Intergenerational Income Mobility in Turkey*

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Abstract

In this study, we examine intergenerational income mobility in Turkey using data from the Turkish Statistical Institute's Survey of Income and Living Conditions and the *TS2SLS* methodology. Our findings reveal an intergenerational earnings elasticity of 0.51 between fathers and sons and 1 between fathers and daughters. This gender disparity stems from historically low female labor force participation and self-selection of women into employment in Turkey. Our estimates for household income elasticity for both sons and daughters are similar, at around 0.8. We also observe a slight decrease in intergenerational mobility for more recent birth cohorts, consistent with trends in other countries. Our further analysis using rank-rank slopes and transition matrices indicates weak intergenerational rank mobility and strong persistence at both ends of the income distribution in Turkey.

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

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1 Introduction

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

Previous literature often estimates intergenerational elasticities (*IGE*) to measure the association between the economic outcomes of parents and descendants. The most commonly used measure is the intergenerational *earnings* elasticity, i.e., the coefficient estimate from the log-log regression of descendants' lifetime labor earnings on that of their parents. Several studies also complement their analysis with intergenerational *household income* elasticity to examine the role of household formation and household-level decisions.[2]

While earlier research on intergenerational mobility primarily focused on developed countries, recent studies have increasingly provided estimates of intergenerational earnings and income elasticities for developing countries.[3] Meanwhile, the literature on Turkey has been limited to intergenerational *educational* mobility due to data constraints. As a result, Turkey still 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 aims to address this gap by providing new estimates for Turkey's intergenerational earnings and income elasticities as well as other measures of mobility such as rank-rank slopes and transition matrices.

We use micro datasets from the Turkish Statistical Institute's (*TurkStat*) Survey of Income and Living Conditions (*SILC*) covering the period from 2005 to 2017. To estimate Turkey's intergenerational individual earnings and household income elasticities under data limitations, we employ the two-sample two-stage least-squares (*TS2SLS*) methodology (Björklund and Jäntti, 1997). We also examine heterogeneity in these estimates across gender, time, geography, and income distribution.

To consistently estimate intergenerational elasticities, we first predict parents' earnings using retrospective information on their characteristics. We use pooled cross-sectional datasets from the *SILC* to estimate returns to education and occupation. We then combine these predictions with children's reports of their

[1] See Mogstad and Torsvik (2023) for an elaborate review of the advances in the related literature.
[2] See Lee and Solon (2009), Chetty et al. (2016) and Eshaghnia et al. (2022) among others.
[3] See Narayan et al. (2018) for a broad set of estimates for developed and developing countries.

parents' educational attainment and occupation from *TurkStat*'s Intergenerational Transmission of Disadvantages Module provided with *SILC* cross-section in 2010. By combining these predictions with children's reports of their own income, we are able to estimate our intergenerational mobility measures. We also conduct similar analyses using household income and additional variables.

Our *TS2SLS* estimate for Turkey's intergenerational earnings elasticity is around one-half for father-son pairs. When compared to other countries, Turkey's elasticity is similar to that of the least mobile developed countries, such as the United States. Our analysis also reveals several additional novel findings.

We first document that the estimated intergenerational earnings elasticity between fathers and daughters is twice as large as that between father-son pairs. This stronger persistence can be mainly attributed to Turkey's historically low and selective female labor force participation. Specifically, we demonstrate that parental effects on daughters' outcomes are overestimated due to the self-selection of women into employment. Our estimates for equivalized household income elasticity for sons and daughters, which do not suffer from selection bias like individual earnings estimates do, are comparable and close to four-fifths.

We further complement our analysis by estimating rank-based mobility measures. Our rank-rank slope estimates of two-fifths indicate weaker intergenerational rank mobility in Turkey compared to the US. Additionally, we report quintile group transition matrices to illustrate heterogeneous patterns across the income distribution. Consistent with previous research, we find that intergenerational persistence in Turkey is strongest in the top and bottom quintiles.

We also examine changes in intergenerational earnings and income mobility over time. Our results show a modest decline in intergenerational mobility across birth cohorts, except for sons in the youngest cohorts. This trend is also observed through the rank-rank slope and is robust to changes in inequality across cohorts. We also find that younger cohorts are less likely to experience upward mobility, similar to trends observed in the US and several other countries.

Finally, we conduct a series of alternative estimations and confirm that our estimates are not sensitive to specification differences. We believe these robust findings will complement existing research on intergenerational educational mobility in Turkey and provide further insight into its intergenerational transmission.

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 literature investigating the empirics of intergenerational economic mobility has expanded notably in recent decades. In his seminal paper, Solon (1992) highlights the sources of bias and measurement error in early empirical studies and proposes a standard methodology to accurately estimate intergenerational income persistence.[4] Since then, robust and comparable estimates have proliferated for numerous countries, albeit mainly confined to developed ones.[5] As a result of methodological advances and better data availability, comparable estimates for various developing countries have recently become available (Narayan et al., 2018). Our study is motivated by the lack of such estimates for Turkey.

As one of the most unequal members of the OECD, Turkey's economic inequalities have been extensively studied in the literature. Recent studies include Tansel et al. (2019), where the authors investigate wage inequality among different age, education, gender, and sector groups using data from the Turkish Statistical Institute's (*TurkStat*) Survey of Income and Living Conditions (*SILC*) for the period 2005-2011. Filiztekin (2015) decomposes income inequality across various population subgroups and examines regional idiosyncrasies for the period 1994-2011 using data from *TurkStat*'s Household Budget Survey (*HBS*). Tamkoç and Torul (2020) provide cross-country comparable estimates of Turkey's economic inequalities following 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 is consistent with rapid minimum wage growth during this period.[6] Overall, while prominent patterns in Turkey's cross-sectional inequalities are well-documented, no previous study has accurately investigated Turkey's intergenerational income mobility and its relationship to the evolution of Turkey's economic inequalities.

The shortage of studies on Turkey's intergenerational income mobility can be attributed to the lack of long-running longitudinal datasets. An ideal analysis of intergenerational income mobility requires data from both parents' and descendants' working lives. Such datasets (e.g., the Panel Study of Income Dynamics (*PSID*) for the US and longitudinal income tax records for Sweden and Canada) have enabled researchers to consistently measure intergenerational income mobility in numerous countries.[7] However, the only available panel

[4] 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 actual values.

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

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

[7] See Solon (2002), Corak and Heisz (1999), and Österberg (2000) for the US, Canada, and Sweden, respectively. Also, see Mazumder (2018) for a review on the contributions of *PSID* for unveiling various aspects of intergenerational mobility in the US.

dataset in Turkey — *SILC* panel dataset — follows individuals for a maximum of four years and only provides data on parents if subjects were living with them at the time of the survey. As *SILC* does not provide data for descendants who do not live with their parents, it fails to accurately represent Turkish parent-descendant pairs. Thus, results obtained using *SILC* would provide biased estimates.[8] Our paper offers credible estimates by relying on nationally representative datasets and appropriate methodology.

There are several studies on Turkey's intergenerational educational mobility. Since educational attainment remains constant throughout adulthood and many surveys include questions on parental education, it is relatively easy to meet the data requirements for measuring educational mobility.[9] Tansel (2015) uses *TurkStat*'s Adult Education Survey (*AES*) in 2007 to show that mothers' educational background plays a more pivotal role than fathers', and intergenerational associations are stronger when parental education is below primary school level. 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 find that Turkey has a relatively low degree of mobility compared to developed countries and that primary measures of intergenerational educational mobility evolved in a U-shaped pattern. Aydemir and Yazıcı (2019) focus on cross-regional variation in intergenerational educational mobility in Turkey and find a positive relationship between mobility and regional development. Our paper complements these studies by providing the first insights into the empirical transmission of income between generations, contributing to a better understanding of Turkey's intergenerational mobility.

Recently, more studies have revealed intergenerational income mobility for developing countries using two-sample methods (*TSIV* and *TS2SLS*), which have less strict data requirements. For example, Dunn (2007) estimates intergenerational earnings elasticity for Brazil and reports results ranging from 0.69 to 0.85 for father-son pairs. Nunez and Miranda (2010) report results for Chile ranging from 0.57 to 0.74 using the same methodology.[10]

In this paper, we also use the *TS2SLS* method to provide comparable estimates for Turkey.[11] This method allows us to estimate intergenerational earnings elasticity without longitudinal data when children's and fa-

[8] All previous studies that have attempted to measure intergenerational income mobility in Turkey (Mercan, 2012; Mercan and Barlin, 2016; Duman, 2021) have relied on co-residing father-son pairs for their analysis. As a result, their working samples fail to accurately represent Turkey's population, and their estimates are subject to bias.

[9] Despite the widespread availability of data, specifying education in cardinal terms is not straightforward and presents various challenges for econometric analysis. For a more detailed discussion, see Öztunalı and Torul (2022) and Torul and Öztunalı (2017).

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

[11] The *TS2SLS* estimator was first introduced by Angrist and Krueger (1992) and later popularized in the intergenerational mobility literature by Björklund and Jäntti (1997).

thers' earnings are available in two different datasets. We use available parental characteristics to predict parental income and then use it in the intergenerational regression of interest. We use *SILC* cross-sectional datasets to predict parental income and combine these results with the *SILC* Intergenerational Transmission of Disadvantages Module from 2010 to estimate intergenerational elasticities.[12]

3 Theoretical Background

3.1 Issues in *IGE* Estimation

When estimating intergenerational elasticities (*IGE*), the fundamental relationship between a parent's and their child's income can be expressed using the following equation (Becker and Tomes, 1986):

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

where y_c and y_p represent the natural logarithm of a child's and their parent's lifetime earnings, respectively. If both values are directly observable for a *random* sample of families, $\hat{\beta}$ can be estimated using an ordinary least squares (*OLS*) regression. However, most datasets do not provide direct observations of lifetime earnings. Instead, annual earnings are often used as a proxy for lifetime earnings. In this case, the annual earnings of children in year t and parents in year s serve as substitutes for lifetime earnings:

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

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

where ν represents transitory earning shocks. The standard approach in the literature is to use the average of multiple years of observed earnings as a proxy for lifetime earnings. If we assume that transitory shocks are independently and identically distributed (i.i.d.) with a mean of zero, then the probability limit of the *OLS* estimate using averaged earnings can be expressed as follows:

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

[12] Another strand of the literature focuses on 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 and reveal stronger persistence at both ends of the income distribution. Also, Jäntti et al. (2014) use transition matrices to compare intergenerational mobility across countries over the entire income distribution. Chetty et al. (2014) use transition matrices for a comprehensive analysis of intergenerational mobility in the US. Bratberg et al. (2007) and Palomino et al. (2018) use quantile regressions for investigating intergenerational mobility.

The attenuation factor increases with the variance of transitory errors (σ^2_{vp}) and decreases with the number of years (T) used for averaging. To obtain consistent estimates of β, it is ideal to use as many years as possible when averaging parental income.[13] While the convention is to average over at least five years of earnings (Solon, 1992), Mazumder (2005) demonstrates that taking longer multi-year averages progressively improves *IGE* estimates.[14] As a result, even when multiple years of observations are available, *OLS* estimates of *IGE* may still be downward-inconsistent.[15]

Another potential source of bias is the variation in income over an individual's life cycle, which is not accounted for in the equations above. To accurately estimate intergenerational earnings elasticity, it is necessary to consider the earnings of both generations at appropriate stages in their life cycles. However, surveys often report descendants' earnings relatively early and parents' earnings late in their life cycles. Empirically, the relationship between current and lifetime income varies over the course of an individual's life. Therefore, a more accurate formulation of earnings would take this into account instead of using equations (2) and (3):

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

where λ_t represents the strength of the relationship between lifetime income (y) and annual earnings (y_t) for both generations. As indicated by the subscript, λ_t varies with age and is not necessarily equal to one. Consequently, even if transitory errors are assumed to be homoskedastic and independently and identically distributed (i.i.d.), bias in *IGE* estimates may still arise due to an individual's age at the time of measurement. Therefore, equation (4) can be reformulated as follows:

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

where $\overline{\lambda}_{pt}$ and $\overline{\lambda}_{ct}$ represent the multi-year 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 age 20 and increase monotonically until age 40 (reaching 1 around this peak) before decreasing to between 0.6 and 0.8 later in life. This implies that measuring children's earnings

[13] Note that σ^2_{vc} does not appear in equation (4), indicating that under the assumption of purely transitory and homoskedastic errors, *IGE* can be consistently estimated even when only a single year of child's earnings is used. However, averaging over a child's earnings affects the precision of the *IGE* estimate. The variance of transitory earning shocks experienced by children σ^2_{vc} appears in the probability limit of the R statistic: $\text{plim}\,\hat{R} = \frac{\beta\sigma^2_{yp}}{\sqrt{(\sigma^2_{yp}+\sigma^2_{vp})(\sigma^2_{yp}+\sigma^2_{vc})}}$.

[14] 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.

[15] Furthermore, the bias can be exacerbated by persistent earning shocks. For further discussion on the topic, see Mazumder (2005) and Muller (2010).

further from age 40 would bias *IGE* estimates downward, while the opposite effect would occur for fathers. Therefore, the variation in earnings over an individual's life cycle is likely to further bias *IGE* estimates 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.[16]

Equation (6) assumes that the variance of transitory earning shocks (σ_v^2) is constant over an individual's life cycle. However, empirical evidence from Baker and Solon (2003) and Grawe (2006) suggests that σ_{vt}^2 also depends on age and reaches its minimum around age 40. Furthermore, Nybom and Stuhler (2016) demonstrate that the path of λ_t varies significantly with educational attainment. Therefore, in this paper, we use earning measures that are representative of age 40 while accounting for education to minimize bias stemming from both λ_t and σ_{vt}^2. We discuss our methodology for addressing this issue and our robustness experiments in greater detail in the following sections.

Finally, using an unrepresentative sample can severely bias *IGE* estimates. Attrition, self-selection, and sampling design may contribute to unrepresentative samples depending on the nature of the dataset used. As Solon (1992) elaborates, the estimated *IGE* will be downward biased due to a low signal-to-noise ratio when the sample is too homogeneous.

3.2 *IV* and *TS2SLS* Estimation

Another approach to address the errors-in-variables problem is to use instrumental variable (*IV*) estimation. This method involves exploiting the variation in parental earnings (y_p) by using parental education (e_p) as an instrument to estimate equation (1). However, parental education may not be a valid instrument because it could directly affect descendants' earnings even after controlling for parental earnings. In this scenario, the structural equation can be formulated as follows:

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

[16] Böhlmark and Lindquist (2006) reach similar conclusions using Swedish register data. Grawe (2006) also finds that *IGE* estimates decrease as fathers' age increases after inspecting 20 studies and several datasets.

Nonetheless, 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 (Björklund and Jäntti, 1997).[17] Therefore, 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).[18] As its name suggests, *TS2SLS* makes use of an outside dataset to predict parental earnings using parental characteristics reported by children. The *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 represents 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 parental characteristics reported by children are not noisier than parents' own reports. Our datasets meet these 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 (i.e., 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 for comparisons between population subgroups since it would represent persistence with respect to the group-specific mean.

An alternative approach for circumventing these limitations is to use *rank*-based measures to investigate

[17] The literature on the effects of parental education on children's economic outcomes generally agrees with this assumption (Heckman and Mosso, 2014; Becker et al., 2018).

[18] 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*.

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 parents:[19]

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

where R_c and R_p represent 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.[20] Another appeal of the rank-rank slope is that it can be used to compare the degree of mobility across subgroups since ranks come from the national distribution.

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 from 2005 to 2017.[21] *SILC* is published annually in the form of both cross-sectional and panel datasets that are nationally representative.[22] *SILC* cross-sectional datasets cover at least 9,200 households per year and offer detailed information on the income sources of individuals and households. The *SILC* 2010 cross-sectional dataset additionally provides the *Intergenerational Transmission of Disadvantages Module*.

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 using the Turkish consumer price index (*CPI*), with 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 who work less than 30 hours a week. These practices 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.[23] We present the resultant descriptive statistics for individuals meeting the

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

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

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

[22] *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 *TurkStat's* official website.

[23] 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 comparability of the analyses on the evolution of economic inequalities. These guidelines are particularly instrumental in income definitions, including left truncation. See Krueger et al. (2010) for further details.

above criteria in the second and third columns of Table 1 and Online Appendix Table A.1.

We also construct the *annual earnings* variable following the same *RED* guidelines. We calculate *annual earnings* of individual i in year t, $ae_{i,t}$ as follows:

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

where $nw_{i,t}$ and $rw_{i,t}$ represent annual cash and other real payments, α^{TR} represents the share of labor income in Turkey's national income in the year of observation, and $nse_{i,t}$ and $rse_{i,t}$ represent cash and other real incomes from self-employment, respectively. We also calculate *equivalized household income* using the modified *OECD* equivalence scale. This scale assigns a weight of 1 to the first adult, 0.5 to each subsequent person aged 14 or older, and 0.3 to each child under 14. In the rest of the paper, we refer to it as *household income*.

We use the *SILC* 2010 cross-sectional dataset in our main analysis.[24] The *Intergenerational Transmission of Disadvantages Module* attached to this dataset provides information on children's incomes and their parents' education status and occupational code (`ISCO-88`) when they were 14 years old. As shown in Table 1, out of the 25,463 individuals between the ages of 25 and 59 who answered the module questions, 11,703 are full-time workers. There are no significant differences in descriptive statistics between these two samples. Our two-sample *IV* estimates are based on the children observed in this dataset.

[24] Unlike previous studies on intergenerational mobility in Turkey (Mercan, 2012; Mercan and Barlin, 2016; Duman, 2021), we do *not* use the *SILC* panel dataset for our main analysis. This is because the dataset only contains information about children who live with their parents, which results in an unrepresentative sample. Further discussion on this topic can be found in Online Appendix A.

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

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

Notes: The numbers in parentheses are standard deviations reported alongside mean values. The values reported in a single column represent 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 self-employed category includes individuals who identified themselves as either self-employed or as an employer with positive self-employment income.

We use the *SILC* cross-sectional datasets pooled over 2005-2017 to predict parents' earnings based on children's reports. We also use this pooled dataset to estimate age-income profiles for different educational attainment groups. We use these estimates to correct for life-cycle effects in children's incomes in the *SILC* 2010 cross-section. Due to data limitations, we rely on information from the same pooled dataset for both children observed in the 2010 cross-section and their parents. Specifically, we lack an external dataset to link parents' education and occupation with their income. We discuss this in more detail in Section 6.

5 Estimation Strategy

We start by age-correcting individual earnings and household incomes to mitigate possible life-cycle bias. As explained in Section 3.1, measuring the incomes of both generations around the age of 40 can minimize this bias (Haider and Solon, 2006).[25] We employ a method similar to that of Jäntti et al. (2014) to construct age-corrected income measures of children in our main sample (*SILC* 2010).

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 perform this estimation separately for each gender and education group to account for differences in age-income profiles.

We use the following regression equation to estimate the age effects on income measures:

$$\log(y_i) = \alpha_{lg} + \sum_{j=1}^{8} \beta_{lgj}\, \texttt{age}_{ij} + \sum_{k=2005}^{2017} \gamma_{lgk}\, \texttt{year}_{ik} + \epsilon_i \qquad \text{if} \quad \texttt{educ}_i = l \quad \& \quad \texttt{sex}_i = g \tag{12}$$

where $\log(y_i)$ represents the natural logarithm of the income measure of person i, `age` represents the dummy variables of age categories in 5-year intervals: ages 20 to 24, 25 to 29,..., 55 to 59, and `year` represents the year of observation. We estimate this equation separately for each gender (`sex`) and education category (`educ`): secondary education or lower, high school graduates, and university graduates. We then use the estimated coefficients and standard errors of the age intervals to construct children's age-corrected income measures (corresponding to the age interval of 35-39) as follows:[26]

$$\widetilde{\log(y_{c,i})} = \hat{\alpha}_{lg} + \hat{\beta}_{lg4} + \hat{\gamma}_{lg2010} + \epsilon_i \frac{\hat{\sigma}_{lg4}}{\hat{\sigma}_{lgj}} \qquad \text{if} \quad \texttt{educ}_i = l \quad \& \quad \texttt{sex}_i = g \quad \& \quad \texttt{age}_i = j \tag{13}$$

where $\widetilde{\log(y_{c,i})}$ represents the age-corrected income of the child, σ_{lpj} represents the standard error of residuals for the corresponding group, and $j = 4$ represents the group of individuals between the age of 35-39.[27] We use these age-corrected income measures of descendants in the second stage of our *TS2SLS* estimation.

For the first stage of our *TS2SLS* estimation, we predict parental incomes using information on parents'

[25] 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 most representative of lifetime income. However, this age varies across individuals. Among their *IGE* estimates using annual incomes, the estimate based on the age-37 incomes of children is closest to their benchmark *IGE* estimate.

[26] For an extensive investigation of age-income profiles in Turkey using *TurkStat*'s Household Labor Force Survey (*HLFS*), see Aktuğ et al. (2021). We also use the coefficients of age and education from 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 those from Aktuğ et al. (2021) in Online Appendix Table A.12.

[27] Note that we preserve individual-specific variations as we construct age-corrected income measures using the reported ones instead of merely predicting them.

education and occupation, which is available in the *SILC* 2010 cross-section. The estimation equation takes the following form:

$$\log(y_i) = \alpha_g + \sum_{l=1}^{6} \beta_{1gl}\texttt{educ}_{il} + \sum_{m=1}^{9} \beta_{2gm}\texttt{occup}_{im} + \sum_{j=1}^{8} \beta_{3gj}\texttt{age}_{ij} + \sum_{k=2005}^{2017} \gamma_{gk}\texttt{year}_k + \epsilon_i \quad \text{if} \quad \texttt{sex}_i = g \tag{14}$$

We estimate this equation for both income measures: annual earnings and household income.[28] We then use the estimated coefficients to predict parental income measures again for the age interval 35-39:

$$\widehat{\log(y_{p,i})} = \hat{\alpha}_g + \hat{\beta}_{1gl} + \hat{\beta}_{2gm} + \hat{\beta}_{3g4} + \hat{\gamma}_{g2010} \quad \text{if} \quad \texttt{educ}_i = l \;\; \& \;\; \texttt{occup}_i = m \;\; \& \;\; \texttt{sex}_i = g \tag{15}$$

Finally, we regress the age-corrected income measures of children on their parents' predicted income measure using the following equation:[29]

$$\widetilde{\log(y_{c,i})} = \alpha + \beta_{IGE}\widehat{\log(y_{p,i})} + \epsilon_i \tag{16}$$

6 Results

6.1 Benchmark Results

We present our intergenerational earnings elasticity estimates in Table 2. We find that the canonical intergenerational mobility measure, the intergenerational elasticity of earnings for father-son pairs, is 0.51. This implies 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 (e.g., the United States) yet displays higher mobility than many developing ones.[30] Moreover, our estimates suggest a weaker effect of mothers' income on children's economic outcomes than that of fathers. This contrasts with Tansel et al. (2019), which argues for a stronger effect of mothers' education on children's educational attainment.[31]

[28] We report the first-stage estimation results in Online Appendix Table A.9.

[29] We use a bootstrap procedure to calculate the standard errors of our estimators. We first draw a bootstrap sample from the pooled data and estimate the coefficients to predict parental income measures. We next draw a sample of children from the 2010 module dataset and use the estimated coefficients to predict parental income measures. 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.

[30] Grawe (2004) reports even lower *IGE* estimates for some other countries, such as 0.24 in Nepal and 0.32 in Pakistan. However, we exclude these estimates because they are based on small samples.

[31] We also caution that using elasticities based on mothers' earnings can be misleading for the reasons discussed below and in Online Appendix B.

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

	Father	Mother
Sons	0.51 (.018) [7809]	0.35 (.025) [3101]
Daughters	1.00 (.042) [1743]	0.80 (.042) [670]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets.

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 samples of father-son pairs. All studies use fathers' predicted earnings and children's observed annual earnings, employing either the *TS2SLS* or *TSIV* method to estimate intergenerational elasticity. Most studies report several estimates; among those, we have chosen the ones that are most comparable with our methods and sample specifications. For details, see Online Appendix Table A.16.

As mentioned, we use 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). However, this assumption may be invalid 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. Ideally, we should use data from the 1990s for the first-stage estimation.[32] However, no data from the pre-2002 period is available for Turkey. While we cannot eliminate potential biases, our robustness checks could partially alleviate concerns: we display in Online Appendix Table A.10 that our estimates from the separate use of single-year cross-sections

[32]The parental age data in our dataset is too noisy, which prevents us from identifying 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 find 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).

for the first stage estimation reveal little sensitivity to year choice and do not exhibit a clear time pattern.[33]

One of the most noticeable results from Table 2 is the considerably higher elasticity estimates observed for daughters. In particular, *IGE* estimates for daughters are nearly twice as large as those for sons. The elasticity of daughters' earnings with respect to fathers' earnings is approximately one.[34] This contrasts with findings for most developed countries, where the *IGE* of daughters' income is lower than that of sons, except for the United Kingdom (Dearden et al., 1997). Notably, sample sizes are considerably smaller for daughters. This is expected, as Turkey has the lowest female labor force participation rate among the OECD countries, recently hovering around only 30% (Aktuğ et al., 2021). Therefore, our estimates may be biased by women's self-selection into employment since we focus on full-time working individuals (Heckman, 1979). That is, the daughters in our sample may differ from the general population in some unobservable ways that are correlated with both their own earnings and their parents' earnings.[35]

As revealed by the markedly 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. For example, Lee and Solon (2009), Hertz et al. (2008), and Chetty et al. (2014)) use *household* or *family* income instead of *individual* earnings. Household income is a broader measure that better reflects children's living standards by construction. Moreover, household income more accurately captures the economic status of married women than their own earnings, especially when female labor participation is low (Chadwick and Solon, 2002).

We supplement our analysis by estimating the intergenerational household income elasticities and present the results in Table 4. Comparing these estimates with those based on individual earnings in Table 2 offers several insights. First, the household income elasticities for sons and daughters in columns 1 and 2 are nearly identical, indicating a similar degree of intergenerational persistence in household living standards for both genders.[36] A key source of this similarity is the inclusion of all daughters with positive household incomes

[33] Dunn (2007) performs a similar exercise by changing the first-stage dataset over 20 years. He finds at most a 13% change in his estimates, while ours change at most 10% for father-son pairs. We also repeat this exercise using another canonical dataset by *TurkStat*, Household Budget Survey (*HBS*), which provides data starting from 2002. We present our results in Online Appendix Table A.11. These findings indicate that our results are robust over the use of alternative datasets too.

[34] To exemplify, this large estimate could be observed under a peculiar scenario where daughters inherit the same degree of economic inequality as their fathers.

[35] Further discussion on possible mechanisms linking female labor force participation and our results is provided in Online Appendix B.

[36] Since the variable of interest is now *household income* instead of *individual earnings*, the resultant sample sizes are larger for both genders. Similarly, the sample sizes in our estimations using equations (12) and (14) are also larger.

instead of only full-time workers. To better understand the role of selection, we estimate the same elasticities using working descendant samples in columns 3 and 4. The elasticity estimates for working daughters are approximately 20% higher than those for the full sample, while they remain similar for sons. On the other hand, the elasticity of household income for full-time workers differs less between sons and daughters than the elasticity of earnings. This suggests that the self-selection of women only partly explains the substantial differences between the estimates of earnings elasticity for sons and daughters.

Table 4: *TS2SLS* Estimates of Intergenerational Household Income Elasticity in Turkey

	Full Sample		**Only Full-Time Working Children**	
	Father	Mother	Father	Mother
Sons	0.77 (0.018) [10170]	0.98 (0.032) [4109]	0.79 (0.020) [7809]	0.99 (0.035) [3101]
Daughters	0.82 (0.018) [10426]	1.03 (0.033) [4350]	0.99 (0.034) [1743]	1.12 (0.046) [670]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets.

Second, the estimated household income elasticities are all above 0.77, significantly exceeding the earnings elasticities in Table 2. In contrast, the estimated household income elasticities with respect to parental earnings are only slightly higher than the estimated earnings elasticities (Online Appendix Table B.3). This suggests that parental advantages are more strongly transmitted across generations when considering the overall household well-being of parents. Furthermore, the household income elasticity estimates based on mothers' characteristics are higher than those based on fathers' characteristics. This suggests that using highly dispersed female earnings to predict mothers' earnings lowers the *IGE* estimates for mothers (9). We argue that the elasticity estimates based on mothers' household income are more reliable than those based on earnings because the latter 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., 2019).

6.2 Intergenerational Rank Mobility

We next report our rank-based mobility estimates, for which we offer a theoretical background in Section 3.3. Briefly, these measures capture the association between the *relative positions* of children and parents in

the distribution rather than their incomes. First, we rank both children and their parents according to their earnings and household incomes. Then, we estimate the rank-rank slope by regressing children's percentile rank on their parents'.

We present our rank-rank slope estimates for earnings in Table 5 and for household incomes in Table 6. Consistent with our previous results, the gap between the estimates for daughters and sons disappears when we use household incomes.[37] In the following, we focus on our *household income* estimates because it better reflects the overall economic status of individuals and allows for a better comparison between sons and daughters.

Table 5: Rank-Rank Slope Estimates for Earnings

	Father's Rank	Mother's Rank
Sons	0.326 (0.011) [7809]	0.284 (0.019) [3101]
Daughters	0.503 (0.019) [3101]	0.567 (0.031) [670]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets. Sons and daughters are ranked separately. Fathers and mothers are ranked separately.

Table 6: Rank-Rank Slope Estimates for Household Income

	Father's Rank	Mother's Rank
Sons	0.410 (0.009) [10170]	0.386 (0.016) [4109]
Daughters	0.421 (0.006) [10426]	0.385 (0.011) [4350]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets. Both sons and daughters are ranked together, whereas fathers and mothers are ranked separately. See Online Appendix Table A.14 for the estimated rank-rank slopes when sons and daughters are ranked separately.

Our estimates from Table 6 imply that a ten-percentile increase in 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

[37] Since rank-rank slope is a scale-invariant measure, this finding confirms that the shrinking gap between these estimates is not a mechanical result of dispersion differences between earnings and household incomes.

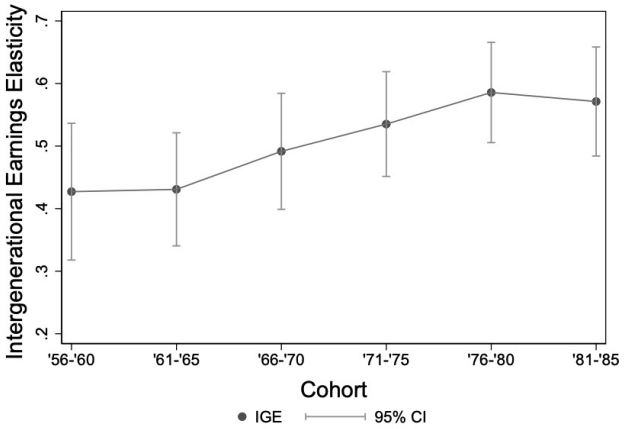
(0.34 by Chetty et al. 2014) and in the Nordic countries (around 0.2 by Bratberg et al. 2017).[38]

6.3 Intergenerational Mobility over Time

We next explore how intergenerational mobility has changed for different birth cohorts. Since our data only contains one cross-section of children, we can only comment on changes in mobility by comparing different cohorts of descendants. This means that we cannot disentangle the cohort-fixed effects from the time trend. As a result, our findings may not accurately reflect changes in intergenerational mobility over time and should be interpreted with caution.

We present our *IGE* estimates for sons in Figure 1. Our results indicate a clear upward trend in intergenerational persistence, except for the youngest cohort. However, we should note that our data may not be suitable for examining changes in mobility over time, and visual inspection alone could be misleading.[39] We nevertheless conduct a similar analysis for daughters and sons separately and present our household income elasticity estimates for both genders across birth cohorts in Figure 2. Our results reveal similar trends for both genders, except that intergenerational persistence steadily increases for daughters, including the youngest cohort.

Figure 1: *IGE* Estimates by Birth Cohorts

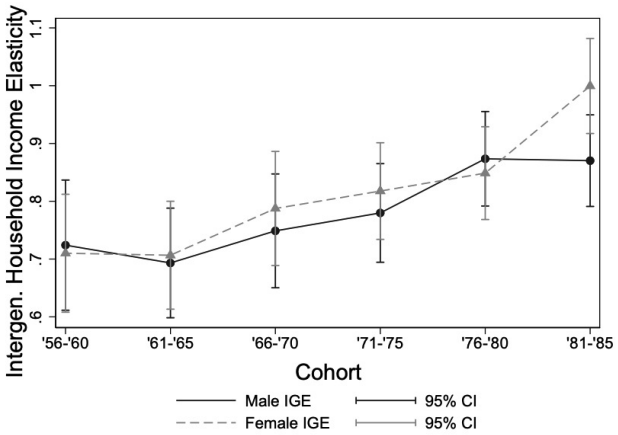


Notes: Confidence intervals are calculated using bootstrap standard errors. The x-axis displays the birth cohort of sons. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort.

[38] We also use rank-based measures to examine regional patterns of intergenerational mobility in Turkey. However, the available data is not ideal for such analysis. Therefore, we relegated our results to Online Appendix C for future reference.

[39] Several factors may affect the accuracy of our results. First, the differences in the estimated elasticities between cohorts could be due to varying educational opportunities available to each cohort (Torul and Öztunalı, 2017). Second, the variation in educational attainment among fathers of different cohorts could also impact our results. This can be problematic as we assume that the returns to education are the same for all fathers.

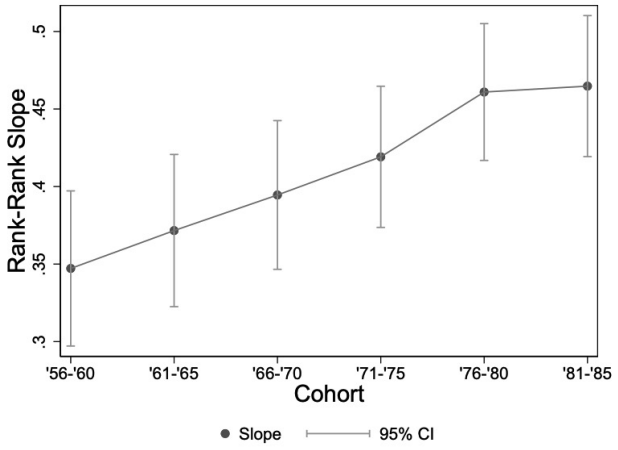
Figure 2: Household Income Elasticity Estimates by Birth Cohort of Sons and Daughters



Notes: 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 also explore how positional mobility changed across different cohorts. Figure 3 displays the evolution of the rank-rank slope estimates for fathers' and sons' household incomes. Our results show a significant decrease in positional mobility over time. This confirms that the decline in Turkey's mobility is not a mechanical by-product of increasing economic inequality over cohorts. These trends are similar to those observed in other countries such as the US (Davis and Mazumder, 2017) and Denmark (Landersø and Heckman, 2017).

Figure 3: Positional Mobility by Birth Cohorts of Sons



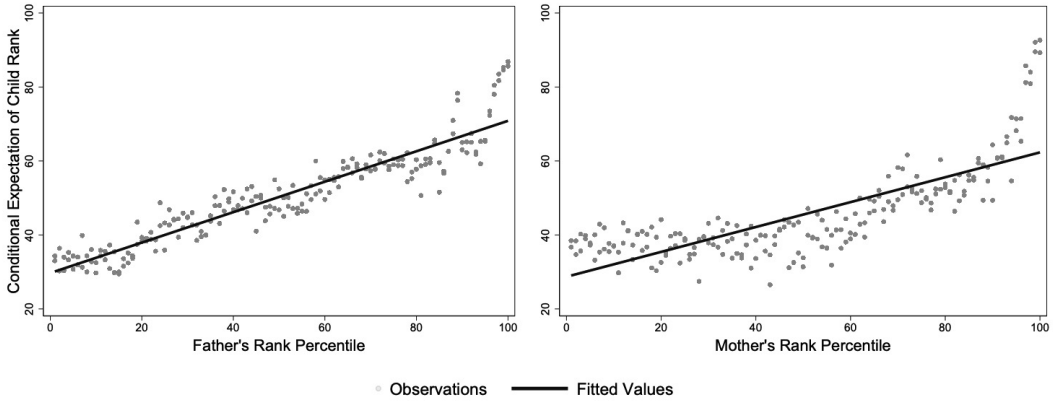
Notes: Confidence intervals are calculated using bootstrap standard errors. Both fathers and sons are ranked according to their household income. Sons are ranked within their own cohort, and fathers are ranked with fathers with children in the same cohort. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort.

6.4 Intergenerational Mobility across the Income Distribution

Both *IGE* and the rank-rank slope measure only the *average persistence* in the society; they do not provide information about the actual mobility dynamics around this average (Jäntti et al., 2014). Recent studies show that the degree of mobility varies significantly across income distribution. Palomino et al. (2018), using quantile regression methodology, show that *IGE* estimates exhibit a U-shaped pattern across the distribution in the US. Similarly, Bratberg et al. (2017) report higher persistence in the two tails of income distribution for Germany, Norway, Sweden, and the US.

We next present intergenerational mobility curves and quintile transition matrices to illustrate mobility patterns over the national income distribution. We use household income to rank children and predicted household income to rank parents to cover the entire distribution.

Figure 4: 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 4 plots the mean ranks of children with parents in each percentile. Our results show that the expected child rank rises sharply over the parental rank at the top of the distribution. Moreover, while children's rank increases almost linearly over their fathers' rank, it exhibits a non-monotonic pattern over their mothers' rank. Specifically, the expected rank of children is almost orthogonal to their mothers' rank unless she comes from the richer half of the income distribution.[40] When born to above-median mothers, children's expected rank increases almost exponentially over their mother's rank.

Figure 5 displays the quintile transition matrices for 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

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

with household income in the quintile provided by the row.[41]

Figure 5: Household Income Quintile Group Transition Matrices for Fathers

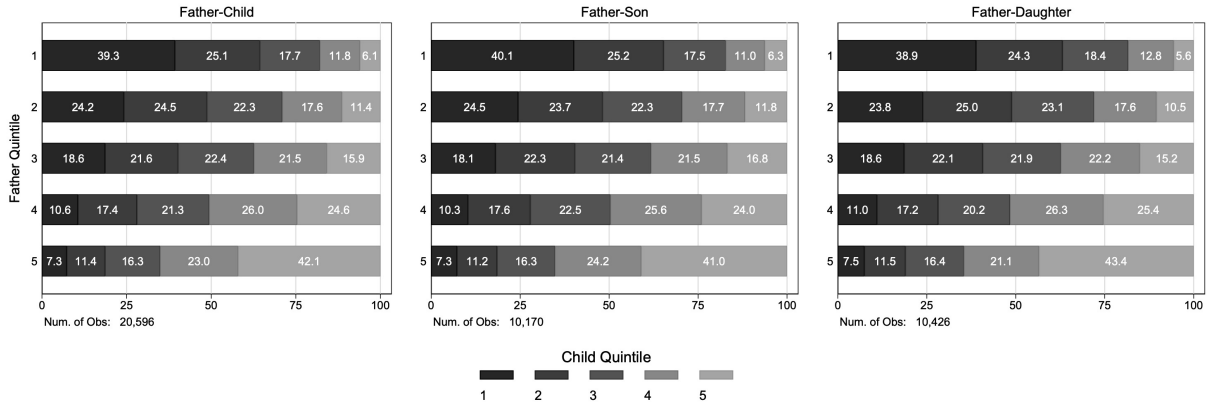


Figure 6: Household Income Quintile Group Transition Matrices for Mothers

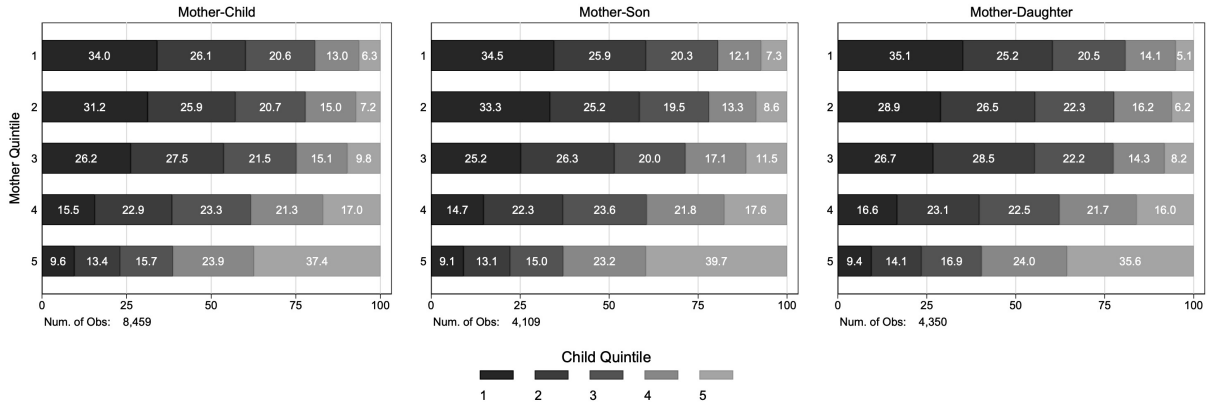


Figure 5 reveals that the richest and poorest quintiles exhibit the highest persistence levels: 39% (*42%*) of children with fathers from the first (*fifth*) quintile remain in the same position. Further, intergenerational mobility patterns of sons and daughters do not differ much. Figure 6 displays similar matrices for mother-child pairs. Again, intergenerational persistence changes non-monotonically over mothers' positions, as seen in the mobility curves.

6.5 Robustness Checks

We next check the robustness of our main estimates in Table 2 by running alternative regressions. First, we change our sample selection criteria and treatment of outliers. While it is necessary to introduce certain stan-

[41] Note that perfect mobility requires a value of 0.20 in each cell, whereas zero mobility requires a value of 1 in diagonal cells and 0 elsewhere.

dards to define active workers, excluding a considerable part of the population might cause inconsistencies, particularly for women in our sample. Accordingly, we repeat our regressions, including part-time workers and everyone with non-zero earnings. We present our results in Table 7. When there is no earnings threshold, daughter elasticities increase significantly, indicating the presence of a considerable number of females with very low incomes in the population.[42]

Table 7: *TS2SLS* Estimates Using Different Income Criteria

	Includes Part-Time, Annual Earnings>244 Liras		**Everyone with Non-zero Earnings**	
	Father	Mother	Father	Mother
Sons	0.52	0.37	0.52	0.37
	(0.018)	(0.026)	(0.018)	(0.027)
	[7992]	[3195]	[8634]	[3101]
Daughters	1.04	0.83	1.23	0.91
	(0.042)	(0.043)	(0.048)	(0.053)
	[1950]	[763]	[3452]	[1056]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets. In columns 1 and 2, we include part-time workers but still exclude those with very low annual earnings (below 244 Turkish Liras). In columns 3 and 4, we include everyone with positive earnings in the sample.

Following Haider and Solon (2006), we use age-corrected income measures in our benchmark estimations. We also report our estimates based on reported incomes with age controls instead of age-corrected counterparts in Online Appendix Table A.6. 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 earnings, and top-coding very high earnings. Following their methodology, we re-estimate our benchmark father-son regressions and report our results in Table 8. The resulting estimates do not vary significantly with the choice of outlier treatment. However, elasticity estimates are slightly higher when we use reported household incomes of sons aged 30-34 instead of 35-39.

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

Table 8: *TS2SLS* Estimates for Sons with Different Outlier Treatments

	Benchmark		Bottom-Coded		Top-Coded		Both	
Sample	Earnings	Household Income	Earnings	Household Income	Earnings	Household Income	Earnings	Household Income
Complete Sample	0.52	0.76	0.53	0.76	0.51	0.74	0.53	0.76
	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
	[5117]	[6690]	[5641]	[6690]	[5117]	[6690]	[5641]	[6690]
Age 30-34	0.52	0.86	0.54	0.85	0.51	0.85	0.53	0.84
	(0.051)	(0.049)	(0.050)	(0.048)	(0.050)	(0.048)	(0.050)	(0.047)
	[1007]	[1192]	[1083]	[1192]	[1007]	[1192]	[1083]	[1192]
Age 35-39	0.53	0.77	0.54	0.76	0.52	0.76	0.53	0.75
	(0.053)	(0.054)	(0.055)	(0.053)	(0.052)	(0.053)	(0.054)	(0.052)
	[872]	[1004]	[930]	[1004]	[872]	[1004]	[930]	[1004]

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

We also estimate intergenerational elasticities using the income measures of children predicted the same way as their parents. We present these results in Table 9. Our findings indicate that intergenerational persistence of earnings is largely captured by the observed characteristics of children. However, household income elasticities differ from those reported in Table 4, suggesting a significant contribution of correlation between parental incomes and unobserved heterogeneity in children's incomes.

Table 9: *TS2SLS* Estimates using Predicted Incomes for Both Generations

	Earnings		**Household Income**	
	Father	Mother	Father	Mother
Sons	0.48	0.28	0.50	0.53
	(0.009)	(0.018)	(0.009)	(0.018)
	[7809]	[3101]	[8403]	[3447]
Daughters	0.88	0.70	0.82	0.88
	(0.026)	(0.024)	(0.014)	(0.018)
	[1743]	[670]	[3509]	[1888]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets. Sample sizes are smaller than the benchmark case for household income as occupation information is lacking for some individuals who report a positive household income.

Finally, we repeat our estimations using parental education and occupation as separate instruments in the first stage. We present our results in Table 10. 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 improves the predictions for parental income measures, it could also bias the estimates upward. Conversely, using occupation as the only predictor of parental income measures results in slightly lower estimates. This suggests that the direct effect of occu-

pation 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, which could potentially bias our results. However, the direction of this bias cannot be determined.

Table 10: Estimated Elasticities using a Single Instrument for Parental Income

	Instrument: *Education*				Instrument: *Occupation*			
	Earnings		**Household Income**		**Earnings**		**Household Income**	
	Father	Mother	Father	Mother	Father	Mother	Father	Mother
Sons	0.92	0.75	1.01	1.08	0.45	0.31	0.66	1.01
	(0.033)	(0.047)	(0.022)	(0.034)	(0.019)	(0.025)	(0.022)	(0.049)
	[7809]	[3101]	[10170]	[4109]	[7923]	[3135]	[10318]	[4150]
Daughters	1.39	1.26	1.08	1.14	0.95	0.79	0.70	1.11
	(0.064)	(0.067)	(0.022)	(0.036)	(0.047)	(0.045)	(0.022)	(0.052)
	[1743]	[670]	[10426]	[4350]	[1775]	[682]	[10652]	[4424]

Notes: Bootstrap standard errors are in parentheses, and sample sizes are in brackets. Sample sizes are larger when occupation is used as an instrument since some individuals report their parents' occupation but not their education.

7 Concluding Remarks

This paper examines the extent of intergenerational income mobility in Turkey and provides cross-country comparable estimates of intergenerational earnings and income elasticity. It aims to complement the previous literature on Turkey's intergenerational educational mobility and contribute to a more comprehensive understanding of intergenerational transmission in Turkey.

Using *TurkStat*'s *SILC* micro datasets and the *TS2SLS* methodology, we estimate intergenerational individual earnings and household income elasticities for father-son, father-daughter, mother-son, and mother-daughter pairs. Throughout our analysis, we reflect on the relationship between the returns on education and occupation, the structure of the female labor force, and intergenerational mobility. We further investigate intergenerational mobility heterogeneity over time, and income distribution. We also complement our estimates using alternative mobility measures such as the rank-rank slope and transition matrices. Our findings offer several novel insights that are robust and significant.

We first report that the intergenerational earnings elasticity for father-son pairs is around one-half as in the US. There are, however, notable gender differences in our intergenerational mobility estimates. Specifically, the intergenerational earnings elasticity between fathers and daughters is twice as large as that between fathers and sons. This result is due to Turkey's low female labor force participation rate and the self-selection

of women into employment. Thus, when measured using household income, intergenerational mobility elasticities are similar (around four-fifths) for both sons and daughters. Our estimates further suggest a modest decline in intergenerational mobility for the more recent cohorts as in other countries. Our rank-rank slope estimate of two-thirds suggests weaker rank mobility in Turkey than in the US. Our estimated quintile transition matrices reveal heterogeneity across the income distribution and provide evidence of stronger intergenerational persistence at both ends of the parental income distribution. Various auxiliary regressions we estimate confirm that our main results are robust over numerous alternative specifications and datasets.

Intergenerational mobility governs *de facto* equality of opportunity. Moreover, the *Great Gatsby Curve* literature documents that intergenerational mobility correlates strongly with income inequality. As such, it is crucial for policymakers seeking to address economic inequalities to have a thorough understanding of how economic well-being is transmitted across generations. This paper aims to shed light on intergenerational income mobility in Turkey and contribute to the development of more effective policies for addressing economic inequalities and promoting social mobility.

Due to data limitations, our analysis is primarily descriptive. We believe that further research into the significant gender differences in intergenerational mobility in Turkey, particularly in light of the country's low female labor force participation rate and the notable gender pay gap, would be a valuable direction for future work.

Data Statement

The datasets we use for our analyses (*Survey of Income and Living Conditions* and *Household Budget Survey*) are confidentially acquired from the Turkish Statistical Institute and cannot be made publicly available. The replication files that use these datasets are available from the corresponding author upon request.

Supplementary Material

The link to the electronic supplementary material is as follows: Online Appendix

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