INTERGENERATIONAL EARNINGS MOBILITY IN TURKEY:

A COMPARABLE ESTIMATE

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ABSTRACT

Intergenerational Earnings Mobility in Turkey:

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In this paper, we empirically examine the extent of intergenerational income mobility in Turkey. We do this by providing cross-country comparable estimates of intergenerational earnings and income elasticities (IGE) using a *two-sample instrumental variable method.* In doing so, we exploit retrospective information on parental education and occupation from the Survey of Income and Living Conditions by TurkStat. First, we find that the intergenerational earnings elasticity between fathers and sons in Turkey is around 0.5 indicating a similar level of mobility with the US. Second, we reveal an immense effect of parents' earnings on daughters' earnings with the estimated elasticities around 1. We document that this results from historically low labor force participation and the self-selection of females into employment in Turkey. Accordingly, household income mobility appears to be similar for both sons and daughters. Third, we observe a decline in mobility for more recent cohorts. Fourth, descendants residing in more affluent regions of Turkey are more likely to have experienced upward mobility. Finally, we complement our analysis using alternative mobility measures such as rank-rank slope, degree of upward mobility and presenting mobility transition matrices, which reveal stronger persistence on extreme ends of the income distribution. Our findings mostly align with the previous literature on intergenerational educational mobility in Turkey.

ÖZET

Türkiye'de Kuşaklararası Gelir Hareketliliği:

Karşılaştırılabilir Bir Tahmin

Bu çalışmada Türkiye'de kuşaklararası gelir hareketliliğinin boyutunu inceledik. Bunu yaparken *çift-örneklem araç değişken metodunu* kullanarak kuşaklararası ücret ve gelir esnekliğini hesapladık. Bu hesaplamada Türkiye İstatistik Kurumu Gelir ve Yaşam Koşulları Anketi verilerinde bulunan ebeveynlerin geriye dönük eğitim ve meslek bilgilerinden faydalandık. İlk olarak, babalar ve oğullar arasında kuşaklararası ücret esnekliğini 0.5 olarak hesapladık. Bu değer, Türkiye'de kuşaklararası hareketliliğin Amerika Birleşik Devletleri'yle benzer seviyede olduğunu göstermektedir. İkinci olarak, bulgularımız kız çocuklarının ücreti üzerinde ebeveyn ücretlerinin yüksek etkisi olduğunu göstermekte. Ancak, analizimiz bu yüksek etkinin Türkiye'de kadınların işgücüne düşük katılımından kaynaklandığını ortaya koymakta. Kuşaklararası hanehalkı gelir hareketliliğinin kız ve erkek çocukları için benzer düzeylerde olması bunu onaylar niteliktedir. Son olarak, Türkiye'de kuşaklararası hareketliliğin zaman içerisinde düştüğünü gözlemledik. Ek olarak, bulgularımızı ebeveynlerin ve çocukların gelir dağılımındaki pozisyonlarının ilişkisine dayanan eğim ve geçiş matrisleri gibi alternatif hareketlilik ölçütleriyle de destekledik. Sonuçlarımız, halihazırda bulunan Türkiye'de kuşaklararası eğitim hareketliliği üzerine bulgularla uyum göstermektedir.

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CHAPTER 1

INTRODUCTION

Cross-sectional inequalities have been the subject of considerable attention in recent decades.[1] Rapidly growing *intergenerational mobility* literature focuses on how existing inequalities persist across generations. [2] While the extent of mobility has been measured for many countries, Turkey remains an exception. This study investigates the intergenerational mobility in Turkey and provides a cross-country comparable measure of mobility.

Previous empirical studies estimate *intergenerational elasticities* (IGE) to measure the association between the economic outcomes of parents and children. The most commonly used summary measure is the intergenerational *earnings* elasticity, i.e., the coefficient from log-log regression of children's lifetime earnings on parents'. Although the earlier literature mainly focus on measuring mobility in developed countries, estimates of intergenerational earnings elasticity in developing countries have recently proliferated.[3] Meanwhile, the literature has been limited to intergenerational *educational* mobility in Turkey due to data limitations. Accordingly, despite its persistently high income inequality and distinct labor market structure, Turkey lacks a detailed analysis of intergenerational income mobility.

This study provides a detailed analysis of intergenerational income mobility in Turkey using the Turkish Statistical Institute's (TurkStat) Survey of Income and Living Conditions micro data sets covering 2005 to 2017. Our main contribution is to estimate intergenerational earnings and income elasticities using the *two-sample instrumental variable* (TSIV) methodology to overcome the data restrictions. (Björklund and Jäntti, 1997) We also show that the extent of

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[1]See Piketty (2014), Atkinson (2015), and Milanovic (2016) for recent discussions. See also Krueger et al. (2010) and the special issue of *Review of Economic Dynamics*, which focuses on cross-country comparison of inequalities.

[2]See Corak (2013) and Black and Devereux (2011) for a comprehensive discussion on the subject.

[3]For instance, Narayan et al. (2018) provide estimates for a broad set of countries. Also, a special issue of *The B.E. Journal of Economic Analysis & Policy* contains an analysis of intergenerational mobility in few developing countries.

mobility considerably differs over *gender*, *geography*, and *time* in Turkey. Our findings complement the previously documented patterns of intergenerational educational mobility and inequalities in Turkey.

To consistently estimate the intergenerational elasticities, we first predict parents' earnings, and income using retrospective information on parental characteristics. We use children's report of their parents' educational attainments and occupations, which is available in the *Intergenerational Transmission of Disadvantages Module* provided with the 2010 SILC cross-sectional data set. For the predictions of parental earnings and income, we use pooled SILC cross-sectional data. We found that the TSIV estimate of intergenerational earnings elasticity is around 0.52 for father-son pairs. Cross-country comparison indicates that Turkey exhibits a mobility level similar to the least mobile developed countries such as the US and the UK. Several additional findings emerge from our analysis.

First, we document that the intergenerational earnings elasticity between daughters and fathers is around 1, which suggests that earnings inequalities between fathers are perfectly inherited by their daughters. Later, we show that this striking result is due to Turkey's historically low female labor force participation rate. In particular, parental effect on daughters' outcomes is overestimated due to the self-selection of females into employment. Accordingly, our estimates of intergenerational elasticity of equivalised household income imply similar mobility levels for daughters and sons. We show that parental earnings are correlated with both their childrens' and their spouses' earnings similarly and document that assortative mating plays a key role in the intergenerational persistence of household income.

Second, we complement our analysis by estimating rank-based mobility measures. Unlike IGE, our rank-rank slope estimates imply a slightly lower level of mobility in Turkey than in the US. Further, using rank-based measures, we show that descendants residing in more affluent regions are more likely to have experienced upward mobility. Moreover, we present quintile group transition matrices to illustrate patterns across the income distribution. In line with the previous literature, intergenerational persistence appears to be strongest in the top and bottom quintile.

Third, we investigate intergenerational mobility over time. Our findings imply a decline in intergenerational mobility over birth cohorts except for the youngest cohort for sons. We observe a similar trend using rank-rank slope, which is robust to changes in inequality over cohorts. We also show that younger cohorts are less likely to experience upward mobility.

Finally, we provide alternative estimations and verify that our estimates are not sensitive to different specifications.

The rest of the paper is organized as follows: In Section 2, related literature is reviewed; in Section 3, the theoretical background is established; in Section 4, data is described; in Section 5, estimation methodology is presented and results are reported, and in Section 6, findings are discussed and concluded.

CHAPTER 2

LITERATURE REVIEW

The number of studies measuring the degree of intergenerational transmission has increased rapidly in recent decades. Solon's (1992) seminal work, pointing out the sources of bias in the earlier studies, provided a standard methodology to measure intergenerational persistence.[1] Since then, the earlier focus has been on measuring mobility for developed countries. (e.g., Österbacka (2001) on Finland, Bratberg et al. (2005) on Norway and Corak and Heisz (1999) on the US and Canada.) However, following the developments in the methodology and data availability, comparable estimates for many developing countries also became available. (Narayan et al. (2018)) Our study is mainly motivated by the lack of such a measure and a comprehensive analysis of intergenerational economic mobility for Turkey.

Being among the most unequal countries within the OECD, Turkey's economic inequalities are well studied in the literature. Tansel et al. (2018), focusing on wage inequality, report 90/10 and 90/50 ratios for different gender, age, sector, and education groups. They find a slight increase in wage inequality using the Survey of Income and Living Conditions(SILC) over the 2005-2011 period. Filiztekin (2015) decomposes income inequality over various sub-groups of the population while also studying regional idiosyncrasies. The most recent study by Tamkoc and Torul (2020) provides cross-country comparable measures of economic inequalities in Turkey. Moreover, they show a recent downward trend in wage inequality which aligns with the rapid minimum wage growth. While patterns in cross-sectional inequalities across subgroups and over time are well-documented, no study has investigated the transmission of inequality across generations yet.

The main reason behind the absence of such studies is the lack of long-running longitudinal data sets for Turkey. Ideally, an analysis of

[1] For example Becker and Tomes (1986) reports intergenerational earnings elasticity estimates ranging between 0.15-0.28 which turned out to be strikingly smaller than the actual value.

intergenerational income mobility necessitates data throughout both parents' and their descendants' working life. Such datasets like the Panel Study of Income Dynamics (*PSID*) for the U.S. and longitudinal income tax records for Sweden and Canada enabled researchers like Solon (2002), Corak and Heisz (1999), and Österberg (2000) to consistently measure intergenerational income mobility. In this context, Mazumder (2018) reviews the contributions of the PSID to understanding the various aspects of intergenerational mobility in the United States. Unfortunately, the SILC follows individuals over at most four years. Moreover, SILC provides data on parents only if they are living with their children at the time of the survey. The only study that attempted to measure intergenerational income mobility in Turkey, Mercan and Barlin (2016), use these co-residing father-son pairs in their analysis. Therefore, their estimates not only suffer from measurement error but also depend on an unrepresentative dataset. By using a nationally representative dataset, we believe our paper provides a more reliable estimate.

On the other hand, few studies are available on intergenerational *educational* mobility in Turkey. Since educational attainment is usually constant through adulthood and many surveys include questions on parental education, data requirements are relatively easier to meet.[2] Using the Adult Education Survey (*AES*) in 2007, Tansel (2015) studies intergenerational mobility over time. The author also finds that mothers' educational background more strongly affects children's outcome than fathers' and intergenerational associations are stronger when parental educational attainment is the lowest.[3] Oztunali and Torul (2019), also using a similar methodology, reveal that children's likelihood of having the same educational attainment as his/her more educated parent declines over time. They also document that the degree of intergenerational educational mobility

[2]Despite the widespread availability of data, the cardinal specification of education is not straightforward and poses various challenges through the econometric analysis. For the extended discussion see Oztunali and Torul (2019) and Torul and Öztunali (2017)

[3]The lowest educational attainment group is defined as "illiterate or literate but not graduate of any school".

exhibits immense heterogeneities over various socio-economic factors. Aydemir and Yazici (2019), using micro-data from their own survey, find a positive relationship between intergenerational educational mobility and regional development. Our paper, complementing these studies, provides a complete illustration of intergenerational mobility in Turkey.

Recent *Fair Progress* report by Narayan et al. (2018) paints the most comprehensive picture of intergenerational mobility around the world. Unfortunately, Turkey is not among the 75 countries for which the intergenerational income elasticities are provided. Another comprehensive work by Hertz et al. (2008) presents 50-year trends of mobility for 42 developed and developing nations also excludes Turkey. Lately, studies on intergenerational income mobility in developing economies enumerated. Among them, Dunn (2007) estimates intergenerational earnings elasticity in Brazil to be in the range of 0.69-0.85. Nunez and Miranda (2010) find estimates for Chile in the range of 0.57-0.74 using data on father-son pairs. Both of these studies, among many, use the two-sample instrumental variable (TSIV) method, which has looser data requirements.[4]

In this paper, we similarly use the TSIV method to provide a cross-country comparable estimate. Two-sample instrumental variable estimator was first introduced by Angrist and Krueger (1992) and later popularized in the intergenerational mobility literature by Björklund and Jäntti (1997). The TSIV method allows estimation of intergenerational elasticity when children's and fathers' incomes are available in two different datasets in the absence of longitudinal data. Specifically, available parental characteristics are used to predict parental income, which is then used in intergenerational regression. Often, fathers' educational attainment and social class are used to predict their income, as in Dearden et al. (1997) and Lefranc and Trannoy (2005). Nevertheless, other instruments such as sector and geographical dummies as in Piraino (2007) for Italy

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

and firm-size as in Lefranc et al. (2014) might also be included in the prediction of parental income.[5]

Another strand of literature focuses on variations in intergenerational mobility levels across the earnings distribution or over various subgroups. While early literature solely focuses on father-son pairs, recent studies also report estimates based on samples of father-daughter, mother-son, and mother-daughter pairs. Among the first attempts, Chadwick and Solon (2002) reveal that intergenerational elasticity of earnings is lower for daughters in the U.S. Similar patterns have been observed by Jäntti et al. (2014) in Nordic countries and by Lefranc et al. (2014) in Japan. However, Dearden et al. (1997) document that the pattern is reversed for Britain. Intergenerational mobility also exhibits immense heterogeneities across different parts of the income distribution. Österberg (2000) and Dearden et al. (1997) complement their estimates with transition matrices, both revealing stronger persistence at the tails of the income distribution. Also, Jäntti et al. (2014) use transition matrices to compare intergenerational mobility across countries over the whole income distribution.[6] Further, Bratberg et al. (2007) and Palomino et al. (2018) use quantile regressions and draw similar conclusions analyzing Norway and the US, respectively.

[5]Previous work by Checchi et al. (1999) on intergenerational mobility in Italy relies on the relatively crude measure: mean earnings of each occupation.

[6]See also Chetty et al. (2014) for the state-of-the-art utilization of transition matrices for a comprehensive analysis of mobility in the US.

CHAPTER 3

THEORETICAL BACKGROUND

3.1 Issues in the IGE Estimation

In the estimation of IGE, the baseline relation between parents' and children's income status is summarized by the equation(Becker and Tomes (1986):[1]

$$y_c = \alpha + \beta y_p + \epsilon \tag{3.1}$$

where y_c and y_p represent children's and parents' log lifetime earnings, respectively. If both are directly observed for a *random* sample of families, one could estimate β applying least squares regression.

However, lifetime earnings are not directly observable. 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, where the relation is,

$$y_{ct} = y_c + v_{ct} \tag{3.2}$$

$$y_{ps} = y_p + v_{ps} \tag{3.3}$$

where v stands for transitory earning shocks. The conventional method is to average over multiple years of observed earnings. In that case, assuming transitory shocks are i.i.d., the probability limit of the OLS estimate using averaged earnings is

$$plim\hat{\beta} = \beta \frac{\sigma^2_{yp}}{\sigma^2_{yp} + \sigma^2_{vp}/T} \tag{3.4}$$

Notice that the attenuation factor increases with the variance of transitory errors, σ^2_{vp}, 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.[2] While the convention is to average over at least 5 years

[1] Most of the empirical literature reports IGE estimated using father-son pairs due to the availability of data. We, instead, will also present our results for mother-son, mother-daughter, and father-daughter pairs.

[2] Notice that σ^2_{vc} does not appear in equation 4, implying, under the assumption of purely

following Solon (1992), Mazumder (2005) shows that taking progressively longer multiyear averages further improves the IGE estimates.[3] As a result, even when multiple years of observations are available, OLS estimates of IGE might well be downward-inconsistent.[4]

Another source of bias is the life-cycle variations of income which is not represented in the equations above. While we are interested in both generations' adult earnings, we systematically observe children relatively early and parents relatively late in their life cycles. As Haider and Solon (2006) have shown, the relationship between lifetime income and current income varies over the life cycle. Therefore, instead of equations 2 and 3, a more accurate formulation would be

$$y_t = \lambda_t y + v_t \tag{3.5}$$

for both generations, where λ_t depends on age and need not equal one. Correspondingly, even when transitory errors are assumed to be homoscedastic and i.i.d., the individual's age at the time of measurement might generate bias in the IGE estimates. Hence, equation 4 can be rewritten as:

$$\text{plim}\hat{\beta} = \beta\overline{\lambda}_{ct}\overline{\lambda}_{pt}\frac{\sigma^2_{yp}}{\overline{\lambda^2}_{pt}\sigma^2_{yp} + \sigma^2_{vp}/T} \tag{3.6}$$

where $\overline{\lambda}_{pt}$ and $\overline{\lambda}_{ct}$ represent the multiple-year average of λ_t for parents and children, respectively. Haider and Solon (2006) provide evidence that the λ_t equals 1 around age 40 for men, using data on complete earnings histories of individuals in the US. Their estimates of λ_t start as low as .2 at age 20, monotonically rising

transitory and homoscedastic errors, the IGE can be consistently estimated even when a single year of children's earnings is used. However, averaging over children's earnings alter the precision of the IGE estimate. As the variance of transitory earning shocks experienced by the children,$\sigma^2_v c$ appears in the probability limit of R statistic, $plim R = \frac{\beta\sigma^2_{yp}}{\sqrt{(\sigma^2_{yp}+\sigma^2_{vp})(\sigma^2_{yp}+\sigma^2_{vc})}}$.

[3]More precisely, the IGE estimate for the US rises from about .25 when T=2 to .45 when T=7, and up to .61 when T=16.

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

until age 40, then falls again to about $.6 - .8$ later in life.[5] Hence, the life-cycle variation of earnings is likely to bias IGE estimates further down. The main implication behind this result is that people with higher lifetime earnings tend to have steeper initial earning growth, and differences in earnings observed at earlier ages understate the differences in lifetime earnings.[6]

Equation 6 also assumes the variance of transitory earning shocks, σ_{v}^{2}, is constant over the life cycle. However, Baker and Solon (2003) and Grawe (2006) provide evidence that σ_{vt}^{2} too depends on age and is at its minimum around age 40. Hence, we try to acquire earning measures representative of age 40 earnings to minimize bias stemming from both λ_t and σ_{vt}^{2}. Methods employed to this end are discussed in detail in the following sections.

Lastly, reliance on unrepresentative samples biases IGE estimates severely. Depending on the nature of the dataset used; attrition, self-selection, or sampling design may result in unrepresentative samples. As Solon (1992) emphasized, when the sample is relatively more homogenous, the estimated IGE will be downward biased due to the lower "signal-to-noise" ratio. Even when that is not the case, the IGE estimate will represent the mobility within the subgroup instead of the whole population. We believe that the most serious pitfall that biased the estimates of Mercan and Barlin (2016) was using a sample of children co-residing with their parents, which is unrepresentative of the population of interest.

3.2 IV and TSIV Estimation

Another approach to address the errors-in-variables problem is using IV estimation. The idea is to exploit variation in parents' earnings, y_p, by using parental education, e_p as an instrument to estimate equation 1. However,

[5] Whereas measuring children's earnings further from the age of 40 would bias IGE estimates downward, for fathers, the effect would be in the opposite direction.

[6] Böhlmark and Lindquist (2006) come to similar conclusions using Swedish register data. See also Grawe (2006), which inspects 20 studies and various data sets and show that estimates of IGE fall as the father's age increases.

parents' education is not necessarily a valid instrument since it might directly affect descendants' earnings status even after controlling for parental earnings. In this scenario, the structural equation can be specified as:

$$y_c = \alpha + \beta_1 y_p + \beta_2 e_p + \epsilon \tag{3.7}$$

Nonetheless, as argued in Björklund and Jäntti (1997), the inconsistency of the IV estimator is in an upward direction whenever the direct effect of parental education on the earnings of children is positive.[7] Hence, the IV estimate provides an upper bound and is often used together with the downward-inconsistent OLS estimate to bracket the IGE.

A special case of IV estimation is the two-sample IV, which is introduced to the intergenerational mobility literature by Björklund and Jäntti (1997). Two-sample IV, as the name suggests, makes use of an outside data set to predict parental earnings using parental characteristics reported by children. TSIV estimate is equivalent to

$$\hat{\beta} = \frac{Cov(y_c, \mathbf{X_p})}{Cov(y_p, \mathbf{X_p})} \tag{3.8}$$

where $\mathbf{X_p}$ is the vector of explanatory variables used to predict parental earnings. Notably, denominator and numerator are estimated from different samples.[8] As Björklund and Jäntti (1997) indicate, the TSIV estimator is equivalent to the IV estimator whenever both samples are from the same population, and parents' characteristics reported by children are not noisier than the parents' own report. The conditions are well met by our data set since parental characteristics are not drawn from an outside sample; instead, they are simply attached to a single cross-section of our larger pooled data.

[7] 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 examples from the intergenerational mobility literature.

[8] The exact name of the method is the two-sample 2SLS which is equivalent to TSIV when the same sample is used in both stages. Inoue and Solon (2010) provide a comparison of TS2SLS and TSIV.

While it is possible to draw informative conclusions about intergenerational mobility even under limited data, using OLS and IV estimates together, interpretation of IGE estimates is not possible with unrepresentative data sets. In this context, the TSIV method mostly derives its value from rendering representative data sets useful for analysis.

CHAPTER 4

DATA AND KEY VARIABLE DEFINITIONS

We use micro-data from the Survey of Income and Living Conditions (SILC) covering the period 2005-2017 by the Turkish Statistical Institute (TurkStat).[1] SILC has been published annually in the form of both cross-sectional and panel data sets that are nationally representative.[2] SILC cross-sectional data set covers at least 9,200 households per year and provides detailed information on income sources of households and individuals. SILC 2010 cross-section additionally provides *Intergenerational Transmission of Disadvantages Module*, which contains valuable information for our analysis.

Throughout our analysis, we restrict our sample to individuals between 20 and 64 years of age and with positive household incomes. We convert nominal variables into real units by deflating via the Turkish consumer price index (CPI), for which we use the base year as 2005. In estimations that we focus on employed individuals we also exclude those whose *annual* earnings are below 244 Turkish liras (i.e., half of the monthly minimum wage in the year 2005) or work less than 30 hours a week. The descriptive statistics of the sample consisted of individuals satisfying the above criteria presented in the second and third columns of Table 1 and Table A.1.

In addition to income variables provided in the data, we construct *annual earnings* and *hourly wage rates* following the RED guidelines. (Krueger et al. (2010)) *Annual earnings* of individual i in year t is calculated as follows:[3]

$$ae_{i,t} = nw_{i,t} + rw_{i,t} + \alpha^{TR}(nse_{i,t} + rse_{i,t}) \tag{4.1}$$

[1] Reference year in SILC is the preceding calendar year. Accordingly, the datasets we have used were published between 2006-2018.

[2] SILC was first introduced in 2006 to provide income distribution statistics compatible with the European Union's official statistics. Thus, it provides detailed information on the income sources of households and individuals. More detailed information can be found at the official site of TurkStat.

[3] See Tamkoc and Torul (2020) for a comprehensive analysis of inequalities in Turkey, which also adheres to the RED guidelines.

where $ae_{i,t}$ denotes *annual earnings*, $nw_{i,t}$ and $rw_{i,t}$ denotes annual cash and other real payments, α^{TR} denotes the share of labor income in Turkey's national income at the year of observation, $nse_{i,t}$ and $rse_{i,t}$ denotes the cash and other real incomes from self-employment. Annual hours worked, $ah_{i,t}$, are calculated as weekly hours worked times weeks worked throughout the year.[4] We calculate hourly wage rate as:

$$w_{i,t} = \frac{ae_{i,t}}{ah_{i,t}} \tag{4.2}$$

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

We particularly focus on the SILC 2010 cross-sectional data set for our analysis. The additional module provides children's reports of their parents' education status and occupational code(ISCO-88) when the child was 14 years old. As shown in Table 1, 25,463 individuals between the ages of 25 and 59 answer the module questions, and 11,703 are full-time workers. [5] Descriptive statistics show no significant differences between these two samples.[6] Our two-sample IV estimates are based on the children observed within this data set. However, we use SILC cross-sectional data sets pooled over the period 2005-2017 to predict fathers' earnings using children's reports.

As mentioned before, the most salient problem rendering the SILC panel data set unusable is that we only observe children who live with their parents. Noticeably, all income measures are lower and less dispersed for children who live with their parents than their complete-sample counterparts, as displayed in column 4 of Table 1.[7] These differences cannot be explained solely with the

[4]SILC contains information on weekly hours worked and the number of months employed. However, 7.5% of those who report at least 30 weekly working hours did not answer the number of months employed. We have imputed month= 12 for those individuals.

[5]Consequently, our analysis in this section does not include individuals between the age of 20 and 25. Therefore, some estimates are slightly different and have smaller sample sizes.

[6]Figure A1 displays overlaid histograms of age and log earnings.

[7]Also in column 4 of Appendix Table A.1, and Table A.2

Table 1. Descriptive Statistics (SILC 2010 Cross-Section)

	Full Sample		Module Sample		Full-Time Workers		Live w/ Parent	
Male								
Age	39.99	(17.04)	40.31	(9.70)	39.16	(8.91)	33.85	(7.93)
Secondary Education or lower	0.68		0.64		0.62		0.61	
High-School Graduate	0.19		0.21		0.22		0.26	
University Graduate	0.11		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	0.68		0.85					
# of Observations	**19633**		**12499**		**9583**		**2010**	
Female								
Age	40.59	(17.73)	40.13	(9.69)	37.43	(8.34)	32.50	(6.60)
Secondary Education or lower	0.79		0.78		0.47		0.27	
High-School Graduate	0.12		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	(0.68)	8.80	(0.70)	9.24	(0.73)	9.16	(0.56)
Non-zero Earners	0.19		0.25					
# of Observations	**21046**		**12964**		**2120**		**379**	
Total								
Age	40.3	(17.40)	40.22	(9.70)	38.85	(8.83)	33.64	(7.75)
Secondary Education or lower	0.74		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					
# of Observations	**40679**		**25463**		**11703**		**2389**	

Note: Numbers in parentheses are standard deviations reported alongside mean values. Values reported in a single column are shares of the sample. 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.

different age compositions. As Figure 1 shows, even when observations are weighted to match complete-sample age distribution, earnings are much lower for those living with their parents.[8]

[8] See also Figure A.2

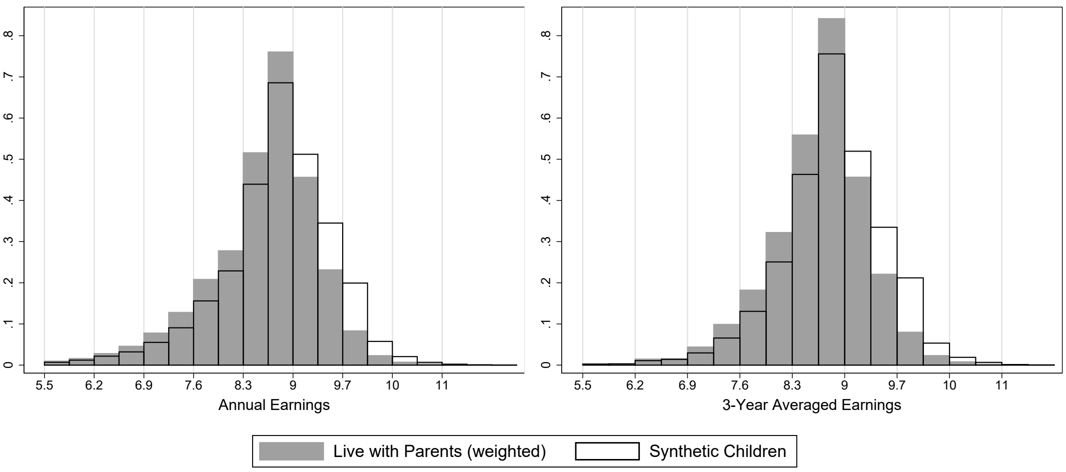


Figure 1. Earnings Histogram of Males

Notes: In both panels frequency of earnings of children who live with their parents and earnings of all individuals between ages 20-36 and report positive income are overlaid. The left-side panel depicts annual earnings from a cross-sectional dataset, while the right-side panel depicts 3-year averages of annual earnings from the panel dataset.

CHAPTER 5

RESULTS

A pervasive source of bias in the estimation of intergenerational elasticity is the life cycle effect.(Haider and Solon (2006)) As discussed in Section 3.1,the income of both generations should be measured around the age of 40 to address this issue. Controlling for the age in the IGE estimation would only partially decrease this bias. Accordingly, we prefer to construct age-corrected income measures with a similar method to the one applied by Jäntti et al. (2014).

First, using the pooled SILC cross-sectional dataset, we estimate the age effects on income measures. We do this separately for each gender and educational attainment group to account for the differences in age-income profiles. We repeat our regressions using five different income measures as the dependant variable: annual earnings, income, non-entrepreneurial income, hourly wage and household income.

The regression equation we use is as follows:

$$\log(y_i) = \alpha + \sum_{j=1}^{9} \beta_j \texttt{age}_{ij} + \sum_{k=2005}^{2017} \gamma_k \texttt{year}_{ik} + \epsilon_i \text{ if } \texttt{educ}_i = l \;\&\; \texttt{sex}_i = p \tag{5.1}$$

where $\log(y_i)$ refers to the logarithm of the income measure of person i ; `age` refers to dummy variables of age categories of 5-year intervals: ages 20 to 24, 25 to 29,...,55 to 59; `year` refers to the year of observation. We repeat this observation for each gender represented by `sex` and each of three educational attainment categories represented by `educ`: secondary education or lower, high school graduate, and university graduates. Then, the coefficients of age intervals are used to construct individuals' relevant income measures at the age interval of 35-39. [1] [2]

[1] See Aktuğ et al. (2020) for an extensive analysis of age-income profiles in Turkey using the Household Labor Force Survey(HLFS) by TurkStat. We also use the coefficients of age and education provided in their paper to predict individuals' *labor income* at the age interval of 35-39. Coefficients estimated from our sample are presented and compared with theirs in Appendix Table A.3

[2] 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. Results are available upon request.

Note that the individual-specific variations are preserved as we construct the age-corrected income measures using the ones reported instead of merely predicting them. In our estimations throughout the following section, we use age-corrected income measures for descendants.

5.1 Two-Sample Instrumental Variable Estimation

In this section, we present the TSIV estimation results. In the first stage, we predict parental incomes using the information on parents' education and occupation using the pooled cross-sectional data set.

Our first-stage estimation equation is as follows:

$$\log(y_i) = \alpha + \sum_{j=1}^{7} \beta_{1j}\texttt{educ}_{ij} + \sum_{l=1}^{9} \beta_{2l}\texttt{occup}_{il} + \sum_{m=1}^{7} \beta_{3m}\texttt{age}_{im} + \sum_{k=2005}^{2017} \gamma_{ik}\texttt{year}_{k} + \epsilon_i \quad \text{if} \quad \texttt{sex}_i = p \tag{5.2}$$

The above estimation is used to acquire coefficients for five different income measures: annual earnings, income,non-entrepreneurial income, hourly wage, and household income. Then parental income measures, again for the age interval 35-39, are predicted using the estimation coefficients.[3] We report first stage estimation results in Appendix Table A.4.

In the second stage, we regress age-corrected income measures of descendants on parents' predicted income measures. We present our intergenerational elasticity estimates in Table 2. The canonical measure of mobility, the intergenerational elasticity of earnings for father-son pairs, is 0.52 for Turkey. This finding indicates a relatively high degree of intergenerational persistence for Turkey. The comparable estimates for a few other countries are listed in Table 3. In this context, Turkey seems similar to the least mobile developed countries such as the US and the UK, yet displaying higher mobility than many of the developing countries.[4]

[3] A strong assumption of this procedure is that the relationship between characteristics and income measures in the pooled dataset is valid for the sample of true fathers.(Piraino (2007)) The validity of this assumption is discussed in Section 5.6.

[4] Grawe (2004) also provides even lower IGE estimates, such as 0.24 for Nepal and 0.32 for Pakistan. However, those estimates are excluded since they depend on small samples.

Table 2 also reveals that intergenerational persistence is highest for income, which also includes social assistance and unemployment benefits, and lowest for non-entrepreneurial income. Higher IGE estimates for broader measures of income are consistent with the earlier literature.(Lee and Solon (2009)) However, a lower IGE of non-entrepreneurial income is mainly a result of sample selection. Since self-employed descendants are excluded from the sample, the estimates reflect only the within-group mobility of labor earners.[5] Moreover, our estimates suggest a weaker effect of mothers' income on children's economic outcomes than fathers'. However, this pattern is not compatible with the findings of Tansel et al. (2018), which suggests a stronger effect of mothers' education on children's educational attainment than that of fathers'. We also suggest relying on elasticities with respect to mothers' own earnings can be misleading for the reasons we will discuss in the next section.

Table 2. TSIV Estimates of Intergenerational Elasticity in Turkey

Pairs	# of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7809]	0.52 (0.019)	0.62 (0.022)	0.40 (0.017) [5673]	0.49 (0.020)
Father-Daughter	[1743]	1.00 (0.042)	1.09 (0.047)	0.72 (0.038) [1451]	0.89 (0.039)
Mother-Son	[3101]	0.35 (0.025)	0.52 (0.038)	0.29 (0.025) [2037]	0.30 (0.025)
Mother-Daughter	[670]	0.81 (0.041)	0.99 (0.057)	0.61 (0.041) [509]	0.73 (0.041)

Note: Robust standard errors in parentheses. Numbers in brackets are the sample sizes.

5.2 Intergenerational Mobility and Gender

The most noticeable result from Table 2 is the considerably higher income persistence observed between parents and daughters compared to the persistence between parents and sons. All IGE estimates are nearly twice as high for daughters as for sons. For instance, the elasticity of daughters' earnings with respect to

[5]Despite their unrepresentative nature, we prefer to keep estimates based on non-entrepreneurial income as they would be relevant for the research specifically focusing on labor earners. (e.g., Tansel et al. (2018), Aktuğ et al. (2020)

Table 3. Two-Sample Estimates of Intergenerational Earnings Elasticity Across Countries

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)	0.435
Turkey	**This study**	**0.52**
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

Note: All estimates are based on samples of father-son pairs. Most studies report several estimates, among those we pick the most comparable with our methods and sample specifications.

fathers' earnings practically equals 1, which theoretically indicates economic inequalities across fathers would be directly inherited by their daughters. In contrast with our results, the IGE of daughters' income is lower than the IGE of sons' income for most of the developed countries except for the U.K. documented by Dearden et al. (1997).

Figure 2 illustrates the steeper earnings growth of females over the fathers' earnings rank compared to males. 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 groups to become as low as 20% for the 9th, and practically zero for the top earnings decile. Similarly, we observe a steeper earnings increase for females over educational attainment levels 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.[6] We also observe that fathers' earnings have a greater positive effect on the likelihood of higher educational attainment of their daughters than their sons.[7] (See Appendix Table A.7) We argue that substantial parental impact on daughters' educational

[6]See also Aktuğ et al. (2020), which documents the gender pay gap throughout the life cycle over educational attainment levels.

[7]This pattern is in accordance with previous findings of Oztunali and Torul (2019) and Tansel et al. (2018) which documents higher intergenerational educational persistence for daughters compared to sons.

outcomes and higher relative returns to female education together account for the higher intergenerational elasticity estimates for daughters.

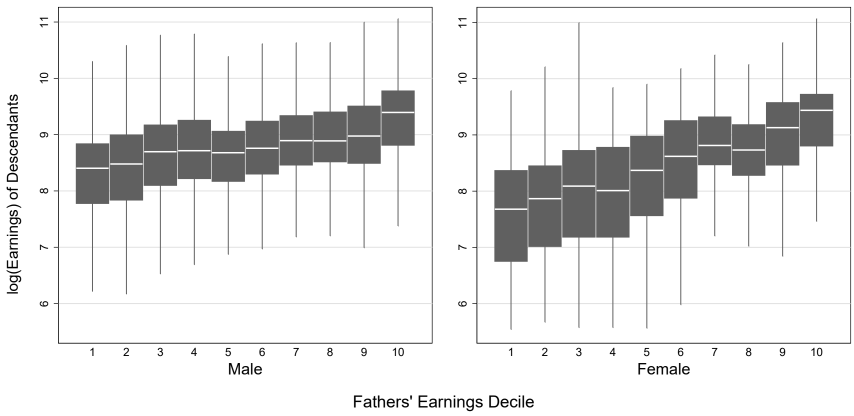


Figure 2. Earnings of Males and Females over Father's Earnings Distribution

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

To further illustrate this dynamic, we decompose our estimates of intergenerational persistence for both genders by educational attainment groups using the method proposed by Hertz (2008).(See Appendix) Table 4 presents both between-group and within-group components of our IGE estimates for each educational attainment group. Within-group IGE estimates are more or less similar for both genders except for the higher elasticity observed among secondary school graduate or lower educated daughters, 0.419, compared to sons, 0.294. However, this does not really contribute much to higher IGE levels, as displayed in row (A), due to the smaller share of this educational attainment group within full-time working daughters. On the other hand, contribution of between-group effects alone accounts for the substantial difference between the IGE estimates for sons and daughters as displayed in row (B).[8] Note that while the contribution of the lowest educational attainment group stems from the very low mean earnings level of daughters in this group, the contribution of university graduates stems from

[8]Between-group effects reflects the differences between mean earnings of children across educational attainment groups and association of children's educational outcome with fathers' earnings.

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 increasing 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	0.608	0.222	0.168	0.467	0.178	0.354
	Mean log Earnings of Children	8.51	8.97	9.57	7.83	8.71	9.47
	Mean log Earnings of Fathers	8.16	8.48	8.68	8.19	8.66	8.87
	Pooled IGE		**0.522**			**0.997**	
A	Within-group IGE	0.294	0.137	0.149	0.419	0.197	0.140
A	Contribution of within-group IGE	0.126	0.025 $\sum$ =0.182	0.030	0.117	0.015 $\sum$ =0.173	0.040
B	Between-group effects	0.188	0.126	0.170	0.860	0.073	0.152
B	Contribution of between-group effects	0.115	0.028 $\sum$ =0.340	0.196	0.401	0.013 $\sum$ =0.823	0.408
	Group-specific persistence: A+B	0.241	0.053 $\sum$ =0.522	0.227	0.519	0.029 $\sum$ =0.997	0.449

Note: Earnings of children are corrected to represent age 35-39 earnings. Earnings of fathers are predicted according to equation 12 using information on education and occupation. Contribution of between group and within group effects are acquired by weighting with group size.

We showed that strikingly high parental effect on daughters' economic outcomes operates via the education channel. However, the considerably high share of university graduates among working women suggests that the idiosyncratic nature of the Turkish female labor force should be taken into account while interpreting mobility patterns. The Turkish female force participation rate is the lowest among the OECD countries, which is only around 30%. (Aktuğ et al. (2020)) Since our analysis is limited to full-time working females we systematically observe females with higher earnings prospects.(Heckman (1979)) From an intergenerational perspective, the self-selection of females to the labor force reveals itself as i) increasing labor force participation rate and ii) increasing share of university graduates among females over parental income rank in the data. As shown in the left panel of Figure 3, working females are more likely to be descendants of higher-earning fathers, whereas the employment probability of males does not vary across fathers' earnings distribution at all. Right panel of Figure 3 reveals stark differences between educational attainment of working females and their full-sample counterparts. Notably, the spread between the fraction of university graduates among working females and their full-sample counterparts widens over father earnings deciles providing further evidence that we observe a select group of females. Thus, the variation in the educational attainment of daughters associated with the variation in parental characteristics is amplified as we focus only on the working females. As strikingly high estimates of

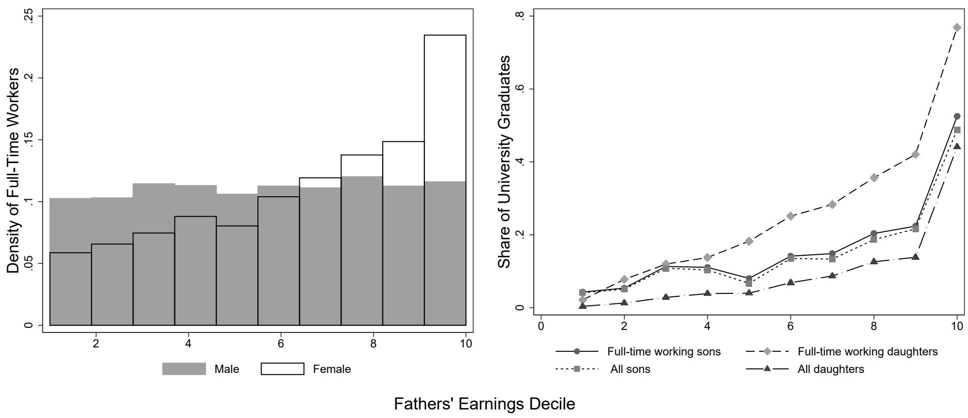


Figure 3. Labor force participation and rate of university graduates by gender

Notes: On the left panel, histograms of employed individuals for both genders are overlaid. Each bin represents a decile of predicted father earnings. On the right panel, shares of university graduates in each father earnings decile are plotted separately for both genders and both sample 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. Obviously, full-sample only includes individuals who report parental characteristics.

intergenerational elasticity for daughters exemplify, the choice of outcome measure might lead to biased estimates which do not necessarily reflect the true nature of underlying intergenerational transmission. Extant literature relies on different outcome measures depending on the particular focus of the study. Some 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. Household income, being a broader measure, better reflects the childrens' living standards as it accounts for a comprehensive set of family characteristics. More importantly, household income is more informative of married women's economic status while own earnings are not as reliable where female labor participation rate is low. (Chadwick and Solon (2002))

Following the above considerations, we supplement our analysis by estimating the intergenerational elasticity of household income which we present in Table 5.[9] Comparison between these estimates with the ones that rely on individual earnings, reported in Table 2, yields several implications. First, relevant to our previous discussion, household income elasticities are nearly the same for sons and daughters, implying a similar degree of persistence in household living standards for both sons and daughters. The main reason behind this result is that we can extend our analysis to include all daughters with positive household incomes instead of only full-time workers. In columns (2) and (4) of Table 5, we estimate the same elasticities using the sample of working descendants. We show that the intergenerational elasticities of daughters' household income are higher for working daughters while showing no change for sons.

Table 5. TSIV 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
	(0.017)	(0.019)	(0.014)	(0.015)
	[10170]	[7809]	[10170]	[7809]
Father-Daughter	0.82	0.98	0.62	0.81
	(0.017)	(0.033)	(0.013)	(0.028)
	[10426]	[1743]	[10426]	[1743]
Mother-Son	0.98	0.99	0.41	0.43
	(0.031)	(0.034)	(0.018)	(0.019)
	[4109]	[3101]	[4109]	[3101]
Mother-Daughter	1.03	1.11	0.44	0.60
	(0.032)	(0.046)	(0.018)	(0.028)
	[4350]	[670]	[4350]	[670]

Note: Column (3) and (4) displays elasticity of children's household income with respect to parents' individual earnings. We use equivalised household income which is calculated according to the modified OECD equivalence scale which attributes a weight of 1 to the first adult, 0.5 to the each subsequent person aged 14 or older and 0.3 to each child aged under 14.Robust standard errors in parentheses. Numbers in brackets are the sample sizes.

Second, we show that elasticities estimated using household income for both generations, as in columns (1-2), are at least 0.77, which is considerably

[9]See Appendix Table A8 and Table A9 for alternative specifications.

higher than estimates of earnings elasticities. In contrast, descendants' household income elasticities with respect to parental earnings, displayed in columns (3-4), are only slightly higher than earnings elasticities. This finding suggests that parental advantages are transmitted even more strongly across generations than previously implied when the overall household well-being of parents is considered. Difference between elasticity estimates with respect to parental household income and individual earnings of the parent is greater for sons. We argue that assortative mating plays a key role here. That is, the children of higher-earning parents not only have better earnings prospects themselves they also tend to marry partners with higher earnings prospects. Table 6 reports the estimated elasticity of earnings with respect to earnings of parents-in-law. Notably, spouses' earnings are as elastic as the own earnings of children. Therefore, parental characteristics further affect their offspring's overall well-being via their effect on marital sorting.

Table 6. Earnings Elasticities with respect to Parents-in-Law

	Father-in-law Earnings	Mother-in-law Earnings
Female	0.89 (0.048) [1202]	0.63 (0.056) [466]
Male	0.56 (0.021) [6371]	0.39 (0.029) [2654]

Note: Robust standard errors in parentheses. Numbers in brackets are the sample sizes. Dependent variable is the earnings of the spouse. The working sample contains only married children.

Third, elasticity estimates with respect to household income implied by mothers' characteristics are higher than those of fathers. This pattern is the opposite of what we observe in Table 2. Previous literature on intergenerational educational mobility in Turkey also finds a more substantial effect of mothers' education on children's education than fathers.(See Oztunali and Torul (2019) and Tansel et al. (2018)) Elasticity estimates with respect to the household income of mothers instead of earnings are more reliable since the latter implicitly assumes that all mothers are employed. Moreover, due to assortative mating in parents' generation, mothers' characteristics also convey information on fathers' earnings, which constitutes an even larger share of household income in parents' generation.[10] We report elasticity estimates and correlations between spouses in Table 7.

Table 7. 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	0.74 (0.037)	0.448	0.70 (0.035)	0.462	0.69 (0.018)	0.638	0.80 (0.017)	0.616
Male	0.42 (0.018)		0.43 (0.019)		0.59 (0.008)		0.47 (0.008)	
Number of Observations	[1274]				[7774]			

Note: Numbers in parentheses are standard errors. Numbers in brackets are the sample sizes. First column indicates which gender is used as dependent variable in elasticity estimations. Sample size of descendants is considerably lower due to low number of employed females.

5.3 Rank-Mobility and Regional Patterns

Intergenerational elasticity is a useful measure to interpret mobility as it accounts for the magnitude of differences in economic outcomes of both parents and children. However, for the same reason, IGE is sensitive to the changes in inequality across generations. Moreover, IGE does not allow comparisons between subgroups of population as it would represent persistence with respect to the group-specific mean. Due to these limitations, several studies use alternative rank-based measures to investigate mobility, whereas IGE is conceptually inappropriate.[11] In this section, we report rank-rank slope estimates representing the association between *positions* of children and parents in the distribution instead of their incomes. We mainly follow the methodology used in the influential

[10] 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 enormous difference is that mothers in our sample are very poorly educated as 57% of them are illiterate and only less than 5% are high-school graduates or better educated. On top of that, the difference between the earnings of males and females with the same educational attainment levels is likely to be greater in the parents' generation. Tamkoc and Torul (2020) documents consistent decline in gender premium over time.

[11] Such as Dahl and Deleire (2008), Davis and Mazumder (2017) and Chetty et al. (2014).

study of Chetty et al. (2014). As their research demonstrates, rank-based measures are instrumental in studying the geographical variation of mobility.

We estimate rank-rank slopes by regressing the percentile rank of children in national household income distribution on the percentile rank of parents' household income rank. We prefer to rank individuals according to household income instead of other outcome measures because it better reflects the overall economic status of individuals and allows for comparison between sons and daughters as discussed in the previous section. Unlike IGE, the rank-rank slope is a scale-invariant measure and hence is not affected by changes in inequality across generations. Another appeal of the rank-rank slope is that it can be used to compare the degree of mobility across subgroups as ranks come from the national distribution. Moreover, we also report the expected rank of the children from families ranked below the median in the national distribution. Formally, $E[R_c|R_p < 50]$, where R_c represents the child's income rank, and R_p represents the parent's income rank. Following Chetty et al. (2014), we will call this measure *absolute upward mobility* in the remainder of the paper.

We report our rank-rank slope estimations in Table 8. Our results show that a 10 percentile increase in a father's rank corresponds to roughly a 4 percentile increase in his sons or daughter's rank. The estimated rank-persistence for mothers is only slightly lower. Our findings suggest rank-mobility in Turkey is weaker than in the US, estimated at 0.34 by Chetty et al. (2014), and in Nordic countries, estimated around 0.2 by Bratberg et al. (2017). Further, we report rank-rank slope and absolute upward mobility estimates for children living in urban and rural areas separately in Table 9. Our findings suggest son's position in the national distribution is much more sensitive to the mother's rank if the son resides in an urban area. Also, absolute upward mobility estimates show that descendants of families with below-median income are, on average rank, 10 percentile points higher if they reside in urban areas instead of rural. Note that we split our sample according to children's residence information instead of parents.

Table 8. Estimated Rank-Rank Slopes

	Father's Rank		Mother's Rank	
Sons	0.408 (.008) [10170]		0.384 (.015) [4109]	
		0.414 (.006) [20596]		0.383 (.010) [8459]
Daughters	0.420 (.008) [10426]		0.384 (.014) [4350]	

Note: Robust standard errors in parentheses. Numbers in brackets are the sample sizes. Both sons and daughters are ranked together whereas fathers and mothers are ranked seperately. See Appendix Table A.8 for estimated rank-rank slopes when sons and daughters are ranked seperately.

Therefore this result is expected because residing in an urban area might also result from experienced upward mobility. Next, we investigate regional variation of

Table 9. 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 (.024) [2095]	0.36 (.011) [6818]	0.37 (.020) [2014]
Daughters	0.33 (.017) [3432]	0.28 (.024) [2135]	0.39 (.011) [6994]	0.38 (.019) [2215]
Absolute Upward Mobility $E[R_c \mid R_p < 50]$				
Sons	35.54	34.17	46.73	43.97
Daughters	32.74	31.09	43.15	39.72

Note: Numbers in parentheses are standard errors. Numbers in brackets are the sample sizes. Urban and rural represents children's residence at the time of the survey.

mobility in Turkey. To acquire sizeable samples, we group NUTS (the Nomenclature of Territorial Units for Statistics) Level-1 level regions into 5 broader geographical units: West, Central, South, North, East.[12] In Table 10, rank-rank slope and absolute upward mobility estimates are presented. Rank-rank slopes are hovering at around 0.3 across regions. Although there exists some variation, no discernible pattern emerges. On the other hand, absolute upward mobility increases with the region's per capita national income. Our estimates imply

[12]We follow the grouping used 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.

descendants of families with below-median income on average rank 15 percentile points higher if they are in West instead of East.

Table 10. Rank-Mobility across Regions

	West		Central		South		North		East	
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	0.38 (.014) [4233]	0.32 (.024) [1605]	0.35 (.025) [1416]	0.37 (.046) [385]	0.34 (.028) [1063]	0.25 (.057) [417]	0.29 (.026) [1159]	0.23 (.039) [727]	0.36 (.019) [2299]	0.40 (.048) [975]
Daughters	0.38 (.014) [4222]	0.35 (.023) [1659]	0.42 (.024) [1478]	0.37 (.045) [444]	0.36 (.026) [1183]	0.36 (.049) [496]	0.33 (.025) [1222]	0.25 (.038) [790]	0.34 (.019) [2321]	0.23 (.049) [961]
Absolute Upward Mobility										
Sons	48.03265	43.52981	46.70012	43.17848	41.92496	40.62716	43.43544	43.07712	32.09036	29.12634
Daughters	45.28439	39.38474	41.1193	37.03065	39.21469	33.23692	39.06911	39.11082	29.09146	27.25578

5.4 Intergenerational Mobility over Time

Despite the limitations posed by the lack of a comprehensive panel data set, we can still observe the degree of mobility experienced by different cohorts. In Figure 4, estimates of IGE and intergenerational correlations are plotted over the birth cohort of sons. Our estimates exhibit an upward trajectory for intergenerational persistence except for the youngest cohort. However, a visual inspection might be misleading as our data is not perfectly suitable to investigate such mobility dynamics over time.[13]

Nevertheless, we repeat a similar exercise separately for daughters and sons. In Figure 5, we plot estimated household income elasticities for both genders over descendants' birth cohorts. Our findings reveal similar trajectories over time for both genders except that persistence steadily increases for daughters, including the youngest cohort.

Finally, we investigate how positional mobility changes over the birth cohorts of children. In panel (a) of Figure 6, we plot estimates of rank-rank slopes between fathers' and sons' household incomes. Our results shows that positional

[13] There are few factors that can possibly confound our results. First, the differences between estimated elasticites might be due to different educational opportunities that each cohort face. (See Torul and Öztunali (2017)) More importantly, variance in educational attainment might be different for fathers of each cohort. This can be more problematic since we have assumed same returns to education for all fathers.

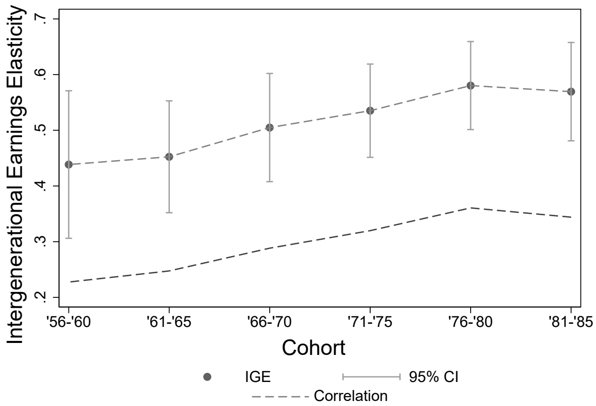


Figure 4. IGE estimates by birth cohort of children

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

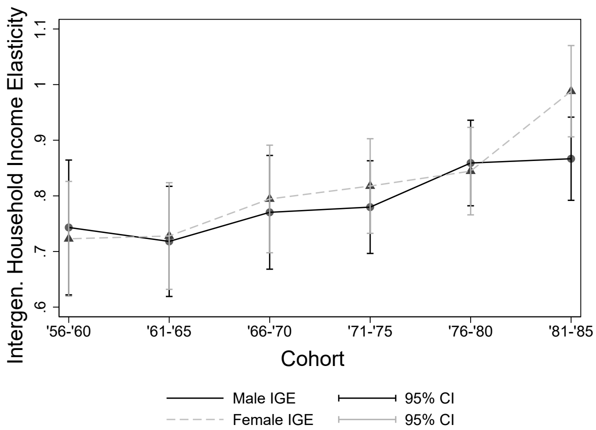
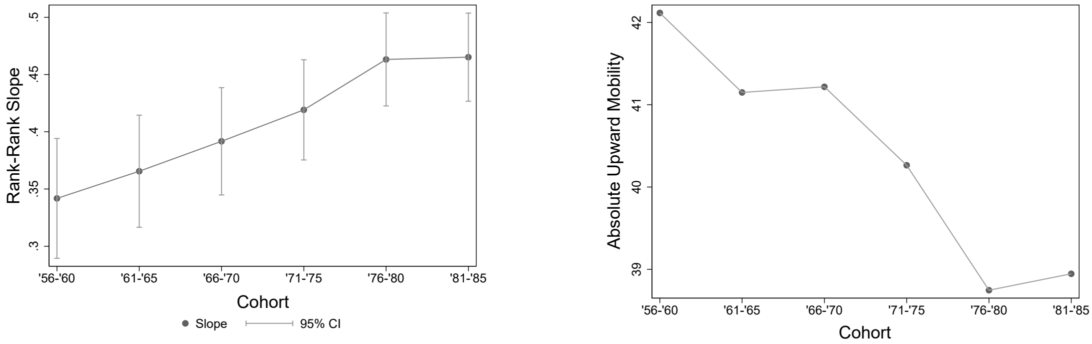


Figure 5. Household income elasticity estimates by birth cohort of sons and daughters

Notes: Confidence intervals are calculated using robust standard errors. On the x-axis birth cohort of children is displayed. The corresponding age interval is 25-29 for the youngest cohort and 50-54 for the oldest cohort. Household income is preferred to provide larger sample sizes and to overcome selection problem for females for the sake of comparability between genders.

mobility considerably decreases as well. This indicates the decline in mobility is not a mechanical result of increasing inequality over birth cohorts of children. In panel (b) of Figure 6, we plot absolute upward mobility estimates over sons' birth cohorts. Similarly, sons from younger cohorts are less likely to experience upward mobility than those from the older cohorts. Our findings shows similarities with tendencies observed for other countries such as the US documented by Davis and

Mazumder (2017) and Denmark documented by Landersø and Heckman (2017).



(a) (b)

Figure 6. Positional mobility by birth cohorts of sons

Notes: Left panel displays estimates of rank-rank slope by each birth cohort of sons. Right panel displays estimates of absolute upward mobility by each birth cohort of sons. Both fathers and sons are ranked according to their equivalised household income. Sons are ranked within their own cohort and fathers are ranked with fathers with children in the same cohort. 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..

5.5 Transition Matrices

Despite their easily interpretable nature and cross-country comparability, both IGE and rank-rank slope measure the *average persistence* within a society but tells a little about the actual dynamics of *mobility* around that average. (Jäntti et al. (2014)) In this section, we report quintile transition matrices to illustrate patterns of mobility across the national distribution. We use household income to rank children and predicted household income to rank parents as it allows us to cover the whole distribution.

Table 11 presents the quintile transition matrices of father-child pairs. Each cell represents the percentage of children with household income in the quintile given by the column conditional on having fathers with household income in the quintile given by the row. Perfect mobility would have been represented by the value of 0.20 in each cell, while perfect immobility would have been represented by the value of 1 only in diagonal cells.

Simple inspection reveals that the highest persistence is observed at the poorest and the richest quintile. In particular, 40 percent of children with fathers

Table 11. Household Income Quintile Group Transition Matrices for Fathers

Father Quantile	Father-Child 1	2	3	4	5	Father-Son 1	2	3	4	5	Father-Daughter 1	2	3	4	5
1	40.17%	24.86%	17.44%	11.59%	5.94%	40.68%	24.99%	17.14%	10.75%	6.45%	40.00%	24.14%	17.83%	12.58%	5.45%
2	25.88%	24.45%	22.65%	16.54%	10.49%	26.34%	23.69%	22.72%	16.19%	11.06%	25.51%	24.85%	23.24%	16.62%	9.78%
3	18.08%	21.88%	22.18%	21.86%	16.01%	17.76%	22.30%	21.22%	21.68%	17.03%	18.05%	22.03%	22.66%	21.88%	15.38%
4	10.11%	17.49%	20.87%	26.15%	25.38%	9.86%	17.49%	22.56%	25.83%	24.25%	10.51%	17.65%	19.25%	26.71%	25.88%
5	7.32%	11.30%	16.44%	22.95%	41.99%	7.23%	11.34%	16.24%	24.55%	40.64%	7.32%	11.32%	16.54%	21.37%	43.46%
	# of Observations: 20,596					# of Observations: 10,170					# of Observations: 10,426				

from the first quintile remain in that position, while 42 percent of children with fathers from the fifth quintile remain there. Mobility patterns do not show any difference between sons and daughters. On the other hand, the persistence of

Table 12. Household Income Quintile Group Transition Matrices for Mothers

Mother Quantile	Mother-Child 1	2	3	4	5	Mother-Son 1	2	3	4	5	Mother-Daughter 1	2	3	4	5
1	31.93%	26.49%	17.27%	14.96%	9.34%	31.44%	28.17%	15.36%	14.75%	10.28%	32.06%	25.81%	18.52%	15.05%	8.56%
2	24.76%	21.69%	23.29%	21.34%	8.92%	26.40%	20.45%	24.61%	19.38%	9.16%	23.50%	22.44%	23.74%	21.86%	8.46%
3	22.10%	22.81%	21.99%	18.26%	14.83%	21.41%	22.40%	20.79%	19.43%	15.97%	22.85%	22.96%	22.29%	18.55%	13.35%
4	13.77%	18.68%	22.58%	24.53%	20.45%	13.42%	18.86%	23.82%	23.82%	20.07%	13.99%	17.92%	22.31%	23.93%	21.85%
5	7.39%	10.34%	14.89%	20.92%	46.45%	6.82%	9.93%	15.26%	22.70%	45.29%	7.90%	11.06%	13.32%	20.65%	47.07%
	# of Observations: 8,459					# of Observations: 4,109					# of Observations: 4,350				

mothers' position is higher on the top quintile compared to the persistence in the bottom quintile, as shown in Table 12. This pattern indicates that economic advantages implied by the mothers' characteristics are more likely to persist across generations compared to disadvantages.

5.6 Robustness Checks

In this section, we check the validity of our main estimates reported in Table 2 by running alternative regressions. Table A.5 in the appendix presents the estimation results using different sample definitions and methods. The resulting estimates slightly vary while preserving the patterns in Table 2. We also estimate the IGE using income measures of children predicted in the same manner as their parents'. The results displayed in Table 4 shows that the transmission between parents and children is, to a large extent, captured by the observed characteristics of children. The difference between the magnitudes stems from the correlation between parental income with the unobserved heterogeneity in children's incomes.

Furthermore, we redo our estimations using parental educational attainment and occupation separately as instruments in the first stage. The estimates are reported in Table 5. When only educational attainment is used to

Table 13. TSIV Estimates using Predicted Incomes for Both Generations

Pairs	# of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7642]	0.46 (0.008)	0.44 (0.009)	0.41 (0.008)	0.47 (0.009)
Father-Daughter	[1613]	0.86 (0.026)	0.87 (0.025)	0.73 (0.025)	0.80 (0.026)
Mother-Son	[3028]	0.27 (0.012)	0.35 (0.015)	0.27 (0.012)	0.24 (0.013)
Mother-Daughter	[629]	0.67 (0.023)	0.77 (0.024)	0.63 (0.024)	0.64 (0.025)

Note: Robust standard errors in parentheses. Sample sizes are exactly the same before.

predict parental income, estimates are too high. The main reason is that, as discussed in Section 3, the IV estimates are likely to be upward-inconsistent due to the direct effect of parental education on children's outcomes. For this reason, while including education as an instrument provides better predictions for the parental income measures, it could also bias the estimates upward. We are still confident in our results since using occupation as the predictor of parental income measures results in only slightly lower estimates. That is also expected since there would be less variation in the regressor.

Table 14. Estimated Elasticities using a Single Instrument for Parental Income

Pairs	Instrument: *Education*					Instrument: *Occupation*				
	# of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage	# of Obs.	Earnings	Income	Non-Entrepreneurial Income	Hourly Wage
Father-Son	[7642]	0.923 (0.033)	0.798 (0.028)	0.943 (0.037) [6618]	0.975 (0.036)	[7751]	0.442 (0.020)	0.511 (0.027)	0.336 (0.016) [5631]	0.408 (0.020)
Father-Daughter	[1613]	1.371 (0.063)	1.324 (0.063)	1.225 (0.066) [1584]	1.307 (0.062)	[1642]	0.964 (0.047)	1.068 (0.057)	0.674 (0.039) [1364]	0.833 (0.044)
Mother-Son	[3028]	0.755 (0.047)	0.748 (0.053)	0.83 (0.066) [6699]	0.787 (0.048)	[3061]	0.299 (0.025)	0.427 (0.043)	0.247 (0.025) [2022]	0.256 (0.025)
Mother-Daughter	[629]	1.281 (0.065)	1.265 (0.073)	1.256 (0.078) [1594]	1.267 (0.065)	[639]	0.782 (0.045)	0.982 (0.064)	0.585 (0.044) [482]	0.699 (0.044)

Note: Numbers in parentheses are standard errors. Numbers in brackets are the sample sizes. Smaller sample sizes are presented below standard errors for regressions based on non-entrepreneurial income.

Throughout estimations presented in this section, we rely on the pooled cross-sectional SILC dataset to predict parental income measures. In this conjecture, we rely on the strong assumption that the relation between the instrumented variables and income observed in our data is valid for the real parents. Therefore, if the education premium and the occupational structure of the society were different in the period when parents were in their 40s than the period we observe, our assumption would be violated. The first problem is that the parental age data is too noisy in our data set so we cannot pin down the parents' exact cohort structure.[14] In the previous literature, earnings of the parents are predicted using a data set from on average 20 years earlier than the data set containing children's earnings (Lefranc and Trannoy (2005), Dearden et al. (1997)) However, no data from before 2005 is available for the first-stage estimation.

Correspondingly, we repeat our estimations using the cross-sectional data from all the available years separately. The results in Table 6 reveal that our estimates show very little sensitivity to the choice of the year for the first stage and do not exhibit a clear time pattern. Dunn (2007) does a similar exercise changing the first-stage data set over 20 years. He finds at most a 13% change in estimates.

Table 15. Intergenerational Elasticity Estimates for Different First-Stage Sample Years

Pairs	Father-Son			Father-Daughter			Mother-Son			Mother-Daughter		
Year of 1st Stage Sample	Earnings	Income	Labor Income	Earnings	Income	Labor Income	Earnings	Income	Labor Income	Earnings	Income	Labor Income
2005	0.467	0.577	0.377	0.871	0.993	0.668	0.371	0.52	0.262	0.73	0.882	0.481
2006	0.47	0.601	0.367	0.893	1.029	0.66	0.362	0.533	0.253	0.693	0.86	0.464
2007	0.486	0.581	0.338	0.895	0.996	0.612	0.316	0.446	0.239	0.656	0.815	0.455
2008	0.472	0.568	0.351	0.867	0.998	0.633	0.323	0.443	0.267	0.65	0.792	0.485
2009	0.501	0.577	0.341	0.89	0.975	0.613	0.34	0.474	0.269	0.669	0.805	0.48
2010	0.54	0.651	0.348	0.953	1.047	0.631	0.36	0.557	0.304	0.723	0.894	0.552
2011	0.526	0.602	0.391	0.942	0.988	0.682	0.347	0.517	0.282	0.697	0.847	0.515
2012	0.513	0.612	0.4	0.929	1.007	0.697	0.348	0.52	0.266	0.711	0.886	0.503
2013	0.527	0.637	0.421	0.958	1.048	0.731	0.334	0.495	0.276	0.682	0.846	0.51
2014	0.548	0.627	0.444	0.993	1.041	0.762	0.337	0.463	0.321	0.706	0.855	0.591
2015	0.537	0.625	0.417	0.988	1.022	0.736	0.358	0.578	0.286	0.764	0.973	0.545
2016	0.516	0.622	0.433	0.984	1.057	0.765	0.305	0.496	0.307	0.681	0.906	0.58
2017	0.496	0.588	0.441	0.951	1.016	0.778	0.301	0.493	0.285	0.686	0.935	0.555

[14] Parents' birth years are reported by children in the module data set. When we compare the birth years of fathers co-residing with their children (already available in the main data set) to the children's report of their fathers' birth year, we see that only 66% of the observations match. For educational attainment, the ratio is similar. However, reported parental education levels are usually lower, indicating a possibility of further educational attainment throughout parents' adulthood.

CHAPTER 6

CONCLUDING REMARKS

In this paper, we explore the dynamics of intergenerational mobility within Turkey. We do so by providing a cross-country comparable intergenerational earnings elasticity estimate, which was previously lacking. This estimate contributes to the framing of the distributional characteristics of Turkey from an international perspective. Our work also complements previous studies on intergenerational educational mobility, such as Tansel et al. (2018), Aydemir and Yazici (2019), Oztunali and Torul (2019), and contribute to a comprehensive illustration of the intergenerational dynamics in Turkey.

We estimate intergenerational elasticities of various income measures employing a two-sample instrumental variables method. For this purpose, we use data from the Survey of Income and Living Conditions over 2005-2017. We report estimates for father-son, father-daughter, mother-son, and mother-daughter pairs. Further, we investigate mobility over time, the income distribution, and various subgroups. We also supplement our findings using alternative rank-based measures. Several patterns emerge from our exercises.

First, we provide evidence for differences in mobility patterns between genders for both parents and descendants. While the persistence of own earnings is stronger for fathers, the persistence of household income implied by mother's characteristics is more impactful on the outcomes of children. Second, earnings persistence appears to be strikingly high for daughters. However, this result emerges due to the remarkably low female labor force participation rate in Turkey. Accordingly, intergenerational mobility is similar for sons and daughters when measured by their household incomes. Third, marital sorting plays a crucial role in intergenerational transmission of economic well-being.

Additionally, the estimated elasticities differ in magnitude depending on the measured income concept. While intergenerational persistence is highest for the broadest income definition, it is lowest for the non-entrepreneurial income.

We report IGE estimates for four different income concepts for future reference: earnings, income, labor income, and hourly wage.

Further, our estimates exhibit a decline in mobility for the more recent cohorts. We also investigate regional patterns of mobility using rank-based measures. Children residing in more developed regions are more likely to have experienced upward mobility. Also, we report quintile transition matrices to reveal heterogeneities in mobility patterns across the earnings distribution. Exhibited patterns imply stronger persistence at the tails of the parental earnings distribution. Finally, we test our estimation results by running auxiliary regressions. The patterns observed in our main results are preserved over alternative regressions.

In brief, this paper casts light on the dynamics of intergenerational income mobility, filling an empirical the distributional dynamics of Turkey. Due to data limitations, this paper is obliged to remain descriptive. We believe that further investigation of stark gender differences in mobility under the light of peculiarly low female labor force participation and high gender pay gap observed in Turkey would be a productive path for future research.

APPENDIX A

Tables and Figures

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

	Full Sample		Usable Sample		Live w/ Parent	
Male						
Age	40.468	(16.934)	39.721	(11.465)	31.606	(9.041)
Secondary Education or lower	0.625		0.58		0.562	
High-School Graduate	0.215		0.215		0.254	
University Graduate	0.159		0.203		0.183	
log(Earnings)	8.494	(1.094)	8.734	(0.861)	8.523	(0.776)
Non-zero Earners	0.68					
# of Observations	**287,638**		**157,944**		**38,541**	
Female						
Age	41.185	(17.605)	36.616	(10.575)	28.791	(7.815)
Secondary Education or lower	0.748		0.439		0.259	
High-School Graduate	0.145		0.193		0.292	
University Graduate	0.106		0.366		0.447	
log(Earnings)	7.972	(1.463)	8.583	(1.002)	8.614	(0.817)
Non-zero Earners	0.21					
# of Observations	**309,173**		**38,728**		**9,294**	
Total						
Age	40.839	(17.288)	39.11	(11.363)	31.059	(8.886)
Secondary Education or lower	0.689		0.552		0.503	
High-School Graduate	0.178		0.211		0.261	
University Graduate	0.131		0.236		0.234	
log(Earnings)	8.363	(1.218)	8.705	(0.893)	8.54	(0.785)
Non-zero Earners	0.44					
# of Observations	**596,811**		**196,672**		**47,835**	

Note: Numbers in parentheses are standard deviations reported alongside mean values. Values reported in a single column are shares of the sample. Last two columns are subsamples of the U.S.able sample. 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		Live w/ Parent	
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							
# 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							
# 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							
# of Observations	**186,236**		**58,211**		**29,781**		**10840**	

Note: Numbers in parentheses are standard deviations reported alongside mean values. Values reported in a single column are shares of the sample. Last two columns are subsamples of the U.S.able 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. (2020)						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***	0.246***	0.377***	0.538***	0.0908**	0.307***	0.541***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)	(0.015)	(0.020)	(0.032)	(0.023)	(0.021)
30 to 34	0.092***	0.156***	0.429***	0.040***	0.109***	0.381***	0.327***	0.531***	0.819***	0.00765	0.339***	0.759***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.011)	(0.015)	(0.019)	(0.030)	(0.025)	(0.021)
35 to 39	0.098***	0.183***	0.531***	0.034***	0.111***	0.447***	0.345***	0.635***	0.945***	0.0400	0.336***	0.889***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.005)	(0.006)	(0.011)	(0.015)	(0.019)	(0.027)	(0.027)	(0.022)
40 to 44	0.099***	0.197***	0.578***	0.015***	0.082***	0.478***	0.399***	0.745***	1.062***	-0.0256	0.415***	1.009***
	(0.002)	(0.004)	(0.006)	(0.004)	(0.005)	(0.008)	(0.011)	(0.016)	(0.020)	(0.028)	(0.028)	(0.023)
45 to 49	0.093***	0.169***	0.571***	-0.013***	0.020**	0.457***	0.345***	0.804***	1.070***	-0.0292	0.391***	1.017***
	(0.002)	(0.004)	(0.007)	(0.004)	(0.007)	(0.010)	(0.012)	(0.017)	(0.021)	(0.029)	(0.039)	(0.027)
50 to 54	0.052***	0.111***	0.536***	-0.035***	0.003	0.449***	0.222***	0.750***	1.071***	-0.151***	0.406***	0.963***
	(0.003)	(0.005)	(0.008)	(0.005)	(0.011)	(0.012)	(0.015)	(0.020)	(0.023)	(0.035)	(0.050)	(0.036)
55 to 59	-0.001	0.059***	0.507***	-0.072***	0.044*	0.416***	0.0330	0.612***	1.043***	-0.234***	0.512***	0.999***
	(0.004)	(0.007)	(0.011)	(0.007)	(0.021)	(0.018)	(0.020)	(0.034)	(0.030)	(0.044)	(0.118)	(0.054)
60 to 64							-0.0869**	0.673***	1.088***	-0.264***	0.207	0.981***
							(0.031)	(0.057)	(0.044)	(0.055)	(0.261)	(0.109)
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
N	296,302	161,101	141,980	60,806	45,448	79,968	59,611	26,763	27,833	12,783	6,908	13,537
R-squared	0.21	0.38	0.28	0.29	0.38	0.33	0.0572	0.135	0.202	0.0516	0.0514	0.204
F-statistic	4,140	7,779	4,035	1,445	1,829	3,294	180.6	177.5	281.7	32.78	18.07	142.9

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. 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
N	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

Note: Numbers in parentheses are standard errors. * for $p < .05$, ** for $p < .01$, and *** for $p < .001$. 20-24 age category is the basis. Elementary occupations and illiterates are the base occupation and education categories.

Table A5. TSIV Estimates for Different Child Income Definitions

Pairs	Reported Child Income					Age Corrected Child Income, Age<35					Reported Child Income, Age<35			
	# of Obs.	Earnings	Income	Labor Income	Hourly Wage	# of Obs.	Earnings	Income	Labor Income	Hourly Wage	Earnings	Income	Labor Income	Hourly Wage
Father-Son	[7642]	0.522	0.614	0.395	0.497	[3040]	0.563	0.66	0.441	0.503	0.499	0.601	0.393	0.453
		(0.019)	(0.022)	(0.017)	(0.020)		(0.028)	(0.035)	(0.025)	(0.029)	(0.028)	(0.034)	(0.024)	(0.029)
				[5558]					[2517]			[2517]		
Father-Daughter	[1613]	0.961	1.035	0.701	0.867	[740]	0.913	0.955	0.692	0.828	0.806	0.839	0.609	0.746
		(0.045)	(0.048)	(0.039)	(0.043)		(0.067)	(0.069)	(0.061)	(0.062)	(0.065)	(0.067)	(0.059)	(0.060)
				[1341]					[684]			[684]		
Mother-Son	[3028]	0.0.334	0.511	0.277	0.279	[1023]	0.376	0.508	0.31	0.328	0.339	0.461	0.277	0.298
		(0.025)	(0.039)	(0.025)	(0.025)		(0.033)	(0.050)	(0.032)	(0.033)	(0.032)	(0.049)	(0.031)	(0.033)
				[2001]					[820]			[820]		
Mother-Daughter	[629]	0.698	0.888	0.518	0.629	[235]	0.693	0.805	0.568	0.639	0.617	0.704	0.507	0.578
		(0.049)	(0.065)	(0.046)	(0.047)		(0.060)	(0.074)	(0.057)	(0.055)	(0.059)	(0.073)	(0.057)	(0.053)
				[475]					[217]			[217]		

Note: Numbers in parentheses are standard errors. Numbers in brackets are the sample sizes. Smaller sample sizes are presented under the standard errors for regressions based on labor income.

Table A6. Intergenerational Non-Entrepreneurial Income Elasticity Estimates using Different Age-Correction Sources

Pairs	Corrected for Age (Aktuğ et al. (2020))	Corrected for Age (SILC)
Father-Son	0.391 (0.017)	0.38 (0.017)
Father-Daughter	0.725 (0.038)	0.704 (0.038)
Mother-Son	0.278 (0.024)	0.264 (0.025)
Mother-Daughter	0.6 (0.041)	0.57 (0.041)

Note: Numbers in parentheses are standard errors.

Table A7. Estimated 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)
N	10,426		10,170	
Pseudo R^2	0.1920		0.0997	

Note: P_{sec}, P_{high} and P_{uni} stands for probability of having educational attainment level of secondary education or lower, high school graduate and university graduate respectively. Coefficients are estimated using multinomial logit model. Standard errors in parentheses.

Table A8. TSIV Estimates of Intergenerational Elasticity of Non-Equivalised 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 (0.021) [10170]	0.81 (0.023) [7809]	0.48 (0.013) [10170]	0.49 (0.015) [7809]
Father-Daughter	0.80 (0.021) [10426]	0.98 (0.040) [1743]	0.49 (0.013) [10426]	0.69 (0.027) [1743]
Mother-Son	1.08 (0.043) [4109]	1.08 (0.048) [3101]	0.34 (0.018) [4109]	0.36 (0.020) [3101]
Mother-Daughter	1.10 (0.043) [4350]	1.18 (0.061) [670]	0.35 (0.018) [4350]	0.50 (0.028) [670]

Note: Column (3) and (4) displays elasticity of children's household income with respect to parents' individual earnings.Robust standard errors in parentheses. Numbers in brackets are the sample sizes.

Table A9. TSIV Estimates of Intergenerational Elasticity of Household Income-Excluding Coresiding 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 (0.025) [7705]	0.78 (0.027) [6112]	0.46 (0.016) [7705]	0.47 (0.017) [6112]
Father-Daughter	0.77 (0.023) [9379]	1.01 (0.045) [1423]	0.47 (0.014) [9379]	0.68 (0.030) [1423]
Mother-Son	1.03 (0.056) [2964]	1.01 (0.061) [2316]	0.31 (0.023) [2964]	0.33 (0.024) [2316]
Mother-Daughter	1.07 (0.050) [3993]	1.17 (0.072) [578]	0.32 (0.020) [3993]	0.47 (0.033) [578]

Note: Column (3) and (4) displays elasticity of children's household income with respect to parents' individual earnings.Robust standard errors in parentheses. Numbers in brackets are the sample sizes.

Table A10. Estimated Rank-Rank Slopes

	Father's Rank		Mother's Rank	
	0.411		0.388	
Sons	(.008)		(.015)	
	[10170]	0.414	[4109]	0.383
		(.006)		(.009)
	0.417	[20596]	0.380	[8459]
Daughters	(.008)		(.014)	
	[10426]		[4350]	

Note: Robust standard errors in parentheses. Numbers in brackets are the sample sizes. Sons and daughters are ranked seperately. Fathers and mothers are ranked seperately.

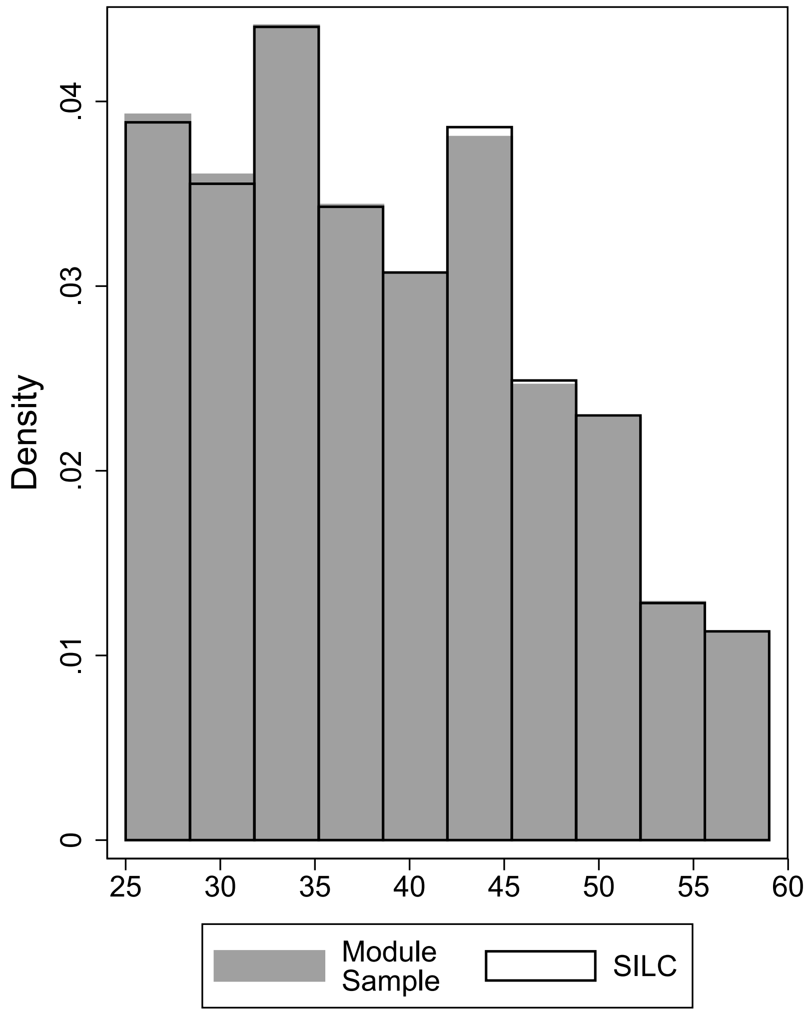
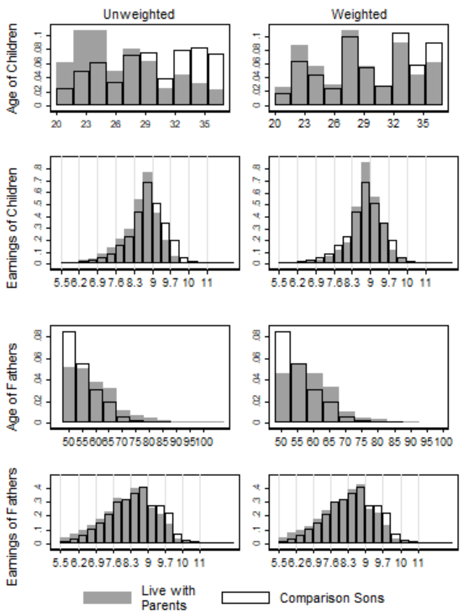
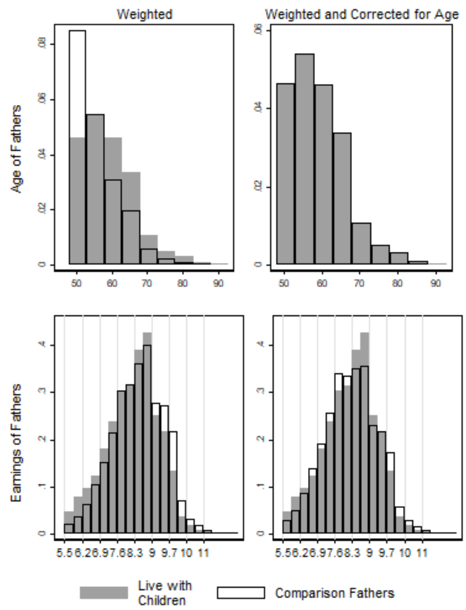


Figure A1. SILC 2010 Module Age Distribution

Note: Age histograms of all individuals surveyed in the SILC 2010 data set and of the individuals who answered module questions are overlaid.



(a)



(b)

Figure A2. Comparison of Weighted Sample of Co-residing Children and Full Sample

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

APPENDIX B

GROUP-SPECIFIC DECOMPOSITION OF IGE

In this Appendix, we present details of the decomposition used for calculations in Table 4. We adhere to the exposition used by Hertz (2008) in the original paper.

Hertz (2008) shows that intergenerational elasticity estimated in the pooled regression can be written as:

$$\hat{\beta} = \sum_i \hat{\pi}_i \left(\hat{\beta}_i \frac{\hat{\sigma}^2_{yp,i}}{\hat{\sigma}^2_{yp}} + \frac{\left(\overline{y}_{p,i} - \overline{y}_p\right)\left(\overline{y}_{c,i} - \overline{y}_c\right)}{\hat{\sigma}^2_{yp}} \right) \tag{B.1}$$

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

Therefore, the above equation represents 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 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 to group-share weighted within-group and between-group effects.

In Table 4, we have grouped parent-child pairs according to the educational attainment levels of children. For illustrative purposes, we repeat a similar decomposition exercise by grouping parent-child pairs according to the children's residency area. In Table C1, we report our estimates along with corresponding formal expression of each measure.

In contrast with our previous decomposition, 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. Note that the between-group effect would be larger if the group's mean is higher(or lower) than the sample mean for both generations.

Table B1. 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	$\frac{\left(\overline{y}_{p,i}-\overline{y}_p\right)\left(\overline{y}_{c,i}-\overline{y}_c\right)}{\hat{\sigma}^2_{yp}}$	0.264	0.064	0.270	0.065
Contribution of between-group effects	$\hat{\pi}_i \frac{\left(\overline{y}_{p,i}-\overline{y}_p\right)\left(\overline{y}_{c,i}-\overline{y}_c\right)}{\hat{\sigma}^2_{yp}}$	0.087	0.043	0.089	0.044
		$\sum$ =0.130		$\sum$ =0.132	
Group-specific persistence	$\hat{\pi}_i \left(\hat{\beta}_i \frac{\hat{\sigma}^2_{yp,i}}{\hat{\sigma}^2_{yp}} + \frac{\left(\overline{y}_{p,i}-\overline{y}_p\right)\left(\overline{y}_{c,i}-\overline{y}_c\right)}{\hat{\sigma}^2_{yp}}\right)$	0.240	0.534	0.244	0.578
		$\sum$ =0.774		$\sum$ =0.822	

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