

EVOLUTION OF INTERGENERATIONAL EDUCATIONAL MOBILITY IN TURKEY

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‡For the latest version, please visit: <http://web.boun.edu.tr/torul/eiemt.pdf>

‡For the online appendix, please visit: http://web.boun.edu.tr/torul/oa_eiemt.pdf

Abstract

Since the foundation of the Republic of Turkey in 1923, Turkey has experienced a remarkable socio-economic transformation. Throughout this development process, while many key aggregate economic indicators evolved considerably and have been studied extensively, heterogeneities and the distributional properties of these socio-economic variables have not been subject to rigorous academic scrutiny. In this study, we analyze cross-sectional heterogeneities in educational attainment and the evolution of the intergenerational educational transmission dynamics in Turkey for cohorts born between 1951 and 1985 via micro data from the Survey of Income and Living Conditions 2011 by the Turkish Statistical Institute. The primary results of our analysis is that the probability of a randomly selected individual to have the same educational attainment as his/her more educated parent - which we refer to as intergenerational educational persistence - has declined notably, thereby individuals born in recent cohorts enjoyed greater prospects of intergenerational educational upward mobility. In conjunction with this development, within-cohort inequality of educational attainment has declined considerably across cohorts, producing an inverse relationship between the degree of intergenerational educational mobility and educational inequality over time, i.e. the time-series analog of the Great Gatsby Curve in the context of educational attainment in Turkey. Our analysis also reveals that descendants' gender, degree of urbanization of the place of residence, educational attainment of the less-educated parent, and financial conditions during the adolescence of the descendant are among other major socio-economic dimensions along which intergenerational educational mobility patterns exhibit immense heterogeneities.

Keywords: Social Mobility; Education Inequality; The Great Gatsby Curve

JEL Classification: I20, I24, J62, N30, E24

1 Introduction

Turkey has undergone a major socio-economic transformation since the foundation of the Republic of Turkey in 1923, throughout which the economy expanded in scale and evolved structurally. Turkey's population increased from 13.6 million in 1927 to approximately 80 million in 2016, and the Turkish GDP per capita increased from 975 to 20,222 in 2011 international dollars between 1923 and 2014. Alongside this expansion, Turkey has experienced a structural change characterized by rapid urbanization and de-agriculturalization: the share of population living in villages and towns decreased sharply from 75.8% in 1927 to 7.5% in 2017, the share of agriculture in overall employment declined from 90% in 1923 to 23% in 2013; and the share of agriculture in GNP decreased from 43% in 1923 to 11% in 2006.¹

Improvements in the education system and increase in overall educational attainment have been two central components of this socio-economic transformation. Throughout this development process, Turkey experienced remarkable improvements in the literacy rate, the number of public and private universities, and the number of students per teacher in primary education, among other key educational variables.²

As main macroeconomic variables and overall educational figures have been evolving rapidly, academic studies addressing the Turkish development process focused predominantly on the evolution of *aggregate* economic variables; and due to limitations in the availability of micro-level data, changes in *distributional* properties of pivotal economic variables and the evolution of socio-economic inequalities, which can be argued to be at least as important as levels exhibited by aggregates in some cases, have not been subject to rigorous quantitative academic scrutiny.

In this study, we aim to reveal how the Turkish development process formed, fortified and eliminated socio-economic asymmetries and inequalities by focusing on the evolution of the cross-sectional and intergenerational dynamics governing educational attainment (i.e. the role of parental education in determining the educational attainment of descendants). Have descendants with different levels of parental education been equally likely to attain college education? Have advantages in intergenerational educational transmission of particular groups persisted over time? Has the gender of descendants been a source of heterogeneity in the dynamics of intergenerational educational mobility? Does proximity to urban locations correlate with educational attainment of descendants and affect their intergenerational educational mobility prospects? Do socio-economic variables have similar effects on the likelihood of different educational achievements? Do indicators of overall intergenerational educational mobility of a cohort correlate with within-cohort educational inequality?

In order to address these questions, we use micro-data by the Turkish Statistical Institute's (TurkStat) Survey of Income and Living Conditions (SILC) in 2011 (the module survey on the intergenerational transmission of disadvantages), and limit our attention to descendants born between 1951 and 1985, which covers a substantive part of the aforementioned Turkish development process.³

¹See [Turkish Statistical Institute \(2017\)](#) and [Turkish Statistical Institute \(2014\)](#) for population and the share of agriculture in GDP. For GDP per capita see [Inklaar et al. \(2018\)](#).

²[Lee and Lee \(2016\)](#) show that average years of schooling in Turkey increased from 0.48 in 1925 to 7.44 in 2010. According to [Turkish Statistical Institute \(2014\)](#), the adult literacy rate increased from 18.7% in 1935 to 95.3% in 2013. According to [Council of Higher Education \(2005\)](#) the first higher education institute that can be categorized as a university (Istanbul University) is established in 1933, and between 1923 and 2004 the number of higher education (tertiary) institutes increased from 1 to 79. The number of students per teacher in primary education declined from 33.1 in 1923 to 21.3 in 2011 according to [Turkish Statistical Institute \(2014\)](#).

³Using TurkStat's Adult Education Surveys 2007 and 2012, we verify that our results are robust to the choice of micro-data sets.

Our results indicate that the likelihood of a descendant to have the same level of education as his/her more educated parent, which we refer to as *intergenerational educational persistence*, has been declining steadily on average over time. However, the evolution of this probability is contingent on the educational attainment of the descendant’s parents: while the frequency of educational persistence has monotonically declined in families with low-educated parents (secondary school-graduate or lower), such a drastic evolution in the same probability has not been observed in families with high-educated (university-graduate) parents. Because of this heterogeneity in conditional educational persistence, relative high education prospects in Turkey, which we define as the probability of getting a college degree for descendants born to parents with secondary school education or below relative to those born to college-graduate parents, has increased consistently over new-born cohorts. In conjunction with the continuous decline in within-cohort educational inequality, this process has delivered an educational time-series equivalent of the Great Gatsby curve of the intergenerational income mobility literature, i.e. a positive relationship between intergenerational educational persistence and within-cohort educational inequality. We further document that sources of intergenerational educational transition probability heterogeneities in Turkey have not been confined only to parental education: our analysis reveals that intergenerational educational transition probabilities have also depended immensely on descendants’ gender, place of residence, and financial conditions experienced by descendants’ household at the time of their adolescence.

The rest of the paper is organized as follows: section 2 provides a description of the literature on intergenerational educational mobility and educational inequality in Turkey; section 3 describes the data and methodology we use in our analyses; section 4 reports and discusses our empirical findings; and section 5 concludes.

2 Related Literature

Despite the drastic evolution the Turkish economy has undergone over the second half of the twentieth century, throughout which both aggregate and cross-sectional distributional properties of many key economic variables transformed radically, the focus of academic research has been confined predominantly to the study of economic aggregates, mainly because of the lack of detailed micro-level data. As a result, except for a small number of relatively recent studies on wage, income, consumption and wealth inequality (Duygan and Guner (2006), Elveren and Galbraith (2009), Elveren (2010), Torul and Öztunalı (2018), Tamkoc and Torul (2018) and Aktug et al. (2018)), the evolution of distributions of economic variables in Turkey has not been unveiled at the micro-level, extensively.

As briefly discussed, changes in the education system and improvements in overall educational attainment have been two integral parts of the Turkish transformation process. The education system has been subject to numerous reforms in order to improve educational outcomes,⁴ and average educational attainment estimates have increased drastically over time. Sari and Soytas (2006) find cointegrating relationships between GDP and enrollment ratios in various levels of education in Turkey, and claim that there are long-run relationships between GDP and education. They further argue that secondary school and high school enrollment ratios Granger-cause GDP both in the short run and in the long run. Tansel and Bodur (2012) show that return to education has declined from 1994 to 2002 in Turkey by relying on a quantile regression methodology. Using data from Household Income and Consumption Expenditures Survey (HICES) in 1987, 1994, and 2005, Duman (2008) shows that the share of individuals with a university degree in the richest quintile of Turkey has

⁴Among others, see Kirdar et al. (2015) for the effects of the 1997 compulsory education reform in Turkey.

increased from 18.36% in 1987 to 27.73% in 2005, whereas the same share has declined from 0.75% to 0.50% in the poorest quintile, suggesting that the increase in overall educational attainment is not distributed evenly across different income quintiles in Turkey. In another study, [Duman \(2010\)](#) calculates educational Gini and Theil coefficients in Turkey via years of schooling data for which they benefit from [Barro and Lee \(2013\)](#), and shows that the degree of educational inequality via the Gini coefficient has historically been higher among females than males, although there is rapid convergence between the genders via the Theil coefficient.

[Tansel \(2002\)](#) and [Tansel \(2016\)](#) are the first studies focusing on the intergenerational transmission of education in the Turkish context.⁵ Using data from the 1994 Household Budget Survey by TurkStat, [Tansel \(2002\)](#) explores the determinants of descendants's educational outcomes, and finds that educational attainment of descendants between ages 14 and 19, 16 and 19, and 19 and 20 positively and significantly depend on parental education, and this intergenerational relationship is stronger for female descendants.⁶ [Tansel \(2016\)](#) uses data from the Adult Education Survey in 2007 by TurkStat, and investigates the intergenerational educational transmission channels from both i) ordinal and ii) cardinal perspectives (i.e. by defining educational attainment as i) highest degree attained and ii) years of education completed), similar to the methodology that we adopt in this paper. The author finds that i) intergenerational educational correlation coefficient between descendants' and fathers' completed years of education has not declined significantly over time, ii) descendants' likelihood of attaining university degree positively and significantly depends on fathers' educational attainment, and iii) female descendants face worse education prospects than their male counterparts in attaining both high school and university degrees. Despite the similarities in methodology,⁷ in this paper we believe we conduct a more thorough analysis: on top of documenting the heterogeneous evolution of intergenerational educational mobility dynamics thoroughly in as much detail as possible, we also explore the evolution of educational inequality, and investigate the time-series relationship between intergenerational educational mobility and within-cohort educational inequality, i.e. the educational equivalent of the Great Gatsby Curve, which has not been examined in any previous study on Turkey.

[Akarçay-Gürbüz and Polat \(2017\)](#) is another recent study addressing the patterns of intergenerational mobility in Turkey. Using micro-data from 1990 and 2000 censuses, the authors perform two-stage IV-probit and two-stage residual inclusion regressions (2SRI) to address the potential omitted variable bias issue that may affect the estimated marginal effect of parental education on the educational outcome of descendants. The comparison of results obtained by an intergenerational

⁵For cross-country panel studies on this subject, see [Torul and Öztunali \(2017\)](#), [Hertz et al. \(2007\)](#) and [Schneebaum et al. \(2015\)](#). For country-specific studies, see [Aydemir et al. \(2013\)](#) for Canada, [Blanden and Macmillan \(2014\)](#) for the United Kingdom, [Bloome and Western \(2011\)](#), [Huang \(2013\)](#) and [Martin \(2012\)](#) for the United States, [Checchi et al. \(2013\)](#) for Italy, [Daouli et al. \(2010\)](#) for Greece, and [Emran and Shilpi \(2015\)](#) for India.

⁶[Duman \(2010\)](#) replicates this exercise for girls who are between 6 and 15 years old, and confirms that educational attainment in this sample also positively and significantly depends on parental education and income, whereas living in a rural region and having a large family have negative and significant associations with girls's educational attainment.

⁷[Tansel \(2016\)](#) explores the effects of paternal and maternal parental education separately, whereas we adopt a slightly more gender-neutral approach by defining parental education as the highest degree of education that is observed in a parental couple. While we conceptually depart from [Tansel \(2016\)](#) by doing so, in practice our measure for parental education usually corresponds to paternal education due to the educational disadvantage experienced by females in Turkey. Furthermore, [Tansel \(2016\)](#) groups individuals under birth-cohorts spanning 10 years, implicitly assuming that all individuals in these 10-year birth-cohorts exhibit same mobility patterns, whereas the birth-cohort of an individual corresponds to the birth year in our study. Our analysis reveals that as intergenerational educational mobility in Turkey varies considerably over 10 years, constructing 10-year birth cohorts as unit of analysis could be overly restrictive, and as such can lead to misleading inferences.

probit regression with those obtained by an IV-probit implies that due to omitted variable bias, the marginal effect of paternal education on the educational outcome of the descendant is overstated in the usual probit regression. When the authors define educational attainment as a categorical variable and rely on the 2SRI methodology, they find that the usual probit regression understates the marginal effect of maternal education and overstates that of paternal education. In contrast to our study, [Akarçay-Gürbüz and Polat \(2017\)](#) do not study the evolution of intergenerational educational mobility and educational inequality patterns in Turkey.

[Aydemir and Yazici \(2017\)](#) is the most recent paper focusing on the nature of the intergenerational educational transmission in Turkey. Using micro-data from their own survey, the authors estimate intergenerational educational correlation and regression coefficients for various subregions of Turkey, study how regional development affects intergenerational transmission of education, and investigate how mobility measures correlate with various region-specific variables, such as regional development and parental educational inequality within a region.⁸ [Aydemir and Yazici \(2017\)](#) argue that compared to developed countries, the degree of intergenerational educational mobility in Turkey is considerably lower, and the magnitude of the association between parents’s and descendants’s education is inversely related to the degree of regional development. The authors also find a negative and significant relationship between the degree of intergenerational mobility and parental educational inequality across regions, which implies that the Great Gatsby Curve Hypothesis is valid cross-regionally in Turkey. While [Aydemir and Yazici \(2017\)](#) study the determinants of cross-sectional variation in intergenerational educational mobility relying on a cardinal definition of educational attainment, our paper explores the *evolution* of mobility dynamics from both ordinal and cardinal perspectives, and focuses on the association between the degree of educational mobility and within-cohort inequality over time.

3 Data and Methodology

3.1 Data Description

Throughout our analysis, we use micro-data from the Survey of Income and Living Conditions (SILC) in 2011 by the Turkish Statistical Institute (TurkStat).⁹ We specifically concentrate on individuals who were born between 1951 and 1985 and were at least 25 years old at the time of the survey, who can thus be regarded as having completed their educational phase.¹⁰ The number of observations that satisfy these criteria in SILC in 2011 is 25,016. [Table 1](#) displays the descriptive statistics of our working sample.

We treat educational attainment mainly as an *ordinal* variable throughout our analysis. In doing so, we define three levels of education: namely *low education* (individuals with lower-secondary education degree or below, i.e. International Standard Classification of Education (ISCED) 0-1-2 categories or simply those do *not* a high-school diploma), *intermediate education* (those with

⁸In addition, the authors also explore the role of grandparents’s education on descendants’s educational outcomes.

⁹For robustness purposes, we also redo our analysis via TurkStat’s Adult Education Survey (AES) 2007 and 2012, as briefly discussed. Our resultant findings are available in the Online Appendix. In a nutshell, we confirm that our findings via AES are both qualitatively and quantitatively similar to those via SILC, hence we verify that our results are robust over the choice of micro-data sets.

¹⁰We follow the standard adult education definition by the OECD Education at a Glance, which measures education by “the highest level of education completed by the 25-64 year-old population”. We exclude individuals born after 1985 because a sizable fraction of these respondents were still continuing their education at the time of survey.

upper-secondary education, belonging to ISCED 3-4 categories or high-school graduates) and *high education* (individuals with a tertiary education degree, belonging to ISCED 5-6 categories). We follow an ordinal approach and adopt this categorization strategy as i) years of schooling information, especially of parents is not directly available in the Turkish micro-data sets,¹¹ ii) the cutting points of our education categories correspond to major educational milestones in an individual’s life and deliver statistically significant economic returns in Turkey (Tamkoc and Torul (2018) and Aktug et al. (2018)) while also not being prevalent in frequency, iii) this categorization strategy still enables us to obtain significant, easily interpretable and tractable results while addressing the points raised in i) and ii). We also complement our analyses via the cardinal approach, i.e. the regression analyses based on descendants’s and parents’s years of schooling ordinary least squares (OLS) estimations. While acknowledging its shortcomings,¹² we do so for the sake of comparability of our findings with the earlier education literature adopting a cardinal methodology.

Table 1: Descriptive Statistics by the Survey of Income and Living Conditions 2011

Cohort	Share in Sample	Respondent’s Years of Education		Share of Respondents wrt. Education			Share of Fathers wrt. Education			Share of Mothers wrt. Education		
		Mean	Std. Dev.	Low	Int.	High	Low	Int.	High	Low	Int.	High
1951-1959	0.19	7.93	6.61	0.82	0.10	0.08	0.96	0.02	0.01	0.99	0.01	0.00
1960-1969	0.28	8.01	5.90	0.77	0.15	0.09	0.97	0.02	0.01	0.99	0.01	0.00
1970-1979	0.33	8.47	5.59	0.69	0.18	0.13	0.92	0.05	0.03	0.97	0.02	0.01
1980-1985	0.21	9.48	5.53	0.57	0.23	0.19	0.87	0.08	0.05	0.94	0.04	0.02
Whole Sample	1.00	8.45	5.90	0.71	0.17	0.12	0.93	0.05	0.03	0.97	0.02	0.01

3.2 Estimation Methodology

Throughout most of our analysis, we conduct *ordered logistic (logit) regressions* in order to estimate conditional educational intergenerational transition probabilities of descendants.¹³ Using these estimated transition probabilities, we construct overall intergenerational educational mobility variables that describe the probabilities of *downward mobility*, *upward mobility*, and *persistence* that have been faced by a random member of each birth-cohort. Our most general specification of the latent

¹¹The micro-data sets by TurkStat provide information on the highest degree a descendent attained along with his/her completion year, but not the *actual* years of education. Given data limitations, we impute years of education by subtracting birth year plus 6 years, the most frequent legal age at which individuals start their education in Turkey, from the completion year, and impose an upper bound of 20 years. Therefore, as this variable is prone to suffer from measurement error, e.g. as in the case of individuals who started their education early or late, or experienced breaks during their educational attainment, we do not base the entirety of our analysis on imputed years of schooling, and instead we focus mostly on the highest degree of education attained by the respondent.

¹²In particular, the cardinal econometric specification of the earlier intergenerational educational mobility literature, which is adopted directly from the income mobility literature, relies on strong modeling assumptions, such as *linearity*, *symmetry*, *cardinality* and *monotonicity* on the relationship between descendants’ and parents’ years of schooling. These restrictions implicitly assume that a year in tertiary education, a year in the first grade or a year towards non-graduation has identical marginal effects as any other year of education, which contradicts with the well-acknowledged *sheepskin effect* in education (Hungerford and Solon, 1987). Our estimations via the cardinal approach yield sizeably heterogeneous coefficient estimates when *parental educational background* is controlled for, which casts doubt on the appropriateness of the cardinal approach for the study of Turkey’s intergenerational educational mobility. We discuss this issue in more detail in the next sections. For an extended discussion on the ordinal and cardinal approaches in intergenerational educational mobility, see Torul and Öztunali (2017).

¹³In our supplementary Online Appendix, we verify that our results via *generalized* ordered logistic (logit) regressions deliver quantitatively similar results.

variable (E_{it}^*) determining the educational outcome of the descendant i born in year t is described by (1):

$$E_{it}^* = (\kappa_1 + \kappa_2 t)P_{it} + (\gamma_1 + \gamma_2 t)F_{it} + \sum_{j=1}^6 (\alpha_{1j} + \alpha_{2j} t)D_{ijt} + (\psi_1 + \psi_2 t)U_{it} + (\nu_1 + \nu_2 t)I_{it} + \sum_{k=1940}^{1985} \eta_k Y_{kit} + \epsilon_{it} \quad (1)$$

where P_{it} , which is the primary explanatory variable of interest in our analysis, corresponds to the educational attainment (the highest degree of education attained) of the parent with better education. In later parts of our analysis, we control for the gender of the descendant with the dummy variable F_{it} taking a value of 1 for female descendants and 0 for males. Next, in addition to controlling for the educational attainment of the better-educated parent, we control for the educational attainment of the other parent via dummy variables D_{ijt} .¹⁴ Again, in later parts of our analysis, we also introduce the degree of urbanization of the place of residence (at the time of the survey) as a regressor with the dummy variable U_{it} which takes the value 1 (0) if the respondent was living in an urban (rural) area. In addition, we also incorporate the effects of perceived financial conditions of the descendant's household during his/her adolescence (at the age of 14) via the variable I_{it} , which is an ordinal financial well-being variable. Finally, we also control for cohort fixed-effects via dummy variables Y_{kit} which takes the value 1 if the individual is born in year k , and 0 otherwise. In accordance with our definitions of education categories in the previous section, as described by (2), conditional on the value of the latent variable (E_{it}^*) the educational outcome of the descendant takes the value 1, 2 or 3 in the case of low, intermediate and high education, respectively:

$$E_{it} = \begin{cases} 1 & \text{if } E_{it}^* \leq \theta_1 \\ 2 & \text{if } \theta_1 < E_{it}^* < \theta_2 \\ 3 & \text{if } \theta_2 \leq E_{it}^* \end{cases} \quad (2)$$

In order to estimate the coefficients listed above, we run ordered logit regressions using weights provided by SILC in 2011. After the estimation of regression coefficients and calculation of predicted conditional transition probabilities, we construct the intergenerational educational transition matrix, displayed in Table 2 for each birth-cohort and calculate our overall mobility measures based on this matrix.¹⁵ First, we define three types of intergenerational mobility movements depending on the educational attainment of the descendant and his/her parents's level of education: descendant i of birth-cohort t for whom $E_{it} = P_{it}$ is categorized as one that experienced *intergenerational educational persistence*, and if $E_{it} > P_{it}$ ($E_{it} < P_{it}$) then this descendant is labelled as one that experienced *intergenerational educational upward (downward) mobility*. Then, for the members of the cohort born in year t , we construct intergenerational educational persistence \mathcal{P}_t (3), upward mobility \mathcal{U}_t (4) and downward mobility variables \mathcal{D}_t (5) as follows:

¹⁴As both paternal and maternal education can take three distinct values, there are nine parental couple dummy variables: $D(1, 1)$, $D(1, 2)$, $D(1, 3)$, $D(2, 1)$, $D(2, 2)$, $D(2, 3)$, $D(3, 1)$, $D(3, 2)$, and $D(3, 3)$. The numbers in parentheses correspond to paternal and maternal education of the respondent, respectively. 1, 2, and 3 stand for low, intermediate, and high educational attainment. $D(i, j)$ takes the value of 1 for a descendant whose paternal and maternal education are i and j respectively, and 0 otherwise.

¹⁵Aydemir and Yazici (2017) verify, as we do, that grandparents's educational attainment has no significant effect on descendants's educational attainment when parental education is controlled for. Hence, the use of a Markov-chain transition probability matrix, which is prevalent also in the earlier literature, is appropriate for the study of intergenerational educational mobility in Turkey.

$$\mathcal{P}_t = \frac{\sum_{j=1}^3 \Pr_t(E = j|P = j) \times N_t(P = j)}{\sum_{j=1}^3 N_t(P = j)} \quad (3)$$

$$\mathcal{U}_t = \frac{\sum_{j=1}^2 \Pr_t(E > j|P = j) \times N_t(P = j)}{\sum_{j=1}^2 N_t(P = j)} \quad (4)$$

$$\mathcal{D}_t = \frac{\sum_{j=2}^3 \Pr_t(E < j|P = j) \times N_t(P = j)}{\sum_{j=2}^3 N_t(P = j)} \quad (5)$$

where $N_t(P = j)$ refers to the number of descendants born in year t whose parental education is equal to j .

Table 2: Intergenerational Educational Mobility Transition Matrix

Parent \ Descendant	Low	Intermediate	High
Low	Low-type persistence	Low-type upward mobility	
Intermediate	Intermediate-type downward mobility	Intermediate-type persistence	Intermediate-type upward mobility
High	High-type downward mobility		High-type persistence

In Turkey, where parental education distribution is skewed heavily toward low education, our overall mobility measures \mathcal{P}_t , \mathcal{U}_t and \mathcal{D}_t tend to mimic the intergenerational educational mobility dynamics of descendants born into families with low parental education. This is by construction, since our overall mobility variables depend on the distribution of parental education. In order to address this issue, we construct four additional variables on *relative high education prospects* of descendants, which are based *only* on the conditional transition probabilities of descendants with different levels of parental educational backgrounds. As described in (6), (7), (8) and (9), these variables are inversely related to the extent of the disadvantage in earning a college degree experienced by descendants with low-educated parents relative to those with high-educated parents:

$$\mathcal{RHEP}_{L\&M/H} = \frac{\Pr(E = 3|P = 1 \vee 2)}{\Pr(E = 3|P = 3)} \quad (6)$$

$$\mathcal{RHEP}_{L/H} = \frac{\Pr(E = 3|P = 1)}{\Pr(E = 3|P = 3)} \quad (7)$$

$$\mathcal{RHEP}_{M/H} = \frac{\Pr(E = 3|P = 2)}{\Pr(E = 3|P = 3)} \quad (8)$$

$$\mathcal{RHEP}_{L/M} = \frac{\Pr(E = 3|P = 1)}{\Pr(E = 3|P = 2)} \quad (9)$$

Note that *regardless* of the number of university graduates in a cohort, the relative high education prospect variables defined in (6), (7), (8) and (9) take values closer to unity if parental education is *not* decisive in descendants' prospects in university graduation. If, on the contrary, parental education

is pivotal in descendants’s prospects of graduation from university, and as such most university graduates come from families with university-graduate parents, the relative high education prospect variables take values closer to zero. Thus, relative high education prospects variables yield parental-distribution-independent estimates of intergenerational educational mobility.

While the previous literature on the cross-country comparison of intergenerational educational mobility patterns focuses mostly on *relative* intergenerational mobility, i.e. the relationship between parents’ educational attainment relative to the average parental education of the cohort and descendants’ educational attainment relative to the cohort average, we base the majority of our discussion on *absolute* mobility patterns due to our concerns regarding the unrealistic assumptions embedded in the relative mobility approach (i.e. *linearity*, *cardinality*, *symmetry* and *monotonicity* in the relationship between years of schooling of parents and descendants) and data-quality quality issues we describe in the [Appendix](#).¹⁶ However, in order to enhance the comparability of our findings with the previous literature, we complement our ordinal results with intergenerational years of schooling regression and correlation coefficients (β_t and ρ_t) after imputing parental years of education, the details of which we discuss in [Appendix](#). The previous literature on the cross-cohort evolution of intergenerational educational mobility dynamics (e.g. [Hertz et al. 2007](#), and [Schneebaum et al. 2015](#)) relies on *years of schooling* OLS linear regressions in order to explore intergenerational educational mobility patterns over time and across countries. Specifically, earlier studies regress years of schooling of descendants on years of schooling of their parents, and report the intergenerational regression and correlation coefficients by estimating the following OLS equation:

$$\tilde{E}_{it} = \alpha_t + \beta_t \tilde{P}_{it} + u_{it} \quad (10)$$

where \tilde{E}_{it} denotes years of schooling of descendant i born in year t , \tilde{P}_{it} denotes descendant i ’s parents’s *average* years of schooling, α_t denotes birth-cohort specific constant, and β_t governs the degree of intergenerational educational mobility: i.e. if $\beta_t = 0$, parental education does not correlate with descendants’ education at all, hence there is perfect mobility.¹⁷ In line with this standard methodology, we regress descendants’ observable years of schooling on their parents’ imputed average years of schooling and estimate the regression coefficients of interest. Since β_t estimated with OLS may be biased in the case where the variance of parental years of schooling ($\sigma_{\tilde{P}}^2$) and descendants’s years of schooling ($\sigma_{\tilde{E}}^2$) are different from each other, we also calculate and report our estimates of the intergenerational correlation coefficient by controlling for differences in standard deviations of generations, as suggested by [Hertz et al. \(2007\)](#):

$$\rho_t = \beta_t \frac{\sigma_{\tilde{P}_t}}{\sigma_{\tilde{E}_t}} \quad (11)$$

¹⁶We argue for the unrealism of the implicit assumptions behind relative mobility estimates based on our observations from the actual data: we verify that for a given birth-cohort, the relationship between parents’ and descendants’ years of schooling varies *drastically* over the level of education of the better-educated parent: the years of schooling OLS estimations deliver considerably different regression coefficients when we cluster our working sample over parental education background (via highest degree attained), as we report in [Appendix Table C.1](#). Briefly, the regression and correlation coefficients decrease over parental education, suggesting that the intergenerational educational *immobility* in the lower end of the distribution is more persistent, especially for the earlier cohorts. Thus, our years of schooling estimations confirm that a single OLS linear regression coefficient by the entire sample is merely the result of a country-wide average, and as such, it falls short of explaining the heterogeneous mobility patterns experienced by different subgroups in the society.

¹⁷Earlier literature in intergenerational mobility interprets an intergenerational regression and correlation coefficient with a low magnitude or low level of significance as being indicative of a greater degree of intergenerational mobility.

where ρ_t denotes the correlation coefficient between education of descendants and parents, and σ_{P_t} and σ_{E_t} denote standard deviation of years of schooling for parents and descendants, respectively.

4 Results

In this section we report and discuss our results by the empirical methodology described in the previous section. We first explore the evolution of the intergenerational linkage between parents' and descendants' education across cohorts, and next focus on the role of other familial and individual characteristics that cause heterogeneities among different subgroups of the society. Finally, we explore the evolution of the relationship between within-cohort inequality and various metrics of intergenerational educational mobility.

4.1 Intergenerational Educational Mobility Dynamics

We start reporting our results by displaying the evolution of intergenerational educational mobility patterns in Turkey for those born between 1951 and 1985. We first focus on aggregate mobility variables (such as average persistence and upward mobility), and then we explore the roles of conditional transition probabilities and parental educational distributions in generating the observed time-series behaviors exhibited by these aggregate mobility variables.

The first column of [Table 3](#) (Model 1) corresponds to the regression model we rely on to calculate the predicted probabilities in this section. Model 1 reveals that the education level of the better-educated parent and its interaction with the birth-cohort of the descendant are positively and significantly associated with the educational attainment of the descendant. Specifically, a one level increase in parental education is associated with approximately 9.9 times the increase in the odds of higher educational attainment. However, since the odds ratio of the parental education and cohort interaction variable is significant and smaller than one, Model 1 suggests that the effect of parental education on the odds of higher educational attainment decreases in magnitude over time.

[Figure 1 \(a\)](#) exhibits the evolution of intergenerational educational persistence (\mathcal{P}_t), i.e. the probability of a randomly drawn descendant from a specific birth-cohort to have the same educational attainment as his/her better-educated parent, which can be interpreted as the degree of intergenerational *immobility*. Our analysis yields a persistence coefficient of 84% for the cohort born in 1951, 61% for the cohort born in 1985, and an average persistence coefficient of 74% for the entire sample. [Figure 1 \(a\)](#) depicts that Turkey's average intergenerational educational persistence has decreased monotonically over time.

In [Figure 1 \(b\)](#), we display the empirical correspondents of the diagonal components of the intergenerational transition matrix in [Table 3](#) to explore the underlying dynamics generating the overall persistence trends observed in [Figure 1 \(a\)](#). [Figure 1 \(b\)](#) reveals that the reduction in overall intergenerational persistence stems mainly from the decreasing low-type persistence in Turkey, i.e. the decreasing frequency of low-educated descendants born to low-educated parents. Specifically, low-type persistence has declined from 81% for the cohort born in 1951 to 53% for the cohort born in 1985, with an average of 71% for the entire sample. On the contrary, intermediate-type and high-type persistence have continuously increased (from 1% to 3% in the case of intermediate-type persistence and from 1% to 5% in the case of high-type persistence between 1951 and 1985 birth-cohorts). Since both the levels and growth rates of the latter persistence types have been substantially lower than that of low-type persistence, their contribution to the overall persistence has been outweighed by

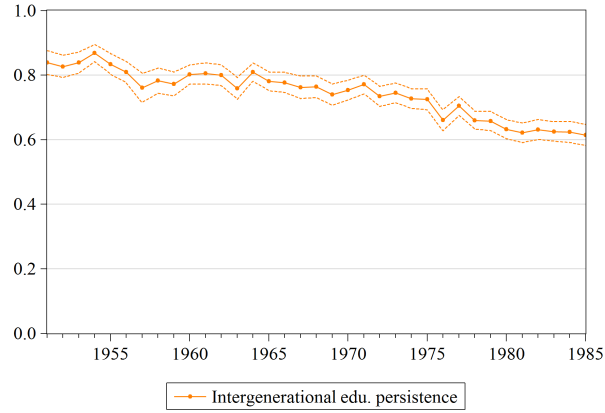
Table 3: Odds Ratios by Ordered Logit Regressions

Variable	Model				
	(1)	(2)	(3)	(4)	(5)
P_{it}	9.123*** (16.98)	10.270*** (17.25)	8.610*** (14.36)	7.884*** (15.71)	8.014*** (15.62)
$P_{it} \times t$	0.985*** (-3.06)	0.981*** (-3.62)	0.978*** (-3.71)	0.987*** (-2.56)	0.986*** (-2.76)
F_{it}		0.297*** (-13.95)			
$F_{it} \times t$		1.024*** (6.5)			
$D(1,2)_{it}$			1.845 (1.04)		
$D(1,2)_{it} \times t$			1.003 (0.16)		
$D(2,2)_{it}$			4.438*** (2.89)		
$D(2,2)_{it} \times t$			0.982 (-0.93)		
$D(1,3)_{it}$			0.608 (-0.23)		
$D(1,3)_{it} \times t$			1.001 (0.00)		
$D(3,2)_{it}$			1.286 (0.33)		
$D(3,2)_{it} \times t$			1.027 (0.95)		
$D(2,3)_{it}$			1.131 (0.06)		
$D(2,3)_{it} \times t$			0.993 (-0.09)		
$D(3,3)_{it}$			1.219 (0.21)		
$D(3,3)_{it} \times t$			1.047 (1.31)		
U_{it}				4.757*** (14.01)	
$U_{it} \times t$				0.976*** (-5.23)	
I_{it}					1.225*** (6.05)
$I_{it} \times t$					1.001 (1.02)
Wald χ^2	2306.71	2560.59	2366.92	2817.21	2529,.28
Presudo R^2	0.0969	0.1120	0.0994	0.1180	0.1076
# Obs.	24,407	24,407	24,407	24,407	23,960

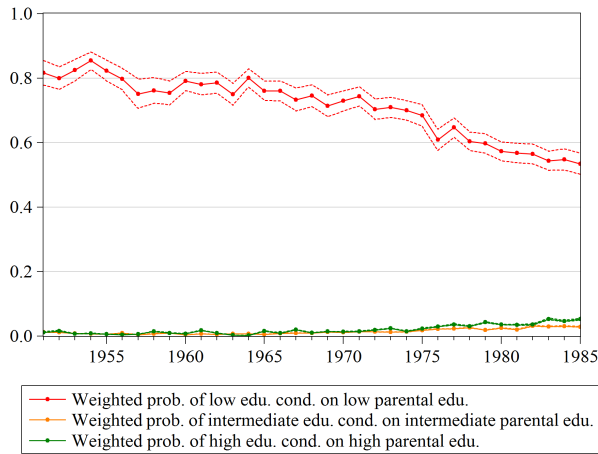
Numbers without parentheses stand for the odds ratio (the change in $\frac{Pr(E=3)}{1-Pr(E=3)}$ as a result of increasing an explanatory variable by one unit) of the variable shown in the respective row. Each model also involves cohort fixed-effects that are not reported. Z statistics are reported in parentheses. *, **, and *** indicate statistical significance at 99%, 95%, and 90% confidence levels, respectively.

Figure 1: Intergenerational Educational Persistence

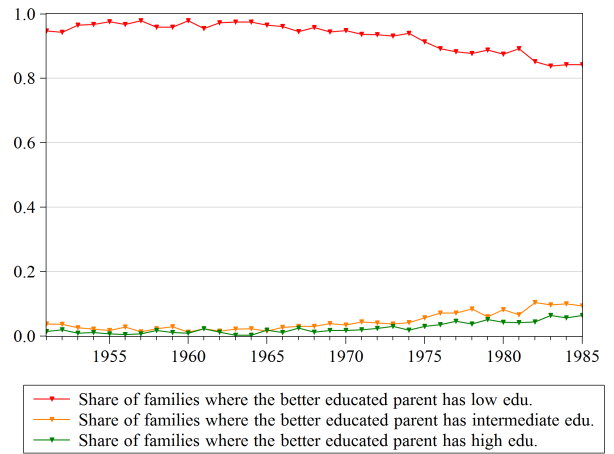
(a) PERSISTENCE (P_t)



(b) TYPES OF PERSISTENCE



(c) SHARES OF FAMILY TYPES WRT. BETTER-EDUCATED PARENT



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Red, orange and green lines correspond to conditional education probabilities of low, medium and high education, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

low-type persistence. Consequently, overall persistence in Turkey has mimicked the dynamics of low-type persistence over time.

The sharp downward trend displayed by low-type persistence in [Figure 1 \(b\)](#) has been the product of both the decline in (i) the share of families in which both parents have low educational attainment and (ii) the probability of low educational attainment conditional on low parental education. [Figure 1 \(c\)](#) portrays the evolution of the distribution of parental education over time. The share of families in which both parents have low educational attainment has declined from 95% for the 1951 birth-cohort to 84% for the 1985 birth-cohort, while the share of families in which the better-educated parent has intermediate (high) educational attainment has increased from 4% (1%) for those born in 1951 to 9% (6%) for those born in 1985.

[Figure 2](#) demonstrates that in addition to the change in the distribution of parental education, the decline in the probability of observing low-educated descendants conditional on low parental education has been another major factor contributing to the downward time-trend in intergenerational persistence. The predicted probability of low educational attainment conditional on low parental education has declined from 86% for the 1951 birth-cohort to 63% for the 1985 birth-cohort, while the probability of intermediate (high) educational attainment conditional on intermediate (high) parental education has oscillated around 30% (80%) within the period of interest. Thus, both the decline in the frequency of families with low parental education and the sharp decline by the probability of low educational attainment conditional on low parental education have been instrumental in generating the downward time-trend in overall persistence in Turkey.

4.2 Intergenerational Educational Mobility and Other Factors

After reporting on the overall relationship between descendants' and parents' education, in this section we study the role of other explanatory variables within our ordinal framework. In particular, we study heterogeneities in intergenerational educational mobility stemming from gender, parental couple structure, financial conditions during the upbringing of the descendant, and the degree of urbanization of the current (at the time of survey) place of residence.

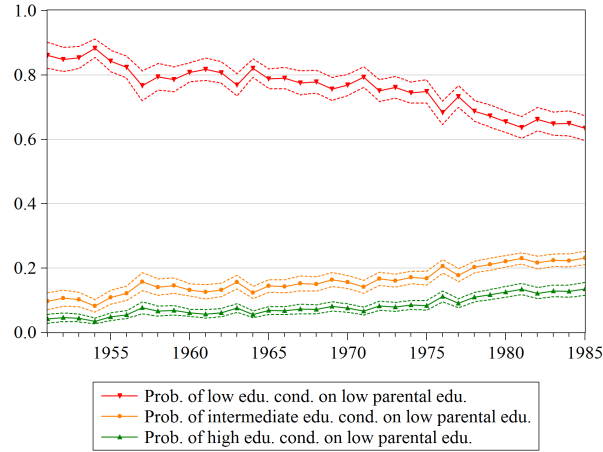
4.2.1 Intergenerational Educational Mobility and Gender

We incorporate the indicator variable F_{it} (gender) and its interaction with descendants's birth-cohort ($F_{it} \times t$) into our econometric specification, and report our findings in Model 2 of [Table 3](#). In this regression model, parental education has a higher odds ratio than that by the Model 1. More importantly, F_{it} has an odds ratio that is considerably lower than unity, implying that female descendants in Turkey have been more disadvantaged than their male counterparts in their better-education prospects. However, the odds ratio of the gender and cohort interaction variable is statistically significant and greater than one, which indicates that the disadvantage experienced by female descendants has decreased over time.

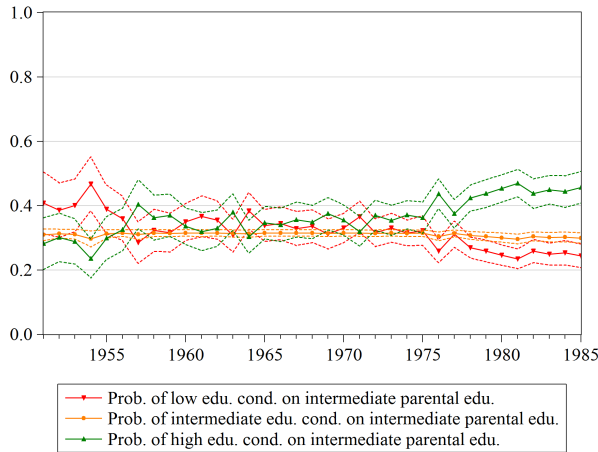
[Figure 3 \(a\)](#) displays the intergenerational educational persistence variables by the predicted transition probabilities and the distribution of parental education for descendants of both genders. [Figure 3 \(a\)](#) demonstrates that the degree of intergenerational educational persistence has always been higher for female descendants: the intergenerational persistence for male descendants has steadily declined over time, starting from 79% for the earliest to 57% for the latest cohort. In the case of female descendants, the respective estimates have been noticeably higher: 89% for the 1951 and 65% for the 1985 birth-cohorts.

Figure 2: Intergenerational Educational Transition Probabilities

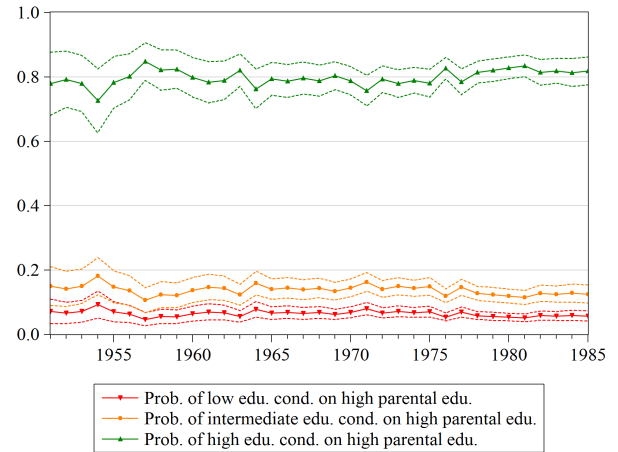
(a) CONDITIONAL ON LOW PARENTAL EDU.



(b) CONDITIONAL ON INTERMEDIATE PARENTAL EDU.



(c) CONDITIONAL ON HIGH PARENTAL EDU.

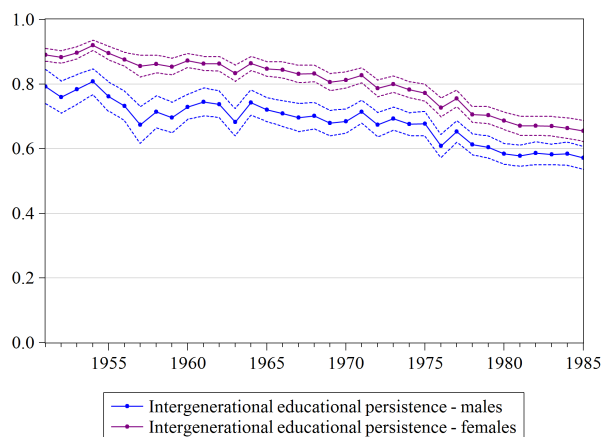


† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Red, orange and green lines correspond to conditional education probabilities of low, medium and high education, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

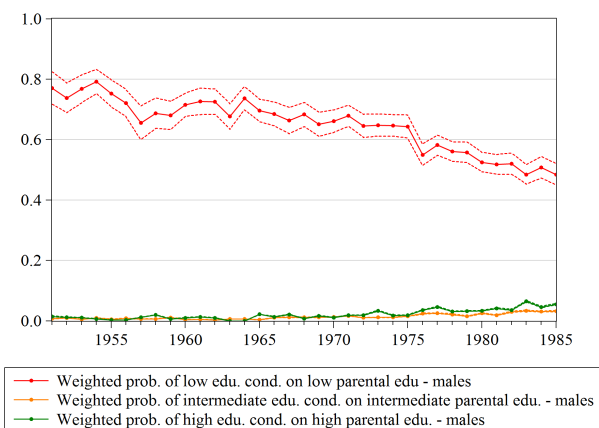
Similar to our analysis in the previous section, we next decompose overall persistence into the three types of conditional persistences. Figure 3 (b) and Figure 3 (c) portray the results of this exercise for descendants for both genders. Figure 3 (c) demonstrates that the decline in persistence for both male and female descendants have stemmed from the drastic fall in low-type persistence: Low-type persistence for male (female) descendants has decreased from 77% (87%) to 48% (58%) over the period of interest. Thus, the observed difference in gender-specific persistence variations can at least partially be attributed to the difference in low-type persistence levels between genders.

Figure 3: Intergenerational Educational Persistence Type by Gender

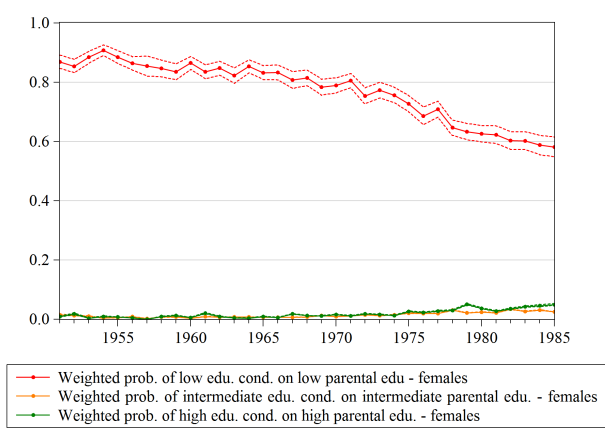
(a) PERSISTENCE (P_t)



(b) PERSISTENCE TYPES - MALE DESCENDANTS



(c) PERSISTENCE TYPES - FEMALE DESCENDANTS



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. In panel (a) purple and blue lines correspond to female and male intergenerational educational persistence, respectively. In panels (b) and (c) red, orange and green lines correspond to low-type, intermediate-type and high-type intergenerational educational persistence, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

As the distribution of parental education is similar across genders, the difference between the rate of change in low-type persistence across genders is expected to stem mainly from the discrepancies

in the evolution of conditional transition probabilities with respect to gender. Figure 3 (c) confirms this conjecture: the probability of low educational attainment conditional on low parental education for male descendants has fallen from 80% for those born in 1951 to 59% for those born in 1985, whereas the same probability for female descendants has decreased from 93% for those born in 1951 only to 68% for those born in 1985. Moreover, Figure 4 shows that the heterogeneity in transition probabilities over gender has not been limited to the case of families with low parental education: historically, female descendants born into families with intermediate parental education have experienced a relatively higher (lower) probability of low (high) educational attainment compared to their male counterparts. In the case descendants born to at least one university-graduate parent, the probability of university graduation for male and female descendants have converged statistically for the cohorts born in the early 1980s.

These results contradict with the findings on the role of gender in intergenerational educational mobility dynamics across European countries explored in Torul and Öztunali (2017): in most European countries, the gender disadvantage experienced by females born in the 1940s vanished over time, and the playing field leveled for those between early 1960s and late 1970s depending on the country of interest. For those born after, the gender gap has *reversed* and females born in early 1980s in Europe face *better* education prospects than their male counterparts. Our results for Turkey indicate that Turkey has not yet experienced the reversal of the gender-gap in intergenerational educational mobility observed in other European countries.

4.2.2 Intergenerational Educational Mobility and Parental Couple Composition

In our benchmark estimation, we define parental education as the education level of the *better-educated* parent, and thereby control parental education with a single independent variable. In this section, in order to control also for the effect of the less-educated parent, we modify our default specification by introducing an additional indicator variable that captures the educational attainment of the less educated parent, which we report in Model 3 of Table 3.

Model 3 of Table 3 reveals that controlling for the education of the less-educated parent does not considerably affect the magnitude of the odds ratio associated with the education level of the better-educated parent: P_{it} still has an odds ratio of 9.165. Among the newly-introduced parental couple dummy variables, $D(2, 2)_{it}$ has a positive and significant odds ratio, which indicates that compared to families with an intermediate paternal and low maternal education, descendants born into families where both parents are intermediately-educated have a greater (approximately 4.6 times) odds of high educational attainment.¹⁸ However, the time interaction of this dummy variable is insignificant, hence the magnitude of this parental couple effect does not systematically change over time. When we turn our attention to the dummy variables for families where at least one parent has high education, we do not observe any significant coefficients, suggesting that the transition probabilities in families where at least one parent has high education do not vary significantly with respect to the educational attainment of the other parent. As a result, while having at least one parent with high education is associated with a greater probability of high educational attainment, the gender of the parent with high education does not have a significant role in the determination of this conditional probability.

¹⁸Note that in Model 3, $D(1, 1)_{it}$, $D(2, 1)_{it}$, and $D(3, 1)_{it}$ are not included as dummy variables in order to prevent multicollinearity problems between P_{it} and the parental couple dummy variables. By doing this, we also implicitly assume that a parental couple with intermediate (high) paternal and low maternal education constitutes the reference family type among families where the better-educated has intermediate (high) education.

Figure 4: Conditional Intergenerational Educational Transition Probability by Gender



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Red, orange and green lines correspond to conditional education probabilities of low, medium and high education, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

Figure 5 displays the transition probabilities among children born into families where the education attainment of the better-educated parent is intermediate and high. According to Figure 5 (a) and (e), children born into families with both intermediate paternal and maternal education have been less (more) likely to have low (high) educational attainment compared to those who were born into families where only one parent has intermediate education. Transition probabilities of descendants with only one intermediately-educated parent have not depended on the gender of the parent with higher educational attainment. In the case of families where at least one parent is university-graduate, the better degree held by the less-educated parent has improved education prospects of descendants, albeit statistically insignificantly under most scenarios.

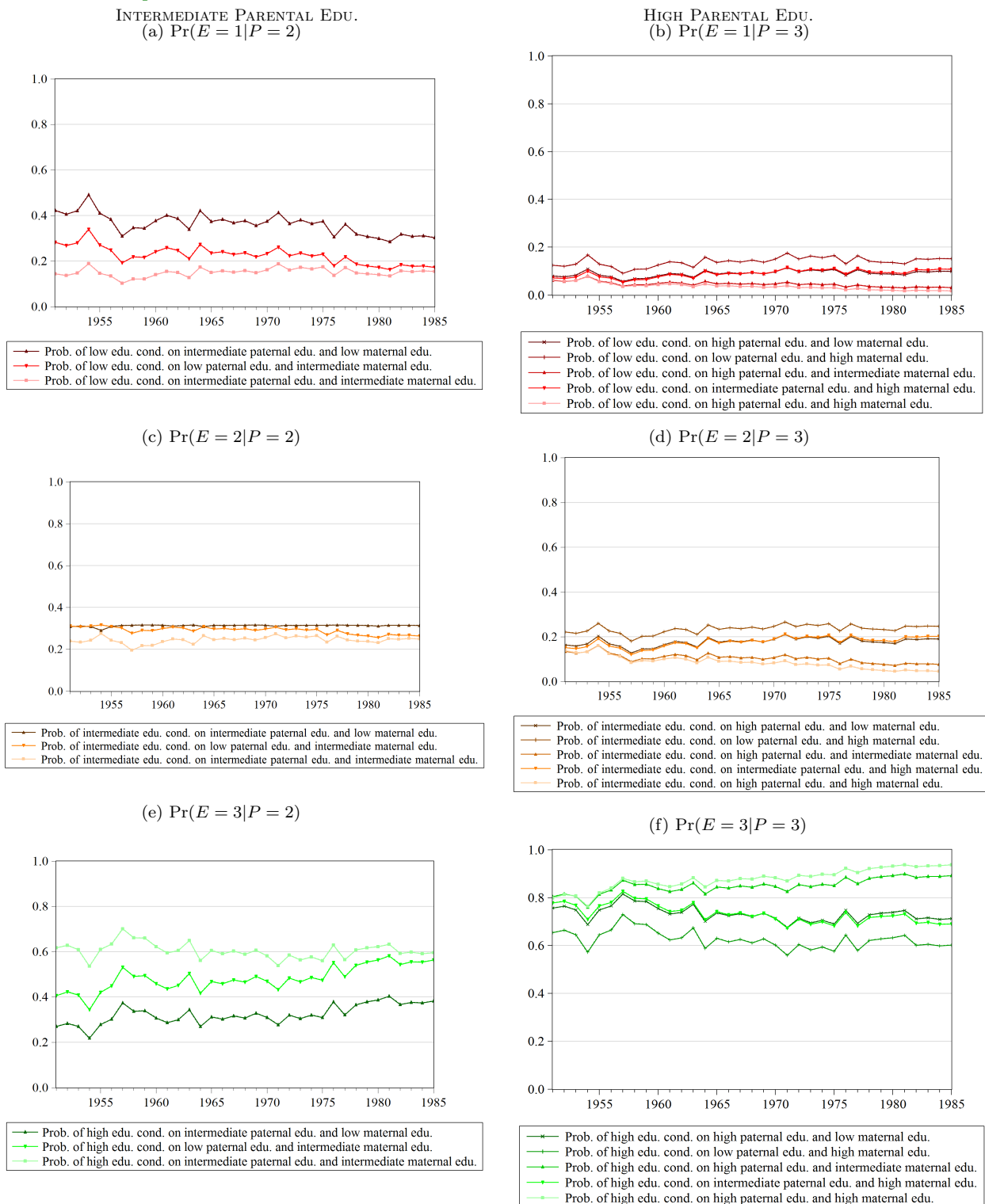
4.2.3 Intergenerational Educational Mobility and Urbanization

We next document heterogeneities in intergenerational educational mobility dynamics with respect to the current (at the time of survey) place of residence.¹⁹ We estimate the transition probabilities in this section via Model 4 of Table 3, in which the urbanization dummy variable (U_{it}) has a significant odds ratio of 4.757 while its birth-cohort interaction has a significant odds ratio that is smaller than one (0.987). These estimates imply that conditional on having the same parental educational backgrounds, descendants who are currently residing in urban places have enjoyed better upward educational mobility prospects, which has decreased over time. Figure 6 (a) and (b) show that while urban and rural persistences have both declined over time, descendants who are currently living in rural residences have historically been exposed to a higher degree of intergenerational educational immobility compared to their counterparts residing in urban locations. For descendants who currently live in urban areas, intergenerational educational persistence has fallen from 79% for the 1951-born cohort to 57% for the 1985-born cohort, whereas the respective estimates for those currently residing in rural places persistence are 95% for the 1951-born cohort and 73% for the 1985-born cohort. According to Figure 6 (c) and (d), the discrepancy between the urban and rural persistences has stemmed from both an initial distributional disadvantage in the rural areas, and the relatively slower decrease in low-type persistence in these locations (i.e. low-type urban persistence has fallen from 75% to 47%, whereas its rural counterpart has fallen from 95% to 70% over the period of interest).

Figure 6 (e) and (f), and Figure 7 (a) and (b) reaffirm that the difference in the time-trends of low-type persistence between descendants currently living in rural and urban areas is the result of both differences in the distribution of parental education and conditional transition probabilities. Figure 6 (e) and Figure 6 (f) show that the share of families in urban areas where both parents have low education has declined from 92% for the 1951 birth-cohort to 80% for 1985 birth-cohort, whereas the respective estimates for descendants currently residing in rural locations are notably higher 99% and 94%. Figure 7 (a) and (b) further demonstrate that the probability of low educational attainment conditional on low parental education has fallen from 82% to 59% in urban locations, whereas the same estimates for rural locations are 95% to 74% within the period of interest.

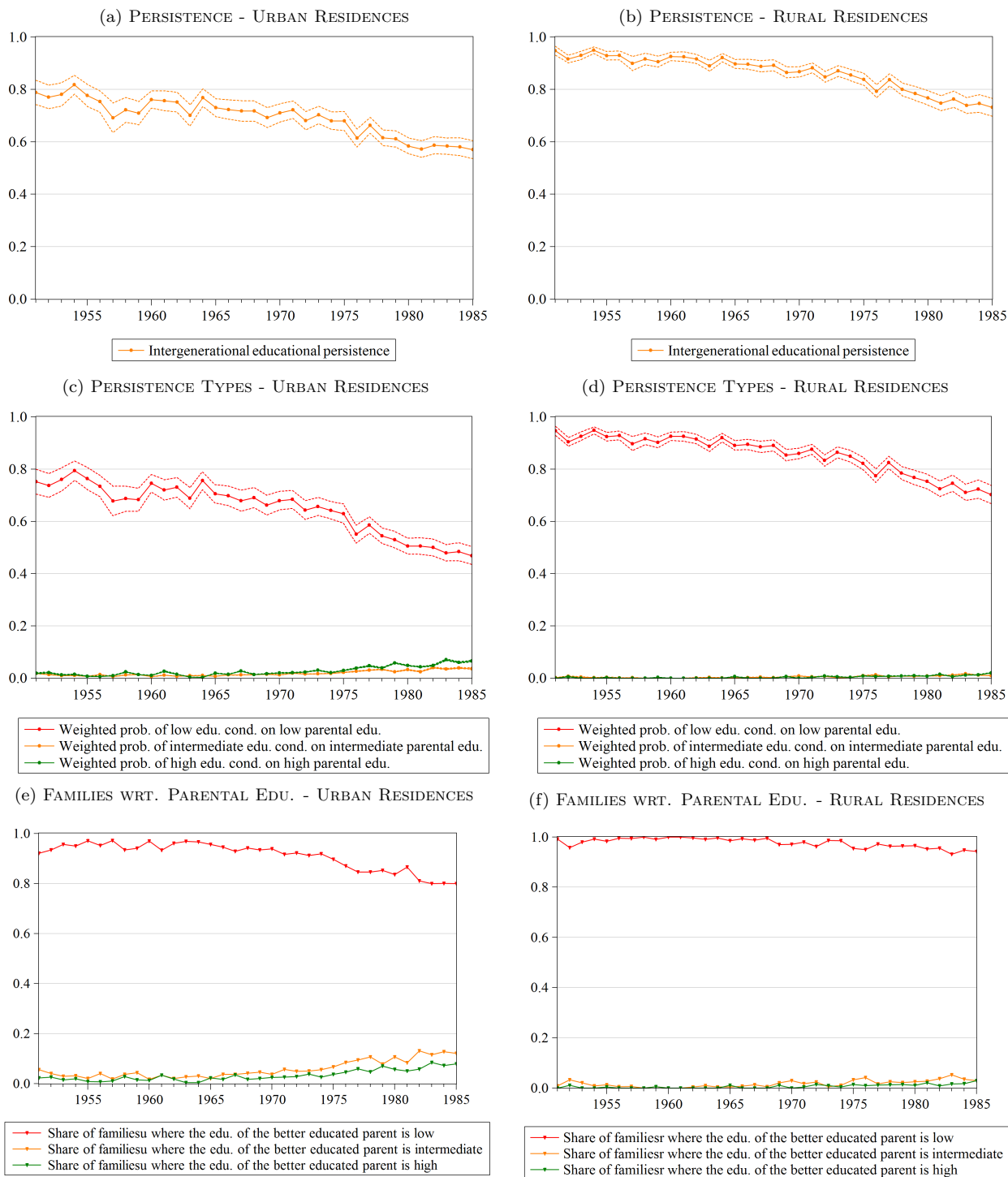
¹⁹We acknowledge that the place of residence during the upbringing of the descendant is potentially more important in the determination of the educational attainment, and the current place of residence is by no means a perfect indicator of the location where a descendant received her education, especially if within-country migration due to various socio-economic factors is a prevalent phenomenon, as in the case of Turkey. Furthermore, the direction of causality in this analysis can also be reverse: i.e. parents may choose to relocate by taking into consideration the prospects of their descendants. Despite these concerns, we still aim to document the drastic heterogeneity in intergenerational educational mobility associated with the degree of urbanization, since Turkey has experienced considerable urbanization over time. For state-of-the-art research on the impacts of neighborhoods on intergenerational mobility, see Chetty and Hendren (2016a) and Chetty and Hendren (2016b), among others.

Figure 5: Conditional Intergenerational Educational Transition Probability Conditional on *Inter-*mediate and *High* Parental Education



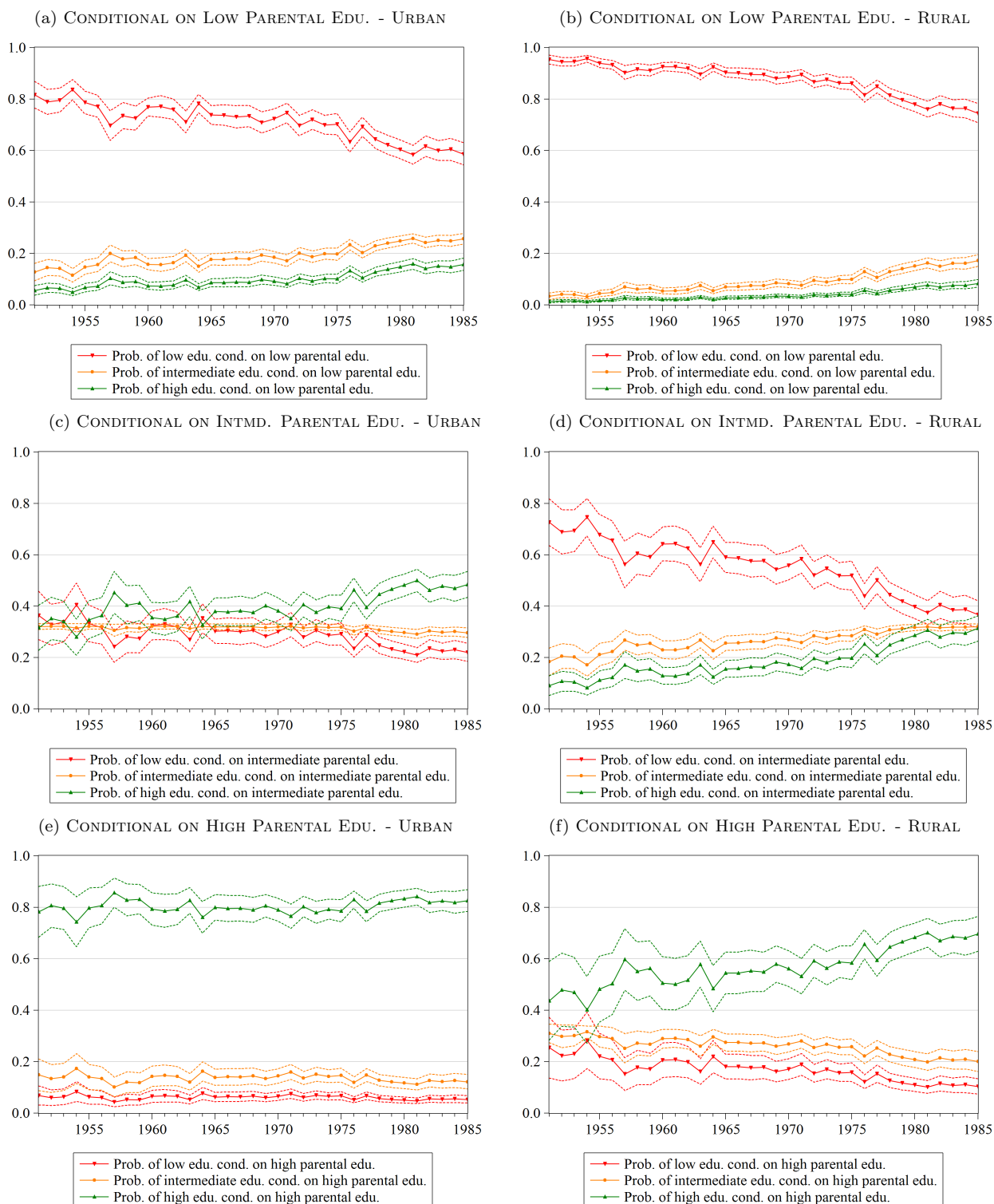
† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Red, orange and green lines (at different depth levels) correspond to low, medium and high educational attainment probabilities, respectively. Standard error bands are omitted in order for legibility purposes, figures with standard error bands are available upon request.

Figure 6: Intergenerational Educational Persistence, Types of Persistence and Shares of Families wrt. Parental Education across Urban and Rural Residences



† This figure shows the estimation results by SILC in 2011. In panels (c) and (d) ((e) and (f)) red, orange and green lines correspond to low-type, intermediate-type and high-type intergenerational educational persistence, respectively. Dates on the horizontal axis correspond to the *birth-cohort* of interest. In panels (e) and (f) red, orange and green lines correspond to the shares of families where parental *better-education* is low, medium and high, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

Figure 7: Intergenerational Educational Transition Probability by The Degree of Urbanization of Current Place of Residence



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Red, orange and green lines correspond to conditional education probabilities of low, medium and high education, respectively. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

4.2.4 Intergenerational Educational Mobility and Parental Financial Status

In addition to the educational and demographic variables we have discussed so far, SILC in 2011 also provides information on descendants’s subjective evaluation of their household’s financial status when they were 14 years old.²⁰ We exploit this variable in order to investigate the effect of household’s financial well-being on the educational prospects of descendants after parental education is controlled for.²¹ The self-reported financial condition variable (I_{it}) has an odds ratio of 1.225, which is statistically significant, while its cohort interaction ($I_{it} \times t$) is not, as we report in Model 5 of Table 3. These findings indicate that better financial conditions are associated with greater odds of high educational attainment and this effect does not fade over time. Figure 8 displays the transition probabilities conditional on parental education and financial conditions of the descendant’s household when he/she was 14 years old. Figure 8 demonstrates that in addition to better parental educational backgrounds, better financial conditions of the household is also associated with higher probabilities of high school and university graduation. For the 1951 (1985) birth-cohort, the probability of high educational attainment conditional on low parental education is 2% (7%) for descendants who experienced worst financial conditions and 7% (22%) for those who experienced best financial conditions. In families with intermediate better-parental education, the probability of high educational attainment conditional on worst financial conditions has increased from 17% to 28%, while for those with best financial conditions, the same probability has increased from 36% to 58% over the sample period. In the case of families with high parental education, the probability of high educational attainment has oscillated around 65% (85%) for those with the worst (best) financial conditions without exhibiting a noticeable time-trend over the period of interest. Overall, our findings deliver dismal conclusions on the equality of educational opportunity in Turkey, since both parental educational background and household’s financial status shape education prospects of Turkish descendants immensely.

4.3 Educational Inequality, Intergenerational Educational Mobility, and Relative High Education Prospects

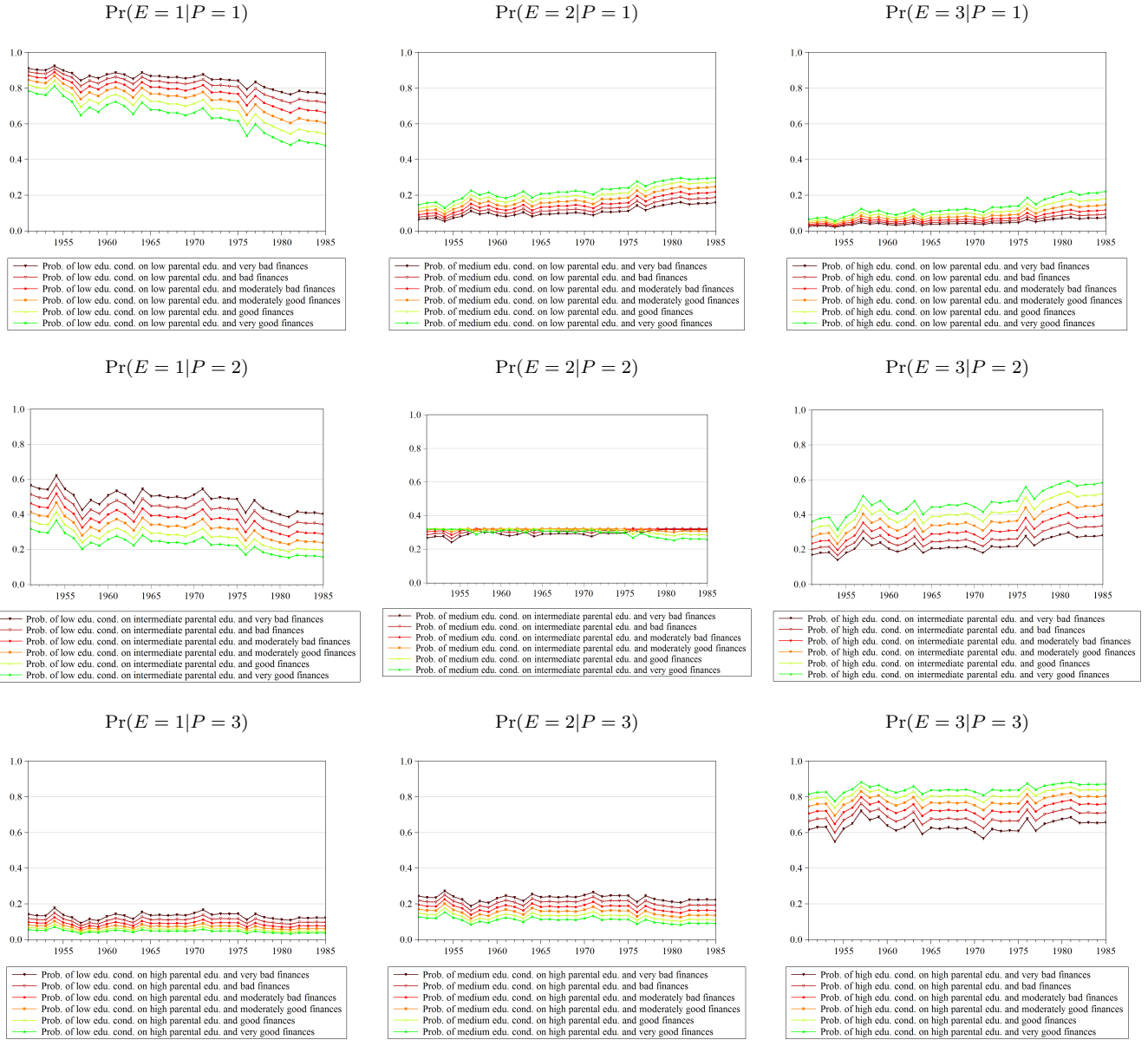
In this section, we investigate whether the Great Gatsby Curve hypothesis, which posits a positive relationship between intergenerational (income) immobility and (income) inequality across countries is also of relevance to the relationship between intergenerational immobility of education and educational inequality within the context of a single country over time.²² For this purpose, we first calculate educational Gini coefficients (via years of education) for each cohort. Next, with the purpose of drawing parallels to the original discussion on the hypothesis, which is based on a continuous variable and its intergenerational elasticity, we estimate intergenerational *education* elasticities, in addition to our ordinal intergenerational mobility measures. We then explore the relationship between educational Gini coefficients and various measures of intergenerational educational mobility.

²⁰In particular, respondents were asked to evaluate the financial conditions of their household when they were about 14 years old, and report via the Likert-scale: “very bad”, “bad”, “moderately bad”, “moderately good”, “good”, and “very good”. Note that the age 14 is a critical threshold with regards to Turkish descendants’s surpassing *low* education (completion of secondary school), and households’s financial status at this age is expected not to vary drastically a few years before and after this age.

²¹While we acknowledge that the subjective evaluation variable is not a perfect quantitative indicator of the descendants’s household’s financial conditions during their adolescence, we still believe that these results may still help us in qualitatively understanding the potential role of financial conditions in their educational mobility prospects. In fact, we also confirm that a correlated alternative financial status variable on *the ability to make ends meet by the household in which when descendant was around 14 years old* yields qualitatively similar results.

²²See Corak (2013) and Krueger (2012) for a detailed discussion on the Great Gatsby hypothesis.

Figure 8: Intergenerational Educational Mobility & Parental Finances

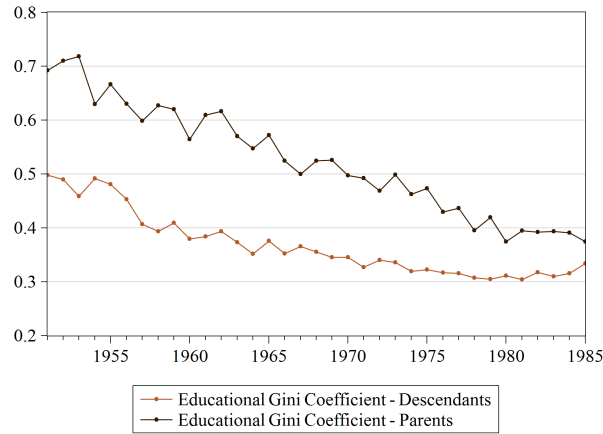


† Dates on the horizontal axis correspond to the *birth-cohort* of interest. $\Pr(E = i | P = j)$ reads as descendants's probability of attaining education level i conditional on being born to a father with an education level of j . Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

4.3.1 Educational Inequality

We measure within-cohort educational inequality in Turkey by calculating the educational Gini coefficient for each birth-cohort via the methodology by [Thomas et al. \(2002\)](#). [Figure 9](#) displays the resultant Gini coefficients for the cohorts born between 1951 and 1985. Overall, our calculations indicate that educational inequality in Turkey has improved in the second half of the twentieth century, since the education Gini coefficient has almost monotonically declined from 0.5 in for those born in 1950s to approximately 0.3 for those born in 1980s.²³

Figure 9: Educational Inequality



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest.

4.3.2 Educational Inequality and Intergenerational Educational Elasticity

We begin our discussion on the Great Gatsby Curve in the context of education in Turkey by exploring the relationship between intergenerational educational elasticity (via descendants’ *observed* years of schooling and parents’ *imputed* years of schooling) and within-cohort educational inequality (via descendants’ years of schooling Gini coefficients). We display our estimates for the intergenerational educational elasticity coefficients of each cohort in [Figure 10](#).²⁴ Our estimations reveal that the intergenerational educational elasticity in Turkey has evolved with a U-shaped pattern.

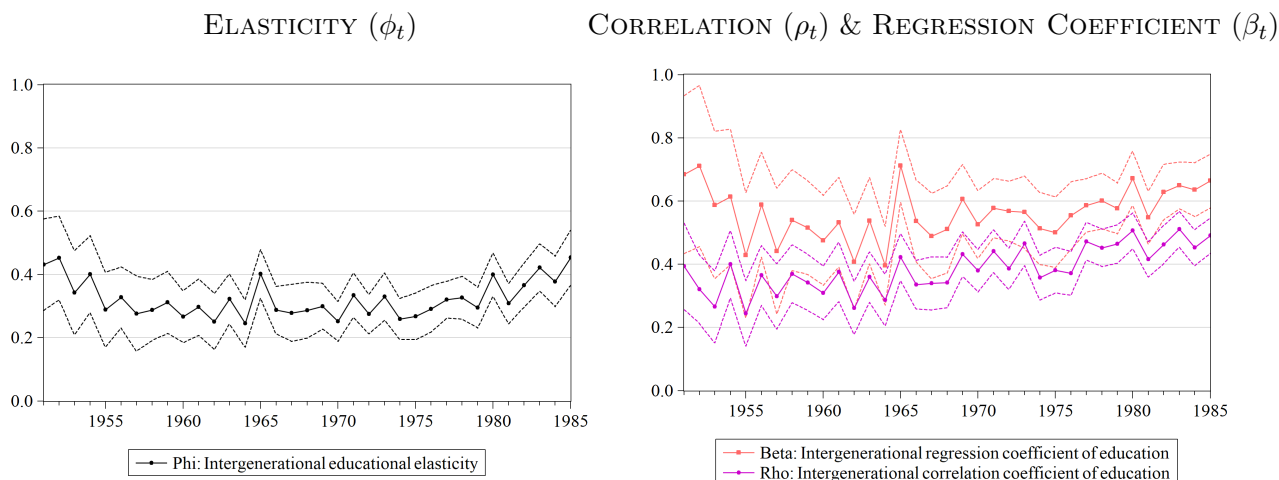
²³[Torul and Öztunali \(2017\)](#), using a smaller sample for Turkey from the European Social Survey data set, find that educational Gini coefficient in Turkey has declined from 0.63 for those who were born in 1940 to 0.29 for those born in 1984.

²⁴Following the intergenerational income mobility literature, we estimate intergenerational educational elasticity, now by treating educational attainment as a continuous cardinal variable, via running the following OLS for birth-cohort separately:

$$\ln(\tilde{E}_{it}) = \alpha_t + \phi_i \ln(\tilde{P}_{it}) + \epsilon_{it} \quad (12)$$

where \tilde{E}_{it} refers to the years of education completed by individual i born in period t and \tilde{P}_{it} corresponds to the average of the imputed years of education for this individual’s parents. Since we have observations with zero (parental or descendent) years of education, due to the high number of individuals who are illiterate or literate but without any diploma in Turkey, the estimation of this regression equation is problematic due to $\ln(0) = -\infty$ problem. In order to circumvent this issue, we assume that those who are illiterate or literate without any diploma have one year of education in this part of our analysis.

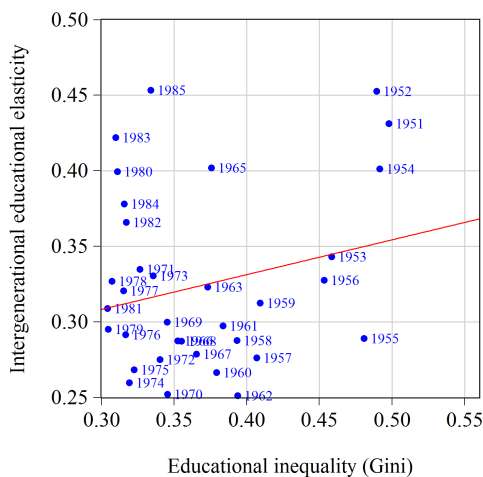
Figure 10: Intergenerational Educational Elasticity, Correlation & Regression Coefficient



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals.

Next, in Figure 11 we plot our intergenerational educational elasticity and educational Gini coefficients against each other. In line with the Great Gatsby Curve Hypothesis, which conjectures a positive cross-sectional relationship between intergenerational elasticity of income and income inequality across countries, we find a positive (albeit insignificant) time-series relationship between intergenerational educational elasticity and within-cohort educational inequality in Turkey.

Figure 11: Educational Great Gatsby Curve

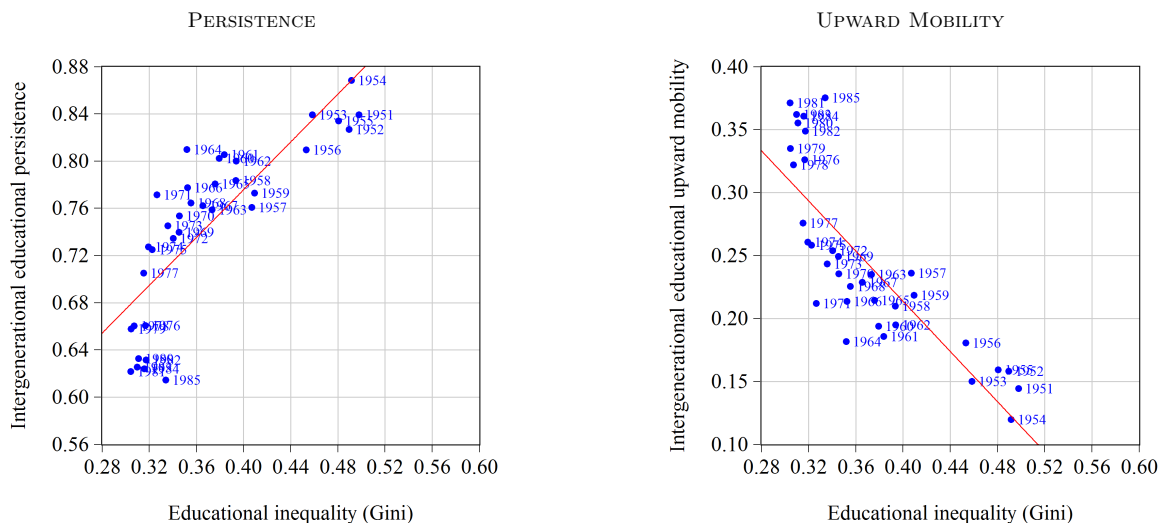


† Dates on the horizontal axis correspond to the *birth-cohort* of interest. OLS linear regression of intergenerational educational elasticity on within-cohort educational Gini coefficient yields a regression coefficient of 0.230 with a standard error and p -value of 0.169 and 0.183, respectively.

4.3.3 Educational Inequality and Relative High Education Prospects

We continue our scrutiny on the link between intergenerational educational mobility and within-cohort educational inequality by relying on our *ordinal* measures. In doing so, we first focus on the relationship between educational Gini coefficients, and intergenerational educational persistence and upward mobility measures. We report our findings in Figure 12. Figure 12 reveals that there exist strong linear associations between educational inequality and our two main ordinal mobility measures: in the form of a positive (negative) relationship between educational inequality and intergenerational educational persistence (upward mobility). In particular, we observe that the cohorts born in 1950s experienced high intergenerational persistence, low upward mobility, and high educational inequality, whereas the cohorts born in 1980s are associated with relatively low levels of persistence, high upward mobility and low inequality.

Figure 12: Intergenerational Educational Persistence, Upward Mobility and Educational Inequality



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. OLS linear regression of intergenerational educational persistence (upward mobility) on within-cohort educational Gini coefficient yields a regression coefficient of 1.012 (-0.996) with a standard error and p-value of 0.123 (0.121) and 0.000 (0.000), respectively.

While our intergenerational educational persistence and upward mobility measures are useful in describing the evolution of intergenerational mobility dynamics in a compact manner, they are not entirely compatible with the discussion on the Great Gatsby Curve: our two ordinal mobility variables are affected by the distribution of parental education by construction, whereas the main mobility measure of the Great Gatsby Curve hypothesis, i.e. intergenerational elasticity, is not. Accordingly, in order to better relate our discussion to the Great Gatsby Curve hypothesis, we proceed with investigating the relationship between within-cohort educational inequality and our ordinal *relative high education prospect* variables. These four relative prospect variables measure the probability of high educational attainment (university graduation) of descendants with low or intermediate parental education relative to those born with high parental education. As such, these variables take the value of unity if there is no heterogeneity in descendants's prospects of high educational attainment over parental education, and are inversely related to the extent of the relative disadvantage experienced by descendants with low levels of parental education.

Figure 13 displays the evolution of the four relative high education prospect measures calculated by the conditional transition probabilities we report in the previous sections. Figure 13 reveals that the probability of high education for descendants with low or intermediate parental education relative to those with high parental education (I, shown on the north-west quadrant of Figure 13), the probability of high educational attainment conditional on low parental education relative to those with high parental education (II, shown on the north-east quadrant), the probability of high educational attainment conditional on intermediate parental education relative to those with high parental education (III, shown on the south-west quadrant) and the probability of high educational attainment conditional on low parental education relative to those with intermediate parental education (IV, shown on the south-east quadrant) all increase over time. These results stem from the fact that the probability of high educational attainment conditional on low parental education has increased the fastest, and its counterpart for descendants born to parents with high parental education has increased the slowest over the sample period.

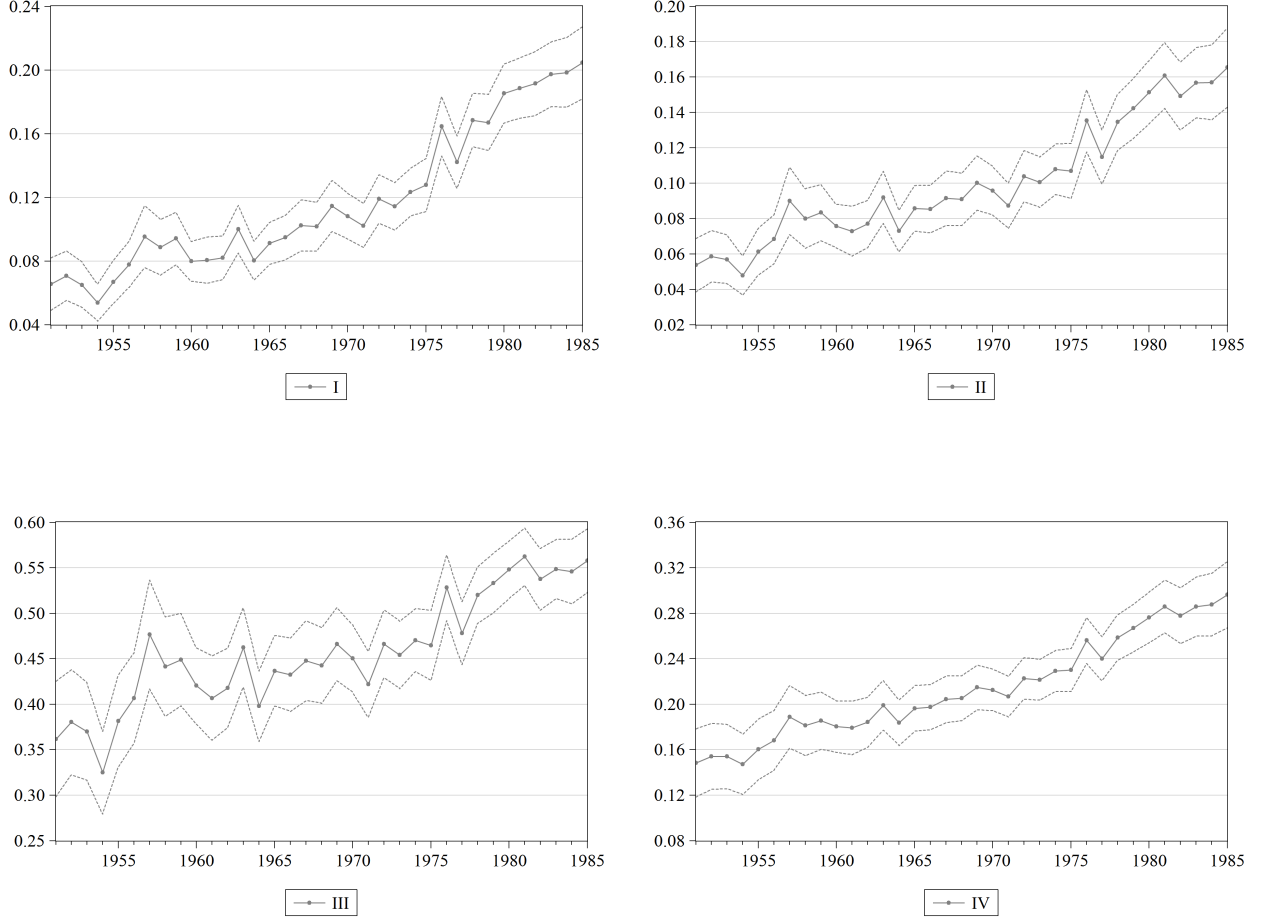
In Figure 14, we plot the educational within-cohort Gini coefficients and our four relative high education prospect variables, which we use as the ordinal equivalents of the intergenerational elasticity coefficient of the Great Gatsby Curve hypothesis, jointly. We report strong negative relationships between educational inequality and relative high education prospect variables in all four cases. Figure 14 suggests that improvements in relative high education prospects of descendants in different forms are all accompanied by reduction in within-cohort educational inequality. Hence, our results indicate that parental education’s decisiveness in the determination of descendants’ likelihood of attaining high education and educational inequality simultaneously decline over time, providing evidence in support of the existence of a time-series educational equivalent of the Great Gatsby Curve in Turkey.

5 Conclusion

In this paper, we investigate the intergenerational relationship between descendants’ and parents’ educational attainment in Turkey for cohorts born between 1951 and 1985. In doing so, we follow both i) an original ordinal methodology and ii) the standard cardinal methodology widely followed by the earlier literature. Our results indicate that while our own ordinal metric of immobility, i.e. intergenerational educational persistence, has decreased over time for the average descendant, conditional transition probabilities have exhibited immense heterogeneities over several socio-economic factors, such as parental educational background, gender, (current) place of residence, and household financial well-being during descendants’ adolescence. For instance, while the probability of attaining low education has sharply declined for descendants born to parents with either low or intermediate education, the same probability has remained rather stagnant for those born to parents with high education. In conjunction with this development, high education prospects of descendants born to parents without a university degree has improved rapidly over the period of interest. In the case of gender differences, our results suggest that the degree of intergenerational educational persistence has been historically higher for female descendants in Turkey, which stems from the fact that the probability of having low educational attainment conditional on low parental education has been higher for female descendants than their male counterparts. We also reveal that, aside from the educational attainment of the better-educated parent, the less educated parent’s educational attainment also can play a decisive role in the determination of the descendant’s educational prospects: in families where the better-educated parent has intermediate educational attainment, descendants’ probability of high educational attainment is considerably higher if both parents have intermediate

education than the case in which only one parent has intermediate education. We also find that the probability of high educational attainment is greater for descendants who had experienced better financial conditions during their adolescence and for those who currently live in urban areas.

Figure 13: Relative High Education Prospect



† This figure shows the estimation results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Dashed lines correspond to upper and lower bounds of the 95% confidence intervals. The measures in the four quadrants refer to high educational attainment probability of descendants conditional on I) low or intermediate parental education relative to those with high parental education II) conditional on low parental education relative to those with high parental education III) conditional on intermediate parental education relative to those with high parental education, and IV) conditional on low parental education relative to those with intermediate parental education.

$$\text{I: } \mathcal{RHEP}_{L\&M/H} = \frac{\Pr(E=3|P=1\vee 2)}{\Pr(E=3|P=3)} = \frac{\Pr(E=3|P\neq 3)}{\Pr(E=3|P=3)}$$

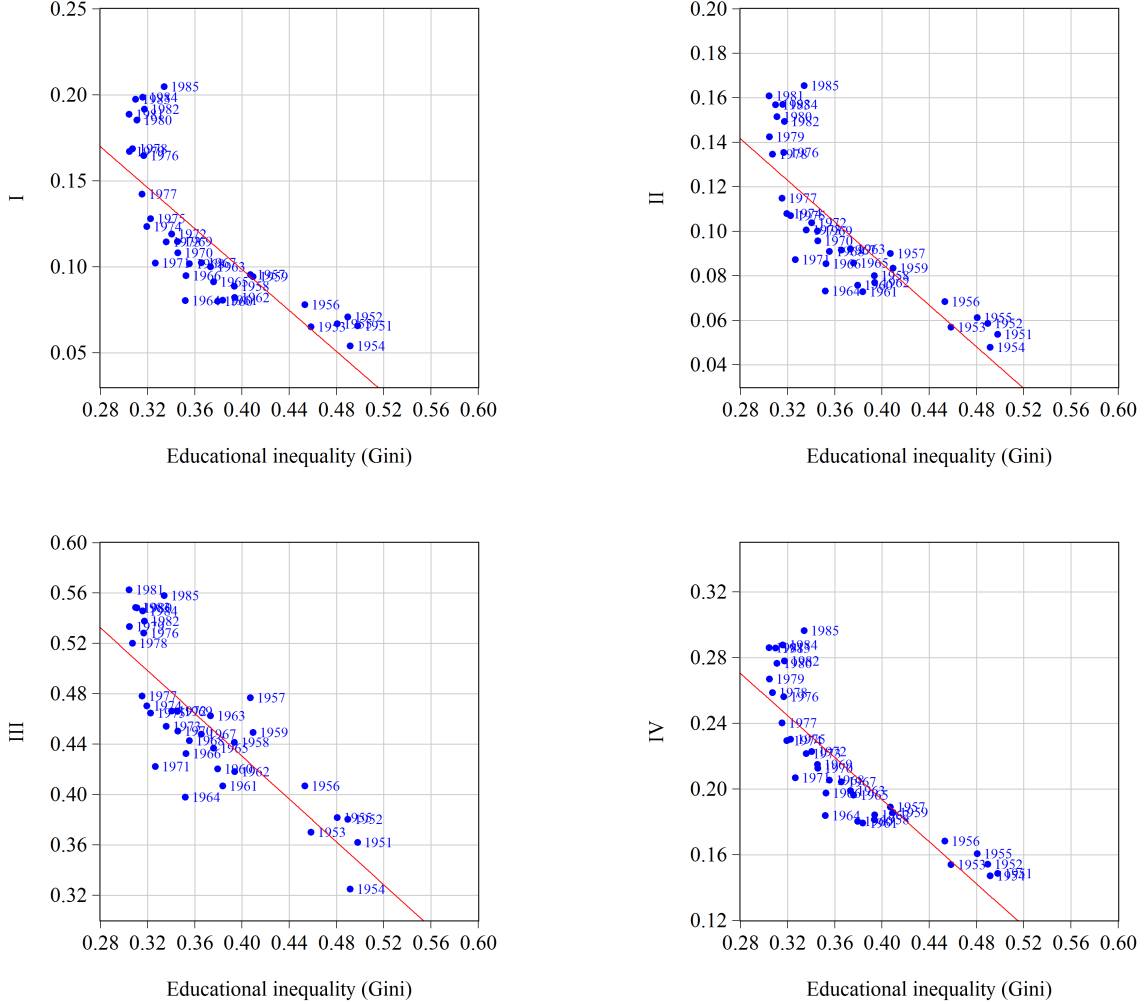
$$\text{III: } \mathcal{RHEP}_{M/H} = \frac{\Pr(E=3|P=2)}{\Pr(E=3|P=3)}$$

$$\text{II: } \mathcal{RHEP}_{L/H} = \frac{\Pr(E=3|P=1)}{\Pr(E=3|P=3)}$$

$$\text{IV: } \mathcal{RHEP}_{L/M} = \frac{\Pr(E=3|P=1)}{\Pr(E=3|P=2)}$$

In addition to unveiling the heterogeneities in intergenerational educational transition probabilities, we also scrutinize the relationship between intergenerational educational mobility and inequality of educational attainment in Turkey with the goal of testing whether the Great Gatsby Curve hypothesis is valid also for educational attainment in a time-series sense. In doing so, we first calculate the educational equivalents of inequality and mobility variables relevant to this hypothesis: educational Gini coefficients and intergenerational elasticity of educational attainment. We then find a slightly positive yet insignificant relationship between intergenerational elasticity and within-cohort

Figure 14: Educational Inequality & Relative High Education Prospect



† This figure shows the estimation results by SILC in 2011. The red line refers to the linear fit between the two variables. The measures in the four quadrants refer to high-education probability of descendants born to I) high-educated parents relative to below-high-educated parents II) high-educated parents relative to low-educated parents III) high-educated parents relative to medium-educated parents, and IV) medium-educated parents relative to low-educated parents.

$$\text{I: } \mathcal{RHEP}_{L\&M/H} = \frac{\Pr(E=3|P=1\vee2)}{\Pr(E=3|P=3)} = \frac{\Pr(E=3|P\neq3)}{\Pr(E=3|P=3)}$$

$$\text{II: } \mathcal{RHEP}_{L/H} = \frac{\Pr(E=3|P=1)}{\Pr(E=3|P=3)}$$

$$\text{III: } \mathcal{RHEP}_{M/H} = \frac{\Pr(E=3|P=2)}{\Pr(E=3|P=3)}$$

$$\text{IV: } \mathcal{RHEP}_{L/M} = \frac{\Pr(E=3|P=1)}{\Pr(E=3|P=2)}$$

OLS linear regressions of the four relative high education prospect variables on educational inequality yield coefficient estimates (and standard errors) of -0.595 (0.082), -0.467 (0.057), -0.850 (0.102), -0.640 (0.067) with corresponding p values of 0.000, 0.000, 0.000, 0.000, respectively.

inequality. However, when we switch to our ordinal equivalent of intergenerational elasticity, i.e. relative high education prospect variables, we obtain positive and statistically significant relationships between various measures of relative high education prospects and educational inequality in Turkey.

We believe that this paper contributes to the intergenerational mobility literature and the literature on Turkish development in various dimensions. First, this paper describes potential sources of discrepancies arising from using different measures of educational attainment (i.e. highest degree completed versus years of education). Second, to the best of our knowledge, this paper is the first study that analyses the time-series relationship between intergenerational educational mobility and within-cohort inequality of educational attainment, especially in the context of a developing country where educational developments have been remarkable, as in the case of Turkey. Finally, we believe that our findings contribute to the literature on Turkish development by shedding light on the evolution of multiple dimensions of educational distributions, and as such, we aim that this paper can contribute to paving the way for future research on the relationship between intergenerational mobility, inequality, and economic development in Turkey.

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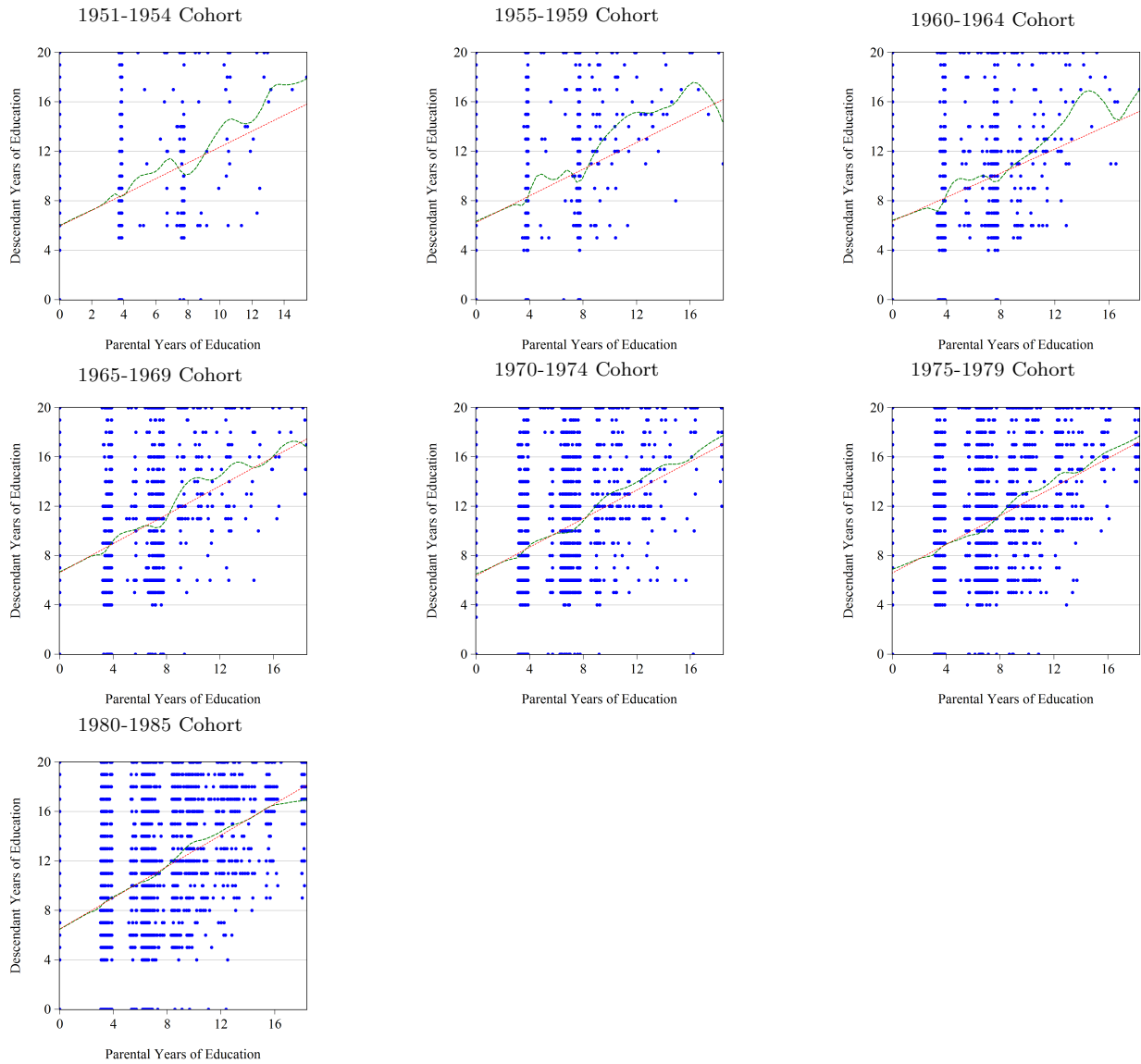
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Appendix

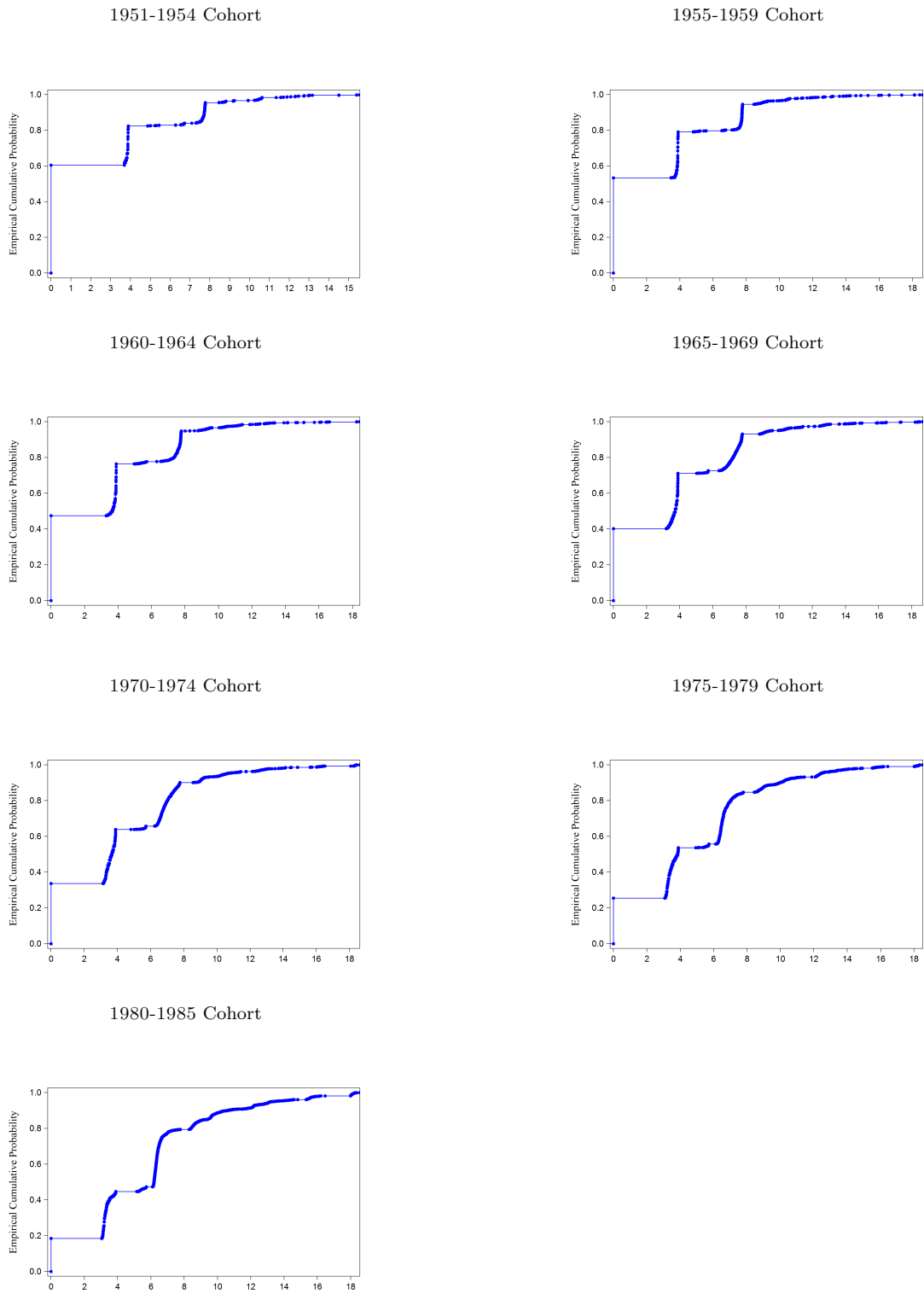
A Tables and Figures

Figure A.1: Intergenerational Years of Education Scatterplots



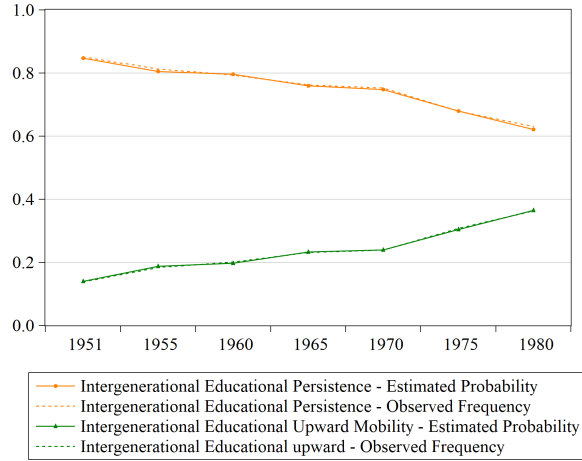
† This figure is based on SILC in 2011. Blue dots correspond to observations. The red dashed line represents the fitted values from the usual intergenerational OLS linear regression; and the green dashed curve is the kernel density of descendant years of education conditional on parental years of education.

Figure A.2: Empirical Cumulative Distributions of Parental Years of Education



† This figure is based on SILC in 2011. Blue curves represent the empirical cumulative distribution of parental education in a cohort.

Figure A.3: Intergenerational Educational Persistence and Upward Mobility: Observed Frequencies vs. Predicted Probabilities

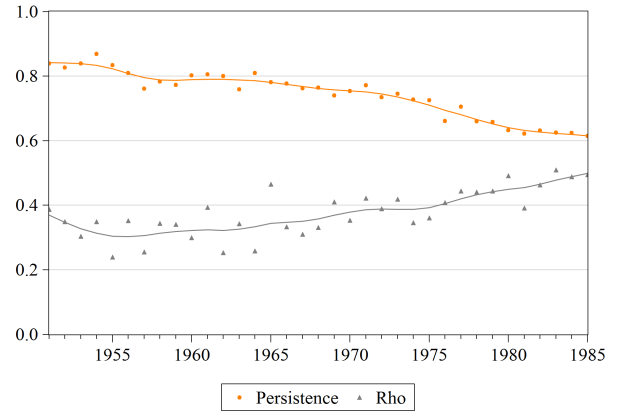
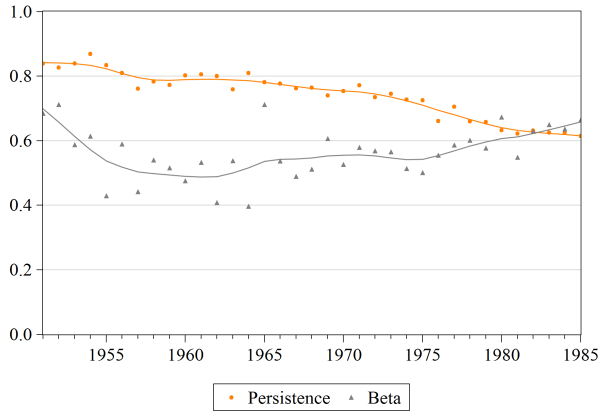


† This figure is based on SILC in 2011. Dates on the horizontal axis correspond to birth cohorts.

Figure A.4: Alternative Intergenerational Educational Mobility Measures

a) INTERGENERATIONAL MOBILITY COEFFICIENT (β)

b) INTERGENERATIONAL MOBILITY CORRELATION (ρ)



† This figure is based on results by SILC in 2011. Dates on the horizontal axis correspond to the *birth-cohort* of interest. Orange circles correspond to annual intergenerational persistence estimates, and orange lines refer to Hodrick-Prescott time trends. $\hat{\beta}$ refers to the estimated intergenerational mobility coefficient in (10), and $\hat{\rho}$ refers to the estimated intergenerational mobility correlation in (11). Gray triangles and lines refer to the corresponding annual values and Hodrick-Prescott time-trends of the respective estimates.

B Imputation Algorithm

SILC 2011 dataset contains information on descendants' years of schooling, as well as their ordinal categorical educational attainment based on ISCED 1997 definitions. Furthermore SILC 2011 dataset keeps track of parents' years birth year - hence only this dataset enables us to precisely imputed parental education. Therefore, using the years of schooling information of descendants and parents' year of birth we pursue the following imputation algorithm:

1. First, using the main SILC dataset, we calculate the sample means $\hat{\mu}_{e,t}$ of years of schooling of *descendants* who were born between 1923 and 1985, where e refers to the education category of interest, and t refers to birth-year of descendants. As true population moments should not vary substantially in narrow time intervals, but calculated sample moments do so empirically, we first calculate moving averages of the moment series via a moving average methodology with a fixed window size of 10 years. We calculate the weighted mean of the moments in reverse historical order, since the erratic nature of the series are more pronounced for the earlier cohorts. For example, we calculate the weighted average of mean years of schooling for the cohort born in 1951 with education category e as $\bar{\mu}_{e,1951} = \frac{1}{10} \sum_{k=1951}^{1960} \hat{\mu}_{e,k}$ or $\bar{\mu}_{e,j} = \frac{1}{10} \sum_{k=j}^{j+9} \hat{\mu}_{e,k}$ for any year j in general.²⁵ Next, we de-trend the weighted average series by using Hodrick-Prescott filter (with $\lambda = 6.25$), and derive the time-trends of mean and standard deviation series, $\tilde{\mu}_{c,t}$ and $\tilde{\sigma}_{c,t}$ to proxy for population moments.
2. At the second step, as we already know the education category and birth year of the parents in the SILC dataset, we match each parent with the average years of schooling exhibited by descendants with the same education category and birth-cohort; and create our imputed parental years of schooling series.

C Absolute vs. Relative Mobility

This paper focuses on the evolution of intergenerational absolute educational mobility patterns over time, as adhering to the usual metrics of relative mobility - the ordinary least squares intergenerational regression coefficient (β) or correlation coefficient (ρ) based on years of education - and keeping track of the changes in the degree of intergenerational educational mobility over time by relying on these metrics can potentially result in misleading conclusions because of a Turkey-specific issue. Specifically, there is a non-linearity (in the form of an exponential relationship indicated by kernel smoothing curves in the intergenerational years of schooling scatterplots in [Appendix Figure A.1](#)) between descendants' and parents' years of education in earlier cohorts. The existence of this non-linearity causes the usual intergenerational ordinary least squares estimation to systematically under-predict descendant education conditional on relatively high levels of parental education: as the marginal effect of parental education is indeed not constant (and relatively small conditional on low levels of parental years of education), the OLS coefficient represents the marginal effect of education in the local neighborhood of the most populated levels of absolute parental education, i.e. 0-4 years. As [Appendix Figure A.3](#) shows, the non-linearity between descendants' and parents'

²⁵For the latest 10 years, we calculate the weighted average of the moments series with the corresponding feasible window size. For instance $\bar{\mu}_{c,1980} = \frac{1}{6} \sum_{k=1980}^{1985} \hat{\mu}_{c,k}$, i.e. a window size of 6 years, or for any other year j within the latest 10 years, $\bar{\mu}_{c,j} = \frac{1}{\min(10, 1985-j+1)} \sum_{k=j}^{\min(j+9, 1985)} \hat{\mu}_{c,k}$. Note that these years will not be utilized as inputs for the imputation algorithm, and are calculated for the sake of completeness.

years of education disappears as time progresses, the OLS predicted values start coinciding with kernel smoothing curves, and the intergenerational OLS coefficient starts correctly representing the constant marginal effect of a change in parental years of education.

According to [Figure 3](#), our ordinal metric of intergenerational educational mobility, i.e. persistence, exhibits a downward time-trend while $\hat{\beta}$ and $\hat{\rho}$ exhibit increasing patterns starting from mid-1960s; and before mid-1960s $\hat{\beta}$ decreases $\hat{\rho}$ follows a stagnant trend as time passes. As [Appendix Figure A.1](#) indicates, the differences in the direction of time-trends exhibited by β and ρ before and after mid-1960s are due to the intergenerational educational relationship’s transition from a non-linear relationship to a linear one over time. The kernel density of descendant education conditional on parental education implies a non-linear relationship between the two variables until the 1960-1964-born birth-cohort, therefore assuming a linear relationship between the two variables results in a bad fit (in the form of under-prediction at high-end of the spectrum of parental education) due to wrong model specification. Furthermore, the degree of the under-prediction issue apparent in the linear model seems to be related the distribution of parental education. As shown in [Appendix Figure A.2](#), the empirical cumulative distributions of parental education before mid-1960s have greater concentrations at zero years than those of the after mid-1960s. As the density of parents with zero years of education declines and the relationship between descendants’ and parents’ years of education transforms into a linear relationship over time, β and ρ start increasing and the OLS linear regressions’s predictions start fitting the data better. Furthermore, as [Appendix Figure A.1](#) indicates, we have smaller samples for older cohorts and this may introduce heterogeneity to the quality of data across cohorts and contribute to the emergence of non-linear relationships in earlier cohorts.

In addition, when we estimate intergenerational regression coefficients (β) by clustering individuals according to their parental education and gender (that is when we estimate [\(10\)](#) conditional on descendant gender and low, intermediate, and high parental education separately), we observe that β of descendants with low and intermediate parental education are somewhat close to each other while β conditional on high parental education is relatively smaller in magnitude. As shown in [Appendix Table C.1](#), for those born in the 1951-1985 period, β is statistically significant at 99% confidence level and is equal to 0.49, 0.41, and 0.34 conditional on low, intermediate, and high parental education, respectively. When we analyze these heterogeneities in β conditional on parental education and descendant gender across cohorts we observe the following pattern: i) β ’s increase over time, ii) holding all else constant, β ’s of female descendants are higher than those of male descendants, iii) for male descendants, while β is significant conditional on low parental education, it is mostly insignificant conditional on intermediate or high parental education, and iv) for female descendants β ’s of those with low and intermediate parental education are significant and close to each other in magnitude while β conditional on high parental education is significant but mostly smaller in magnitude. These findings imply that the marginal effect of an increase in parental years of education depends on the education category of the parent, too. Our estimated correlation coefficients accord well with the raised concerns, as well.

In the light of these findings, we believe that exploring the evolution of intergenerational educational mobility dynamics across cohorts relying on the OLS coefficient estimated without clustering individuals according to their parental education (not the years of schooling completed but the highest degree attained by the better-educated parent) can lead to misleading inferences as i) as only after mid 1960s we start observing a truly linear relationship between parents’ and descendants’ years of schooling and ii) the marginal effect of a one year change in parental education exhibits

heterogeneities with respect to the highest degree attained by the parent and descendant's gender.

Our primary purpose for adopting an ordinal methodology with three ordinal categories of education is to obtain an intergenerational educational mobility metric that enables us to explore the cross-cohort evolution of mobility in Turkey with high precision. As [Appendix Figure A.3](#) indicates, the predicted persistence and upward mobility probabilities are very close to the related frequencies that we observe in our dataset. As such, we believe that for a cross-cohort comparison of intergenerational educational mobility dynamics in Turkey our ordinal approach is more suitable as it yields more reliable and precise results. Hence, in order to base our discussion on the evolution of intergenerational educational mobility dynamics on reliable and precise estimation results, we concentrate more on absolute educational mobility, and accordingly explore mobility dynamics in an ordinal setting, in which educational attainment is defined as the highest degree obtained by an individual.

Table C.1: Intergenerational Regression (β) and Correlation (ρ) Coefficients Conditional on Parental Education Category and Descendant Gender

Cohort	β & ρ - Both Genders			β & ρ - Male			β & ρ - Female		
	$P = \text{Low}$	$P = \text{Int.}$	$P = \text{High}$	$P = \text{Low}$	$P = \text{Int.}$	$P = \text{High}$	$P = \text{Low}$	$P = \text{Int.}$	$P = \text{High}$
1951-1959	0.46*** <i>0.24</i> [11.47]	0.29 <i>0.13</i> [1.11]	0.05 <i>0.04</i> [0.20]	0.32*** <i>0.17</i> [5.87]	0.06 <i>0.03</i> [0.20]	0.38** <i>0.48</i> [2.35]	0.62*** <i>0.37</i> [11.46]	0.50 <i>0.23</i> [1.26]	-0.42 <i>-0.25</i> [-1.00]
1960-1969	0.46*** <i>0.27</i> [17.15]	0.50*** <i>0.25</i> [2.75]	0.28* <i>0.16</i> [1.69]	0.39*** <i>0.23</i> [10.21]	0.44** <i>0.24</i> [2.31]	0.10 <i>0.09</i> [0.48]	0.55*** <i>0.36</i> [15.91]	0.55 <i>0.26</i> [1.61]	0.58*** <i>0.28</i> [3.02]
1970-1979	0.45*** <i>0.27</i> [19.12]	0.41*** <i>0.19</i> [3.50]	0.32*** <i>0.23</i> [3.44]	0.40*** <i>0.24</i> [11.79]	0.26 <i>0.13</i> [1.55]	0.13 <i>0.09</i> [1.03]	0.52*** <i>0.34</i> [16.98]	0.59*** <i>0.25</i> [3.83]	0.48*** <i>0.35</i> [3.82]
1980-1985	0.57*** <i>0.31</i> [17.52]	0.44*** <i>0.22</i> [3.29]	0.46*** <i>0.32</i> [3.46]	0.49*** <i>0.28</i> [11.09]	0.26 <i>0.13</i> [1.28]	0.37** <i>0.26</i> [2.07]	0.68*** <i>0.36</i> [15.15]	0.70*** <i>0.33</i> [4.23]	0.56*** <i>0.38</i> [3.00]
1951-1985	0.49*** <i>0.29</i> [34.29]	0.41*** <i>0.20</i> [5.40]	0.34*** <i>0.24</i> [5.36]	0.39*** <i>0.24</i> [19.95]	0.27** <i>0.14</i> [2.54]	0.22*** <i>0.17</i> [2.63]	0.61*** <i>0.35</i> [32.01]	0.59*** <i>0.28</i> [5.53]	0.46*** <i>0.33</i> [4.92]

Non-italic (italic) numbers without brackets correspond to regression β (and correlation ρ) coefficients. t-statistics are reported in brackets. ***, **, and * indicate statistical significance at 99%, 95%, and 90% confidence levels, respectively.