Educational Mobility Across Multiple Generations in Indonesia*

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Abstract

Standard *inter*generational measures have been shown to understate the long-run persistence of socioeconomic advantages in developed countries. We study theoretically and empirically whether this pattern extends to less developed settings, using Indonesia as a case study. Using the Indonesian Family Life Survey (IFLS) and Census data, we study multigenerational correlations in education across three generations. Contrary to previous findings, we observe greater multigenerational mobility than parent-child correlations alone would suggest. We develop a theoretical framework to highlight two key factors influencing multigenerational dynamics in developing countries: (1) financial and credit constraints, and (2) cultural norms related to marital sorting. To confirm their relevance, we exploit regional variations in exposure to the 1997 Asian financial crisis and in marital customs.

Keywords: intergenerational mobility; multigenerational persistence; education and financial constraints; Indonesia
JEL codes: D1, I24, J24, J62

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1 Introduction

Recent *multi*generational studies find that traditional measures of social mobility, such as parent-child correlations, understate the persistence of socioeconomic advantages across generations. For example, when regressing a child's status on both parent and grandparent status, the coefficient for grandparents is typically positive (see e.g. Lindahl et al. 2014, Neidhöfer and Stockhausen 2019, Colagrossi, d'Hombres and Schnepf 2020). This finding suggests that available estimates of social mobility may not tell us all that much about long-run persistence across multiple generations, challenging common interpretations of intergenerational correlations and the mechanisms driving them.

However, little is known about multigenerational processes for developing countries. Existing estimates, as reviewed by Anderson, Sheppard and Monden (2018) or Stuhler (2024), are drawn almost exclusively from high-income countries, where data spanning multiple generations is more readily available. Important exceptions are Kundu and Sen (2023), who examine mobility across three generations in India, and Celhay and Gallegos (2025), who compare multigenerational mobility in five Latin American countries. While these studies provide first empirical evidence for lower-income countries, as yet we know little about the mechanisms that matter in these contexts.

In this study, we explore *why* multigenerational processes might differ in developing countries, illustrating our arguments using rich survey data spanning three generations from Indonesia. Our central argument is that the dynamics of multigenerational transmission – particularly the relative strengths of multi- versus intergenerational correlations – are bound to differ between the developing and developed world, as well as across different developing countries. The rationale is that structural factors, such as financial constraints or marital customs, operate differently in low-income countries than in high-income countries, but also have distinct dynamic implications. To support these arguments empirically, we exploit regional variations in sudden shifts in economic conditions and in marital customs.

To begin, we first provide a brief overview of standard measures of multigenerational persistence. Most studies compare pairwise regression or correlation coefficients across two or more generations. A key question here is whether those correlations "iterate", i.e. whether the grandparent-child correlation is the product of the corresponding parent-child correlations. Alternatively, many studies report the slope coefficients from a multivariate regression that conditions on both parent's and grandparent's status. We note that there exists a direct mapping between the "*grandparent coefficient*" from such multivariate regressions and the relative size of the bivariate coefficients, which simplifies comparisons across studies. In particular, this coefficient is negative if and only if multigenerational correlations are greater than the product of the underlying parent-child correlations.

Building on standard models of intergenerational mobility, we next show that the sign of this grandparent coefficient depends on the relative strength of different transmission mechanisms. This matters as certain factors, such as parental resources and financial constraints, are more salient for child outcomes in developing countries (Solis 2017, Piraino 2021, Mogstad and Torsvik 2021). Another important factor is assortative matching. For a given level of parent-child correlations, multigenerational persistence may be higher when parents directly choose their children's spouses – as is customary in some developing countries, while arranged marriages have become exceedingly rare in high-income countries (Averett, Argys and Hoffman 2018). Assortative practices also differ greatly across regions and ethnic groups within the developing world.

One implication of these arguments is that, although parent-child mobility is comparatively low in developing countries (Hertz et al. 2008, van der Weide et al. 2024), long-run mobility is not necessarily so. In line with this conjecture, we find that Indonesia has low parent-child mobility in education (consistent with estimates by Hertz et al. 2008, Ahsan, Emran and Shilpi 2024 and van der Weide et al. 2024), yet multigenerational mobility appears not particularly low. In Indonesia, the grandparent coefficient becomes *negative* when conditioning on both the father's and mother's education, while in high-income countries this coefficient is generally positive (Anderson, Sheppard and Monden 2018). Multigenerational mobility is therefore higher in Indonesia than an extrapolation from parent-child correlations would suggest, a pattern that contrasts with findings from Europe (Colagrossi, d'Hombres and Schnepf 2020) or Latin America (Celhay and Gallegos 2025).

In our theoretical analysis, we compare the multigenerational patterns implied by different models of intergenerational transmission. We show that the classic Becker-Tomes framework (1979; 1986) can generate either a negative or positive grandparent coefficient, depending on parameterization. This stands in contrast to a commonly cited variant, described by Solon (2014) and considered in Piraino (2021) and many other studies, in which the grandparent coefficient is necessarily negative – implying high multigenerational mobility. We trace this contrast to a simplification of the model's earnings equation that replaces the original stochastic with a deterministic version. Though otherwise minor, this change greatly affects the model's multigenerational implications. The original Becker-Tomes model can rationalize different multigenerational patterns, and nests a simple latent factor model often used to explain positive grandparent coefficients. More generally, the sign of the grandparent coefficient depends on the relative strength of "direct" income effects and – when extending the Becker-Tomes model to two parents – the structure of assortative mating.

We provide evidence on these hypotheses in the empirical part of the paper, using Indonesia as a case study. We first show descriptively that multigenerational mobility is in fact lower in areas where expenditure shares on education are higher. To provide more targeted evidence on the role of financial constraints, we then consider the 1997 Asian Financial Crisis. This crisis had a devastating effect on educational attainment in Indonesia: within a year, secondary school enrollment decreased from 59.4% to 55.7% for girls, with an even sharper decline for boys (Poppele, Sumarto and Pritchett 1999). Educational spending fell dramatically, in particular among poorer households with young children (Thomas et al. 2004). While the crisis thus had an effect on intergenerational mobility, we are instead interested in its effects on multigenerational associations. In line with our theoretical prediction, we find a decrease in the coefficient on grandparents for those cohorts whose education was most directly impacted by the crisis. Thus, while financial constraints decrease intergenerational mobility in education – consistent with previous research – multigenerational correlations appear to be less affected.

To examine the role of assortative matching, we exploit that in Indonesia marital customs vary widely across provinces and ethnic groups. Our data contain direct information on *who* selected a person's spouse, allowing us to analyze individual-level variation in marital practices. The strength of multigenerational associations varies systematically with marital customs: when a woman's family selects her spouse, the spousal correlation in education is weaker (i.e., spouses are less similar), but the correlation between a spouse and his or her parents-in-law is stronger (i.e., the spouses' parents are more similar to each other). Moreover, under such "family-based" assortative matching, the grandparent coefficient is more positive. These effects align with our theoretical hypothesis; however, they would *amplify* multigenerational transmission, and can therefore not explain the negative grandparent coefficient in Indonesia.

Our results contribute to three strands of the literature. First, they contribute to our understanding of social mobility in developing countries. Intergenerational (parent-child) mobility tends to be lower in the developing world (Maoz and Moav 1999). Comparing 42 countries, Hertz et al. (2008) demonstrate that parent-child correlations in education are higher, and often much higher, in low- compared to high-income countries; van der Weide et al. (2024) expand on this significantly by building a global database of educational mobility covering 153 countries. While there exists therefore ample evidence on intergenerational mobility, our results suggest that the relative strength of inter- versus multigenerational correlations differs in developing countries, such that long-run mobility may not be particularly low.

Second, we contribute to the recent literature on multigenerational processes (e.g., Lindahl et al. 2015). This rapidly growing literature has established that multigenerational correlations tend to be higher than one would expect from an extrapolation of the available parent-child evidence (Clark 2014, Anderson, Sheppard and Monden 2018, Stuhler 2024, Barone and Mocetti 2020). However, it remains unclear how those patterns should be interpreted (Stuhler 2024), and whether they vary across countries. We argue that multigenerational processes are bound to differ between the developed and developing world, as certain transmission mechanisms with distinct dynamic implications are more salient in the latter.

Third, we contribute to the literature on social mobility in Indonesia, an especially interesting setting given its ethnic diversity and substantial public investments in education. A major school construction program in the 1970s significantly improved educational attainment and labor market outcomes, particularly for boys (Ashraf et al. 2020; Duflo 2001), with positive effects for girls in certain ethnic groups (Ashraf et al. 2020, Akresh, Halim and Kleemans 2022). The program particularly benefited children of less-educated parents, raising social mobility (Hertz, Jayasundera et al. 2007) and improving outcomes in the next generation (Mazumder, Rosales-Rueda and Triyana 2019, Akresh, Halim and Kleemans 2022). Still, Indonesia exhibits relatively low parent-child mobility in both education (Ahsan, Emran and Shilpi 2024; Raza and Aytun 2021; Hertz et al. 2008; van der Weide et al. 2024) and income (Sakri, Summer and Yusuf 2022; Zafar 2022).[1] Our study adds to this literature by highlighting the effects of marital customs and financial constraints

[1] A key bottleneck is secondary education: the increased number of boys graduating from primary school led to overcrowding that displaced girls from secondary education (Ahsan, Emran and Shilpi 2023), and the 1997 Asian financial crisis led to a large reduction in secondary school enrollment for both boys and girls (Poppele, Sumarto and Pritchett 1999), especially among poorer families (Thomas et al. 2004).

on multigenerational, rather than just intergenerational, correlations in education.

The paper proceeds as follows: Section 2 discusses the conventional measurements of international and multigenerational transmission; Section 3 presents a theoretical framework to understand patterns in the transmission of education across two and three generations; Section 4 describes the Indonesian data and reports our baseline results on the estimated two- and three-generation correlation coefficients; Section 5 provides empirical evidence on the credit constraints and direct income effects on persistence in Indonesia; Section 6 examines the role of assortative mating practices on long-run persistence; and Section 7 concludes.

2 Measuring inter- and multigenerational transmission

The empirical literature has adopted two types of measures to characterize multigenerational transmission. First, one may consider pairwise regression (or corresponding correlation) coefficients based on linear regressions such as

$$y_{it} = \alpha + \beta_{-k} y_{it-k} + \varepsilon_{it}, \tag{1}$$

where y_{it} refers to the socio-economic status of an individual in generation t of family i and y_{it-k} is the status of an ancestor k generations back. In our data, we can directly estimate parent–child ($k = 1$) and grandparent-grandchild correlations ($k = 2$).[2] In the absence of direct multigenerational estimates, researchers sometimes "iterate" the parent-child correlation β_{-1} to describe the expected rate of persistence across more than two generations. For example, a naive prediction for the grandparent-grandchild correlation β_{-2} would be the product of the two underlying parent-child correlations (i.e., β_{-1}^2 in steady state).

Alternatively, we may report the slope coefficients from a multigenerational (child-parent-grandparent) regression such as

$$y_{it} = \beta_p y_{it-1} + \beta_{gp} y_{it-2} + \varepsilon_{it}, \tag{2}$$

where β_{gp} captures whether grandparent status y_{it-2} has an independent association with child

[2] We consider the implications of a two-parent structure below.

status, even conditional on parent status y_{it-1}.[3]

This "grandparent coefficient" β_{gp} is a useful summary measure of the dynamic properties of the transmission process. In particular, there exists a direct mapping between the coefficients β_{-k} from the pairwise regressions in eq. (1) and the grandparent coefficient β_{gp} from eq. (2). Under stationarity, the grandparent coefficient in a regression of child on parent and grandparent status from the parent's *own* lineage is[4]

$$\beta_{gp} = \frac{\beta_{-2} - \beta_{-1}^2}{1 - \beta_{-1}^2} \tag{3}$$

and therefore is positive if and only if $\beta_{-2} > \beta_{-1}^2$, that is, if intergenerational mobility declines at less than the geometric rate.[5] We label this condition "excess persistence". With excess persistence, a naive extrapolation from standard parent-child correlations would understate the persistence of status differences across multiple generations (i.e., overstate mobility in the long run).

Figure 1 compares estimates of the parent-child correlation in education β_{-1} and grandparent-child correlation β_{-2} for a pooled sample of EU-28 countries (Colagrossi, d'Hombres and Schnepf 2020), six Latin American countries (Celhay and Gallegos 2025), and Indonesia (based on the Indonesian Labor Force Survey, as studied below).[6] Although their empirical specifications are not fully comparable, the estimates align with the conventional wisdom that parent-child correlations are higher in low- than high-income countries. Indonesia has the highest parent-child correlation, implying the lowest level of mobility. If we were to extrapolate naively from these parent-child correlations (β_{-1}^k, hollow bars), we would expect higher multigenerational mobility in Europe compared to the other regions. Indeed, because differences in β_{-1} magnify with each additional generation k, they become more pronounced in relative terms.

However, the actual grandparent-child correlations (solid bars) deviate substantially from these

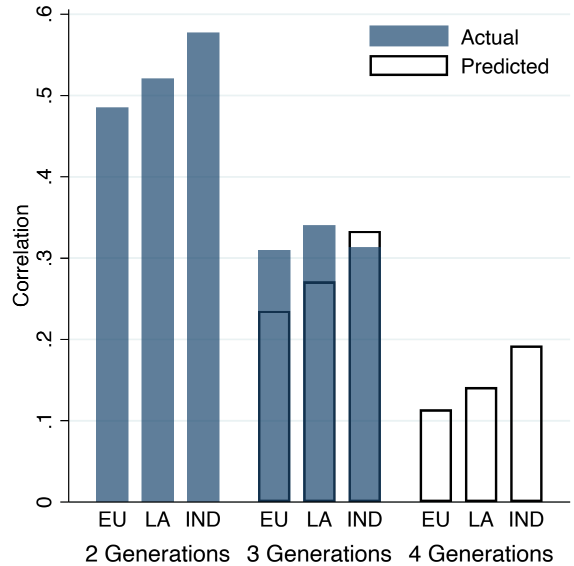
[3]These are the most common measures of multigenerational mobility, but other measures are in use; see in particular the "dynastic" regressions in Adermon, Lindahl and Palme (2021) and name-based measures in Clark (2014) and Barone and Mocetti (2020).

[4]See Braun and Stuhler (2018). The stationarity assumption simplifies the presentation but is not necessary for the result (see Appendix A.1).

[5]Similarly, the grandparent coefficient on a grandparent from the *other* lineage is $\beta'_{gp} = \frac{\beta_{-2} - (\beta'_{-1})^2}{1-(\beta'_{-1})^2}$, where β_{-1} is the correlation between a person and his or her parent-in-law, i.e. $\beta'_{-1} = \frac{Cov(y^m_{it-1}, y^{p,m}_{it-2})}{Var(y^{p,m}_{it-2})}$, where p, m stands for the paternal or maternal line.'

[6]We report the average of the correlation between generations 1 and 2 and the correlation between generations 2 and 3. Parental education is the average education of both parents.

Figure 1: Multigenerational Estimates for Different Regions



Note: The figure shows multigenerational correlations for three regions. The solid bars represent estimates for the EU-28 (from Colagrossi, d'Hombres and Schnepf 2020), six Latin American countries (Celhay and Gallegos 2025), and Indonesia (IFLS, own estimates). The hollow bars show naive extrapolations from the parent-child correlations (see text).

naive predictions. For the European and Latin American regions, the correlations between three generations are much larger than a naive extrapolation from the parent-child evidence would suggest ("excess persistence", i.e. the coefficient β_{gp} from eq. (2) is positive). In contrast, for Indonesia the relationship is the opposite, with the actual grandparent-child correlation being below its predicted value. As a consequence, the ranking of the different regions changes; while Indonesia has the lowest mobility according to conventional parent-child measures, its multigenerational mobility is not particularly low. In the next section we discuss why the relation between inter- and multigenerational correlations might vary across countries, and between more and less developed regions.

3 Theories of multigenerational transmission

This section provides a theoretical framework for interpreting multigenerational transmission patterns. Our key argument is that these patterns, in particular the relation between short and long-run mobility, will be systematically different in developed and developing countries. One corollary is that our understanding of social mobility in the developing world is still quite limited; while it is well-documented that *inter*generational (parent-child) mobility is comparatively low (cf. Figure 1), it does not necessarily follow that multigenerational mobility is also low in developing countries.

We conduct our analysis in three steps. In Section 3.1, we derive implications for long-run mobility – in particular, the sign of β_{gp} in eq. (2) – from standard models of intergenerational transmission. In Section 3.2, we explain why these standard models imply different patterns of multigenerational transmission in developing countries. After probing these implications empirically, we then extend our model in Section 6 to include assortative matching, showing that marital customs are another factor why mobility patterns are bound to differ in developing countries from those observed in developed countries.

3.1 Multigenerational transmission in standard models

A simplified Becker-Tomes model. We start with standard models of intergenerational transmission with a one-parent structure, such as the classic Becker-Tomes model of intergenerational transmission (Becker and Tomes 1979, Becker and Tomes 1986). One frequently cited implication from this model is that β_{gp} in eq. (2) should be negative. To see this, consider a popular variant of their framework as considered by Solon (2004) or Piraino (2021),[7]

$$y_{it} = \rho h_{it} \tag{4}$$

$$h_{it} = \theta y_{it-1} + e_{it} \tag{5}$$

$$e_{it} = \lambda e_{it-1} + v_{it} \tag{6}$$

where y_{it-1} and y_{it} are parent and child income in family i, h_{it} is child "human capital", e_{it-1} and e_{it} are parent and child "endowments" (an umbrella term for a wide set of skills, preferences and other factors that might affect human capital accumulation), and v_{it} is a white noise error term. The parameter λ therefore reflects the "heritability" of endowments across generations, while θ represents a "direct" effect of parental income on child human capital, possibly due to parental investments in the education of their child in the context of imperfect capital markets (Becker and

[7]While Becker and Tomes considered a behavioral model of parental investments, this behavioral model implies the type of "mechanical" transmission equations on which we focus here; see Goldberger (1989), Solon (2004), and Piraino (2021).

Tomes 1986, Piraino 2021). As in this model child income is a deterministic function of child human capital, we can simplify by substituting eq. (5) into (4) and defining $\gamma = \rho\theta$.

To link this model to the estimating eq. (2), consider the difference between (4) and λ times its lag,

$$\begin{aligned} y_{it} - \lambda y_{it-1} &= \gamma y_{it-1} + \rho e_{it} - \gamma\lambda y_{it-2} - \rho\lambda e_{it-1} \\ \Rightarrow \qquad y_{it} &= (\gamma + \lambda) y_{it-1} - \gamma\lambda y_{it-2} + \rho v_{it} \end{aligned}$$

which implies that OLS estimation of eq. (2) would estimate $\beta_{gp} = -\gamma\lambda$, which is *negative* (for $\gamma > 0$ and $\lambda > 0$). This model therefore suggests that socio-economic inequalities are *less* persistent than a naive extrapolation of the available parent-child correlations β_{-1} would suggest. Solon (2014) describes the intuition for this result: If the parent does not earn more despite the advantages of higher income in the grandparent generation, the parent must have poor endowments; and those poor endowments might then be passed on to the child.

The latent factor model. The implication $\beta_{gp} < 0$, as already emphasized by Becker and Tomes, has long been controversial; Goldberger (1989) calls it an "artifact". As it turns out, it is also counterfactual: recent estimates of β_{gp} from developed countries are consistently positive (Anderson, Sheppard and Monden, 2018). To motivate multigenerational studies, researchers have therefore considered alternative models, such as the *latent factor model* (Clark 2014, Braun and Stuhler 2018) given by[8]

$$y_{it} = \rho e_{it} + u_{it} \tag{7}$$

$$e_{it} = \lambda e_{it-1} + v_{it} \tag{8}$$

where u_{it} is a white-noise error term, and the other variables are defined as above. If for simplicity

[8] The latent factor model is not the only potential framework to rationalize $\beta_{gp} > 0$. In particular, grandparents might have a direct influence on the status of their children that is independent from the status of the parents (Mare 2011); and these influences could be greater in developing countries, where multigenerational co-residence arrangements are more common. The evidence on this question has been mixed; Zeng and Xie (2014) find that the education of co-resident grandparents in a sample from China is more predictive than the education of absent grandparents. However, a meta study by Anderson, Sheppard and Monden (2018) suggests that the association of child and grandparent education does not vary systematically with contact. Our focus therefore remains on Markovian (i.e., parent-child) transmission models. Stuhler (2024) reviews alternative models, including higher-order Markov processes and transmission models with "multiplicity", in which intergenerational persistence differs for different types of endowments.

we normalize the steady-state variances of both e and y to one,[9] we have

$$\beta_{-1} \equiv \frac{Cov(y_{it}, y_{it-1})}{Var(y_{it-1})} = Cov(\rho e_{it} + u_{it}, \rho e_{it-1} + u_{it-1}) \\ = \rho^2 \lambda \tag{9}$$

$$\beta_{-2} \equiv \frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} = \rho^2 \lambda^2. \tag{10}$$

As long as ρ is less than one – which, given the normalizations, is equivalent to assuming $Var(u) > 0$ – the grandparent-child correlation exceeds the square of the parent-child correlation in this model (i.e., $\beta_{-2} > (\beta_{-1})^2$). Given eq. (3), this in turn implies that the coefficient β_{gp} in (2) is necessarily *positive* ($\beta_{gp} = \frac{\rho^2\lambda^2 - \rho^4\lambda^2}{1-\rho^4\lambda^2} > 0$), and socio-economic inequalities are *more* persistent than a naive extrapolation of the available parent-child correlations β_{-1} suggests. The intuition for this result is that, in this model, parent-child correlations are attenuated as y is only an imperfect proxy for the "true" endowments of a person.

Why do the two models yield opposing implications on multigenerational persistence? The latent factor model abstracts from the "direct" income effect ($\gamma = 0$) that generates the negative sign of β_{gp} in the Becker-Tomes model. Conversely, the simplified variant of the Becker-Tomes model described above imposes a deterministic relation between endowments e and income y (i.e., $Var(u) = 0$), thus abstracting from the imperfect link between endowments and status that underlies the positive sign of β_{gp} in the latent factor model.

The Becker-Tomes model. Perhaps less well known is that the *original* Becker-Tomes model has ambiguous implications for the sign of β_{gp}; it allows for a stochastic component in the relation between endowments and income,

$$y_{it} = \gamma y_{it-1} + \rho e_{it} + u_{it} \tag{11}$$

and therefore nests both the simplified Becker-Tomes model in eqs. (4)-(5) and the latent factor model in eqs. (7)-(8). In this model, regression (2) does not yield $\beta_{gp} = -\gamma\lambda$, unless the error term u has zero variance.[10] Instead, if we normalize the variances of e and y to one, the coefficient can

[9] This normalization simply involves rescaling the model's parameters and, as such, entails no loss of generality.

[10] Specifically, the model implies $y_{it} = (\gamma + \lambda)y_{it-1} - \gamma\lambda y_{it-2} + \rho v_{it} + u_{it} - \lambda u_{it-1}$, and because u_{it-1} is correlated with y_{it-1}, OLS estimation of eq. (2) will not yield an unbiased coefficient $\beta_{gp} = -\gamma\lambda$. Instead, estimates of β_p will

be expressed as (see Appendix A.2)

$$\beta_{gp} = \frac{\frac{\rho^2\lambda}{1-\gamma\lambda}\left(\lambda - \gamma - \frac{\rho^2\lambda}{1-\gamma\lambda}\right)}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \tag{12}$$

where the denominator is positive, and the sign of the numerator is ambiguous and depends on the relative sizes of γ and λ. If parental status y_{it-1} has a comparatively large direct effect on child status, that is $\gamma > \lambda$, the coefficient β_{gp} will still be negative, as in the simplified Becker-Tomes model.[11] Notably, this is the case Becker and Tomes had in mind, consistent with their view that intergenerational persistence is primarily due to parental investments in the human capital of their children.[12]

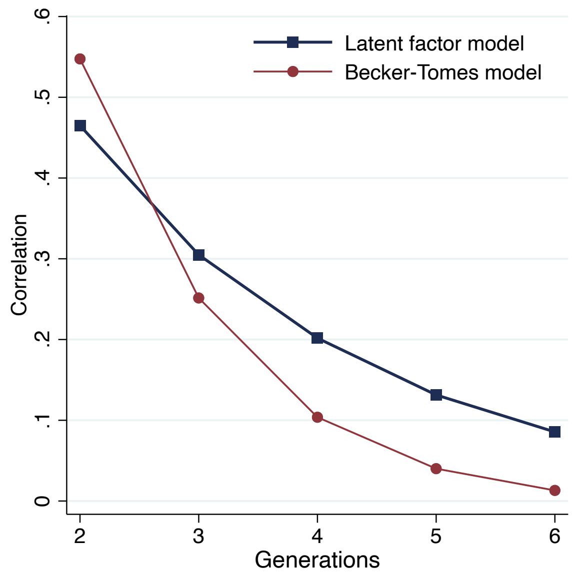
The more general takeaway however is that the sign and size of β_{gp} depend on the *relative* importance of different transmission mechanisms. Figure 2 illustrates this point by plotting the implied multigenerational correlations from two distinct parametrizations of the Becker-Tomes model, one assuming $\gamma = 0$ and implying $\beta_{gp} > 0$ (blue line) and the other assuming $\gamma > 0$ and implying $\beta_{gp} < 0$ (red line). While intergenerational mobility is lower in the "red" model with direct income effects, multigenerational mobility is lower in the "blue" model. The ranking of countries in terms of *inter*generational mobility may therefore tell us little about their ranking in terms of long-run mobility across multiple generations.

be downward biased and estimates of β_{gp} upward biased. See Lindahl et al. (2014) for an IV approach to address this endogeneity using four generations of data.

[11] Since we standardized the variance of y, the variance of u is implicitly determined by the other parameters. As a result, eq. (12) does not directly reveal how the variance of u influences the coefficient β_{gp}. For the non-standardized expression, see eq. (30) in the Appendix.

[12] See footnote 12 in Becker and Tomes (1979). Piketty (2000) notes that "*Becker and Tomes (1986) interpret the high level of mobility that they observe in the US primarily in the liberal right-wing way (ability is moderately heritable and markets are highly efficient).*"

Figure 2: Two Simulated Multigenerational Processes



Note: The figure shows multigenerational correlations for two simulated processes. The first process is based on the latent factor model in eqs. (7)-(8) with parameters corresponding to the average estimates from Colagrossi, d'Hombres and Schnepf (2020), $\lambda = 0.66$ and $\rho = 0.84$ (implying $\beta_{gp} = 0.11$). The second process is based on the Becker-Tomes model in eq. (11) and parameter values $\gamma = 0.33$, $\lambda = 0.33$ and $\rho = 0.84$ (implying $\beta_{gp} = -0.07$).

3.2 The role of financial constraints in multigenerational transmission

As multigenerational patterns depend on the relative importance of different transmission mechanisms, those patterns are bound to differ between developing and developed countries. It is already well-established that developing countries tend to have comparatively low intergenerational mobility; for example, a recent World Bank report by Narayan et al. (2018) notes that "*all 15 economies that rank in the bottom 10 percent by relative IGM are developing economies*"; and similar conclusions are found in earlier studies (Hertz et al. 2008, and Brunori, Ferreira and Peragine 2013).

Less obvious is *why* parent-child mobility is lower in developing countries.[13] In the Becker-Tomes model, β_{-1} increases in the parameters γ, λ or ρ, each of which represent distinct transmission mechanisms. However, the literature generally points to the "direct" income effects represented by γ as a key mechanism for why β_{-1} is larger in developing countries. Specifically, Piraino (2021) and Mogstad and Torsvik (2021) emphasize the role of liquidity and credit constraints, which are

[13] A related question is how mobility varies with economic growth; see Maoz and Moav (1999) for a theoretical framework and Neidhöfer et al. (2024) for recent empirical evidence.

more salient for parental investments in child education in developing countries than in developed countries (Attanasio and Kaufmann 2009, Solis 2017).

The hypothesis that the direct income effects represented by γ tend to be larger in developing countries has important implications for multigenerational transmission. In Appendix A.2, we show that in the Becker-Tomes model the derivative of the grandparent coefficient β_{gp} with respect to γ is negative ($\frac{\partial \beta_{gp}}{\partial \gamma} < 0$). Ceteris paribus, the coefficient β_{gp} should therefore be more negative in developing countries in which liquidity and credit constraints are more binding.[14] Credit constraints would therefore lead not only to high parent-child correlations (as is well-known), but also a β_{gp} coefficient that is less positive or even negative (a novel implication).

Thus, even if parent-child mobility is low in developing countries, *long-run* mobility may not necessarily be low (e.g., as the "red" Country in Figure 2). The intuition for this result is that while credit constraints have a direct effect on educational attainment (leading to low parent-child mobility), they do not necessarily affect the transmission of endowments from one parent to the next, and hence have less severe implications for a family's prospects in the long run. In our empirical analysis, we will probe this hypothesis by exploiting information about household educational expenditures as well as geographical variation in credit constraints driven by the 1997 Asian financial crisis.

Of course, the Becker-Tomes model leaves out many other important mechanisms. Apart from financial and credit constraints, Piraino (2021) identifies two other important factors that may reduce mobility in the developing world: labor market segmentation, in particular between formal and informal sectors, and informational frictions, on the labor market or in terms of parental beliefs about the returns to educational investments. In Section 6, we highlight marital customs and assortative mating as another distinct factor shaping multigenerational dynamics in developing countries.

[14] From the "duality" in eq. (3), it follows that the ratio between multi- and intergenerational correlations β_{-k}/β_{-1} would be comparatively low.

4 Data and empirical results

4.1 Data

Our main data source is the Indonesian Family Life Survey (IFLS), a nationally representative socioeconomic and health survey covering approximately 83% of the Indonesian population living in 13 of the nation's 26 provinces (Frankenberg et al., 1995).[15] We pool five waves of the IFLS (1993, 1997, 2000, 2007, and 2014) to form a panel dataset. Since our objective is to explore the transmission of education across three generations, we conduct our analysis using only individuals for whom we have information on their complete education and that of their ancestors. These individuals are initially observed as children in the first survey wave, and their educational attainment is measured at age 25, which we assume to be the age by which formal education is typically completed. Our sample of individuals from three generations is then defined as follows: (1) third-generation individuals, *G1*, were born between 1975 and 1988; (2) their parents, *G2*, who are household heads in the first IFLS wave (the median year of birth is 1952 for fathers and 1957 for mothers); (3) the grandparents *G3* of G1 and thus parents of G2, (the median year of birth ia 1913 and 1920 for paternal and maternal grandfathers, respectively, and 1922 and 1927 for grandmothers).

Our outcome of interest is educational attainment, which we measure as the highest level of education obtained by age 25.[16] In the IFLS, individuals are asked about the different levels of schools they have completed. We translate this information into years of education according to the time it normally takes to complete a particular level. If an individual takes more years than typically needed to complete one specific school level, we still assign to that person the years of education which typically correspond to that school level. As such, our measure of education should be interpreted as the equivalent number of years required to complete one specific school level.[17]

[15] The provinces surveyed include North Sumatra, West Sumatra, South Sumatra, and Lampung on the Sumatra island, all five provinces in Java (DKI Jakarta, West Java, Central Java, DI Yogyakarta, and East Java), and four provinces from the remaining major island groups (Bali, West Nusa Tenggara, South Kalimantan, and South Sulawesi).

[16] More details on the education measure and steps for validation with the census data are available in Appendix A.5.

[17] In each survey wave, information on individuals' educational attainment is collected through multiple questions, sometimes yielding inconsistent responses for the same individual. These discrepancies typically arise when both the head of the household and individual household members provide education information. For example, an individual may report having completed secondary education, while the head of household reports that the same individual attained only primary education. In such cases, we resolve inconsistencies by assigning the modal education level across responses for each individual. Additionally, heads of household are asked to report the educational attainment of their parents and in-laws, even if these individuals are not members of the household—either due to death or

In our analysis, we also use information from the IFLS on provinces of birth, migration, marital traditions, education expenditures and earnings. Section A.3 in the Appendix provides more details on the construction of these variables. Our estimation ("restricted") sample includes only individuals for whom we observe the education of all four grandparents and both parents, totaling 8,277 individuals.

4.2 Descriptive statistics

Table 1 reports descriptive statistics by generation. The average years of education increased dramatically over the three generations. The increase is more pronounced for women than men and reflects a significant decrease in the proportion of individuals with zero education across generations.[18] More specifically, differences in mean schooling across generations are partly due to a concentration around zero for the G3 generation, more dropouts during primary school and a concentration around six years of schooling (equivalent to primary school completion) for the parent generation (G2), and a concentration around nine years of schooling (completed middle school) and 12 years (completed high school) for the child generation (G1).

In the second generation, men earn more and have more "prestigious" jobs than women (in defining occupational prestige we follow the score by Ganzeboom, De Graaf and Treiman, 1992).[19] In terms of marital traditions, the practice of the family selecting the spouse is more common among women than men. About 27% of the mothers (women in the second generation) in our estimation sample report that their parents selected the spouse for them. Provinces where more than 40% of the women declare that their spouse has been selected by their parents include South Sulawesi (75% of the women declare that their husband has been selected by their parents), South Kalimantan (45%), East Java (44%), Central Java (43%), West Sumatra (42%).

because they reside elsewhere.

[18] While more than 70% of the grandmothers and about 60% of the grandfathers have zero education, only around 19% of mothers and 11% of fathers (in the G2 generation) and almost none in the G1 generation have no schooling (see Figure A1).

[19] The measure in Ganzeboom, De Graaf and Treiman (1992) defines occupational prestige based on individuals' education and income levels across 16 countries—both developed and developing—using data from various years between 1968 and 1982. The resulting continuous scale ranges between 10 (for cook's helpers and agricultural workers) and 90 (for judges).

Table 1: Descriptive Statistics for the Restricted Sample

	G1: Men	G1: Women	G2: Father	G2: Mother
Median Year of Birth	1982	1982	1952	1957
Years of Education	9.66	9.74	6.07	4.77
% Migrant	3.6	3.3	4.6	5.2
% Family Selects the Spouse	-	-	19.1	27.9
Age at Childbirth	-	-	31.8	26.1
Earnings	-	-	29,838	11,147
Occupational Prestige	-	-	38.5	36.9
Observations	4,260	4,017	8,277	8,277
Lineage	Paternal		Maternal	
G3	Grandfather	Grandmother	Grandfather	Grandmother
Median Year of Birth	1913	1922	1920	1927
Years of Education	2.30	1.34	2.59	1.48
Age at Childbirth	37.4	27.6	36.7	27.7
Observations	8,277	8,277	8,277	8,277

Note: The table reports the mean of variables used in the empirical analysis. An individual is defined as a "migrant" if he/she has changed the province of residence between birth and age 12. Earnings are expressed in thousands of Rupiah. Only some individuals born between 1975 and 1988 report earnings and occupation by 2014, hence we do not report the statistics for this generation (G1). For G2, age at child birth is measured as the average for all children within a household. For G3, age at child birth is measured at the time of birth of G2. We report the averages of this variable without outliers. Occupational prestige is based on the score defined in Ganzeboom, De Graaf and Treiman (1992).

4.3 Intergenerational correlations

We begin the analysis by estimating the intergenerational transmission of education in Indonesia using the restricted sample of 8,277 grandchildren (G1), for whom we have educational outcomes for both of the parents (G2) and all four of the grandparents (G3). We first report the intergenerational correlation coefficient for the various pairs of G3 (grandparents), G2 (parents), and G1 (children), by lineage. Table 2 shows that the G1-G2 correlation coefficient using the average years of schooling for parents is 0.516 while the G2-G3 correlation is 0.639. These estimates are in line with earlier work, showing that intergenerational mobility in Indonesia is relatively low compared to more developed countries (Hertz et al. 2008, van der Weide et al. 2024).[20]

[20]While we focus on linear summary measures, Ahsan, Emran and Shilpi (2024) document important non-linear patterns in Indonesia. In particular, while the conditional expectation function for children's schooling given parental schooling is linear in urban areas, it is convex in rural Indonesia.

Table 2: Estimated Intergenerational Correlation from the IFLS Sample

Lineage		Observed			Predicted
G2	G3	G1-G2	G2-G3	G1-G3	G1-G2xG2-G3
Father	Paternal (avg)	0.486	0.508	0.248 (0.015)	0.247 (0.009)
Father	Maternal (avg)	0.486	0.490	0.292 (0.014)	0.238 (0.010)
Mother	Paternal (avg)	0.464	0.470	0.248 (0.015)	0.218 (0.010)
Mother	Maternal (avg)	0.464	0.568	0.292 (0.014)	0.264 (0.010)
Both (avg)	All (avg)	0.516	0.639	0.313 (0.014)	0.330 (0.010)

Note: G1 denotes the child generation; G2 denotes the parent; G3 denotes the grandparents. Total number of observations is 8,277. Robust standard errors clustered at the family level in parentheses.

4.4 Multigenerational correlations

We next estimate the transmission of education across three generations. As shown in Table 2, the G1-G3 coefficients vary between 0.25 and 0.31, depending on specification. To understand whether these three-generation estimates suggest more or less persistence than what one might have expected based on the available two-generation estimates, we also compute the predicted three-generation correlation as would be implied by the product of the corresponding parent-child correlations (see Section 2). Those predicted correlations are not so different from the actual three-generation correlation: they are slightly smaller when considering individual lineages (rows 1-4), but slightly larger if averaging across all members of a given generation (last row). As already illustrated in Figure 1, this pattern contrasts with the pattern found for developed countries, in which multigenerational persistence is generally higher than implied by parent-child correlations (Anderson, Sheppard and Monden 2018). Therefore, while *inter*generational correlations are comparatively high in Indonesia, *multi*generational correlations are not particularly high.

To probe these patterns further, Table 3 reports estimates from three-generation regressions based on eq. (2). Our main finding here is that the estimated grandparent coefficient is negative and marginally significant when we control for the average educational attainment across all four grandparents *and* the average educational outcomes of both parents (G2) (column 1). This result is consistent with the simplified Becker and Tomes model, which predicts that conditional on parent education, an increase in the education of grandparents reduces the grandchild's education (see

Section 3.1). However, it contrasts with more positive estimates from developed countries (e.g. Anderson, Sheppard and Monden 2018, Narayan et al. 2018), Latin America (Celhay and Gallegos, 2015), and China (Zeng and Xie 2014.)[21]

Table 3: Estimated Multigenerational Correlations using the IFLS Sample

	Dependent Variable: Child's Education				
Parent	Average	Father		Mother	
Grandparents	Average	Paternal	Maternal	Maternal	Paternal
	(1)	(2)	(3)	(4)	(5)
Parental Education	0.503***	0.405***	0.376***	0.398***	0.403***
	(0.014)	(0.012)	(0.012)	(0.014)	(0.013)
Grandparental Education	-0.044*	0.001	0.091***	0.053***	0.050**
	(0.024)	(0.020)	(0.018)	(0.019)	(0.019)
Observations 8,277	8,277	8,277	8,277	8,277	8,277
R-squared	0.267	0.236	0.240	0.217	0.217

Note: Multigenerational estimates from eq. (2), the dependent variable is the child's years of education (G1). Column 1 controls for the average years of education of the parents (G2) and the average years of education of all four grandparents (G3). Columns 2 and 3 control for the father's education (G2) and either the average years of education of the paternal or maternal lineage (G3). Columns 4 and 5 control for the mother's education (G2) and either the average years of education of the maternal or paternal lineage (G3). Standard errors are clustered at the family level. *** p<0.01, ** p<0.05, * p<0.1.

The remaining columns of Table 3 illustrate that by excluding one lineage from the estimation of the multigenerational process, we may incur an omitted variable bias that results in a more positive grandparent coefficient. In columns 2 and 4, we include the educational outcome of one parent and the average educational outcomes among grandparents from the *same* lineage.[22] In columns 3 and 5, we instead include educational outcomes for one parent (G2) and the grandparents (G3) from the *other* lineage. The finding of a more positive grandparent coefficient when controlling for the educational outcome of only one parent is in line with prior evidence (e.g. Anderson, Sheppard and Monden 2018, Colagrossi, d'Hombres and Schnepf 2020). Interestingly, when including *paternal* education for G2, the grandparent coefficient is more positive if considering *maternal* grandpar-

[21] Zeng and Xie (2014) finds a positive coefficient among co-resident grandparents and zero effects from non-co-resident grandparents.

[22] As we show in Appendix Table A2, the patterns are similar when considering the education of each grandparent separately.

ents. This observation likely reflects the omitted variable bias from excluding the parent of the grandparents' lineage, as we formalize in Section 6.1.[23]

5 Evidence on financial constraints and direct income effects

In the Becker-Tomes model, γ measures the strength of the direct effect of parental income on child human capital. This effect is likely to reflect various mechanisms, one of which is the ability of higher-income parents to invest in human capital enhancing inputs, such as educational resources, play materials, high-quality childcare and schooling, as well as extra-curricular experiences.[24] Its strength thus also depends on parents' ability to borrow: the stronger the credit constraints, the stronger the link between parental income and parental investments that affect child outcomes (Becker and Tomes 1986). Such income effects are thought to be a key mechanism to explain why intergenerational correlations are larger in developing countries. But as shown in Section 3, conditional on parent-child transmission, credit constraints have the opposite implication for the multigenerational patterns: the higher γ, the more negative the coefficient β_{gp}.

In this section, we bring two pieces of evidence to test the implication of the Becker-Tomes model about this relationship between γ and the strength of the multigenerational coefficient β_{gp}. We conduct this analysis not just for the pooled sample, but also by gender. There is a vast literature documenting large gender differences in educational attainment in developing countries. In India, for example, girls are less likely to be enrolled in private schools relative to boys in the same household (Maitra, Pal and Sharma 2016). In Indonesia, households that become credit constrained due to crop loss have been shown to cut back school expenditures, particularly so if the child is female rather than male (Cameron and Worswick 2001). Lower parental propensity to invest in daughters may be driven by a number of factors, including cultural norms that view boys as contributing to old-age security in some contexts (Maitra, Pal and Sharma 2016), as well as gender differences in the actual or perceived labor market returns to education.[25]

[23] To check whether the finding of convex intergenerational conditional expectation functions for children' in rural regions documented in Ahsan, Emran and Shilpi (2024) has distinct multigenerational implications, we compare the multigenerational transmission patterns in rural and urban areas in our sample. Table A4 shows that the grandparent coefficient is more positive in rural regions, suggesting that non-linearities in the intergenerational relationship may also map into distinct multigenerational patterns.

[24] Another theory about the link between family income and child outcomes is the family stress channel, which posits that parental income (or lack thereof) has an impact on parental stress and the quality of parent-child interactions, which have an important influence on child human capital.

[25] The latter is supported by empirical studies showing that factors which improve the job prospects for women,

Regardless of the driving factor(s), if parents have a different propensity to invest in their sons and daughters' education, then the link between parental income and child education would likely also differ by gender. However, it is a priori unclear whether we would expect a stronger link for boys or for girls. If parents allocate only a basic amount for daughters while investing the remainder in sons, the correlation between parental income and educational investment will be stronger for boys. If, on the other hand, parents prioritize investing in sons and invest in daughters only if sufficient financial resources are available, the pattern would be the opposite.

5.1 Variation in educational expenditures

The first piece of evidence we bring to bear on the link between γ and β_{gp} exploits geographical variation in households' educational expenditures. Table 4 compares districts with varying levels of educational expenditure, defined as the district's average of the share of household income which goes to children's schooling, adjusted for the number of children. The average value of the share of household income allocated to children's schooling across districts is 0.16, with a standard deviation of 0.06.[26]

Column (1) reveals that in districts with higher educational spending, the grandparent coefficient in the multigenerational regression eq. (2) is more negative. While purely descriptive, this evidence aligns with the theoretical result that when the direct transmission channel (parameter γ) is relatively more important than the family endowment (parameter λ), the multigenerational coefficient β_{gp} is more negative.[27]

such as manufacturing growth in Bangladesh (Heath and Mobarak 2015) or access to jobs in the business process outsourcing industry in India (Jensen 2012), result in significantly higher educational attainment for girls.

[26] We use the expenditure in education as reported by IFLS respondents, see Section 4. For a more detailed description of the result in Table 4, see Appendix A.6. In this Appendix we also report the results of the same analysis where instead of a continuous measure of the expenditure share we use an indicator for whether this share is below or above the median of the share's distribution across districts (see Table A3).

[27] The smaller estimate for the parental coefficient in the multigenerational regression (second row of Table A3) may instead reflect a lower relevance of the family endowment channel in these areas.

Table 4: Multigenerational Transmission by Household Expenditures

	Dependent Variable: Child's Education		
	All Children (1)	Male (2)	Female (3)
Parental Education	0.591***	0.529***	0.655***
	(0.042)	(0.059)	(0.051)
× Expenditure Share	-0.257**	-0.105	-0.415***
	(0.130)	(0.181)	(0.153)
Grandparental Education	0.077	0.142*	0.009
	(0.061)	(0.086)	(0.076)
× Expenditure Share	-0.298*	-0.491**	-0.097
	(0.173)	(0.250)	(0.206)
Observations	7,109	3,637	3,472
R-squared	0.332	0.318	0.347

Note: OLS estimates of eq. (2), interacted with the average households' expenditure shares in education at the district level (and incl. the expenditure shares' main effect). To ensure sufficient data for estimating regional expenditure shares, we only include those children (G3) who reside in one of the 34 districts originally surveyed in the IFLS. Standard errors are clustered at the family level, *** p<0.01, ** p<0.05, * p<0.1.

Columns (2) and (3) of Table 4 report the results of the same regression, breaking the sample down by gender. For sons, the grandparent coefficient is positive in regions with low educational expenditures, but it appears to diminish in areas with higher spending on education. It is important to note that this pattern is descriptive, and the average share of household income spent on educational expenditures is an imperfect proxy for financial constraints. Moreover, the share could reflect a host of other area-level factors determining the demand and supply of educational inputs.

5.2 Income shocks and financial constraints

In this section, we present a second piece of analysis, aiming to further isolate variation in credit constraints across areas. To do this, we leverage geographical variation in the effects of the Indonesian economic crisis of 1997 on local economic conditions and credit access.

The Indonesian economic crisis of 1997 was triggered by the collapse of the Thai baht, with effects felt in nearby economies soon after (Kusnanto 2002). In January 1998, the Indonesian rupiah fell nearly 80% from its pre-crisis value against dollar. The crisis led to a 13.7% economic contraction and an inflation rate as high as 77.6% in 1998 across the affected countries, with Indonesia, Korea, and Thailand being the three hardest-hit economies (International Monetary Fund 1998). However, there were vast regional differences in the way that the crisis affected households. Broadly speaking, the provinces of Java and Bali were the most severely hit by the crisis, while the provinces of Sumatera, Sulawesi and Maluku were less affected by or even benefited from the crisis due to elevated prices of their traded products. The provinces in West and East Nusatenggara, Kalimantan and Irian Jaya were somewhat affected, but also suffered from an El Niño drought and forest fires at the same time as the crisis (Kusnanto 2002).

The timing of the crisis and the fact that we have data on multiple cohorts of children means that we can exploit both cross-cohort and cross-province variation in children's exposure to the crisis in a difference-in-differences (DiD) design. Specifically, children who were born in 1979 or before and who were 18 or older when the crisis hit were too old to see their education affected by the crisis.[28] In contrast, children born before that could have seen parental investments in their education affected.

To isolate the link between credit constraints on the grandparent coefficient in multigenerational regressions, we estimate the following regression controlling for cohort trends and province fixed effects:

$$\begin{aligned} Y_{icp} = \quad & \rho_c + \delta_p + \beta_1 P_{icp} + \beta_2 GP_{icp} + \beta_3 P_{icp} \times Post_c + \beta_4 GP_{icp} \times Post_c + \beta_5 P_{icp} \times Exp_p \\ + \quad & \beta_6 GP_{icp} \times Exp_p + \beta_7 Post_c \times Exp_p \\ + \quad & \beta_8 P_{icp} \times Post_c \times Exp_p + \beta_9 GP_{icp} \times Post_c \times Exp_p + \epsilon_{icp} \end{aligned} \tag{13}$$

where Y_{icp} is individual i's years of education, P_{icp} their parents' average education and GP_{icp} their grandparents' average education; ρ_c are birth cohort fixed effects, δ_p are province fixed effects; $Post_c$ is a dummy indicating whether individual i was born after 1979, and Exp_p is a province p-level measure of exposure to the crisis, defined as the percent change in unemployment between 1996 and 1997 in province p. In the model above, the coefficient of interest is β_9, which indicates

[28] In our sample, 99% completed 16 or less years of education (and hence finished by age 22) and 85% completed less than 12 or less years of education (and hence finished by age 18).

how the coefficient on the grandparental education changes among the treated cohorts as they are more exposed to the crisis (and more credit-constrained). We estimate this model for the whole sample and then again break it down by gender.

Table 5: DiD Estimates of the Impact of the Crisis on the Grandparent Coefficient

	Dependent Variable: Child's Education		
	Full sample	Males	Females
Grandparental Education $\times Post \times Exp$	-0.147	-0.565**	0.240
	(0.154)	(0.228)	(0.215)
Grandparental Education $\times Exp$	-0.278	0.009	-0.493**
	(0.181)	(0.334)	(0.172)
Grandparental Education $\times Post$	0.012	0.046	-0.016
	(0.031)	(0.039)	(0.052)
Grandparental Education	0.058*	0.041	0.058
	(0.032)	(0.035)	(0.055)
Observations	7,217	3,689	3,528
R-squared	0.352	0.341	0.374

Note: OLS estimates of eq. (13). The dependent variable is the child's years of education, crisis exposure ("*Exp*") is measured as the proportional change in the province-level unemployment rate between 1996 and 1998 relative to the unemployment rate in 1996. Treated cohorts are born after 1979 ("*Post*") and therefore aged 17 or younger when the crisis hit, control cohorts are born on or before 1979. As shown in eq. (13), we control for province of birth and cohort fixed effects and all interaction effects between crisis exposure, the "Post" dummy, and parental education. *** p<0.01, ** p<0.05, * p<0.1

The results of this regression are shown in Table 5. The estimates of our coefficient of interest β_9 (interaction of grandparental education with "Post" and "Exp") is negative, though not statistically significant in the overall sample. Splitting by gender reveals a very similar pattern as before: the grandparent coefficient becomes statistically significantly more negative in areas and cohorts that are more exposed to the crisis (and presumably more affected by financial constraints) for boys, whereas the coefficient is smaller and insignificant for girls.

Overall, the two pieces of empirical analysis we have presented in this section are consistent with the implications of the Becker-Tomes model about a potential link between financial constraints and the strength of multigenerational transmission. However, this link appears pronounced only for boys in the Indonesian context.

6 Assortative mating

An estimation that omits the education of one parent may lead to inflated multigenerational coefficients, as part of the correlation in education between the omitted parent and the offspring is captured by the education of the grandparents (Anderson, Sheppard and Monden, 2018). We already verified this theoretical prediction in our Indonesian context (see Table 3 and Appendix Table A2). As we show below, the extent to which the education of grandparents may capture the influence of the omitted parent will depend on the degree of *assortative mating*, that is, the similarity between spouses in their educational attainment.

More broadly, assortative mating will alter patterns of multigenerational transmission. This observation is especially important for cross-country comparisons, as differences in multigenerational estimates may partly reflect differences in the structure and degree of assortative mating, in addition to differences in the intergenerational transmission processes. Cultural norms regarding the process by which spouses match tend to differ significantly between developed and developing countries. Marital customs also vary greatly between developing countries and between ethnic or religious groups. In high-income countries, the spousal search tends to be "direct", in that individuals choose their partner themselves. In contrast, in many developing countries, the selection process involves other members of the family – often, the parents of the spouses.

In Indonesia, 28% of women and 19% of men born between the 1920s and the 1960s reported that their parents chose their spouse in the IFLS. This practice varies by socioeconomic background, with their likelihood being negatively correlated with socio-economic status.[29] We also observe considerable variation in these practices across provinces: in South Sulawesi, over 75% of women reported parental involvement in spouse selection, while in South Sumatra, only about 6% did so. This strong variation in the *structure* of assortative processes reflects the differential ethnic composition across provinces (Ashraf et al. 2020).

[29] For every additional year of education of the wife, the probability that her partner was selected by her parents decreases by about 1.2 percentage points, while for every additional log point of parental earnings, the probability decreases by about 3 percentage points.

6.1 The role of assortative processes in multigenerational transmission

To understand the implications of assortative mating – and of different *structures* of the assortative process – consider a version of the latent factor model that incorporates assortative mating. Specifically, assume that a child's endowment is determined by the average of the father's and mother's endowments,

$$y_{i,t} = \rho e_{i,t} + u_{i,t} \tag{14}$$

$$e_{i,t} = \tilde{\lambda}\bar{e}_{i,t-1} + v_{i,t}, \tag{15}$$

with $\bar{e}_{i,t-1} = (e^m_{i,t-1} + e^p_{i,t-1})/2$, and where the m and p superscripts denote the maternal and paternal lineage. This simple model is sufficient to derive our key implications, but it can be extended to allow for direct transmission effects, gender-specific transmission pattern, or assortative matching in multiple dimensions (e.g., Collado, Ortuño-Ortín and Stuhler, 2023).

Direct assortative mating. First, consider the implications of "direct" assortative mating between spouses based on their latent endowments (normalized to variance one), as represented by the linear projection

$$e^m_{i,t-1} = me^p_{i,t-1} + w_{i,t-1} \tag{16}$$

where $m = Cov(e^m_{i,t-1}, e^p_{i,t-1})$. As in the model without assortative mating, the multigenerational correlations can still be expressed as

$$\beta_{-k} = \rho^2\lambda^k$$

but λ is now defined as $\lambda = Cov(e_{i,t}, e^x_{i,t-1}) = \tilde{\lambda}\left(1 + Cov(e^m_{i,t-1}, e^p_{i,t-1})\right)/2 = \tilde{\lambda}\,(1+m)\,/2$. Intuitively, the transferability of endowments from one parent to the child as captured by λ reflects both the transferability of the *average* parental endowments ($\tilde{\lambda}$) and the extent of assortative mating between parents (m). As $m \leq 1$ it follows $\lambda \leq \tilde{\lambda}$, implying that parent-child correlations are lower if measuring the outcome of only one parent as opposed to the average over both parents.

The grandparent coefficient in a regression of offspring status on parent and grandparent status from the *same* lineage (i.e., father and paternal grandparent on the paternal lineage p, or mother and maternal grandparent on the maternal lineage m)

$$y_{it} = \beta_p y^x_{it-1} + \beta_{gp} y^{x,y}_{it-2} + \epsilon_{it} \quad \text{for } x = \{m, p\},\ y = \{m, p\} \tag{17}$$

still equals

$$\beta_{gp} = \frac{\beta_{-2} - \beta^2_{-1}}{1 - \beta^2_{-1}} = \frac{\rho^2\lambda^2 - \rho^4\lambda^2}{1 - \rho^4\lambda^2}, \tag{18}$$

in line with our results for the one-parent version of the latent factor model, but with the parameter λ now also reflecting the strength of the assortative process.

Conversely, the grandparent coefficient in a regression of offspring status on parent and grandparent status from *different* lineages (i.e., father and maternal grandparent, or mother and paternal grandparent),

$$y_{it} = \beta'_p y^x_{it-1} + \beta'_{gp} y^{y,z}_{it-2} + \epsilon_{it} \quad \text{for } y \neq x \text{ and } z = \{m, p\} \tag{19}$$

equals

$$\beta'_{gp} = \frac{\beta_{-2} - \left(\beta'_{-1}\right)^2}{1 - \left(\beta'_{-1}\right)^2} = \frac{\rho^2\lambda^2 - m^2\rho^4\lambda^2}{1 - m^2\rho^4\lambda^2}, \tag{20}$$

implying $\beta'_{gp} > \beta_{gp}$ if assortative mating is imperfect ($0 \leq m < 1$). We therefore expect the grandparent coefficient to be less positive when including grandparent(s) from the *own* lineage (e.g., including father and paternal grandmother/grandparents), and more positive when including a parent from the *other* lineage (e.g. father and maternal grandmother/grandparents). We confirmed this hypothesis in Table 3 and Appendix Table A2.

Finally, the grandparent coefficient in a regression on the status of grandparent and *both* parents,

$$y_{it} = \beta_x y^x_{it-1} + \beta_y y^y_{it-1} + \beta''_{gp} y^{x,z}_{it-2} + \epsilon_{it} \quad \text{for } y \neq x \text{ and } z = \{m, p\} \tag{21}$$

equals $\beta''_{gp} = Cov(y_{it}, \tilde{y}^{x,z}_{it-2})/Var(\tilde{y}^{x,z}_{it-2})$, where $\tilde{y}^{x,z}_{it-2}$ is the residual from regressing $y^{x,z}_{it-2}$ on y^x_{it-1} and y^y_{it-1}. The slope coefficients in this auxiliary regression equal $\left(\rho^2\lambda - m^2\rho^4\lambda\right) / \left(1 - m^2\rho^4\right)$ on y^x_{it-1} and $\left(m\rho^2\lambda - m\rho^4\lambda\right) / \left(1 - m^2\rho^4\right)$ on y^y_{it-1}. After simplification, we have

$$\beta''_{gp} = \frac{\rho^2\lambda^2(\rho^2 - 1)(m\rho^2 - 1)}{1 - m^2\rho^4 + \rho^4\lambda^2\left(m^2(2\rho^2 - 1) - 1\right)} \tag{22}$$

where $\beta''_{gp} < \beta'_{gp}$ if $0 < \rho < 1$, $0 \leq m \leq 1$, and $0 < \lambda \leq 1$. The numerator is necessarily positive, because both $(\rho^2 - 1)$ and $(m\rho^2 - 1)$ are negative (as $\rho < 1$ and $m < 1$). The denominator is also positive, so β''_{gp} is necessarily positive in this model, similarly as β_{gp} is positive in the one-parent latent factor model.

Family-based assortative mating. What happens when instead, the spouses' families are involved in the assortative process? To illustrate the potential implications on inter- and multigenerational mobility, we assume that this "family-based" assortative matching can be represented by the linear projection

$$e^x_{i,t-1} = me^{y,m}_{i,t-2} + v_{i,t-1} \qquad \text{for } x = \{m, p\},\ y = \{m, p\} \text{ and } y \neq x \tag{23}$$

i.e. we assume that the mothers of each spouse in the parent generation (G2) "choose" the respective partner for their child. This assortative process implies the spousal correlation[30]

$$Cov(e^p_{it-1}, e^m_{it-1}) = m\lambda_I,$$

where $\lambda_I = \frac{\tilde{\lambda}}{2-m\tilde{\lambda}}$. Note that for a given matching parameter m, the spousal correlation in this model with family-based sorting now tends to be smaller than the corresponding correlation in the model with "direct" assortative mating (as $\lambda_I \leq 1$), an implication that we can test in our data.

The intergenerational correlation is now given as[31]

$$\beta_{-1} = \rho^2\lambda_I,$$

which, for given values of $\{\rho, \lambda, m\}$, is *smaller* than the corresponding moment in the latent factor model with "direct" assortative mating (as $\lambda_I \leq \lambda$, see above), while the three-generation

[30] Note that $Cov(e^p_{it-1}, e^m_{it-1}) = Cov(me^{m,m}_{i,t-2}, \tilde{\lambda}(e^{m,m}_{i,t-2} + e^{m,p}_{i,t-2})/2) = m\tilde{\lambda}\left(1 + Cov(e^{m,m}_{i,t-2}, e^{m,p}_{i,t-2})\right)/2 = m\tilde{\lambda}/(2 - m\tilde{\lambda})$, where the last step follows because in steady state we have $Cov(e^p_{it-1}, e^m_{it-1}) = Cov(e^{m,m}_{i,t-2}, e^{m,p}_{i,t-2})$.

[31] The corresponding correlations in e are $Cov(e_{i,t}, e^m_{i,t-1}) = Cov(\tilde{\lambda}(e^m_{i,t-1} + e^p_{i,t-1})/2, e^m_{i,t-1}) = \tilde{\lambda}\left(1 + Cov(e^m_{i,t-1}, e^p_{i,t-1})\right)/2 = \frac{\tilde{\lambda}}{2-m\tilde{\lambda}} = \lambda_I$, which for $m > 0$ again tends to be smaller than the corresponding moment in the latent factor model with "direct" assortative mating (in which $Cov(e_{i,t}, e^m_{i,t-1}) = \tilde{\lambda}(1 + m)/2$). Following similar steps, we can derive $Cov(e_{it}, e^{m,m}_{it-2}) = \frac{\tilde{\lambda}^2 + m\tilde{\lambda}(2-m\tilde{\lambda})}{4-2m\tilde{\lambda}}$.

correlation is

$$\beta_{-2} = \rho^2 \frac{\tilde{\lambda}^2 + m\tilde{\lambda}\left(2 - m\tilde{\lambda}\right)}{4 - 2m\tilde{\lambda}},$$

which, for given values of $\{\rho, \lambda, m\}$, is *larger* than the corresponding moment in the latent factor model with "direct" assortative mating. Unless $m = \tilde{\lambda} = 1, theratio \frac{\beta_{-2}}{\beta_{-1}} = \frac{\tilde{\lambda}+m\left(2-m\tilde{\lambda}\right)}{2}$is therefore necessarily larger than the corresponding ratio in the latent factor model with "direct" assortative mating (which equals $\frac{\beta_{-2}}{\beta_{-1}} = \frac{\tilde{\lambda}+m\tilde{\lambda}}{2}$).

What are the implications for the grandparent coefficient in a multigenerational regression? The grandparent coefficient in a regression of offspring status on parent and grandparent status from the *same* lineage (i.e., father and paternal grandparent, or mother and maternal grandparent), as in eq. (17), equals

$$\beta_{gp} = \frac{\beta_{-2} - \beta_{-1}^2}{1 - \beta_{-1}^2} = \frac{\rho^2 \tilde{\lambda} \frac{\lambda_I + m}{2} - \rho^4 \lambda_I^2}{1 - \rho^4 \lambda_I^2} \tag{24}$$

which is larger than β_{gp} in the latent factor model with direct assortative mating in eq. (18), because β_{-2} is larger and β_{-1} is smaller.

The family-based assortative mating considered here therefore implies *stronger* multigenerational transmission. The intuition is that if the parents choose their child's spouse, the characteristics of that spouse will tend to depend not only on the child's own but also the parents' traits. This introduces another source of persistence that is not fully captured by conventional parent-child correlations. However, this prediction hinges on the specific structure of the assortative process. While we assumed matching on parents' endowments e, alternative structures are also plausible. The broader takeaway from our discussion, therefore, is not a definitive prediction about the sign of β_{gp}, but rather the understanding that this coefficient – and the relative strength of inter- and multi-generational correlations – depends on the structure of the assortative process, and will therefore differ between countries or groups following different marital norms.

6.2 Evidence on assortative mating and multigenerational transmission

To empirically assess whether the structure of the marriage market in Indonesia impacts the multi-generational transmission process, we exploit the rich information collected in the IFLS about marital customs. As mentioned, a large fraction of individuals in the second generation of our sample declares that the spouse was selected by their family, a practice which is more common among the less educated. We first investigate whether spousal correlations in education vary depending on who selected the spouse, and then compare inter- and multigenerational coefficients for different groups.

Table 6 shows the coefficient estimates from different spousal regressions, where the dependent variable is the years of education of an individual and the independent variables are the years of education of their spouse (Column 1) and the parents of their spouse (Columns 2-3). Each variable is interacted with an indicator for family-based matching (*FamilyChoice*), which equals 1 if the wife in the couple declares that her husband was selected by her parents.[32]

Column 1 of Table 6 shows that, when the family selects a woman's spouse, the correlation between the years of education of the two partners (a proxy for assortative mating) is smaller. In contrast, the correlation between the husband and his father in-law, or between the wife and her mother in-law, is more positive (Columns 2-3). These results are consistent with the family-based assortative mating process described in Section 6.1, which implies that, in families where the parents select the spouse for their child, the spouses are more different from each other but more similar to their respective in-laws than in families where the spouses choose each other without their parents' involvement.

In Section 6.1, we showed that family-based matching would imply a *larger* multigenerational coefficient. To test this implication, we estimate the multigenerational process in eq. (2) by interacting each regressor with the same indicator *FamilyChoice* as in Table 6 that equals one if a woman (G2)'s family chose her spouse.[33] Table 7 reports the estimates of the baseline coefficients and of the coefficients for this interaction. The dependent variable variable is always the child's years of schooling. In Columns 1-4 we use only one lineage of parents and different lineages of grandparents. In Column 5 we consider the average education of the two parents and the average education of all grandparents.

These results show that, conditional on grandparental education, parental education is less

[32]The sample used in this analysis includes all couples observed in the IFLS data for whom information on the parents of both spouses and on who selected their spouse is available. Hence, this sample is larger than the one used for our main analysis, which also requires the observation of a third generation.

[33]In Table 6, we use the wife's answer about whether her husband was chosen by her family as a proxy for traditional marital practice. The results also hold when using instead the husband's report that his wife was selected by his parents.

Table 6: Assortative Mating over Two Generations

Dependent Variable	Husband's Education	Husband's Education	Wife's Education
Spouse	Wife	Wife	Husband
Parent	–	Wife's Father	Husb.'s Mother
	(1)	(2)	(3)
Spousal Education	0.724***	0.663***	0.607***
	(0.0102)	(0.0111)	(0.0120)
Spousal Education	-0.0492**	-0.0703***	-0.138***
$\times 1(FamilyChoice)$	(0.0213)	(0.0254)	(0.0168)
Parental Education		0.123***	0.170***
		(0.00995)	(0.0125)
Parental Education		0.0700**	0.0677**
$\times 1(FamilyChoice)$		(0.0274)	(0.0329)
$1(FamilyChoice)$	-0.459***	-0.502***	0.348***
	(0.129)	(0.145)	(0.109)
Constant	2.747***	2.680***	1.818***
	(0.115)	(0.115)	(0.0801)
Observations	11,875	11,007	10,595
R-squared	0.563	0.579	0.636

Note: The dependent variable is the years of education of the husband (columns 1 and 2) or the wife (column 3). The independent variables are the years of education of the wife (column 1), the wife and her father (column 2), or the husband and his mother (column 3). The indicator *FamilyChoice* equals 1 if the wife declares that her husband was selected by her family. Controlling for birth cohort of the wife fixed effects, standard errors are clustered at the level of the wife's *kabupaten* (district) of birth.*** p<0.01, ** p<0.05, * p<0.1

predictive of the child's education when the mother's family was involved in the choice of her spouse (the child's dad). In contrast, grandparental education is more predictive of the child's education when the parents were matched by the grandparents. In fact, the coefficient on grandparental education is negative and statistically significant when the parents did not select the spouse of their daughter (coefficient "GP Education" in Columns 5), but turns positive when they did (interaction with $FamilyChoice$).

While other mechanisms may be at play, this evidence presented here aligns with the theory outlined in Section 6.1. In particular, it suggests that a common practice in Indonesian household formation – parental selection of children's spouses – contributes to the long-term persistence

Table 7: Multigenerational Transmission and Assortative Practices

	Dependent Variable: Child's Education				
Parent	Father		Mother		Average
Grandparent	Paternal	Maternal	Maternal	Paternal	Average
	(1)	(2)	(3)	(4)	(5)
Parental Education	0.419***	0.390***	0.409***	0.412***	0.515***
	(0.014)	(0.014)	(0.016)	(0.014)	(0.016)
Parental Education	-0.058**	-0.050*	-0.035	-0.028	-0.033
$\times 1(FamilyChoice)$	(0.029)	(0.029)	(0.035)	(0.031)	(0.038)
Grandparental Education	-0.016	0.074***	0.030	0.029	-0.069***
	(0.022)	(0.021)	(0.022)	(0.021)	(0.027)
Grandparental Education	0.100*	0.074*	0.080*	0.090*	0.119*
$\times 1(FamilyChoice)$	(0.053)	(0.043)	(0.044)	(0.053)	(0.061)
$1(FamilyChoice)$	0.320*	0.300*	0.007	0.006	0.158
	(0.174)	(0.174)	(0.165)	(0.165)	(0.176)
Constant	7.130***	7.121***	7.681***	7.674***	6.984***
	(0.105)	(0.105)	(0.097)	(0.098)	(0.102)
Observations	8,160	8,160	8,160	8,160	8,160
R-squared	0.237	0.241	0.218	0.218	0.269

Note: The table reports the estimated parameters of different variants of eq. (2). The indicator *FamilyChoice* equals 1 if the mother declares that her husband was selected by her family. Grandparental education is the average of the years of education completed by the parents of the father (columns 1 and 4) or the mother (columns 2 and 3). Each regression controls for birth cohort of the wife fixed effects, standard errors are clustered at the family level. *** p<0.01, ** p<0.05, * p<0.1.

of educational outcomes across generations. Declines in this practice over time (the fraction of women declaring that their partners was selected by their parents was more than 20% in the early 1960s and around 7% for the most recent generations) will thus also affect the pattern of multigenerational transmission. However, while these results suggest that family-based matching affects the multigenerational transmission process, they do not explain our baseline finding in Section 4.3 that the grandparent-child coefficient is small or even negative in Indonesia.

7 Conclusion

Economic mobility across generations is a central policy concern, especially in developing countries where mobility is low and economic hardship constrain opportunities for social and economic advancement. But while we have much evidence on *inter*generational mobility from one generation to the next, much less is known about the long-run persistence of socioeconomic advantages across multiple generations. Our central argument is that multigenerational dynamics are bound to differ between the developing and developed world, as well as across developing countries. The observation of high intergenerational persistence in developing countries does therefore not necessarily imply strong long-run persistence across multiple generations.

Using complete educational histories for three generations, we first showed that multigenerational correlations decay more quickly in Indonesia than in high-income countries. To understand why, we then compared the multigenerational implications of different mechanisms in standard models of intergenerational transmission. The pattern observed in Indonesia aligns with predictions from the well-known Becker-Tomes model, but contrasts with those found in developed countries. We argue that such differences arise because different transmission mechanisms, such as direct parental investments, credit constraints, and marital customs, have distinct dynamic implications. If certain mechanisms are more salient or function differently in developing countries, multigenerational dynamics will differ.

Our rich survey data allowed us to study some of these mechanisms, and to explore their implications for multigenerational transmission. We first considered the role of direct parental investments and financial constraints. In the Becker-Tomes model, the coefficient on grandparent status in a child-parent-grandparent regression should be more negative when financial constraints are more important. Consistent with this prediction, we found that this "grandparent coefficient" is more negative for boys in areas where expenditures on education are higher. Going beyond descriptive associations, we leveraged plausibly exogenous variation in financial constraints induced by the 1997 Asian Financial Crisis, showing that the coefficient is lower for boys who lived in regions that were more negatively affected by the downturn. Binding financial constraints could thus be one reason for the multigenerational patterns observed in Indonesia.

Marital customs are another key factor influencing multigenerational dynamics. Recognizing that approximately 28% of women and 19% of men in our sample reported having their spouses chosen by their parents, we derived the theoretical implications of such "family-based" assortative mating. When a woman's family selects her spouse, we expect a weaker correlation in education between spouses, a stronger correlation between an individual and their parents-in-law, and overall higher multigenerational persistence. Family-based marital sorting, as is common in many developing countries, may thus generate distinct patterns of persistence. Exploiting variation in reported marital customs across Indonesian households, we found support for all three predictions.

Overall, these findings underscore the complexity of multigenerational dynamics, which reflect the relative strengths of different mechanisms. Our work is of course far from conclusive in identifying the factors that shape long-run persistence. And while our analysis benefited from the availability of rich survey data in Indonesia, our specific results may not directly translate to other contexts. Nonetheless, our findings highlight why multigenerational dynamics will follow distinct patterns in developing countries and point to potential mechanisms to understand these patterns.

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A Appendix

A.1 The grandparent coefficient under non-stationarity

In a multivariate regression of child outcome y_{it} on parent outcome y_{it-1} and grandparent outcome y_{it-2}, the coefficient on the latter is positive if and only if the iteration of parent-child coefficients understates the observed persistence across three generations.

Without assuming stationarity, the grandparent coefficient equals (Frisch-Waugh-Lovell theorem)

$$\beta_{gp} = \frac{Cov(y_{it}, \tilde{y}_{it-2})}{Var(\tilde{y}_{it-2})} \tag{25}$$

where $\tilde{y}_{it-2}$ is the residual from regressing y_{it-2} on y_{it-1}, i.e.

$$\tilde{y}_{it-2} = y_{it-2} - \frac{Cov(y_{it-1}, y_{it-2})}{Var(y_{it-1})} y_{it-1}$$

We therefore have

$$\begin{aligned}
\beta_{gp} &= \left(\frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} - \frac{Cov(y_{it-1}, y_{it-2})}{Var(y_{it-1})} \frac{Cov(y_{it}, y_{it-1})}{Var(y_{it-2})} \right) \frac{Var(y_{it-2})}{Var(\tilde{y}_{it-2})} \\
&= \left(\beta_{-2} - \beta_{-1}^{gp \to p} \beta_{-1}^{p \to c} \right) \frac{Var(y_{it-2})}{Var(\tilde{y}_{it-2})}
\end{aligned} \tag{26}$$

where $\beta_{-1}^{gp \to p}$ and $\beta_{-1}^{p \to c}$ are the two-generational slope coefficient in a regression of parent on grandparent, or child on parent outcome, respectively. We have $\beta_{gp} > 0$ if and only if $\beta_{-2} > \beta_{-1}^{gp \to p} \beta_{-1}^{p \to c}$.

A.2 The grandparent coefficient in the Becker-Tomes model

To derive the grandparent coefficient in the Becker-Tomes model we first derive the parent-child correlation β_{-1} and grandparent-child correlation β_{-2}, and then use the "duality" result in eq. (12) in the main text. We assume that the model is stationary and normalize the variance of e to one. Given eqs. (8) and (11), the intergenerational correlation equals

$$\begin{aligned}
\beta_{-1} &= \frac{Cov(y_{it}, y_{it-1})}{Var(y_{it-1})} \\
&= \frac{Cov(\gamma y_{it-1} + \rho e_{it}, y_{it-1})}{Var(y_{it-1})} \\
&= \gamma + \rho\lambda \frac{Cov(e_{it-1}, y_{it-1})}{Var(y_{it-1})} \\
&= \gamma + \frac{\rho^2 \lambda}{(1 - \gamma\lambda) Var(y_{it-1})}
\end{aligned} \tag{27}$$

where $Cov(e_{it-1}, y_{it-1}) = Cov(e_{it-1}, \gamma y_{it-2} + \rho e_{it-1}) = \lambda\gamma Cov(e_{it-2}, y_{it-2}) + \rho = \rho/(1 - \gamma\lambda)$, as in steady state $Cov(e_{it-1}, y_{it-1}) = Cov(e_{it-2}, y_{it-2})$.

The grandparent-child correlation equals

$$\begin{aligned}\beta_{-2} &= \frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \frac{Cov(\gamma y_{it-1} + \rho e_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \gamma \frac{Cov(y_{it-1}, y_{it-2})}{Var(y_{it-2})} + \rho \frac{Cov(e_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \gamma \beta_{-1} + \frac{\rho^2 \lambda^2}{(1-\gamma\lambda) Var(y_{it-2})} \end{aligned} \tag{28}$$

Exploiting the "duality" result in eq. (3) it follows that

$$\beta_{gp} = \frac{\beta_{-2} - \beta_{-1}^2}{1 - \beta_{-1}^2}$$

Normalizing the variance of y to one, we thus have

$$\begin{aligned}\beta_{gp} &= \frac{\gamma\left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right) + \frac{\rho^2\lambda^2}{1-\gamma\lambda} - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \\ &= \frac{\gamma\frac{\rho^2\lambda}{1-\gamma\lambda} + \frac{\rho^2\lambda^2}{1-\gamma\lambda} - 2\gamma\frac{\rho^2\lambda}{1-\gamma\lambda} - \left(\frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \\ &= \frac{\frac{\rho^2\lambda}{1-\gamma\lambda}\left(\lambda - \gamma - \frac{\rho^2\lambda}{1-\gamma\lambda}\right)}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \end{aligned} \tag{29}$$

which is eq. (12) in the main text. The denominator is non-negative, as $\beta_{-1} = \gamma + \frac{\rho^2\lambda}{1-\gamma\lambda} \leq 1$ by the definition of correlations. Assuming $\rho > 0$ and $\lambda > 0$, we therefore have $\beta_{gp} > 0$ iff $\lambda - \gamma - \frac{\rho^2\lambda}{1-\gamma\lambda} > 0$. Notice that if $\gamma = 0$, expression (29) simplifies to

$$\beta_{gp} = \frac{\rho^2\lambda\left(\lambda - \rho^2\lambda\right)}{1 - \left(\rho^2\lambda\right)^2} = \frac{\rho^2\lambda^2 - \rho^4\lambda^2}{1 - \rho^4\lambda^2},$$

which is the grandparent coefficient in the latent factor model.

To understand how β_{gp} varies with γ, we however cannot normalize the variance of y, since this variance itself depends on γ. More generally, its steady-state variance can be derived as $Var(y_{it}) = (\rho^2 + \sigma^2 + 2\gamma\rho^2\lambda/(1-\gamma\lambda))/(1-\gamma^2)$, where σ^2 denotes the variance of the error term u_{it} in eq. (11). The parameter σ^2 did not appear in the expressions in the main text, as it is implicitly determined by the other parameters when y is normalized. In this case, the grandparent coefficient is given by (the following steps have been derived using the software *Mathematica*)

$$\beta_{gp} = \frac{\lambda\rho^2\left(\gamma^2\lambda\sigma^2 + \gamma\left(\lambda^2 - 1\right)\rho^2 - \gamma\left(\lambda^2 + 1\right)\sigma^2 + \lambda\sigma^2\right)}{-2\rho^2\sigma^2(\gamma\lambda - 1) + \sigma^4(\gamma\lambda - 1)^2 - \left(\lambda^2 - 1\right)\rho^4}. \tag{30}$$

Its derivative with respect to γ is

$$\frac{\partial \beta_{gp}}{\partial \gamma} = \frac{-\lambda\rho^2\left(\rho^2\sigma^4\left(\gamma^2\left(\lambda^4+\lambda^2\right)-4\gamma\lambda-\lambda^2+3\right)+\left(\lambda^2-1\right)\rho^4\sigma^2\left(2\gamma\lambda-\lambda^2-3\right)\right)}{\left(2\rho^2\sigma^2(\gamma\lambda-1)-\sigma^4(\gamma\lambda-1)^2+\left(\lambda^2-1\right)\rho^4\right)^2} + \frac{\lambda\rho^2\left(\left(\lambda^2-1\right)\sigma^6(\gamma\lambda-1)^2+\left(\lambda^2-1\right)^2\rho^6\right)}{\left(2\rho^2\sigma^2(\gamma\lambda-1)-\sigma^4(\gamma\lambda-1)^2+\left(\lambda^2-1\right)\rho^4\right)^2}, \tag{31}$$

which is negative (if $\lambda > 0$, $\rho > 0$). In contrast, the sign of the derivative of β_{gp} with respect to σ depends on parameter values and can be either positive or negative.

A.3 Detailed information on key variables from the IFLS

Individual demographics. We assign to each individual the year of birth reported in the most recent wave where he/she is present, assuming this is the most accurate information in case there is any inconsistency surrounding the reported year of birth. Some household members are also asked about the year of birth of their parents: we exploit this information to generate a variable reporting the year of birth of the grandparents in our three-generation dataset. We check for data consistency by examining the distribution of the years of birth of the grandparents and parents (see Section 4.2).

Province of birth and migration. Each wave of the survey elicits information on place of birth, residence, and relocation. Province of birth is consistent across waves for the vast majority of individuals in our sample. Information on place of residence is reported from age 12.[1]

Marital traditions. The surveys elicit information on the mechanism of marriage formation. In particular, we focus our attention on the question about who in the household selects the spouse. Possible answers include "parents", "self" or "family".[2]

Education expenditures. Each household is asked the total school-related expenditures during the relevant school year. Specifically, households are asked the amount they spent on school fees (including registration, examinations), school supplies (including books, uniforms), and logisitcs (including trnasportation, food and housing costs). We match this information on education

[1] With this information, we have checked that only a small number of individuals were subject to the "transmigration" policy (more details on the policy is discussesd in Bazzi et al. (2016).

[2] Note that more questions about marital traditions are asked in the survey. In particular, we have information about the dowry type and amount and the number of wives for individuals who have more than one. However, since not all individuals answer the question about dowry it is not possible to discriminate whether individuals did not pay for dowry or whether it is just missing information. The cases of polygamy are very few.

expenditures to the parental earnings in each household to calculate the expenditure shares in education. We then take the average of these shares among all households in each district (*kabupaten*), taking into account distriction-level variation in the cost of education within Indonesia.

Earnings. In each survey wave, all household members report their earnings or profits.[3] We can therefore create one unique measure of earnings, which include earnings for some individuals and profits for others. For some individuals we have observation of earnings in all five waves, while for others we have only one observation. As a measure, we take the average across all the available observations. We adjust earnings for inflation using the consumer price index at the national level and express all measures in 2015 terms.

A.4 Additional materials for descriptive statistics

The IFLS has a relatively low rate of attrition - in 1997, the IFLS reinterviewed 94% of households in the first wave of the IFLS. In cases where survey respondents moved in the intervening years, interviews were conducted at the new locations. The third and fourth waves have 95.3% and 93.6% re-interview rates with initial households respectively.

Individuals in our sample from the third generation are equally split between men and women and across cohorts (see Figure A4). Some individuals in the third generation are siblings. In Table A1, we report the proportion of second generation individuals with different number of children and the average years of education conditional on the number of children: over 60% of them have more than one child and the relationship between the number of children and the years of education is negative. For the second generation, the median year of birth among fathers is 1952, while for mothers it is 1957. Figure A5 plots the estimated density of the birth years of parents, which shows that the youngest parents are born in the late 1960s. Figure A6 plots the same estimated distribution for grandparents: they are born between the late 19th century and the late 1940s and, as expected, paternal grandfathers are the oldest group on average, while maternal grandmothers are the youngest. This is also reflected in the median year of birth, where the difference between year of birth of grandfathers and grandmothers is 9 years for the paternal grandparents and 7 years for the maternal grandparents.

[3]These two measures never overlap (individuals either have earnings or profits), depending on the type of job of the individual.

A.5 Validation of education measure

To construct a dataset containing information on three generations, we exploit the longitudinal nature of the IFLS. Within households, all individuals who appear in one survey are followed up in subsequent surveys. If an individual exits the original household and forms a new household, this individual and all members of the new household are interviewed in the next wave. This is true even if individuals move to a province which is not included in the original survey design. When individuals move to a new household, they retain their individual-level identification number, allowing us to track, for example, individuals who were children in earlier waves and form new households in later waves. Given the long time span of the surveys (21 years), we have information on individuals from their childhood into their adulthood.

The panel nature of the dataset implies that we potentially have information on the education of an individual at a maximum of five different points in time and from different questions at each point in time. We take advantage of the panel structure of the data to check for consistency in the self-reported education across waves. In some cases, we observe inconsistency in the reported education across survey waves. For example, it is possible that a person reports having a high school degree in 1993 and then reports having only completed elementary school in 1997 and is also possible that a person reports having a high school degree in one wave but the head of the household states that the same person only has elementary education. In these cases of inconsistency, we take the mode of multiple answers for each individual across the waves as the assigned education level.

To construct the measure for the parents and grandchildren, we use the following procedure. If an individual first enters the IFLS at 25 years of age or more, we keep the level of education reported in that wave as his highest level of education, as long as the information is coherent within that wave.[4] If an individual appears in multiple waves, with the first appearance at or below 24 years of age, we take the education reported in the first wave where the person is above 25 as the highest level of education attained, as long as the reported education level is increasing across waves prior to reaching 25 and is consistent with the first wave where the person is above 25. If there are inconsistencies in the reported level of education within an individual across waves, then we take the mode of education reported in all the waves where the person is above 25.

To construct the education measure of grandparents, we use two sources of information. If

[4] We have also considered checking consistency not only within the first wave but also across all the waves a person appears in. We prefer using the information in the first observation because this is the closest to age 25. Using the mode across waves instead of the first observation, when there is inconsistency across waves gives slightly higher average education for all.

the grandparent is still alive and resides in the same household as the parent, then we have both the self-reported education as well as the level reported by the heads of household. Otherwise, we only have information on the education of grandparents as reported by the heads of household. In practice, co-resident grandparents are a minority. To have a consistent measure, we prefer to use education as reported by the head of the household even for co-resident grandparents.

Validation of the education measure

To validate our data cleaning procedure and to check whether the self-reported educational attainment from the IFLS are accurate, we compare our measure of education among the IFLS respondents with the level of education reported by the same cohorts in the 1995 and 2005 Indonesian population census. Figure A2 shows the average years of education for the parents (G2): comparing the measure from the IFLS with that from the Census. We restrict the comparison sample from the Census to include only the provinces covered by the IFLS.[5] Although not perfectly overlapping, the averages are rather close for all the cohorts we are considering, suggesting that the measure of education we built is quite precise. Similarly, Figure A3 show the difference between the IFLS and the 1995 or 2005 census in the average level of education and in the proportion of individuals with no education in each cohort for the grandparents (i.e. the levels of education of the parents reported by the head of the households). Both graphs confirm that the measure of education reported in the IFLS is in line with information from the Census.

A.6 Multigenerational regression by quartiles of expenditure in education at the district level

As mentioned in Section A.3 one of the questions asked in the IFLS is the yearly expenditure in school fees for children. Using this information, we build a measure for the relevance of parental investments in the human capital accumulation process at the district (*kabupaten*) level, capturing that in different areas education may be more or less expensive. We then estimate the coefficients of the multigenerational regression interacted with these measures, to investigate whether, in line with the theory, the grandparent coefficient is more negative in more expensive areas.[6]

[5] We keep individuals born until 1980 since they are 25 in the 2005 census.

[6] An alternative to estimate the relevance of parental investment can be to assign to each family the respective reported level of expenditure and investigate how the different paramters vary according to this measure. However, the individual level information on expenditure in children's education possibly captures not only the relevance of parental investment in human capital accumulation (parameter γ), but also the effect of the interaction between parental education and own willingness to spend in children's education (for example, it is possible that more educated

In particular, we first compute for each family the average per-child expenditure in education, by taking the ratio between the overall reported expenditure in education and the number of children who are still in school. We then average this measure at the district (*kabupaten*) level and consider the ratio between this number and the average household income in each district. Dropping outliers, the mean expenditure share across the 34 districts we consider is 0.16. This share also reflects how expensive education is in each area. For example, the correlation between this measure and the share of children attending private schools in the district is 0.5. We then interact this number ($ExpSh$) with both the parental and the grandparental education in the multigenerational regression eq. (2), and estimate the different parameters also including in the equation the baseline effect of the expenditure share:

$$y_{it,k} = \beta_p y_{it-1} + \beta_{p,exp} ExpSh_k \times y_{it-1} + \beta_{gp} y_{it-2} + \beta_{gp,exp} ExpSh_k \times y_{it-2} + \beta_{exp} ExpSh_k + \varepsilon_{it,k}. \quad (32)$$

where k is the district, and y_{it-1} and y_{it-2} are the average education of parents and grandparents, respectively. Estimates of parameters β_p, $\beta_{p,exp}$, β_{gp} and $\beta_{gp,exp}$ are reported in Table 4.

To make sure that our results are not driven by some extreme value, we also estimate the same equation, where instead of interacting the parental and grandparental education with a continuous measure of the expenditure share, we use dummies ($ExpSh_b$) for whether district-level expenditure share is above or below the median expenditure share (the district-level median expenditure share is 0.26).

$$y_{it,k} = \sum_{b=1}^{2} \beta_{p,b} ExpSh_{k,b} \times y_{it-1} + \sum_{b=1}^{2} \beta_{gp,b} ExpSh_{k,b} \times y_{it-2} + \sum_{b=1}^{2} \beta_b ExpSh_{k,b} + \varepsilon_{it,k}. \quad (33)$$

In Table A3 we report the coefficient estimates of both these models.

parents are more willing to invest in their children).

A.7 Tables and Figures

Table A1: Education and Proportions of Generation 2 by Number of Children

	Proportion	Years of Education	
		Fathers	Mothers
1 Child	35.8	6.05	5.13
2 Children	30.7	6.08	4.91
3 Children	19.3	6.30	5.01
4 Children	9.6	6.00	4.53
5 Children	3.6	5.85	3.61
6 Children	0.9	4.94	3.61
7 Children	0.2	6.83	5.67
8 Children	0.1	4.00	5.00

Table A2: Robustness of Multigenerational Regression Estimates

	Dependent Variable: Child's Education							
Grandparents	Maternal				Paternal			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.378***	0.262***	0.388***	0.265***		0.272***		0.272***
	(0.012)	(0.014)	(0.011)	(0.014)		(0.015)		(0.014)
Mother		0.217***		0.223***	0.400***	0.224***	0.414***	0.228***
		(0.016)		(0.016)	(0.013)	(0.015)	(0.012)	(0.015)
Grandfather	0.072***	0.006			0.052***	-0.029*		
	(0.014)	(0.014)			(0.016)	(0.015)		
Grandmother			0.063***	-0.013			0.018	-0.051***
			(0.018)	(0.018)			(0.019)	(0.019)
Constant	7.215***	7.051***	7.245***	7.046***	7.669***	7.047***	7.699***	7.031***
	(0.083)	(0.083)	(0.083)	(0.083)	(0.078)	(0.083)	(0.078)	(0.082)
Observations	8,277	8,277	8,277	8,277	8,277	8,277	8,277	8,277
R-squared	0.240	0.267	0.238	0.267	0.217	0.267	0.216	0.268

Note: The table above reports the estimates of multigenerational correlations in education from eq. (2) for different combinations of parents and grandparents education. The dependent variable is the child's years of education (G1). Standard errors are clustered at the family level (all children with the same mother are clustered together). *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Multigenerational Transmission by Household Expenditures

	Dependent Variable: Child's Education					
	All Children (1)	Male (2)	Female (3)	All Children (4)	Male (5)	Female (6)
Parental Education	0.591***	0.529***	0.655***			
	(0.042)	(0.059)	(0.051)			
× Expenditure Share	-0.257**	-0.105	-0.415***			
	(0.130)	(0.181)	(0.153)			
× Low Expenditure				0.546***	0.484***	0.606***
				(0.024)	(0.032)	(0.031)
× High Expenditure				0.493***	0.499***	0.487***
				(0.017)	(0.021)	(0.022)
Grandparental Education	0.077	0.142*	0.009			
	(0.061)	(0.086)	(0.076)			
× Expenditure Share	-0.298*	-0.491**	-0.097			
	(0.173)	(0.250)	(0.206)			
× Low Expenditure				0.033	0.119**	-0.059
				(0.041)	(0.052)	(0.055)
× High Expenditure				-0.032	-0.060*	-0.003
				(0.025)	(0.031)	(0.032)
Constant	5.965***	6.112***	5.783***	6.651***	6.790***	6.518***
	(0.242)	(0.320)	(0.305)	(0.123)	(0.164)	(0.156)
Observations	7,109	3,637	3,472	7,109	3,637	3,472
R-squared	0.332	0.318	0.347	0.333	0.320	0.350

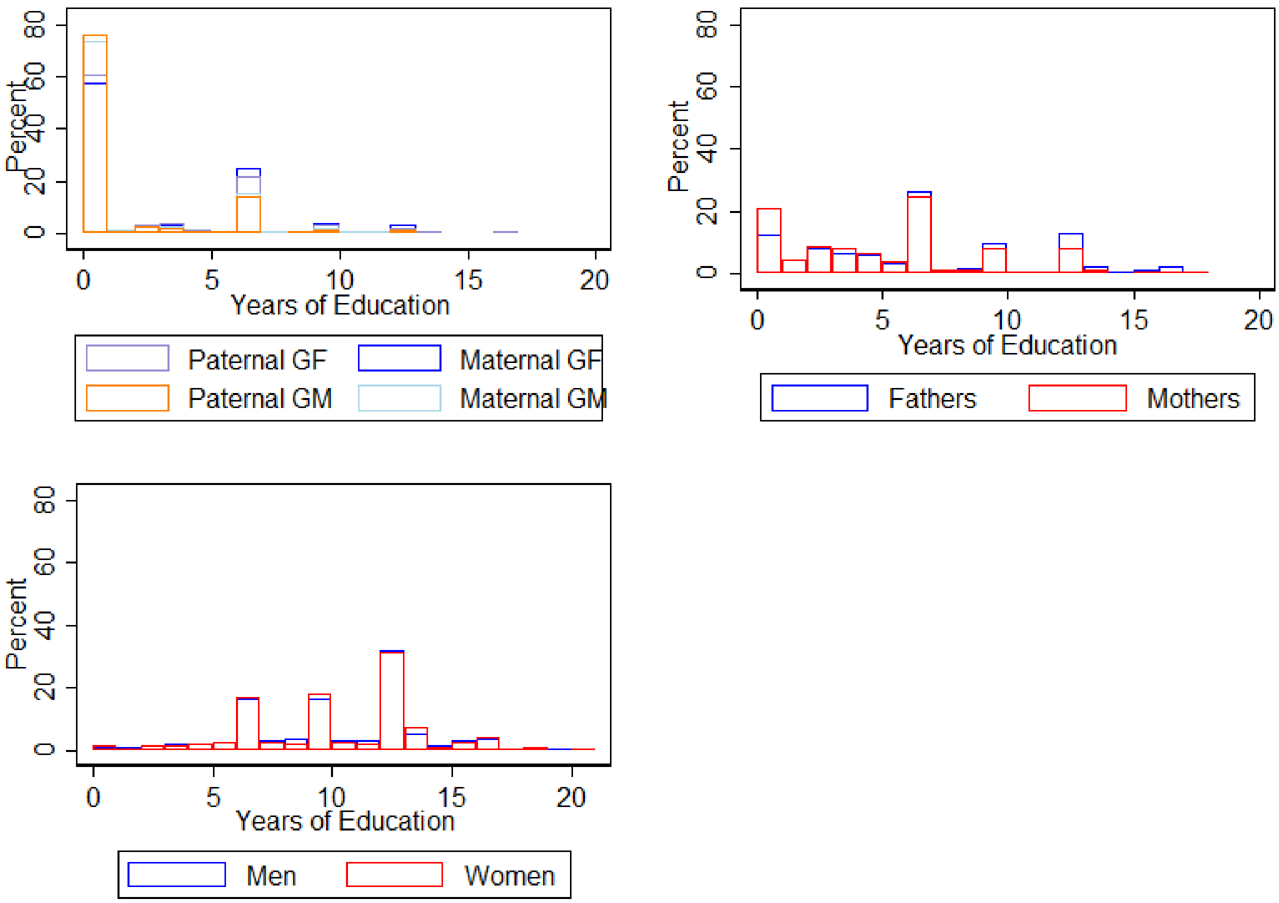
Note: The table above reports the estimates of eq.(2) interacted with measures of households' expenditure shares in education at the district level (Columns (1)–(3) use a continuous measure of the average expenditure share at the district level, Columns (4)–(6) use two dummies indicating whether the district-level average expenditure share is below ("Low Expenditure") or above ("High Expenditure") the median expenditure shares across districts). It also controls for the main effect of the expenditure shares in education. Standard errors are clustered at the family level (all children with the same mother are clustered together). Observations for the overall sample are fewer than those used to estimate the parameters displayed in Table 3 because we only include those children (G3) who reside in one of the 13 provinces which were originally surveyed (while the IFLS included only main respondents who lived in 13 out of 26 regions, it also tracks family members when they move. However, because we want to assign G3 children to an area for which we have enough data to credibly estimate parental expenditure in education, we only include those who live in one of the 13 originally surveyed regions). *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Multigenerational Transmission - Urban vs Rural Areas

	Dependent Variable: Child's Education					
	Birthplace			Birthplace (adjusted)		
	Urban	Rural	Interaction	Urban	Rural	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)
Grandparental Education	-0.0442	0.00758	-0.0442	-0.0728**	-0.0134	-0.0728**
	(0.0284)	(0.0297)	(0.0284)	(0.0340)	(0.0311)	(0.0340)
× Rural			0.0517			0.0594
			(0.0395)			(0.0446)
Parental Education	0.460***	0.528***	0.460***	0.430***	0.527***	0.430***
	(0.0216)	(0.0175)	(0.0216)	(0.0223)	(0.0181)	(0.0223)
× Rural			0.0678**			0.0972***
			(0.0267)			(0.0276)
Rural			-1.123***			-1.148***
			(0.172)			(0.173)
Mean of dep. var.	11.3	9.34	10	10.8	9.06	9.7
Observations	2,582	4,704	7,286	3,051	5,226	8,277
R^2	0.299	0.271	0.333	0.207	0.246	0.274

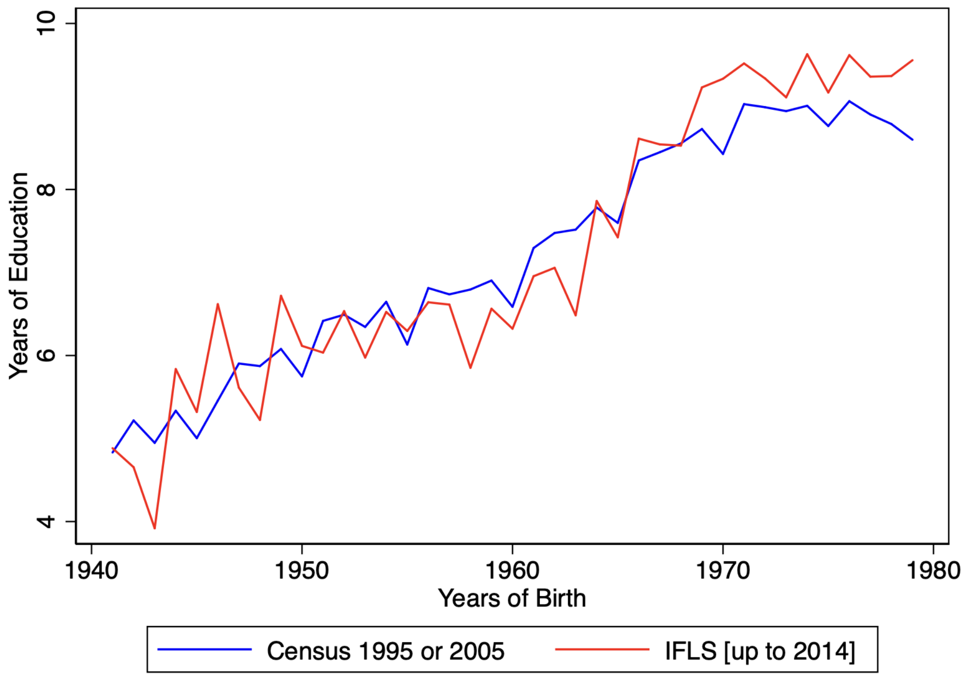
Note: The table above reports estimates of eq. (2) interacted with whether the birthplace of the children (G3) is in a rural area. Standard errors are clustered at the family level. A birthplace is designated to be rural if an individual is born in a village. A birth place is otherwise designated to be urban if an individual is born in a small town or big city. Due to missing observations on the type of birthplace for 991 individuals in our restricted sample (11% of the 8,277 sample), we use the type of residence at the time of the first IFLS survey for the individual. 522 (6.3% of the total sample) individuals with missing birthplace information reported living in a rural area, and 449 (5.7%) reported living in an urban area. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1: Years of Education, Separately for Three Generations



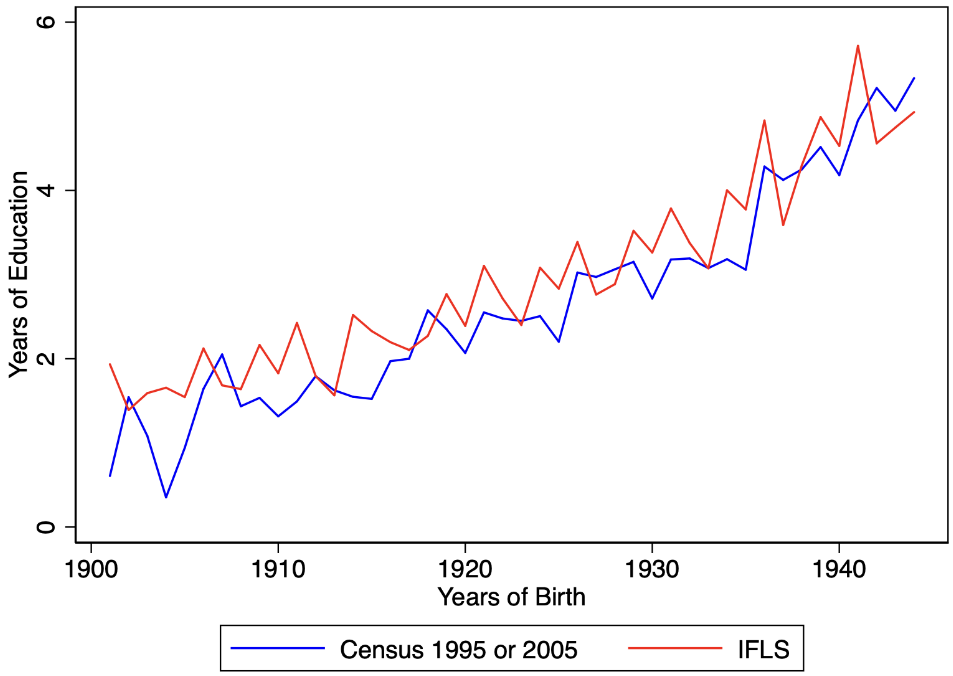
Note: The panels show the distribution of education among the grandparents, parents, and the grandchildren in the IFLS sample.

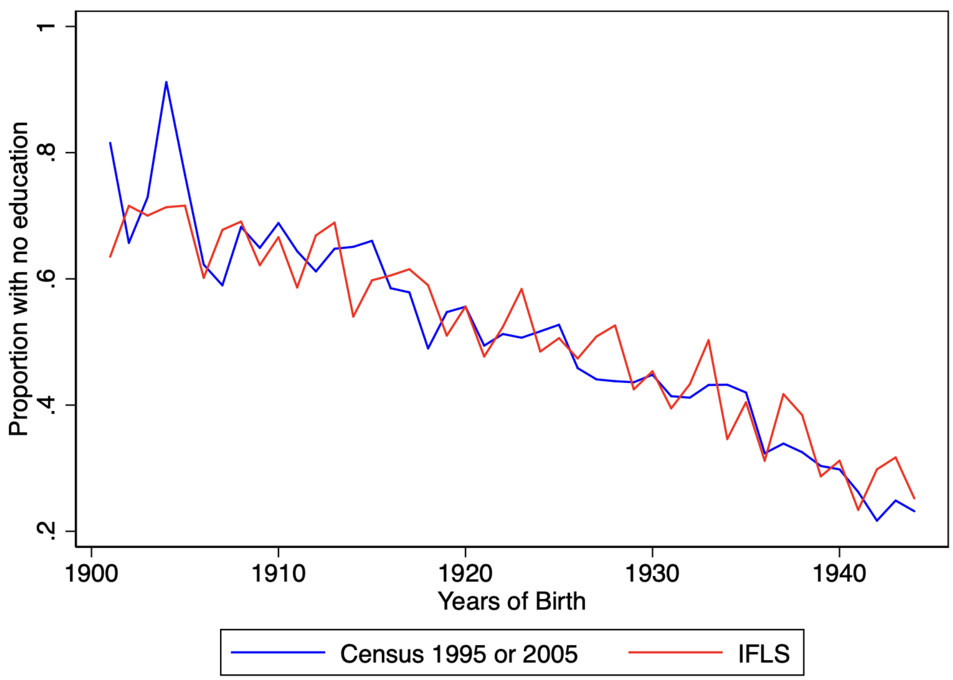
Figure A2: Education by Cohort for Parents in IFLS and Census



Note: The figure plots the average years of education per cohort (born between 1940 to 1980) in the 1995 or 2005 Census and in the IFLS panel.

Figure A3: Education by Cohort for Grandparents in IFLS and Census



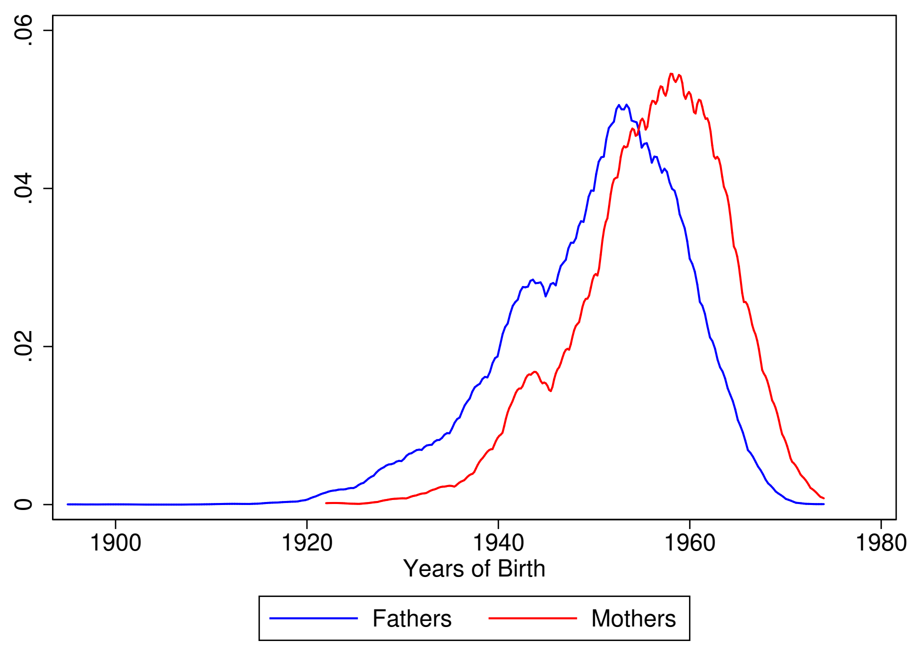


Note: The top panel plots the average years of education per cohort (born between 1900 to 1940) in the 1995 or 2005 Census and in the IFLS panel. The bottom panel plots the proportion of respondents with no education per cohort (born between 1900 to 1940) in the 1995 or 2005 Census and in the IFLS panel.

Figure A4: Years of Birth, Cohorts 1975-1988

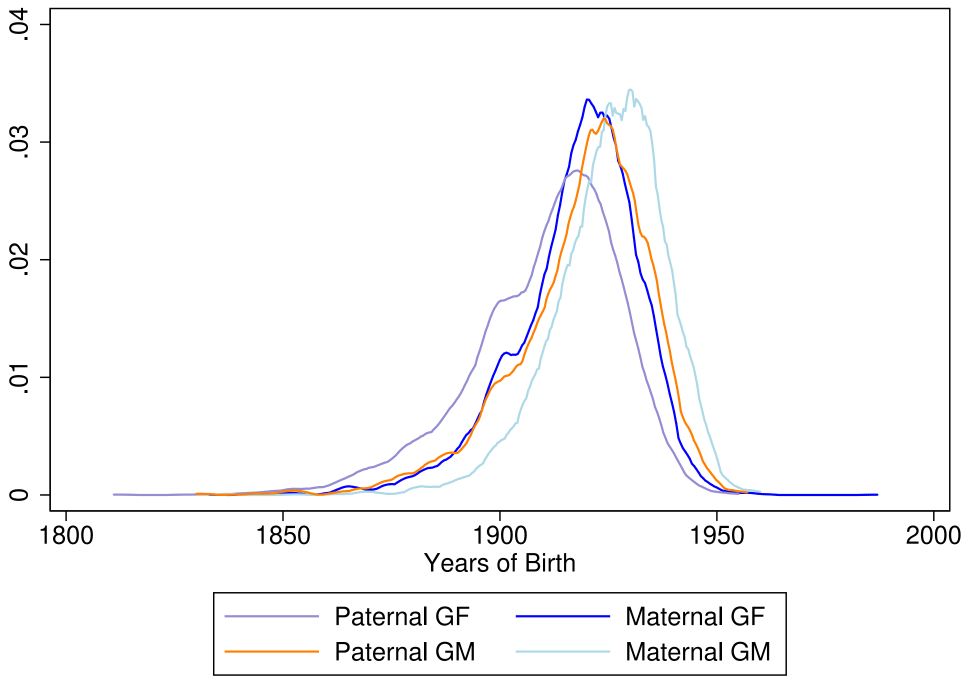
Notes: The figure plots the distribution of birth cohorts in our grandchildren sample by gender.

Figure A5: Distribution of Years of Birth, Parents



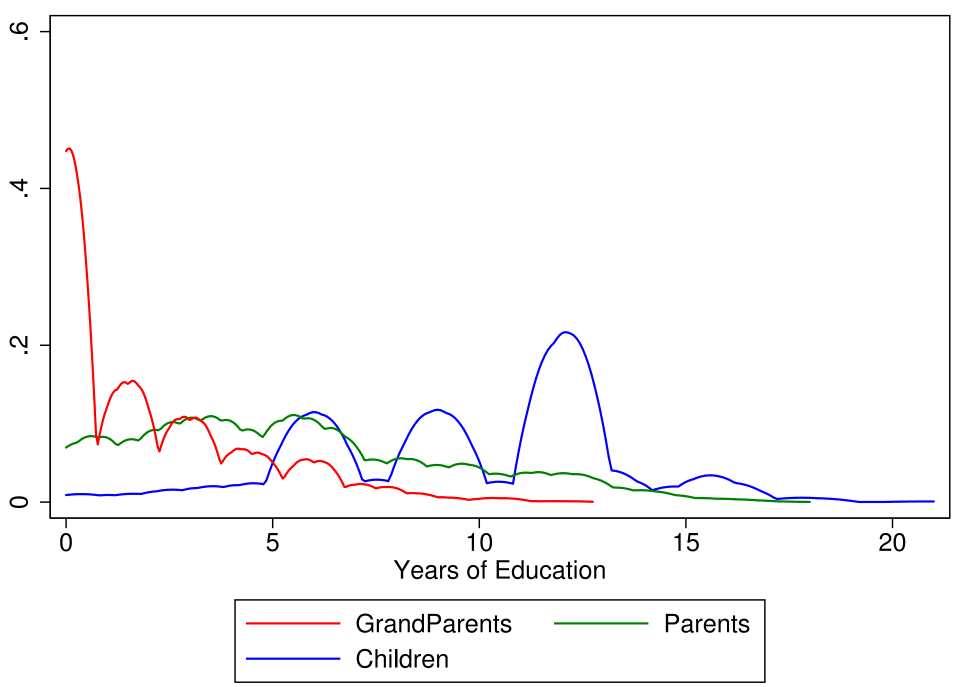
Note: Kernel density estimation for the distribution of years of birth of fathers and mothers of individuals born between 1975 and 1988.

Figure A6: Distribution of Years of Birth, Grandparents



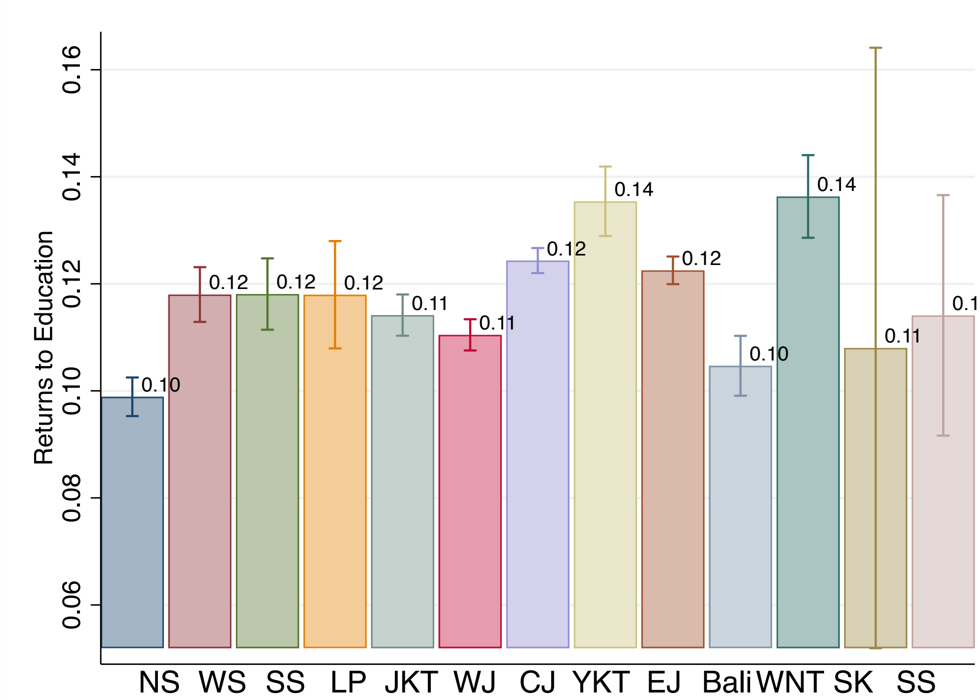
Note: Kernel density estimation for the distribution of years of birth of grandfathers and grandmothers by lineage.

Figure A7: Distribution of Years of Education by Generation in the IFLS



Note: Kernel density estimation for the distribution of years of education of all three generations.

Figure A8: Estimated Returns to Education by Province



Note: The figure plots the estimated returns to education at the province level using information from the 1995 Census. The sample is restricted to individuals born before 1975. NS refers to North Sumatra, WS refers to West Sumatra, SS refers to South Sumatra, LP refers to Lampung, JKT is DKI Jakarta, WJ is West Java, CJ is Central Java, YKT is DI Yogyakarta, EJ is East Java, WNT is West Nusa Tenggara, SK refers to South Kalimantan, and SS refers to South Sulawesi.