register data. See also Grawe (2006), which inspects 20 studies and various datasets and shows that *IGE* estimates decrease as fathers' age increases.

of λ_t varies especially over educational attainment. Hence, in this paper, we rely on the earning measures that are representative of the age of 40 while taking education into account in order to minimize the bias stemming from both λ_t and σ^2_{vt}. We discuss the details of our methodology addressing this issue and our robustness experiments in the following sections.

Lastly, relying on an unrepresentative sample severely biases *IGE* estimates. Depending on the nature of the dataset used, attrition, self-selection, and sampling design may contribute to unrepresentative samples. As Solon (1992) elaborates, the estimated *IGE* will be downward biased due to low "signal-to-noise" ratio when the sample is too homogenous.[19]

3.2 *IV* and *TS2SLS* Estimation

Another approach to address the errors-in-variables problem is using instrumental variable (*IV*) estimation. The idea behind this method is to exploit the variation in parents' earnings y_p by using parental education e_p as an instrument to estimate equation (1). However, parents' education is not necessarily a valid instrument since it might directly affect descendants' earnings even after controlling for parental earnings. In this scenario, the structural equation can be formulated as follows:

$$y_c = \alpha + \beta_1 y_p + \beta_2 e_p + \epsilon \tag{7}$$

Nonetheless, as argued by Björklund and Jäntti (1997), the inconsistency of the *IV* estimator is in the upward direction whenever the direct effect of parental education on the earnings of children is positive.[20] Hence, the *IV* estimate provides an upper bound and is often used together with the downward-inconsistent *OLS* estimate to bracket the *IGE* estimate.

A special case of *IV* estimation is the two-sample two-stage least squares (*TS2SLS*), which is introduced to the intergenerational mobility literature by Björklund and Jäntti (1997).[21] *TS2SLS*, as its name suggests, makes use of an outside dataset to predict parental earnings using parental characteristics reported by chil-

[19]We believe that the most severe pitfall that biased the estimates in the previous studies on Turkey is the use of a sample of children who co-reside with their parents, which is unrepresentative of Turkey's actual population.

[20]The literature focusing on the effect of parental education on the economic outcomes of children mostly agrees with this assumption. Heckman and Mosso (2014) and Becker et al. (2018) are two examples from the intergenerational mobility literature.

[21]Some early studies use the name *TSIV* instead, although *TS2SLS* is equivalent to *TSIV* only when the same sample is used in both stages. Inoue and Solon (2010) provide an elaborate comparison of *TS2SLS* and *TSIV*.

dren. *TS2SLS* estimate is equivalent to:

$$\hat{\beta} = \frac{\text{Cov}(y_c, \text{X}_\text{p})}{\text{Cov}(y_p, \text{X}_\text{p})} \tag{8}$$

where X_p is the vector of explanatory variables used to predict parental earnings. Notably, the numerator and denominator are estimated from different samples. As Björklund and Jäntti (1997) discuss, the *TS2SLS* estimator is equivalent to the *IV* estimator whenever both samples come from the same population, and parents' characteristics reported by children are not noisier than parents' own reports. Our datasets meet the necessary conditions well since parental characteristics are not drawn from an outside sample. Instead, they are simply attached to a single cross-section of our larger pooled dataset.

3.3 Rank Mobility

Intergenerational elasticity is a canonical measure in the social mobility literature as it accounts for the magnitude of differences in the economic outcomes of both parents and children. However, for the same reason, it is sensitive to inequality differences across generations (σ_{yp} vs. σ_{yc}) since the relationship between intergenerational elasticity (*IGE*) and intergenerational correlation (*IGC*) takes the form:

$$IGE = IGC \frac{\sigma_{yc}}{\sigma_{yp}} \tag{9}$$

In addition, *IGE* does not allow comparing between population subgroups as it would represent persistence with respect to the group-specific mean.

An alternative approach to circumvent these limitations is using *rank*-based measures to investigate intergenerational *positional* mobility. The conventional metric in the literature has been the rank-rank slope, which is obtained by regressing children's income rank on that of their parent: [22]

$$R_c = \alpha + \beta^{RR} R_p + \epsilon \tag{10}$$

where R_c and R_p denote the child's and parent's income rank, respectively. Contrary to *IGE*, the rank-rank slope is a scale-invariant measure like *IGC* and is not affected by changes in inequality across generations.[23] Another appeal of the rank-rank slope is that it can be used to compare the degree of mobility across sub-

[22] Among others, see Dahl and Deleire (2008), Chetty et al. (2014), and Davis and Mazumder (2017).

[23] Note that the rank-rank slope is simply the correlation between child's and parent's rank as they are both distributed identically, i.e., discrete uniform distribution between one and a hundred.

groups as ranks come from the national distribution.

Chetty et al. (2014) also report a measure they coin as *absolute upward mobility*, which is the *expected rank* of the children from families *below the median* in the national distribution: $E[R_c|R_p < 50]$. Albeit mechanically connected to the rank-rank slope at the national level, this measure is informative when comparing poorer families across subgroups.[24]

4 Data and Key Variable Definitions

As briefly discussed, we use micro-data from the Turkish Statistical Institute's (*TurkStat*) Survey of Income and Living Conditions (*SILC*) datasets covering the period 2005-2017.[25] *SILC* is published annually in the form of both cross-sectional and panel datasets that are nationally representative.[26] *SILC* cross-sectional datasets cover at least 9,200 households per year and offer detailed information on the income sources of individuals and households. *SILC* 2010 cross-sectional dataset additionally provides the *Intergenerational Transmission of Disadvantages Module*, which contains valuable information for our analysis.[27]

In all datasets used in our analyses, we restrict our working sample to individuals between 20 and 64 years of age and with positive household incomes. We convert nominal variables into real units by deflating them via the Turkish consumer price index (*CPI*), for which we use 2005 as the base year. For the estimations of employed individuals, we exclude those whose annual earnings are below 244 Turkish liras (i.e., half of the monthly minimum wage in 2005) or work less than 30 hours a week. These practices that we follow are the ones proposed by the *Review of Economic Dynamics* (*RED*) Special Issue guidelines (Krueger et al., 2010) for the study of economic inequalities.[28] We present the resultant descriptive statistics of individuals satisfying the above criteria in the second and third columns of Table 1 and Table A.1.

We also construct the *annual earnings* and *hourly wage rate* variables following the same *RED* guidelines. *Annual earnings* of individual i in year t, $ae_{i,t}$ is calculated as follows:

[24]The estimated *absolute upward mobility* clearly equals $\hat{\alpha} + 25\hat{\beta}^{RR}$.

[25]The reference year in *SILC* is the preceding calendar year. The datasets we use were published between 2006 and 2018.

[26]*SILC* was first introduced in 2006 to provide income distribution statistics that are compatible with the European Union's official statistics. More detailed information about *SILC* can be found on the *TurkStat's* official website.

[27]We also use the *SILC* panel dataset over the same interval for our analysis in Appendix D. None of our numerical results in the main text relies on the *SILC* panel dataset.

[28]See Tamkoç and Torul (2020) for a comprehensive investigation of Turkey's economic inequalities by adhering to the same *RED* guidelines. Briefly, *RED* guidelines are a set of standardized procedures to ensure the cross-country compatibility and comparability of the analyses addressing the evolution of economic inequalities. These guidelines are particularly instrumental in income definitions including left-truncation. See Krueger et al. (2010) for further details.

$$ae_{i,t} = nw_{i,t} + rw_{i,t} + \alpha_t^{TR}(nse_{i,t} + rse_{i,t}) \tag{11}$$

where $ae_{i,t}$ denotes *annual earnings*, $nw_{i,t}$ and $rw_{i,t}$ denote annual cash and other real payments, α^{TR} denotes the share of labor income in Turkey's national income in the year of observation, and $nse_{i,t}$ and $rse_{i,t}$ denote cash and other real incomes from self-employment, respectively. *Annual hours worked*, $ah_{i,t}$, is calculated as weekly hours worked times the number of weeks worked throughout the year.[29] We calculate the hourly *wage rate* as follows:

$$w_{i,t} = \frac{ae_{i,t}}{ah_{i,t}} \tag{12}$$

We also construct *equivalized household income* according to the modified *OECD* equivalence scale, which attributes a weight of 1 to the first adult, 0.5 to each subsequent person aged 14 or older, and 0.3 to each child aged under 14. In the rest of the paper, we refer to it as *household income*.

We focus on *SILC* 2010 cross-sectional dataset for our main analysis. The *Intergenerational Transmission of Disadvantages Module* attached to this dataset provides information on children's incomes and reports of their parents' education status and occupational code (`ISCO-88`) when they were 14 years old. As displayed in Table 1, of the 25,463 individuals between the ages of 25 and 59 who answered the module questions, 11,703 are full-time workers. These two samples show no significant differences in their descriptive statistics.[30] Our two-sample *IV* estimates are based on the children observed in this dataset.

We use *SILC* cross-sectional datasets pooled over 2005-2017 to predict parents' earnings using children's reports. Also, we use the pooled dataset to estimate age-income profiles for different educational attainment groups. These estimates are used to correct children's incomes for life-cycle effects in *SILC* 2010 cross-section.

Contrary to the previous studies on intergenerational mobility in Turkey (Mercan, 2012; Mercan and Barlin, 2016; Duman, 2021), we do *not* use *SILC* panel dataset for our main analysis as this dataset contains information only about children who live with their parents. These children's income measures are lower and less dispersed than their complete-sample counterparts, as shown in column 4 of Table 1 (and column 4 of Table A.1 and Table A.2). These differences cannot be explained solely by different age compositions: even when observations are weighted to match the complete-sample age distribution, the earnings of children

[29] *SILC* contains information on weekly hours worked and the number of months employed. 7.5% of those who report working at least 30 weekly hours did not answer the number of months employed. We imputed twelve months for these individuals.

[30] Figure A1 displays the overlaid histograms of age and (log) earnings.

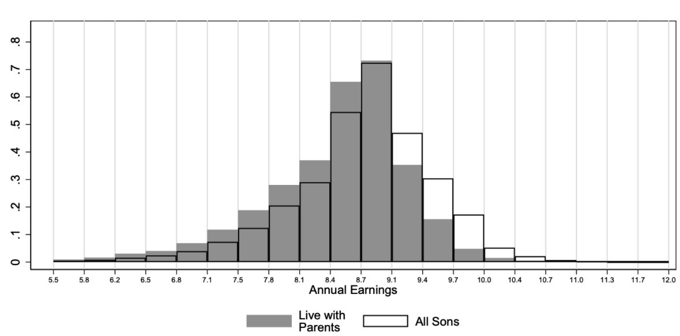
who live with their parents are considerably lower, as depicted in Figure 1 (and Figure A.2).

Table 1: Descriptive Statistics (*SILC* 2010 Cross-Section)

	Full Sample		Module Sample		Full-Time Workers		Live with Parents	
Male								
Age	39.99	(17.04)	40.31	(9.70)	39.16	(8.91)	33.85	(7.93)
Secondary Education or Lower	0.69		0.64		0.62		0.61	
High-School Graduate	0.20		0.21		0.22		0.26	
University Graduate	0.12		0.15		0.17		0.14	
log(Earnings)	8.38	(1.10)	8.60	(0.93)	8.70	(0.85)	8.47	(0.78)
log(Household Income)	8.74	(0.69)	8.82	(0.70)	8.89	(0.68)	8.77	(0.62)
Non-zero Earners	0.69		0.85					
Self-Employed	0.28		0.28		0.30		0.30	
Number of Observations	**19633**		**12499**		**9583**		**2009**	
Female								
Age	40.60	(17.73)	40.13	(9.70)	37.43	(8.34)	32.50	(6.60)
Secondary Education or Lower	0.80		0.78		0.47		0.27	
High-School Graduate	0.13		0.13		0.18		0.27	
University Graduate	0.07		0.09		0.35		0.45	
log(Earnings)	7.75	(1.52)	7.85	(1.56)	8.49	(1.09)	8.65	(0.87)
log(Household Income)	8.72	(0.69)	8.80	(0.70)	9.24	(0.73)	9.16	(0.56)
Non-zero Earners	0.20		0.25					
Self-Employed	0.15		0.17		0.17		0.09	
Number of Observations	**21046**		**12964**		**2120**		**379**	
Total								
Age	40.31	(17.40)	40.22	(9.70)	38.85	(8.83)	33.64	(7.75)
Secondary Education or Lower	0.75		0.71		0.59		0.55	
High-School Graduate	0.16		0.17		0.21		0.26	
University Graduate	0.09		0.12		0.20		0.19	
log(Earnings)	8.23	(1.24)	8.43	(1.15)	8.67	(0.90)	8.50	(0.80)
log(Household Income)	8.73	(0.69)	8.81	(0.70)	8.96	(0.70)	8.83	(0.62)
Non-zero Earners	0.43		0.54					
Self-Employed	0.25		0.26		0.28		0.27	
Number of Observations	**40679**		**25463**		**11703**		**2388**	

Notes: The numbers in parentheses are standard deviations reported alongside mean values. The values reported in a single column denote the shares of the sample. The self-employed are reported as a fraction of non-zero earners. Each column represents the sub-sample of the preceding column. The sample displayed in the last column includes children living with either of their parents. The self-employed category contains individuals who identified themselves either as self-employed or as an employer with positive self-employment income.

Figure 1: Earnings Histogram of Males



Notes: The frequency of earnings of children who live with their parents and the earnings of all individuals between ages 20 and 36 that report positive income are overlaid.

Following these considerations, we leave our analysis based on *SILC* panel dataset to Appendix D, where we provide evidence for the inconsistencies related to *IV* and *OLS* estimations.

5 Estimation Strategy and Results

5.1 Estimation Strategy

We start by age-correcting our income variables to mitigate possible life-cycle bias. As discussed in Section 3.1, the incomes of both generations should be measured around the age of 40 to minimize this bias (Haider and Solon, 2006).[31] We construct age-corrected income measures of children in our main sample (*SILC* 2010) using a similar method by Jäntti et al. (2014).

We first estimate the age effects on income measures using the pooled *SILC* cross-sectional dataset, which is larger and contains more information than single-year cross-sections. We do this separately for each gender and education group to address differences in age-income profiles. We repeat our regressions for five different income measures as the dependent variable: annual earnings, income, non-entrepreneurial income, hourly wage, and household income.

The regression equation we use takes the following form:

$$\log(y_i) = \alpha_{lg} + \sum_{j=1}^{8} \beta_{lgj}\,\texttt{age}_{ij} + \sum_{k=2005}^{2017} \gamma_{lgk}\,\texttt{year}_{ik} + \epsilon_i \qquad \text{if} \quad \texttt{educ}_i = l \;\;\&\;\; \texttt{sex}_i = g \tag{13}$$

where $\log(y_i)$ refers to the natural logarithm of the income measure of person i, `age` refers to the dummy variables of age categories of 5-year intervals: ages 20 to 24, 25 to 29,..., 55 to 59, and `year` refers to the year of observation. We repeat this estimation for each gender (`sex`) and education category (`educ`): secondary education or lower, high school graduate, and university graduates. We then use the resultant coefficients of age intervals and standard errors to construct children's age-corrected income measures (corresponding to the age interval of 35-39) as follows:[32,33]

$$\widehat{\log(y_{c,i})} = \hat{\alpha}_{lg} + \hat{\beta}_{lg4} + \hat{\gamma}_{lg2010} + \epsilon_i \frac{\hat{\sigma}_{lg4}}{\hat{\sigma}_{lgj}} \qquad \text{if} \quad \texttt{educ}_i = l \;\;\&\;\; \texttt{sex}_i = g \;\;\&\;\; \texttt{age}_i = j \tag{14}$$

[31] Nybom and Stuhler (2016) argue that there is no ideal age to measure income. Using Swedish income data, they find that, on average, the age of 33 is the most representative of lifetime income. However, the most representative age is not the same for all individuals: among their *IGE* estimates using annual incomes, the closest one to their estimated *IGE* results from the age-37 incomes of children.

[32] See Aktuğ et al. (2021) for an extensive investigation of the age-income profiles in Turkey using *TurkStat*'s Household Labor Force Survey (*HLFS*). We also use the coefficients of age and education by Aktuğ et al. (2021) to predict individuals' *labor income* at the age interval of 35-39. We present the coefficients estimated from our sample and compare them with the ones by Aktuğ et al. (2021) in Table A.3.

[33] We also construct the 4-year-averaged income measure of individuals using pooled *SILC* cross-sectional dataset for robustness purposes and observe no qualitative change in our estimates. These results are available upon request.

where $\widehat{\log(y_{c,i})}$ denotes the age-corrected income of the child, σ_{lpj} denotes the standard error of residuals for the corresponding group, and $j=4$ represents the group of individuals between the age of 35-39. Note that we preserve individual-specific variations as we construct age-corrected income measures using the reported ones instead of merely predicting them. We use age-corrected income measures of descendants in the second stage of our *TS2SLS* estimation.

For the first stage of our *TS2SLS* estimation, we next predict parental incomes using the information on parents' education and occupation, which is available in the *SILC* 2010 cross-section dataset. The estimation equation takes the following form:

$$\log(y_i) = \alpha_g + \sum_{j=1}^{6} \beta_{1gl}\texttt{educ}_{il} + \sum_{l=1}^{9} \beta_{2gm}\texttt{occup}_{im} + \sum_{j=1}^{8} \beta_{3gj}\texttt{age}_{ij} + \sum_{k=2005}^{2017} \gamma_{gk}\texttt{year}_k + \epsilon_i \quad \text{if} \quad \texttt{sex}_i = g \tag{15}$$

We use the above equation to obtain coefficient estimates for five different income measures: annual earnings, income, non-entrepreneurial income, hourly wage, and household income. We report the first-stage estimation results in Table A.4. We then use the estimated coefficients to predict parental income measures again for the age interval 35-39:

$$\widehat{\log(y_{p,i})} = \hat{\alpha}_g + \hat{\beta}_{1gj} + \hat{\beta}_{2gl} + \hat{\beta}_{3g4} + \hat{\gamma}_{g2010} \quad \text{if} \quad \texttt{educ}_i = l \;\;\&\;\; \texttt{occup}_i = m \;\;\&\;\; \texttt{sex}_i = g \tag{16}$$

Finally, we regress the age-corrected income measures of children on their parents' predicted income measure as follows:[34]

$$\widehat{\log(y_{c,i})} = \alpha + \beta_{IGE}\widehat{\log(y_{p,i})} + \epsilon_i \tag{17}$$

5.2 Main Results

We present our intergenerational elasticity estimates in Table 2. We report that the estimate for the canonical intergenerational mobility measure, the intergenerational elasticity of earnings for father-son pairs, is 0.51. This finding implies a relatively high intergenerational persistence for Turkey. We list comparable estimates for a few other countries in Table 3. Turkey ranks similarly to the least mobile developed countries such as

[34]We calculate the standard errors of our estimators using a bootstrap procedure. In doing so, we first draw a bootstrap sample from the pooled data, which we use to estimate the coefficients to predict parental income measures. Next, we draw a sample of children from the 2010 module dataset and predict parental income measures using the estimated coefficients. We then estimate elasticities and save our results. We repeat this procedure 1000 times and report the standard deviation of the bootstrap estimates as the resultant standard error estimates.

the United States and the United Kingdom, yet displays higher mobility than many of the developing ones.[35]

Table 2: *TS2SLS* Estimates of Intergenerational Elasticity in Turkey

Pairs	Number of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7809]	0.51	0.61	0.40	0.49
		(0.018)	(0.021)	(0.017)	(0.019)
				[5673]	
Father-Daughter	[1743]	1.00	1.09	0.72	0.88
		(0.042)	(0.048)	(0.038)	(0.040)
				[1451]	
Mother-Son	[3101]	0.35	0.52	0.29	0.31
		(0.025)	(0.039)	(0.026)	(0.025)
				[2037]	
Mother-Daughter	[670]	0.80	0.99	0.61	0.72
		(0.042)	(0.055)	(0.042)	(0.042)
				[509]	

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

Our results also reveal that intergenerational persistence is highest with the *income* variable, which additionally includes social assistance and unemployment benefits. On the contrary, our smallest estimate is with the *non-entrepreneurial income* variable. Higher *IGE* estimates from broader income measures are consistent with the earlier literature (Lee and Solon, 2009). However, a lower *IGE* of non-entrepreneurial income mainly results from sample selection: since self-employed descendants are excluded from the sample, these estimates reflect only the within-group mobility of labor earners.[36] Moreover, our estimates suggest a weaker effect of mothers' income on children's economic outcomes compared to that of fathers. This finding is contrary to Tansel et al. (2018), which argues for a stronger effect of mothers' education on children's educational attainment.[37]

[35] Grawe (2004) provides even lower *IGE* estimates for additional countries such as 0.24 in Nepal and 0.32 in Pakistan. We exclude those estimates since they result from small samples.

[36] We keep estimates based on non-entrepreneurial income despite its unrepresentative nature, as they would be relevant for the research focusing specifically on labor earners. (e.g., Tansel et al. 2018, Aktuğ et al. 2021).

[37] We also suggest that relying on elasticities concerning mothers' earnings can be misleading for the reasons discussed in the next subsections.

Table 3: Two-Sample Estimates of Intergenerational Earnings Elasticity by Country

Country	Study	Elasticity
Sweden	Björklund and Jäntti (1997)	0.28
Japan	Lefranc et al. (2014)	0.33
France	Lefranc and Trannoy (2005)	0.41
Italy	Piraino (2007)	0.44
Turkey	**This study**	**0.51**
United States	Björklund and Jäntti (1997)	0.52
United Kingdom	Dearden et al. (1997)	0.58
Chile	Nunez and Miranda (2010)	0.59–0.73
Brazil	Dunn (2007)	0.85
Ecuador	Grawe (2004)	1.13

Notes: All estimates are based on the samples of father-son pairs. All studies use predicted earnings of fathers, observed annual earnings of children and use either *TS2SLS* or *TSIV* method to estimate intergenerational elasticity. Most studies report several estimates; among those, we pick the most comparable ones with our methods and sample specifications. See Table A15 for details.

We use the data pooled over 2005-2017 to predict parental income measures throughout our estimations. In this conjecture, we assume that the relationship between the instrumented variables and income observed in our data is valid for the actual parents (Piraino, 2007). Therefore, if the education premium and occupational structure of the society were different in the period when parents were in their late 30s/early 40s compared to the period we observed, our assumption would be invalid. Ideally, data from the 1990s should be used for the first-stage estimation.[38] However, no data from the pre-2002 period is available for Turkey. While it is not possible to mitigate potential biases, our robustness checks could partially alleviate concerns: we display on Table A.5 that our estimates from the separate use of single-year cross-sections for the first stage estimation reveal little sensitivity to year choice.[39] Moreover, they do not exhibit a clear time pattern. We also repeat this exercise using another canonical dataset by *TurkStat*, Household Budget Survey (*HBS*), which offers data starting from 2002. We present our consequent results in Table A.6. These findings demonstrate that our results are robust over the use of alternative datasets too.

5.3 Intergenerational Mobility and Gender

One of the most striking results from Table 2 is the considerably higher elasticity estimates between parents and daughters. In particular, all *IGE* estimates for daughters are nearly twice as large as their son counterparts. The elasticity of daughters' earnings with respect to fathers' earnings is approximately one, which

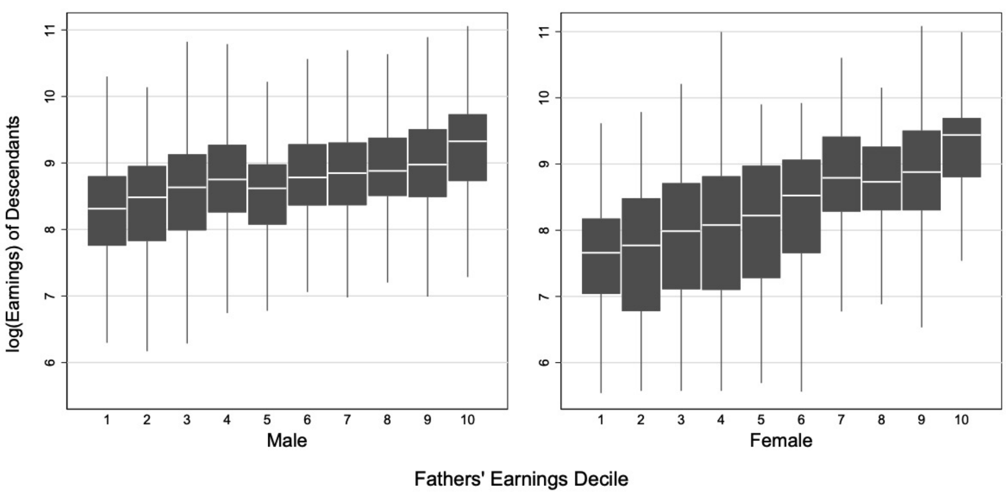
[38] Parental age data is too noisy in our dataset, which does not allow pinning down parents' exact cohort structure. When we compare the birth years of fathers co-residing with their children (already available in the primary dataset) with the children's reports of their fathers' birth years, we document that only 66% of the observations match. In the previous literature, parents' earnings are predicted using a dataset from, on average, 20 years earlier than the dataset containing children's earnings (Lefranc and Trannoy, 2005; Dearden et al., 1997).

[39] Dunn (2007) does a similar exercise by changing the first-stage dataset over 20 years. He finds at most a 13% change in his estimates, whereas ours change at most 10% for father-son pairs.

practically indicates that daughters inherit the same degree of economic inequality as their fathers. Contrary to our findings, *IGE* of daughters' income is lower than that of sons for most developed countries except for the United Kingdom (Dearden et al., 1997).

Figure 2 illustrates that daughters' earnings growth over their fathers' earnings rank is steeper than that of sons. In particular, male descendants of fathers in the bottom earnings decile earn 79% more than their female counterparts. This difference becomes smaller for descendants of fathers from higher income deciles: it is as low as 20% for the 9^{th} and practically zero for the top earnings decile. Similarly, we observe a steeper earnings increase over education for females compared to males: among full-time workers, secondary school graduates or less-educated males earn 48% more than their female counterparts. This ratio is 21% for high-school graduates and 13% for university graduates.[40] We also observe that fathers' earnings have a larger impact on their daughters' likelihood of university graduation compared to their sons (Table A.9).[41] We argue that the substantial parental impact on daughters' educational outcomes and higher relative returns to female education jointly account for daughters' higher intergenerational elasticity estimates.

Figure 2: Earnings of Males and Females over Father's Earnings Distribution



Notes: The upper bar of the boxes corresponds to the third quartile, the lower bar corresponds to the first quartile, and the line inside the boxes denotes the median. The endpoints of whiskers represent the lowest and highest observations within 1.5 times the lower and higher interquartile ranges, respectively.

We next decompose our intergenerational elasticity estimates by education following Hertz (2008) (Appendix C). This scrutiny provides a tractable framework to examine how parental impact through educa-

[40] See also Aktuğ et al. (2021), which documents the gender pay gap over education throughout the life cycle.

[41] This pattern is in accordance with the previous findings by Öztunalı and Torul (2022) and Tansel et al. (2018), which document higher intergenerational educational persistence for daughters than sons.

tional attainment differs by gender. In addition, the effect of labor force composition on *IGE* estimates becomes clearer in this exposition. Table 4 presents both between-group and within-group components of our *IGE* estimates for the educational attainment groups. Our within-group *IGE* estimates are comparable for both genders, except for secondary school graduates or less-educated descendants. This, however, does not contribute much to *IGE* levels due to the limited share of this education group among full-time working daughters, as shown in row (A). The contribution of between-group effects alone accounts for the substantial difference between the *IGE* estimates for sons and daughters, as shown in row (B).[42] Note that while the contribution of the lowest education group stems from the low average earnings of daughters in this group, the contribution of university graduates stems from their larger share among daughters compared to sons. In other words, the advantages of fathers are strongly transmitted to the next generation of working daughters through *level* differences between the lowest educational group and the rest or by raising the *likelihood* of the highest educational attainment.

Table 4: Decomposition of Intergenerational Earnings Elasticity by Educational Attainment

		Male			Female		
		Secondary or Lower	High School	University	Secondary or Lower	High School	University
	Shares	0.609	0.223	0.168	0.467	0.178	0.355
	Mean log Earnings of Children	8.51	8.97	9.58	7.83	8.72	9.47
	Mean log Earnings of Fathers	8.16	8.49	8.68	8.20	8.66	8.88
	Pooled *IGE*		**0.515**			**0.997**	
A	Within-group *IGE*	0.280	0.139	0.135	0.412	0.207	0.143
A	Contribution of within-group *IGE*	0.120	0.026 $\sum=0.173$	0.027	0.115	0.017 $\sum=0.173$	0.041
B	Between-group effects	0.189	0.126	1.176	0.804	0.097	1.214
B	Contribution of between-group effects	0.115	0.028 $\sum=0.341$	0.198	0.376	0.017 $\sum=0.824$	0.431
	Group-specific persistence: **A+B**	0.236	0.054 $\sum=0.515$	0.225	0.491	0.034 $\sum=0.997$	0.472

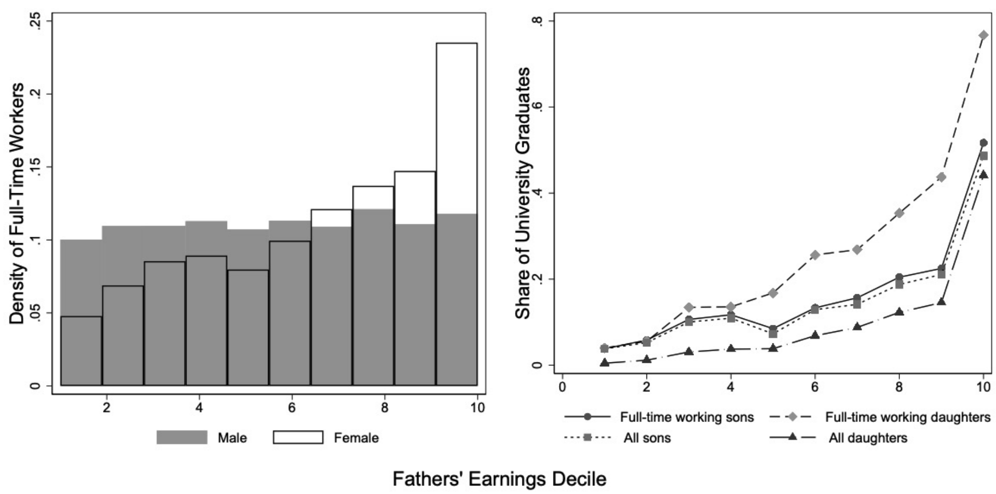
Notes: Children's earnings are corrected to represent the age 35-39 earnings. The earnings of fathers are predicted according to (12) via the information on education and occupation. The contribution of between-group and within-group effects are acquired by weighting with group size.

We discuss that the sizable parental effect on daughters' economic outcomes operates through the education channel. However, the large fraction of university graduates among working women suggests that the Turkish female labor force's distinctive nature should be considered while interpreting mobility results. Specifically, the Turkish female labor force participation rate is the lowest among the *OECD* countries and recently has fluctuated around only 30% (Aktuğ et al., 2021). Since our analysis is limited to full-time work-

[42] Between-group effects represent how fathers' earnings impact children's educational outcomes and how that reflects on *IGE* via differences in mean earnings of children's educational groups.

ing females, we systematically observe females with higher earnings prospects (Heckman, 1979). From an intergenerational perspective, the self-selection of females into the labor force reveals itself as i) increasing the labor force participation rate, and ii) increasing the share of university graduates among females over parental income rank. As shown on the left panel of Figure 3, working females are more likely to be descendants of higher-earning fathers. On the contrary, the employment prospects of males do not vary over their fathers' earnings. The right panel of Figure 3 reveals stark differences between the educational attainment of working females and their full-sample counterparts. The spread between the fraction of university graduates among working females and their full-sample counterparts widens over the earnings deciles of fathers, providing further evidence that we observe a select group of females in the Turkish labor force. Thus, the variation in the educational attainment of daughters associated with the variation in parental characteristics is amplified as we concentrate only on working females in our calculations.

Figure 3: Labor Force Participation and the Share of University Graduates by Gender



Notes: On the left panel, the histograms of employed individuals for both genders are overlaid. Each bin represents a decile of predicted father earnings. On the right panel, the shares of university graduates in each father's earnings decile are plotted separately for both genders, both samples of employed adults, and the full sample. Full-time workers refer to those who work at least 30 hours a week and earn at least half of the monthly minimum wage in the reference year. The full sample only includes individuals who report parental characteristics.

As revealed by the strikingly higher estimates for the intergenerational earnings elasticity of daughters, the choice of the income measure could lead to diverse estimates, which do not necessarily reflect the true nature of the underlying intergenerational transmission. Extant literature relies on different outcome measures. Many studies such as Lee and Solon (2009), Hertz et al. (2008), and Chetty et al. (2014)) use *household* or *family* income instead of *individual* earnings. As a broader measure, the household income variable better reflects children's living standards by construction. In addition, household income is more informative of married women's economic status while own earnings are not as reliable when female labor participation is low (Chadwick and Solon, 2002).

We next supplement our analysis by estimating the intergenerational household income elasticities. We report these results in Table 5.[43] A comparison between these estimates with the ones based on individual earnings in Table 2 yields several lessons. First, contrary to earnings elasticities, household income elasticities are nearly the same for sons and daughters, implying a similar degree of intergenerational persistence in the household living standards for both genders. The main reason behind this equalization is that we now extend our analysis to include all daughters with positive household incomes instead of focusing only on full-time workers.[44] In columns (2) and (4) of Table 5, we estimate the same elasticities using working descendant samples. We show that intergenerational household income elasticity is higher for working daughters while showing no significant difference for working sons.

Table 5: *TS2SLS* Estimates of Intergenerational Elasticity of Household Income

Pairs	**Parent & Child Household Income**		**Parents' Personal Earnings**	
	Full Sample	Only Full-Time Working Children	Full Sample	Only Full-Time Working Children
Father-Son	0.77	0.79	0.57	0.59
	(0.018)	(0.020)	(0.014)	(0.015)
	[10170]	[7809]	[10170]	[7809]
Father-Daughter	0.82	0.99	0.62	0.82
	(0.018)	(0.034)	(0.014)	(0.028)
	[10426]	[1743]	[10426]	[1743]
Mother-Son	0.98	0.99	0.41	0.43
	(0.032)	(0.035)	(0.018)	(0.019)
	[4109]	[3101]	[4109]	[3101]
Mother-Daughter	1.03	1.12	0.44	0.60
	(0.033)	(0.046)	(0.019)	(0.028)
	[4350]	[670]	[4350]	[670]

Notes: Column (3) and (4) displays the elasticity of children's household income with respect to parents' individual earnings. We use equivalized household income via the modified *OECD* equivalence scale. The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

Second, the estimated household income elasticities are all above 0.77, which sizably exceed the earnings elasticities in Table 2. On the contrary, descendants' estimated household income elasticities with respect to parental earnings are only slightly higher than the estimated earnings elasticities. This result

[43] See Table A.10 and Table A.11 for alternative specifications.

[44] Since the variable of interest is now *household income* instead of *individual income*, the resultant sample sizes are larger for both genders. Similarly, the sample sizes in our estimations using equations (11) and (12) are also larger (Table A.7).

suggests that parental advantages are transmitted even more strongly across generations when the overall household well-being of parents is considered. The difference between the elasticity estimates with respect to parental household income and parents' individual earnings is greater for sons. We report that *assortative mating* plays a key role here. That is, the children of higher-earning parents not only have better-earning prospects but also tend to marry partners with higher-earning prospects.[45]

Third, our household income elasticity estimates implied by mothers' characteristics are higher than those by fathers' characteristics. This suggests that using highly dispersed female earnings to predict mothers' earnings pulls *IGE* estimates for mothers downward (9). Moreover, the elasticity estimates via mothers' household income are more reliable than that of earnings since the former implicitly treats all mothers as employed. Previous literature on intergenerational educational mobility in Turkey also finds a stronger effect of mothers' education on children's education (Öztunalı and Torul, 2022; Tansel et al., 2018). Further, due to assortative mating, mothers' characteristics convey additional information on fathers' earnings, constituting an even larger share of household income in parents' generation.[46]

5.4 Intergenerational Rank Mobility and Regional Patterns

We next report our rank-based mobility estimates, for which we offer a theoretical background in Section 3.3. Briefly, these measures represent the association between the *relative positions* of children and parents in the distribution instead of incomes. We investigate the geographical variation of mobility in Turkey following the methodology by Chetty et al. (2014).

We estimate the rank-rank slope by regressing the percentile rank of children in the national household income distribution on the percentile rank of parents' household income. We rank individuals according to their *household income* instead of other income variables because it better reflects the overall economic status of individuals and allows for a better comparison between sons and daughters. We also estimate *absolute upward mobility*, which focuses on the mobility at the lower half of the parental household income distribution.

Table 6 presents our rank-rank slope estimates. These results imply that a ten percentile increase in

[45] See Appendix B for further findings and discussion.

[46] On average, the predicted earnings of fathers are 103% higher than that of mothers, whereas this difference is only 21% for descendants. The main reason behind this sizable difference is that most mothers in our sample are poorly educated (57% of them are illiterate, and only less than 5% are high-school graduates or better educated). In addition, the difference between the earnings of males and females with the same education is plausibly greater in the parents' generation. Tamkoç and Torul (2020) documents a consistent decline in gender premium over time.

a father's rank corresponds to roughly a four percentile increase in his child's rank. The estimated rank persistence for mothers is slightly lower. Overall, our findings suggest that rank-based intergenerational mobility in Turkey is weaker than in the US (0.34 by Chetty et al. 2014) and in the Nordic countries (around 0.2 by Bratberg et al. 2017a).

Table 6: Household Income Rank-Rank Slope Estimates

	Father's Rank		Mother's Rank	
Sons	0.410 (.009) [10170]	0.416 (.009) [20596]	0.386 (.016) [4109]	0.384 (.015) [8459]
Daughters	0.421 (.006) [10426]		0.385 (.011) [4350]	

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Both sons and daughters are ranked together, whereas fathers and mothers are ranked separately. See Table A.12 for the estimated rank-rank slopes when sons and daughters are ranked separately. See Table A.13 for the rank-rank slopes estimated using earnings ranks.

We report our rank-rank slopes and absolute upward mobility estimates for children living in urban and rural areas separately in Table 7. Our findings reveal that a son's position in the national distribution is more sensitive to a mother's rank if the son resides in an urban area. Further, our absolute upward mobility estimates show that the descendants of families with a below-median household income rank, on average, ten percentile points higher in the distribution if they reside in an urban area instead of a rural one.[47]

Table 7: Rank-Mobility across Rural and Urban Residences

	Rural		**Urban**	
Rank-Rank Slope	Father's Rank	Mother's Rank	Father's Rank	Mother's Rank
Sons	0.35 (.017) [3352]	0.29 (.025) [2095]	0.36 (.011) [6818]	0.37 (.020) [2014]
Daughters	0.33 (.017) [3432]	0.28 (.025) [2135]	0.39 (.011) [6994]	0.38 (.019) [2215]
Absolute Upward Mobility $E[R_c \mid R_p < 50]$				
Sons	35.50 (.47)	34.11 (.69)	46.70 (.47)	43.97 (.89)
Daughters	32.65 (.44)	31.01 (.66)	43.07 (.44)	39.64 (.81)

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. *Urban* and *rural* denote children's place of residence at the time of the survey.

[47] Note that we split our sample according to children's place of residence. Therefore, this result could be expected because residing in an urban area could stem from experienced upward mobility.

We next investigate regional patterns in Turkey's intergenerational mobility. To construct healthy-sized subsamples, we regroup NUTS (the Nomenclature of Territorial Units for Statistics) Level-1 level regions into five broader geographical units: *East, West, North, South,* and *Central.*[48] We present our rank-rank slope and absolute upward mobility estimates in Table 8. Our slope estimates hover around 0.3 across regions. Although there exists some variation, no discernible pattern emerges. On the contrary, the estimates for absolute upward mobility increase over the region's per capita national income. Our findings imply that the descendants of families with a below-median income rank, on average, fifteen percentile points higher if they reside in the *West* instead of the *East.*

Table 8: Rank-Mobility across Regions

	East		West		North		South		Central	
Rank-Rank Slope	Father's Rank	Mother's Rank	Father's Rank	Mother's Rank	Father's Rank	Mother's Rank	Father's Rank	Mother's Rank	Father's Rank	Mother's Rank
Sons	0.36	0.40	0.38	0.32	0.30	0.23	0.34	0.25	0.35	0.38
	(.019)	(.050)	(.013)	(.024)	(.026)	(.039)	(.027)	(.058)	(.025)	(.045)
	[2299]	[975]	[4233]	[1605]	[1159]	[727]	[1063]	[417]	[1416]	[385]
Daughters	0.34	0.23	0.39	0.35	0.33	0.26	0.36	0.36	0.43	0.37
	(.019)	(.048)	(.013)	(.024)	(.024)	(.038)	(.025)	(.049)	(.023)	(.045)
	[2321]	[961]	[4222]	[1659]	[1222]	[790]	[1183]	[496]	[1478]	[444]
Absolute Upward Mobility										
Sons	32.10	29.11	47.95	43.47	43.44	43.05	41.93	40.59	46.67	43.13
	(.53)	(.84)	(.57)	(1.05)	(1.03)	(1.15)	(1.03)	(2.20)	(1.01)	(1.88)
Daughters	29.00	27.18	45.22	39.33	39.01	39.03	39.13	33.14	41.03	36.94
	(.52)	(.85)	(.57)	(1.03)	(.84)	(.96)	(.95)	(2.04)	(.98)	(1.77)

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

5.5 Intergenerational Mobility over Time

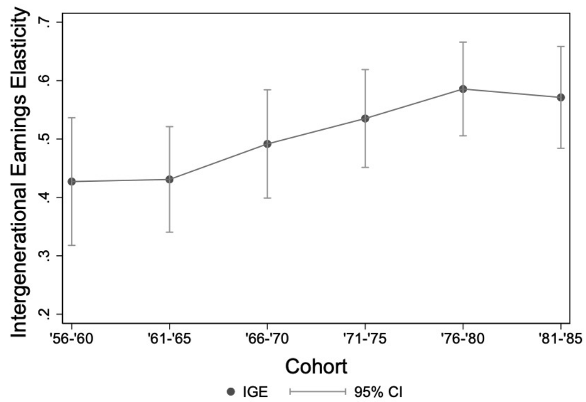
We next examine the evolution of intergenerational mobility experienced by different birth cohorts. We report our *IGE* estimates for sons in Figure 4. Our estimates for intergenerational persistence exhibit a clear upward trajectory (except for the youngest cohort). Admittedly, a visual inspection could be misleading as our data is not ideal for investigating mobility dynamics over time.[49] We, nevertheless, repeat a similar exercise for daughters and sons separately. We plot our household income elasticity estimates for both genders over birth cohorts in Figure 5. Our findings reveal similar trajectories for both genders, except that intergen-

[48]We follow the grouping by Akgündüz et al. (2020): *West* contains NUTS-1 regions 1-4, *Central* contains NUTS-1 regions 5 and 7, *South* contains NUTS-1 region 6, North contains NUTS-1 regions 8-9, and *East* contains NUTS-1 regions 9-12.

[49]There are a few factors that can confound our results. First, the differences among the estimated elasticities might stem from different educational opportunities that each cohort encounter (Torul and Öztunalı, 2017). More importantly, the variance in educational attainment might differ for each cohort's fathers. This can be more problematic since we assume the same returns to education for all fathers.

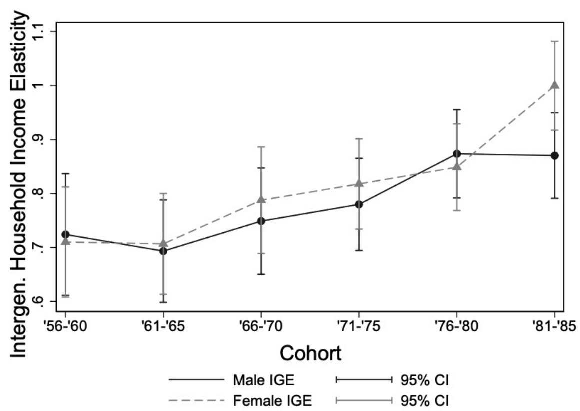
erational persistence steadily rises for daughters (including the youngest cohort).

Figure 4: *IGE* Estimates by Birth Cohorts



Notes: The confidence intervals are calculated using bootstrap standard errors. The x-axis displays the birth cohort of sons. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort.

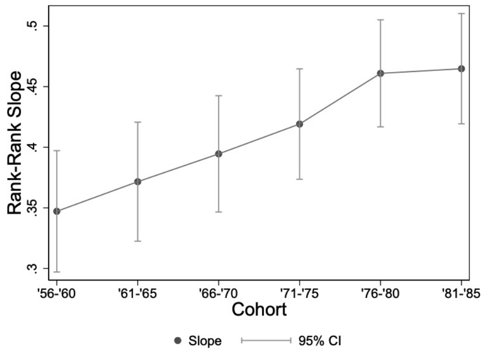
Figure 5: Household Income Elasticity Estimates by Birth Cohort of Sons and Daughters



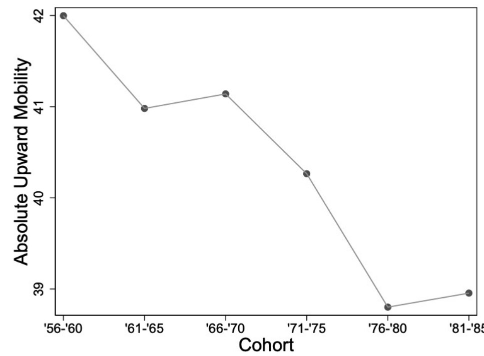
Notes: The confidence intervals are calculated using bootstrap standard errors. The x-axis displays the birth cohort of children. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort. Household income is used to provide larger sample sizes and overcome female selection problems.

We finally investigate how positional mobility varies over cohorts. In panel (a) of Figure 6, we plot the evolution of the rank-rank slope estimates for fathers' and sons' household incomes. Our results demonstrate that positional mobility decreases sizably over time too. This finding confirms that the decline in Turkey's mobility is not a mechanical result of the increasing economic inequality over cohorts. In panel (b) of Figure 6, we plot the absolute upward mobility estimates for sons. Similarly, the sons from younger cohorts are less likely to have experienced upward mobility compared to their older counterparts. These developments exhibit similarities with other countries such as the US (Davis and Mazumder, 2017) and Denmark (Landersø and Heckman, 2017).

Figure 6: Positional Mobility by Birth Cohorts of Sons



(a)



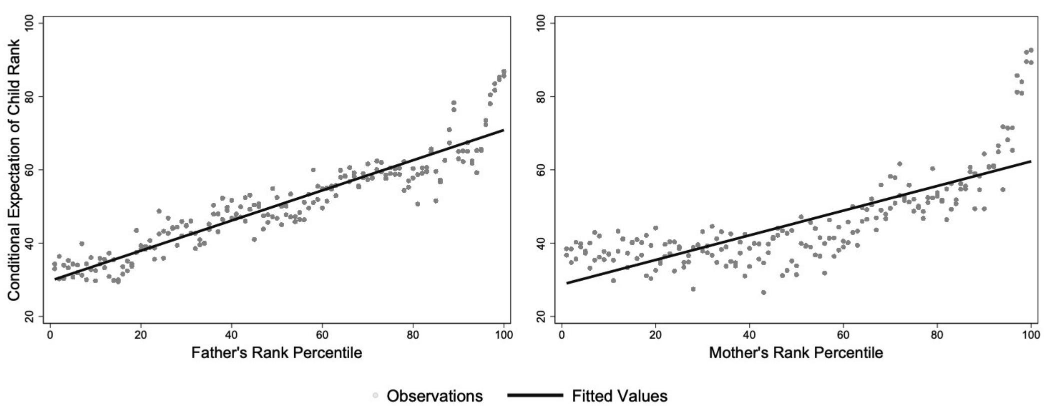
(b)

Notes: The left panel displays the estimates of rank-rank slopes by each birth cohort of sons. The right panel displays the estimates of absolute upward mobility by each birth cohort of sons. Both fathers and sons are ranked according to their equivalized household income. Sons are ranked within their own cohort, and fathers are ranked with fathers with children in the same cohort. The confidence intervals are calculated using robust standard errors. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort. The confidence intervals are calculated using bootstrap standard errors.

5.6 Intergenerational Mobility over Income Distribution

Both *IGE* and the rank-rank slope measure only the *average persistence* in the society; they are silent about the actual mobility dynamics around this average (Jäntti et al., 2014). We next present intergenerational mobility curves and quintile transition matrices to demonstrate mobility patterns over the national income distribution (Bratberg et al., 2017b). We use household income to rank children and predicted household income to rank parents to cover the entire distribution.

Figure 7: Intergenerational Mobility Curves



Notes: As parental household incomes are predicted via educational attainment and occupation, there were a limited number of discrete observations. We added a random noise with the standard deviation of ϵ from (15) to parental household incomes to obtain visually continuous ranks.

Figure 7 plots the mean ranks of children with parents in each percentile. Our results display that the expected child rank rises sharply over parental rank at the top of the distribution. In addition, while children's rank almost linearly increases over their fathers' rank, it exhibits a non-monotonic pattern over their mother's rank. Specifically, the expected rank of children is almost orthogonal to their mother's rank unless she comes from the richer half of the income distribution.[50] When born to above-median mothers, children's expected rank increases almost exponentially over their mother's rank.

Figure 8 presents the quintile transition matrices of the father-child pairs. Each cell represents the percentage of children with household income in the quintile denoted by its color conditional on having fathers with household income in the quintile provided by the row. Note that perfect mobility requires the value of 0.20 in each cell, whereas zero mobility requires the value of 1 in diagonal cells and 0 elsewhere.

Figure 8: Household Income Quintile Group Transition Matrices for Fathers

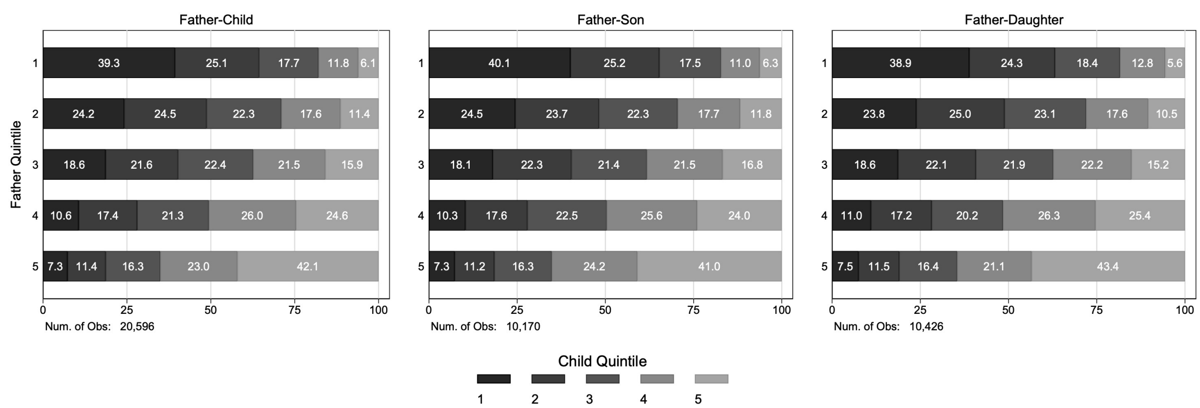
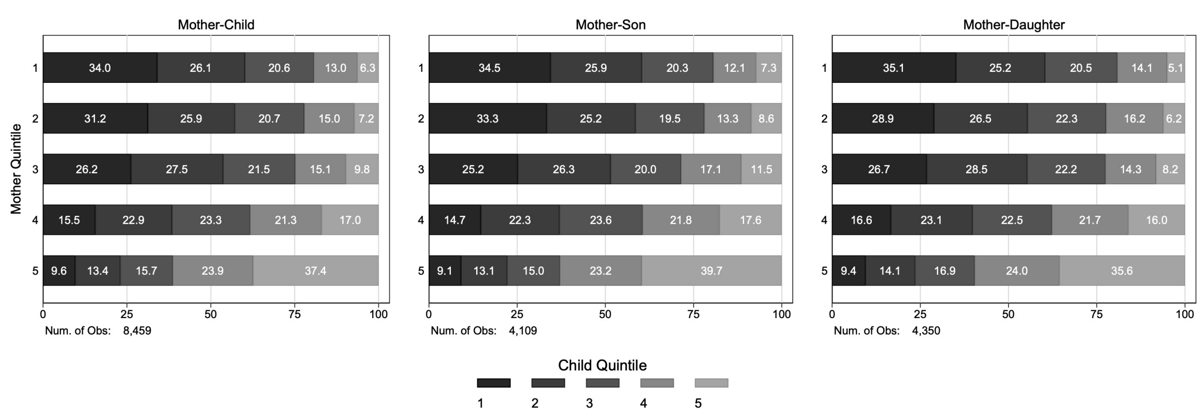


Figure 9: Household Income Quintile Group Transition Matrices for Mothers



[50]This result stems from the clustering of a majority of mothers in the lowest discrete rank.

Figure 8 reveals that the richest and poorest quintiles exhibit the highest two persistences: 39% (*42%*) of children with fathers from the first (*fifth*) quintile remain in the same position. Further, intergenerational mobility patterns of sons and daughters do not differ sizably. Figure 9 presents similar matrices for mother-child pairs. Intergenerational persistence varies non-monotonically over mothers' positions, as seen in the mobility curves.

5.7 Robustness Checks

We next check the robustness of our main estimates in Table 2 by running alternative regressions. First, we alter our sample selection criteria and treatment of outliers. While it is necessary to introduce certain standards to define active workers, excluding a considerable part of the population might cause inconsistencies, particularly for females in our sample. Accordingly, we repeat our regressions while including part-time workers and everyone with non-zero income. We report our results in Table 9. When there is no income threshold, daughter elasticities increase significantly, indicating the presence of a considerable number of females with very low incomes in the population.[51]

Table 9: *TS2SLS* Estimates for Different Income Criteria

	Includes Part-Time, Annual Earnings>244 Liras					Everyone with Non-zero Income			
Pairs	Number of Obs.	Earnings	Income	Labor Income	Hourly Wage	Earnings	Income	Labor Income	Hourly Wage
Father-Son	[7992]	0.52 (0.018)	0.61 (0.021)	0.40 (0.017) [5772]	0.50 (0.019)	0.52 (0.018) [8634]	0.60 (0.021) [9520]	0.40 (0.017) [6297]	0.51 (0.019) [8016]
Father-Daughter	[1950]	1.04 (0.042)	1.11 (0.047)	0.76 (0.038) [1581]	0.89 (0.038)	1.23 (0.048) [2649]	1.11 (0.046) [3499]	0.96 (0.043) [2127]	0.96 (0.041) [2041]
Mother-Son	[3195]	0.37 (0.026)	0.55 (0.040)	0.31 (0.027) [2080]	0.33 (0.026)	0.37 (0.027) [3452]	0.57 (0.039) [3795]	0.31 (0.027) [2284]	0.33 (0.026) [3209]
Mother-Daughter	[763]	0.83 (0.043)	0.99 (0.055)	0.63 (0.044) [561]	0.75 (0.041)	0.91 (0.053) [1056]	1.07 (0.059) [1388]	0.78 (0.049) [782]	0.79 (0.047) [823]

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Smaller sample sizes are presented under the standard errors for regressions based on labor income. Sample sizes change for the second set of regressions as some individuals with positive income do not report either earnings, labor earnings, or worked hours.

Following Haider and Solon (2006), we use age-corrected income measures in our benchmark estimations. We next report our estimates based on reported incomes with age controls instead of age-corrected

[51] It is debatable to call individuals with *annual* earnings below the *monthly* minimum wage as workers. It is, nonetheless, noteworthy that their inclusion in the sample affects *IGE* only for daughters.

counterparts in Table A.7. The resulting estimates are quantitatively similar, and the patterns in Table 2 replicate.

Nybom and Stuhler (2016) investigate the extent of life-cycle bias in *IGE* estimates for father-son pairs using Swedish data. They find that income at the age of 33 is the most representative of life-long income. They also show that the bias in *IGE* is smallest when only 32-year-old individuals are used. As a robustness check, they estimate *IGE* using individuals in their early 30s, limiting the age differences between fathers and sons, bottom-coding very low incomes, and top-coding very high incomes. Following their methodology, we revisit our father-son regressions (with earnings and income) and report our consequent results in Table 10. Intergenerational income elasticity for sons between the ages of 30 and 34 is higher than our benchmark estimates, suggesting that intergenerational mobility is sensitive to the age subjects earn their incomes.

Table 10: *TS2SLS* Estimates for Sons with Different Outlier Treatments

	Benchmark		Bottom-Coded		Top-Coded		Both	
Sample	Earnings	Income	Earnings	Income	Earnings	Income	Earnings	Income
Complete Sample	0.53 (0.022) [5241]	0.59 (0.026) [5241]	0.53 (0.022) [5641]	0.59 (0.026) [6230]	0.52 (0.021) [5241]	0.59 (0.026) [5241]	0.53 (0.022) [5641]	0.59 (0.026) [6230]
Age 30-34	0.53 (0.053) [1027]	0.70 (0.064) [1027]	0.54 (0.051) [1083]	0.75 (0.062) [1091]	0.52 (0.051) [1027]	0.68 (0.062) [1027]	0.53 (0.050) [1083]	0.73 (0.061) [1091]
Age 35-39	0.54 (0.054) [884]	0.60 (0.059) [884]	0.54 (0.055) [930]	0.62 (0.067) [946]	0.53 (0.053) [884]	0.60 (0.058) [884]	0.53 (0.055) [930]	0.61 (0.065) [946]

Notes: We only keep fathers between the ages of 18 and 35 at the son's birth. Low incomes are bottom-coded to the 1^{st} percentile, and/or high incomes are top-coded to the 99^{th} percentile values of the corresponding distribution. Reported earnings without age correction are used in the 2^{nd} and 3^{rd} rows. Bottom and/or top-coded versions of pooled *SILC* datasets are used for the age correction 1^{st} row. Numbers in brackets denote sample sizes.The bootstrap standard errors are in parentheses.

We also estimate *IGE* using the income measures of children predicted the same way as their parents. We present these results in Table 11. Our findings show that the transmission between parents and children is, to a large extent, captured by the observed characteristics of children. The moderate differences in magnitude stem from the correlation between parental income and unobserved heterogeneity in children's incomes.

Table 11: *TS2SLS* Estimates using Predicted Incomes for Both Generations

Pairs	Number of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7642]	0.48 (0.009)	0.45 (0.010)	0.42 (0.009)	0.47 (0.010)
Father-Daughter	[1613]	0.88 (0.026)	0.88 (0.027)	0.74 (0.027)	0.80 (0.027)
Mother-Son	[3028]	0.28 (0.013)	0.37 (0.016)	0.28 (0.015)	0.25 (0.014)
Mother-Daughter	[629]	0.69 (0.024)	0.79 (0.025)	0.65 (0.025)	0.65 (0.026)

Note: The bootstrap standard errors are in parentheses. The sample sizes are the same as before.

We next redo our estimations using parental education and occupation as separate instruments in the first stage. We present our results in Table 12. Our estimates increase considerably when only educational attainment is used to predict parental income. The main reason for this is that the *IV* estimates are likely to be upward-inconsistent due to the direct effect of parental education on children's outcomes, as discussed in Section 3. For this reason, while including education as an instrument provides better predictions for parental income measures, it could also bias estimates upward. Contrarily, using occupation as the predictor of parental income measures results in slightly lower estimates. This suggests the direct effect of occupation on children's income might be in the opposite direction. This result is also expected since there would be less variation in the regressor. Nevertheless, there might well be other parental characteristics related to the child's income, potentially biasing our results. However, the direction of this bias cannot be determined.

Table 12: Estimated Elasticities using a Single Instrument for Parental Income

	Instrument: *Education*					Instrument: *Occupation*				
Pairs	Number of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage	Number of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7642]	0.92 (0.033)	0.79 (0.029)	0.95 (0.040) [6618]	1.01 (0.038)	[7751]	0.45 (0.019)	0.52 (0.025)	0.35 (0.017) [5631]	0.43 (0.019)
Father-Daughter	[1613]	1.39 (0.064)	1.35 (0.062)	1.24 (0.067) [1584]	1.33 (0.063)	[1642]	0.95 (0.047)	1.04 (0.059)	0.65 (0.039) [1364]	0.83 (0.043)
Mother-Son	[3028]	0.75 (0.047)	0.74 (0.053)	0.83 (0.064) [6699]	0.84 (0.050)	[3061]	0.31 (0.025)	0.45 (0.043)	0.26 (0.026) [2022]	0.27 (0.025)
Mother-Daughter	[629]	1.26 (0.067)	1.24 (0.072)	1.22 (0.079) [1594]	1.29 (0.069)	[639]	0.79 (0.045)	0.99 (0.062)	0.59 (0.046) [482]	0.70 (0.044)

Note: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Smaller sample sizes are presented below standard errors for regressions based on non-entrepreneurial income.

6 Concluding Remarks

In this paper, we empirically explore the extent of intergenerational income mobility in Turkey. Consequently, we offer a set of comparable intergenerational income elasticity estimates. Our work complements the previous literature on Turkey's intergenerational educational mobility and contributes to a more comprehensive understanding of intergenerational transmission in Turkey.

We estimate the intergenerational elasticities of various income measures using the Turkish Statistical Institute's Survey of Income and Living Conditions 2005-2017 cross-sectional micro datasets and the *TS2SLS* instrumental variables methodology. We report estimates for father-son, father-daughter, mother-son, and mother-daughter pairs. We reflect on the relationship between mobility, the structure of the female labor force, and returns on education. Further, we investigate the heterogeneity in intergenerational mobility over time, geography, and income distribution. We also supplement our findings using alternative mobility measures such as the rank-rank slope and transition matrices. Several novel patterns emerge from our scrutiny.

First, we document that the intergenerational earnings elasticity for father-son pairs is around one-half, which is similar to the estimates for the US. Second, we show that there are notable gender differences in mobility estimates. In particular, intergenerational earnings persistence is twice as large for daughters compared to sons. This result emerges due to Turkey's remarkably low female labor force participation and self-selection of females into employment. Thus, intergenerational mobility estimates are similar for sons and daughters when measured with household income. Third, while the persistence of earnings is stronger for fathers, the persistence of household income implied by mothers' characteristics is more impactful on children's outcomes. Fourth, marital sorting plays a crucial role in the intergenerational transmission of economic well-being. Fifth, our estimated elasticities differ in magnitude depending on the measured income concept. Specifically, intergenerational persistence is highest with the broadest income definition and lowest with non-entrepreneurial income. We report *IGE* estimates via four different income concepts for future reference: earnings, income, labor income, and the hourly wage rate. Sixth, our estimates exhibit a decline in intergenerational mobility for the more recent cohorts, as seen in other countries. Seventh, we investigate regional patterns in intergenerational mobility using rank-based measures and document that children residing in more developed regions are more likely to have experienced upward mobility. Eighth, we report quintile transition matrices to unveil heterogeneities across the distribution and offer evidence that suggests stronger persistence at the two tails of the parental earnings distribution. Finally, we test our estimation results by running numerous auxiliary regressions. The patterns observed in our main results are robust over numerous alternative regressions.

Overall, this paper aims to cast light on Turkey's intergenerational income mobility to fill the empirical gap in the related literature. Due to data limitations, this paper is obliged to remain descriptive. We believe that further investigation of stark gender differences in intergenerational mobility in light of peculiarly low female labor force participation and the notable gender pay gap in Turkey would be a productive path for future research.

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APPENDIX A

TABLES AND FIGURES

Table A1: Descriptive Statistics (*SILC* Pooled Cross-Sectional 2005-2017)

	Full Sample		Usable Sample		Living with Parents	
Male						
Age	40.468	(16.935)	38.992	(10.542)	31.620	(9.026)
Secondary Education or Lower	0.625		0.571		0.562	
High-School Graduate	0.215		0.218		0.253	
University Graduate	0.160		0.211		0.185	
log(Earnings)	8.495	(1.094)	8.756	(0.848)	8.517	(0.780)
Non-zero Earners	0.685					
Number of Observations	**287,638**		**157,212**		**39,277**	
Female						
Age	41.185	(17.605)	36.181	(9.840)	28.814	(7.792)
Secondary Education or Lower	0.749		0.426		0.256	
High-School Graduate	0.145		0.188		0.286	
University Graduate	0.106		0.386		0.457	
log(Earnings)	7.973	(1.464)	8.595	(1.013)	8.608	(0.831)
Non-zero Earners	0.213					
Number of Observations	**309,173**		**40,840**		**9,668**	
Total						
Age	40.840	(17.289)	38.412	(10.463)	31.066	(8.867)
Secondary Education or Lower	0.689		0.541		0.502	
High-School Graduate	0.179		0.212		0.259	
University Graduate	0.132		0.247		0.239	
log(Earnings)	8.364	(1.219)	8.723	(0.887)	8.535	(0.791)
Non-zero Earners	0.440					
Number of Observations	**596,811**		**198,052**		**48,945**	

Notes: The numbers in parentheses are standard deviations reported alongside mean values. The values reported in a single column are the shares of the sample. The last two columns are subsamples of the whole sample. Usable sample refers to full-time working individuals for whom age, education, and occupation information is present. The sample displayed in the last column includes children living with either of their parents.

Table A2: Descriptive Statistics (*SILC* Pooled Panel 2005-2017)

	Full Sample		Usable Sample		Observed 4 Years		Living with Parents	
Male								
Age	40.34	(17.662)	38.56	(10.697)	41.03	(9.940)	27.36	(5.184)
Secondary Education or Lower	0.58		0.58		0.6		0.51	
High-School Graduate	0.22		0.23		0.22		0.30	
University Graduate	0.19		0.18		0.16		0.17	
log(Earnings)	8.78	(1.098)	8.8	(0.829)	8.82	(0.823)	8.56	(0.738)
Non-zero Earners	0.67							
Number of Observations	**90862**		**46,358**		**23,754**		**8,395**	
Female								
Age	41.19	(18.435)	35.95	(10.006)	37.62	(9.691)	26.50	(5.259)
Secondary Education or Lower	0.76		0.43		0.48		0.24	
High-School Graduate	0.14		0.21		0.2		0.31	
University Graduate	0.09		0.35		0.3		0.43	
log(Earnings)	8.04	(1.428)	8.66	(0.954)	8.63	(0.977)	8.66	(0.770)
Non-zero Earners	0.21							
Number of Observations	**95,374**		**11,853**		**6,027**		**2,445**	
Total								
Age	40.64	(18.071)	38.03	(10.612)	40.34	(9.985)	27.17	(5.213)
Secondary Education or Lower	0.71		0.55		0.58		0.45	
High-School Graduate	0.17		0.22		0.22		0.31	
University Graduate	0.11		0.21		0.19		0.23	
log(Earnings)	8.39	(1.208)	8.77	(0.857)	8.78	(0.860)	8.58	(0.746)
Non-zero Earners	0.43							
Number of Observations	**186,236**		**58,211**		**29,781**		**10840**	

Notes: The numbers in parentheses are standard deviations reported alongside mean values. The values reported in a single column are the shares of the sample. The last two columns are subsamples of the whole sample. The sample displayed in the last column includes children living with either of their parents.

Table A3: *OLS* Estimates for Labor Income Based on Education and Gender

	Aktuğ et al. (2021)						*SILC* Cross-Sectional					
	Male			Female			Male			Female		
	Primary	High School	University	Primary	High School	University	Primary	High School	University	Primary	High School	University
Age												
25 to 29	0.066***	0.097***	0.266***	0.039***	0.072***	0.253***	0.245***	0.402***	0.561***	0.0115	0.322***	0.559***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)	(0.015)	(0.019)	(0.033)	(0.024)	(0.020)
30 to 34	0.092***	0.156***	0.429***	0.040***	0.109***	0.381***	0.326***	0.560***	0.843***	-0.0700*	0.347***	0.769***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)	(0.015)	(0.019)	(0.030)	(0.026)	(0.020)
35 to 39	0.098***	0.183***	0.531***	0.034***	0.111***	0.447***	0.342***	0.667***	0.969***	-0.000254	0.324***	0.887***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.005)	(0.006)	(0.011)	(0.015)	(0.019)	(0.028)	(0.029)	(0.021)
40 to 44	0.099***	0.197***	0.578***	0.015***	0.082***	0.478***	0.394***	0.771***	1.086***	-0.0838**	0.388***	1.007***
	(0.002)	(0.004)	(0.006)	(0.004)	(0.005)	(0.008)	(0.011)	(0.017)	(0.019)	(0.028)	(0.031)	(0.022)
45 to 49	0.093***	0.169***	0.571***	-0.013***	0.020**	0.457***	0.329***	0.819***	1.091***	-0.0724*	0.339***	1.020***
	(0.002)	(0.004)	(0.007)	(0.004)	(0.007)	(0.010)	(0.012)	(0.017)	(0.020)	(0.029)	(0.040)	(0.025)
50 to 54	0.052***	0.111***	0.536***	-0.035***	0.003	0.449***	0.181***	0.753***	1.072***	-0.217***	0.270***	0.900***
	(0.003)	(0.005)	(0.008)	(0.005)	(0.011)	(0.012)	(0.014)	(0.021)	(0.022)	(0.034)	(0.058)	(0.033)
55 to 59	-0.001	0.059***	0.507***	-0.072***	0.044*	0.416***	-0.0278	0.589***	1.007***	-0.267***	0.460***	0.892***
	(0.004)	(0.007)	(0.011)	(0.007)	(0.021)	(0.018)	(0.020)	(0.035)	(0.030)	(0.042)	(0.115)	(0.055)
60 to 64							-0.180***	0.652***	1.002***	-0.329***	0.352	0.741***
							(0.030)	(0.056)	(0.044)	(0.057)	(0.223)	(0.118)
Sector(Public=1)	0.264***	0.341***	0.277***	0.170***	0.336***	0.303***						
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)						
Tenure	0.011***	0.016***	0.004***	0.014***	0.021***	0.007***						
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	296,302	161,101	141,980	60,806	45,448	79,968	61,785	27,368	29,690	14,850	7,361	16,250
R-squared	0.21	0.38	0.28	0.29	0.38	0.33	0.0604	0.135	0.200	0.0500	0.0408	0.189
F-statistic	4,140	7,779	4,035	1,445	1,829	3,294	193.0	180.0	293.8	38.31	15.74	153.7

Notes: The numbers in parentheses are robust standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The 20-24 age category is the basis.

Table A4: First-Stage Estimation Results

	Earnings		Income		Non-Entrepreneurial Income		Hourly Wage		Household Income	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Highest Educational Attainment										
Literate & without diploma	0.165***	0.129***	0.218***	0.157***	0.182***	0.170***	0.128***	0.100***	0.121***	0.227***
	(0.017)	(0.028)	(0.016)	(0.028)	(0.021)	(0.034)	(0.019)	(0.026)	(0.012)	(0.010)
Primary school	0.304***	0.183***	0.441***	0.197***	0.262***	0.226***	0.235***	0.162***	0.392***	0.341***
	(0.015)	(0.019)	(0.013)	(0.020)	(0.018)	(0.023)	(0.016)	(0.018)	(0.010)	(0.007)
Secondary school	0.460***	0.458***	0.578***	0.511***	0.443***	0.512***	0.384***	0.358***	0.538***	0.570***
	(0.015)	(0.024)	(0.014)	(0.024)	(0.019)	(0.026)	(0.017)	(0.023)	(0.010)	(0.011)
High school	0.527***	0.543***	0.632***	0.582***	0.501***	0.592***	0.472***	0.488***	0.629***	0.633***
	(0.016)	(0.022)	(0.014)	(0.022)	(0.019)	(0.025)	(0.017)	(0.021)	(0.011)	(0.011)
Vocational or technical high school	0.616***	0.613***	0.703***	0.636***	0.572***	0.654***	0.574***	0.591***	0.699***	0.680***
	(0.016)	(0.022)	(0.014)	(0.022)	(0.019)	(0.025)	(0.017)	(0.022)	(0.011)	(0.011)
University or higher education	0.872***	0.857***	0.878***	0.847***	0.796***	0.871***	0.902***	0.884***	0.943***	0.893***
	(0.016)	(0.022)	(0.014)	(0.022)	(0.019)	(0.025)	(0.017)	(0.021)	(0.011)	(0.011)
Occupational Code (ISCO-88)										
Legislators, senior officials and managers	0.408***	0.721***	0.801***	0.977***	0.645***	0.990***	0.163***	0.411***	0.690***	0.723***
	(0.009)	(0.025)	(0.008)	(0.022)	(0.012)	(0.026)	(0.010)	(0.026)	(0.007)	(0.017)
Professionals	0.623***	0.744***	0.691***	0.784***	0.665***	0.786***	0.572***	0.589***	0.619***	0.571***
	(0.009)	(0.017)	(0.008)	(0.017)	(0.009)	(0.017)	(0.010)	(0.016)	(0.007)	(0.011)
Technicians and associate professionals	0.415***	0.575***	0.481***	0.593***	0.454***	0.591***	0.320***	0.364***	0.438***	0.419***
	(0.009)	(0.018)	(0.008)	(0.017)	(0.008)	(0.018)	(0.009)	(0.017)	(0.007)	(0.012)
Clerks	0.375***	0.446***	0.338***	0.444***	0.346***	0.450***	0.331***	0.213***	0.312***	0.349***
	(0.008)	(0.016)	(0.007)	(0.016)	(0.008)	(0.016)	(0.009)	(0.015)	(0.007)	(0.011)
Service & sale workers	0.156***	0.165***	0.302***	0.212***	0.215***	0.196***	-0.0671***	-0.153***	0.248***	0.115***
	(0.006)	(0.013)	(0.006)	(0.013)	(0.006)	(0.013)	(0.007)	(0.012)	(0.005)	(0.007)
Skilled agricultural workers	-0.487***	-0.934***	0.0866***	-0.277***	-0.762***	-1.130***	-0.651***	-1.179***	-0.0364***	-0.115***
	(0.008)	(0.018)	(0.007)	(0.020)	(0.013)	(0.035)	(0.008)	(0.018)	(0.005)	(0.007)
Craft workers	0.150***	0.0579*	0.234***	0.183***	0.207***	0.206***	0.0652***	-0.106***	0.171***	0.0394***
	(0.006)	(0.023)	(0.006)	(0.021)	(0.006)	(0.023)	(0.007)	(0.022)	(0.005)	(0.010)
Plant and machine operators	0.254***	0.473***	0.313***	0.475***	0.290***	0.468***	0.136***	0.263***	0.236***	0.237***
	(0.006)	(0.018)	(0.006)	(0.017)	(0.006)	(0.018)	(0.007)	(0.017)	(0.005)	(0.011)
Constant	8.147***	7.804***	8.146***	7.858***	8.234***	7.816***	0.478***	0.357***	8.103***	8.373***
	(0.017)	(0.027)	(0.015)	(0.027)	(0.020)	(0.029)	(0.018)	(0.025)	(0.011)	(0.012)
Age Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	153,695	38,161	153,695	38,161	114,207	33,228	153,695	38,161	171,606	75,970
R-squared	0.362	0.509	0.331	0.424	0.400	0.463	0.346	0.547	0.364	0.457
F-statistic	2403.9	1103.4	2226.4	825.0	1991.9	784.1	2373.3	1283.4	2645.8	1875.7

Notes: The numbers in parentheses are robust standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. The 20-24 age category is the basis.

Table A5: Intergenerational Elasticity Estimates by Different First-Stage Sample Years using *SILC*

Pairs	**Father-Son**			**Father-Daughter**			**Mother-Son**			**Mother-Daughter**		
Year of 1^{st} Stage Sample	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income
2005	0.455	0.565	0.380	0.902	1.034	0.685	0.376	0.524	0.268	0.827	0.995	0.553
2006	0.464	0.596	0.375	0.930	1.076	0.682	0.371	0.530	0.270	0.790	0.955	0.549
2007	0.476	0.571	0.343	0.931	1.042	0.629	0.324	0.457	0.252	0.746	0.901	0.532
2008	0.460	0.552	0.357	0.898	1.027	0.652	0.327	0.449	0.272	0.738	0.878	0.553
2009	0.488	0.565	0.345	0.923	1.019	0.626	0.347	0.472	0.279	0.764	0.886	0.560
2010	0.530	0.646	0.354	0.994	1.106	0.650	0.377	0.554	0.321	0.830	0.982	0.641
2011	0.520	0.595	0.399	0.978	1.038	0.701	0.359	0.519	0.302	0.794	0.941	0.609
2012	0.509	0.603	0.406	0.964	1.055	0.715	0.361	0.534	0.282	0.817	0.996	0.595
2013	0.524	0.638	0.433	0.999	1.111	0.758	0.345	0.492	0.290	0.781	0.927	0.599
2014	0.541	0.623	0.454	1.028	1.096	0.786	0.355	0.486	0.342	0.823	0.969	0.695
2015	0.538	0.632	0.429	1.033	1.091	0.759	0.369	0.594	0.302	0.892	1.115	0.648
2016	0.511	0.621	0.442	1.015	1.111	0.787	0.311	0.500	0.320	0.792	1.015	0.683
2017	0.488	0.580	0.444	0.977	1.059	0.793	0.321	0.529	0.308	0.817	1.087	0.673

Table A6: Intergenerational Elasticity Estimates by Different First-Stage Sample Years using *HBS*

Pairs	**Father-Son**			**Father-Daughter**			**Mother-Son**			**Mother-Daughter**		
Year of 1st Stage Sample	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income	Earnings	Income	Non-Entrepreneurial Income
2002	0.541	0.608	0.516	1.019	1.046	0.863	0.356	0.580	0.205	0.765	1.015	0.445
2003	0.547	0.635	0.371	1.027	1.066	0.675	0.413	0.526	0.379	0.844	0.964	0.699
2004	0.485	0.575	0.308	0.961	1.033	0.585	0.355	0.527	0.448	0.770	0.929	0.881
2005	0.512	0.609	0.450	1.012	1.082	0.800	0.368	0.489	0.424	0.824	0.967	0.800
2006	0.477	0.605	0.433	0.962	1.105	0.776	0.357	0.535	0.303	0.803	0.969	0.606
2007	0.464	0.559	0.430	0.931	1.031	0.762	0.324	0.465	0.279	0.743	0.890	0.588
2008	0.427	0.547	0.325	0.887	1.028	0.612	0.354	0.484	0.248	0.759	0.880	0.512
2009	0.440	0.583	0.325	0.871	1.055	0.604	0.330	0.448	0.278	0.752	0.868	0.559
2010	0.471	0.556	0.316	0.919	1.007	0.584	0.367	0.547	0.222	0.780	0.934	0.462
2011	0.489	0.563	0.364	0.943	0.999	0.660	0.339	0.503	0.219	0.768	0.928	0.478
2012	0.474	0.559	0.326	0.927	1.026	0.603	0.310	0.425	0.220	0.707	0.830	0.471
2013	0.492	0.611	0.315	0.963	1.087	0.585	0.326	0.476	0.257	0.754	0.939	0.541
2014	0.529	0.656	0.323	1.027	1.143	0.607	0.321	0.440	0.234	0.759	0.902	0.507

Notes: TurkStat's Household Budget Survey (*HBS*) is a nationally representative cross-sectional dataset published annually since 2002. This survey mainly focuses on household expenditure but contains information on individual incomes suitable for the scope of our analysis. Questions related to earnings were mostly the same with *SILC*, but variables are constructed by authors to match *SILC* counterparts most accurately. This table is omitted from the main text as it wasn't possible to compare the sampling method with *SILC* and frequent methodology changes in *HBS*. For example, after 2015, the group of "illiterates" is omitted from the education variable. Accordingly, we were not able to use these cross-sections as "illiterates" is a sizeable group in the parents' generation.

Table A7: *TS2SLS* Estimates for Different Child Income Definitions

Pairs	Reported Child Income					Age Corrected Child Income, Age<35					Reported Child Income, Age<35			
	Number of Obs.	Earnings	Income	Labor Income	Hourly Wage	Number of Obs.	Earnings	Income	Labor Income	Hourly Wage	Earnings	Income	Labor Income	Hourly Wage
Father-Son	[7642]	0.522 (0.020)	0.614 (0.023)	0.395 (0.018) [5558]	0.497 (0.021)	[3040]	0.563 (0.029)	0.66 (0.034)	0.441 (0.026) [2517]	0.503 (0.030)	0.499 (0.029)	0.601 (0.034) [2517]	0.393 (0.026)	0.453 (0.030)
Father-Daughter	[1613]	0.961 (0.045)	1.035 (0.049)	0.701 (0.040) [1341]	0.867 (0.042)	[740]	0.913 (0.067)	0.955 (0.071)	0.692 (0.060) [684]	0.828 (0.060)	0.806 (0.066)	0.839 (0.070) [684]	0.609 (0.059)	0.746 (0.060)
Mother-Son	[3028]	0.0.334 (0.024)	0.511 (0.039)	0.277 (0.025) [2001]	0.279 (0.025)	[1023]	0.376 (0.032)	0.508 (0.049)	0.31 (0.031) [820]	0.328 (0.033)	0.339 (0.032)	0.461 (0.049) [820]	0.277 (0.032)	0.298 (0.033)
Mother-Daughter	[629]	0.698 (0.048)	0.888 (0.063)	0.518 (0.045) [475]	0.629 (0.047)	[235]	0.693 (0.059)	0.805 (0.072)	0.568 (0.058) [217]	0.639 (0.055)	0.617 (0.059)	0.704 (0.071) [217]	0.507 (0.058)	0.578 (0.055)

Notes: Age controls are included in the regressions using reported income. The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Smaller sample sizes are presented under the standard errors for regressions based on labor income.

Table A8: Intergenerational Non-Entrepreneurial Income Elasticity Estimates using Different Age-Correction Sources

Pairs	Corrected for Age (Aktuğ et al., 2021)	Corrected for Age (*SILC*)
Father-Son	0.39 (0.018)	0.40 (0.017)
Father-Daughter	0.73 (0.040)	0.72 (0.038)
Mother-Son	0.28 (0.026)	0.29 (0.025)
Mother-Daughter	0.60 (0.046)	0.61 (0.042)

Notes: The bootstrap standard errors are in parentheses.

Table A9: Effect of Father's Earnings on Children's Educational Outcomes: Conditional Logit Coefficients

	Female		Male	
	$\log(P_{high}/P_{sec})$	$\log(P_{uni}/P_{sec})$	$\log(P_{high}/P_{sec})$	$\log(P_{uni}/P_{sec})$
Intercept	-23.05 (0.668)	-32.60 (0.866)	-14.06 (0.477)	-21.60 (0.588)
log Earnings of Fathers	2.52 (0.077)	3.58 (0.099)	1.56 (0.056)	2.40 (0.068)
Number of Obs.	10,426		10,170	
Pseudo R^2	0.1920		0.0997	

Notes: P_{sec}, P_{high} and P_{uni} denote the probability of having educational attainment level of secondary education or lower, high school graduate and university graduate respectively. Coefficients are estimated using the multinomial logit model. The standard errors are in parentheses.

Table A10: *TS2SLS* Estimates of Intergenerational Elasticity of Non-equivalized Household Income

Pairs	**Parent & Child Household Income**		**Parents' Personal Earnings**	
	Full Sample	Only Full-Time Working Children	Full Sample	Only Full-Time Working Children
Father-Son	0.79 (0.023) [10170]	0.81 (0.024) [7809]	0.47 (0.014) [10170]	0.49 (0.015) [7809]
Father-Daughter	0.80 (0.022) [10426]	0.99 (0.041) [1743]	0.49 (0.014) [10426]	0.69 (0.028) [1743]
Mother-Son	1.08 (0.044) [4109]	1.08 (0.050) [3101]	0.34 (0.018) [4109]	0.36 (0.019) [3101]
Mother-Daughter	1.10 (0.043) [4350]	1.18 (0.061) [670]	0.35 (0.018) [4350]	0.50 (0.029) [670]

Notes: Column (3) and (4) displays the elasticity of children's household income with respect to parents' individual earnings. The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

Table A11: *TS2SLS* Estimates of Intergenerational Elasticity of Equivalized Household Income-Excluding Co-Residing Parent-Child Pairs

Pairs	**Parent & Child Household Income**		**Parents' Personal Earnings**	
	Full Sample	Only Full-Time Working Children	Full Sample	Only Full-Time Working Children
Father-Son	0.76 (0.022) [7705]	0.77 (0.022) [6112]	0.56 (0.017) [7705]	0.57 (0.018) [6112]
Father-Daughter	0.83 (0.019) [9379]	1.05 (0.038) [1423]	0.62 (0.015) [9379]	0.86 (0.031) [1423]
Mother-Son	0.95 (0.040) [2964]	0.95 (0.044) [2316]	0.38 (0.022) [2964]	0.40 (0.023) [2316]
Mother-Daughter	1.05 (0.038) [3993]	1.18 (0.054) [578]	0.43 (0.021) [3993]	0.62 (0.032) [578]

Notes: Column (3) and (4) displays the elasticity of children's household income with respect to parents' individual earnings. The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

Table A12: Estimated Rank-Rank Slopes

	Father's Rank		Mother's Rank	
Sons	0.415 (.009) [10170]		0.391 (.016) [4109]	
		0.416 (.006) [20596]		0.385 (.011) [8459]
Daughters	0.417 (.008) [10426]		0.380 (.015) [4350]	

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Sons and daughters are ranked separately. Fathers and mothers are ranked separately.

Table A13: Estimated Rank-Rank Slopes using Earnings

	Earnings Rank of		**Household Inc. Rank of**	
	Father	Mother	Father	Mother
Sons	0.326 (0.011) [7809]	0.284 (0.019) [3101]	0.334 (0.010) [7809]	0.299 (0.018) [3101]
Daughters	0.503 (0.019) [1743]	0.567 (0.031) [670]	0.509 (0.020) [1743]	0.568 (0.030) [670]

Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. Sons and daughters are ranked separately. Fathers and mothers are ranked separately.

Table A14: *TS2SLS* Estimates using age 30-34 for Age-Correction

Pairs	Number of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7809]	0.47 (0.017)	0.57 (0.020)	0.37 (0.016) [5673]	0.46 (0.018)
Father-Daughter	[1743]	0.96 (0.042)	1.04 (0.047)	0.70 (0.038) [1451]	0.85 (0.039)
Mother-Son	[3101]	0.32 (0.024)	0.49 (0.039)	0.27 (0.025) [2037]	0.29 (0.024)
Mother-Daughter	[670]	0.78 (0.041)	0.94 (0.054)	0.59 (0.043) [509]	0.69 (0.040)

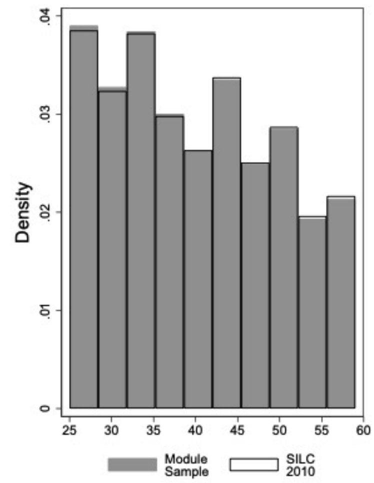
Notes: The bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes.

Table A15: Methodology used in *IGE* Estimation by Country

Country	Study	Estimate	Instruments to Predict Fathers' Income	Birth Cohort of Sons
Sweden	Björklund and Jäntti (1997)	0.28	*Higher than compulsory education*(**D**) *Occupation*(EG), *Living in Stockholm*(**D**)	*1952-1961*
Japan	Lefranc et al. (2014)	0.33	*Education*, *Occupation*(EGP), *Firm Size*(**D**), *Residential Area*	*1935-1975*
France	Lefranc and Trannoy (2005)	0.41	*Education*, *Occupation*(EG)	*1953-1963*
Italy	Piraino (2007)	0.44	*Education*, *Sector of Employment*, *Work Status*, *Residential Area*(**D**)	*1955-1974*
Turkey	**This study**	**0.51** **0.53** **0.54**	*Education*, *Occupation*(ISCO-88)	*1951-1985* *1976-1980* *1971-1975*
United States	Björklund and Jäntti (1997)	0.52	*Education*, *Occupation*	*1951-1959*
United Kingdom	Dearden et al. (1997)	0.58	*Education*, *Occupation*(EG)	*1958*
Chile	Nunez and Miranda (2010)	0.63	*Education*, *Work Status*	*1966-1975*
Brazil	Dunn (2007)	0.85	*Education*	*1962-1971*
Ecuador	Grawe (2004)	1.13	*Education*	*1955-1981*

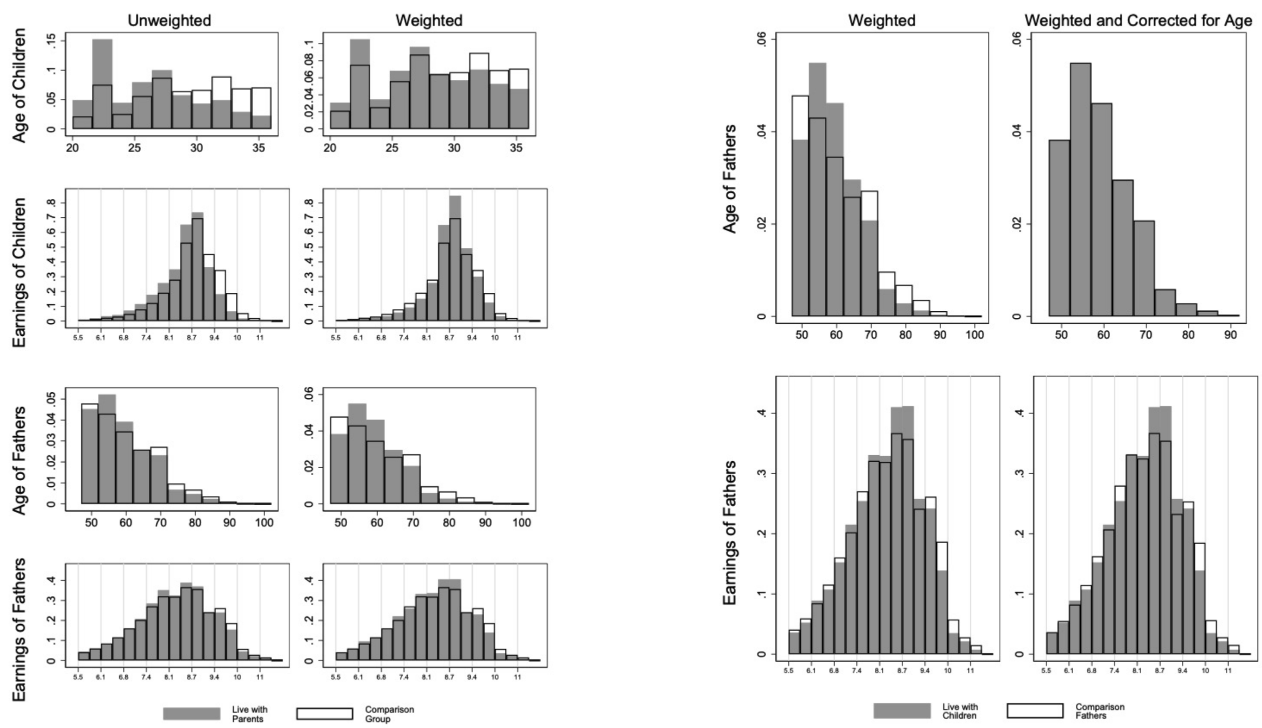
Notes: All estimates are based on the samples of father-son pairs. Dummy variables are indicated by **D**. In most studies, occupation information is coded according to Erikson and Goldthorpe (1992)(EG) or Erikson et al. (1979)(EGP) which is also called Social Status.

Figure A1: *SILC* 2010 Module
Age Distribution



Notes: The age histograms of all individuals surveyed in the *SILC* 2010 dataset and answered the module questions are overlaid.

Figure A2: Robustness Experiment via Probability Weighting



(a) **(b)**

Notes: The left panel provides a comparison between the unweighted and *inverse probability-weighted* distributions of children's and father's age and earnings via the overlaid densities of those who live in the same household and synthetic comparison groups. The right panel provides a comparison of only weighted distributions and weighted and corrected for age distributions.

APPENDIX B

INTERGENERATIONAL MOBILITY AND ASSORTATIVE MATING

Our results from Table 5 show that the elasticity of children's household income is similar for both sons and daughters, contrary to the elasticity of individual earnings. We argue that assortative mating is the primary driver of this observation. That is, the children of higher-earning parents not only have better-earning prospects but also tend to marry partners with higher-earning prospects. Considerable elasticity of individual earnings with respect to the earnings of parents-in-law supports this conjecture. Table B1 shows that the spouses' earnings are as elastic as the own earnings of children. That is, parental characteristics further affect their offspring's well-being through marital sorting.

Table B1: Earnings Elasticities with respect to Parents-in-Law

	Father-in-Law Earnings	Mother-in-Law Earnings
Female	0.89 (0.049) [1202]	0.55 (0.020) [466]
Male	0.62 (0.056) [6371]	0.38 (0.027) [2654]

Notes: Bootstrap standard errors are in parentheses. The numbers in brackets denote sample sizes. The dependent variable is the earnings of the spouse. The working sample contains only married children.

We also observe that contrary to the predicted *earnings* of the mother, *household income* predicted using the mother's characteristics more strongly affects the descendant's household income compared to that of the father. Although mothers' characteristics do not generate a sizable variation in their income, it accounts for a larger part of the variation in parental household income that is correlated with that of children. We provide evidence for assortative mating by presenting elasticity estimates and correlations between spouses in Table B2.

Table B2: Earnings and Income Elasticities/Correlations between Married Couples

Generation	**Children**				**Parents**			
Dependent Variable	*Earnings*		*Income*		*Earnings*		*Income*	
	Elasticity	Correlation	Elasticity	Correlation	Elasticity	Correlation	Elasticity	Correlation
Female	0.75 (0.037)	0.558	0.77 (0.040)	0.568	0.80 (0.022)	0.616	0.69 (0.026)	0.639
Male	0.41 (0.018)		0.42 (0.018)		0.47 (0.011)		0.59 (0.015)	
Number of Obs.	[1274]				[7774]			

Notes: The first column indicates which gender is used as the dependent variable in elasticity estimations. The sample size of descendants is considerably smaller due to the low number of employed females. The numbers in brackets denote sample sizes. Bootstrap standard errors are in parentheses for the parent's generation.

APPENDIX C

GROUP-SPECIFIC DECOMPOSITION OF *IGE*

In this Appendix, we present the details of the decomposition used for the calculations in Table 5. We adhere to the exposition used by the original paper (Hertz, 2008), which shows that intergenerational elasticity estimated in the pooled regression can be written as:

$$\hat{\beta} = \sum_i \hat{\pi}_i \left(\hat{\beta}_i \frac{\hat{\sigma}^2_{yp,i}}{\hat{\sigma}^2_{yp}} + \frac{(\overline{y}_{p,i} - \overline{y}_p)(\overline{y}_{c,i} - \overline{y}_c)}{\hat{\sigma}^2_{yp}} \right) \tag{18}$$

where each group is indexed by $i = 1, \ldots, I$; the share of the parent-child pair that belongs to group i in the total sample is denoted by $\hat{\pi}_i$, the relevant income measure for parents and children are denoted by y_p and y_c with sample means $\overline{y_p}$ and $\overline{y_c}$, and with variances $\hat{\sigma}^2_{yp}$ and $\hat{\sigma}^2_{yp}$, and the within-group estimate of intergenerational elasticity is denoted by $\hat{\beta}_i$.

Therefore, (18) represents the pooled *IGE* as the weighted sum of within-group elasticities and between-group effects. The contribution of the within-group elasticity is represented by the first term, which could be interpreted as the variance-adjusted *IGE*. The second term is group i's variance-weighted contribution to the between-group covariance. Thus, group i's contribution could be decomposed as group-share weighted within-group and between-group effects.

We group parent-child pairs according to the educational attainment levels of the children in Table 5. We repeat a similar decomposition exercise for illustrative purposes by grouping parent-child pairs according to the children's place of residence. We report our estimates along with the corresponding formal expression of each measure in Table C1.

Contrary to our previous decomposition, a larger contribution comes from the within-group elasticities. One reason is that as we divide our sample into a smaller number of groups, the between-group effect is mechanically smaller. The between-group effect becomes larger if the group's mean is higher (or lower) than the sample means for both generations.

Table C1: Decomposition of Intergenerational Household Income Elasticity by Rural and Urban Residences

		Male		**Female**	
		Rural	Urban	Rural	Urban
Shares	$\hat{\pi}_i$	0.33	0.67	0.33	0.67
Mean log Earnings of Children	$\overline{y}_{c,i}$	8.59	9.01	8.51	8.95
Mean log Earnings of Fathers	$\overline{y}_{c,i}$	8.39	8.60	8.39	8.59
Pooled *IGE*	$\hat{\beta}$	**0.774**		**0.822**	
Within-Group *IGE*	$\hat{\beta}_i$	0.697	0.686	0.687	0.751
Contribution of Within-Group *IGE*	$\hat{\pi}_i \hat{\beta}_i \frac{\hat{\sigma}^2_{yp,i}}{\hat{\sigma}^2_{yp}}$	0.153	0.491	0.155	0.534
		$\sum$ =0.644		$\sum$ =0.689	
Between-Group effects	$\frac{(\overline{y}_{p,i}-\overline{y}_p)(\overline{y}_{c,i}-\overline{y}_c)}{\hat{\sigma}^2_{yp}}$	0.264	0.064	0.270	0.065
Contribution of Between-Group effects	$\hat{\pi}_i \frac{(\overline{y}_{p,i}-\overline{y}_p)(\overline{y}_{c,i}-\overline{y}_c)}{\hat{\sigma}^2_{yp}}$	0.087	0.043	0.089	0.044
		$\sum$ =0.130		$\sum$ =0.132	
Group-Specific Persistence	$\hat{\pi}_i \left(\hat{\beta}_i \frac{\hat{\sigma}^2_{yp,i}}{\hat{\sigma}^2_{yp}} + \frac{(\overline{y}_{p,i}-\overline{y}_p)(\overline{y}_{c,i}-\overline{y}_c)}{\hat{\sigma}^2_{yp}}\right)$	0.240	0.534	0.244	0.578
		$\sum$ =0.774		$\sum$ =0.822	

APPENDIX D

OLS, *IV* AND *TS2SLS* COMPARISON

Table D1: *OLS* and *IV* Estimates for Father-Son Pairs

	Number of Years			*OLS*			*IV*		*TS2SLS*
	Child	Father	Number of Obs.	With Age Controls	Corrected for Age	Number of Obs.	With Age Controls	Corrected for Age	2010 *SILC*
Earnings	1	1	[1720]	0.130*** (0.016)	0.157*** (0.018)	[1424]	0.317*** (0.036)	0.440*** (0.047)	0.539*** (0.019)
	1	4	[917]	0.180*** (0.027)	0.201*** (0.030)	[803]	0.336*** (0.048)	0.473*** (0.047)	0.768*** (0.027)
	4	4	[385]	0.128** (0.039)	0.135** (0.045)	[333]	0.192*** (0.053)	0.281** (0.070)	
Income	1	1	[2516]	0.181*** (0.020)	0.208*** (0.021)	[1485]	0.523*** (0.055)	0.646*** (0.070)	0.627*** (0.022)
	1	4	[917]	0.221*** (0.029)	0.239*** (0.033)	[803]	0.539*** (0.073)	0.700*** (0.094)	0.910*** (0.034)
	4	4	[385]	0.201*** (0.041)	0.193*** (0.046)	[333]	0.533*** (0.119)	0.717*** (0.183)	
Labor Income	1	1	[844]	0.200*** (0.029)	0.225*** (0.033)	[657]	0.372*** (0.058)	0.550*** (0.078)	0.423*** (0.017)
	1	4	[397]	0.271*** (0.043)	0.324*** (0.050)	[381]	0.374*** (0.077)	0.588*** (0.090)	0.604*** (0.020)
	4	4	[385]	0.230*** (0.050)	0.287*** (0.054)	[333]	0.352*** (0.090)	0.500*** (0.125)	

Notes: The numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Table D2: *OLS* and *IV* Estimates for Father-Daughter Pairs

	Number of Years			*OLS*			*IV*		*TS2SLS*
	Daughter	Father	Number of Obs.	With Age Controls	Corrected for Age	Number of Obs.	With Age Controls	Corrected for Age	2010 *SILC*
Earnings	1	1	[401]	0.120*** (0.028)	0.136*** (0.033)	[350]	0.385*** (0.070)	0.541*** (0.109)	1.084*** (0.043)
	1	4	[221]	0.136*** (0.051)	0.154** (0.066)	[195]	0.581*** (0.113)	0.661*** (0.176)	1.554*** (0.063)
	3	3	[115]	0.096 (0.064)	0.114 (0.079)	[101]	0.494** (0.153)	0.551** (0.190)	
Income	1	1	[640]	0.202*** (0.042)	0.211*** (0.044)	[363]	0.557*** (0.077)	0.680*** (0.105)	1.162*** (0.048)
	1	4	[405]	0.207** (0.072)	0.247** (0.075)	[226]	0.644*** (0.132)	0.723*** (0.193)	1.616*** (0.072)
	3	3	[217]	0.115 (0.083)	0.143* (0.080)	[118]	0.510** (0.156)	0.475* (0.225)	
Labor Income	1	1	[245]	0.176*** (0.038)	0.185*** (0.042)	[202]	0.377*** (0.089)	0.443*** (0.117)	0.760*** (0.038)
	1	4	[124]	0.397*** (0.108)	0.395** (0.128)	[104]	0.798*** (0.122)	0.997*** (0.242)	1.066*** (0.054)
	3	3	[63]	0.378* (0.151)	0.325* (0.141)	[53]	0.601** (0.182)	0.690* (0.280)	

Notes: The numbers in parentheses are standard errors. In the last columns, 3-year averaged regressions are reported due to the small sample sizes of 4-year averaged regressions. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Table D3: *OLS* and *IV* Estimates for Mother-Son Pairs

	Number of Years		Number of Obs.	*OLS*		Number of Obs.	*IV*		*TS2SLS*
	Son	Mother		With Age Controls	Corrected for Age		With Age Controls	Corrected for Age	2010 *SILC*
Earnings	1	1	[341]	0.067 (0.032)	0.048 (0.035)	[201]	0.376*** (0.099)	0.373** (0.123)	0.351*** (0.024)
	1	4	[98]	0.091 (0.077)	0.055 (0.080)	[60]	0.148 (0.150)	0.113 (0.170)	0.416*** (0.026)
	4	4	[119]	0.181** (0.063)	0.167* (0.064)	[70]	0.332** (0.112)	0.374** (0.140)	
Income	1	1	[575]	0.145*** (0.031)	0.103** (0.032)	[475]	0.423*** (0.080)	0.488*** (0.111)	0.527*** (0.039)
	1	4	[211]	0.246*** (0.062)	0.157* (0.075)	[94]	0.327* (0.129)	0.472* (0.203)	0.419*** (0.029)
	4	4	[210]	0.295*** (0.049)	0.274*** (0.056)	[103]	0.465*** (0.101)	0.556*** (0.130)	
Labor Income	1	1	[211]	0.190*** (0.044)	0.160** (0.046)	[121]	0.387*** (0.078)	0.360*** (0.119)	0.301*** (0.025)
	1	4	[58]	0.336** (0.099)	0.275* (0.102)	[34]	0.266*** (0.103)	0.204** (0.134)	0.515*** (0.039)
	4	4	[68]	0.369*** (0.066)	0.360*** (0.076)	[37]	0.439* (0.086)	0.493 (0.128)	

Notes: The numbers in parentheses are standard errors. In the last columns, 3-year averaged regressions are reported due to the small sample sizes of 4-year averaged regressions. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.

Table D4: *OLS* and *IV* Estimates for Mother-Daughter Pairs

	Number of Years		Number of Obs.	*OLS*		Number of Obs.	*IV*		*TS2SLS*
	Daughter	Mother		With Age Controls	Corrected for Age		With Age Controls	Corrected for Age	2010 *SILC*
Earnings	1	1	[119]	0.153** (0.048)	0.158** (0.054)	[77]	0.275* (0.131)	0.392* (0.155)	0.851*** (0.042)
	1	4	[98]	0.192* (0.084)	0.205* (0.097)	[60]	0.206 (0.130)	0.292** (0.121)	0.975*** (0.045)
	4	4	[119]	0.127 (0.076)	0.218** (0.090)	[70]	0.147 (0.099)	0.191 (0.115)	
Income	1	1	[220]	0.209*** (0.054)	0.206** (0.055)	[114]	0.433** (0.164)	0.564* (0.223)	0.1.067*** (0.057)
	1	4	[103]	0.314*** (0.082)	0.301** (0.089)	[48]	0.397* (0.158)	0.342 (0.191)	1.033*** (0.054)
	4	4	[84]	0.252** (0.075)	0.217* (0.093)	[40]	0.035 (0.131)	0.022 (0.144)	
Labor Income	1	1	[83]	0.201 (0.086)	0.214* (0.094)	[47]	0.330* (0.159)	0.266 (0.191)	0.632*** (0.041)
	1	3	[27]	0.138 (0.184)	0.346 (0.230)	[13]	0.635 (0.378)	0.551* (0.226)	1.029*** (0.060)
	3	3	[22]	0.663** (0.192)	0.702* (0.317)	[11]	0.190 (0.150)	0.219 (0.261)	

Notes: The numbers in parentheses are standard errors. In the last columns, 3-year averaged regressions are reported due to the small sample sizes of 4-year averaged regressions. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$.