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. We estimate multigenerational correlations in education across three generations, using five waves of the Indonesian Family Life Survey (IFLS) and the 1995 and 2005 Censuses. Contrary to previous findings, we find a negative grandparent-grandchild coefficient, implying greater educational mobility than the intergenerational correlations from developing contexts typically suggest. We build a theoretical framework to identify two key factors influencing multigenerational transmission in developing countries: (1) financial and credit constraints, and (2) cultural norms surrounding marital sorting. To test the salience of these mechanisms in Indonesia, we analyze regional variations in marital practices, education expenditures, and the impact of 1997 Asian financial crisis.

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

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1 Introduction

Recent *multi*generational studies suggest that traditional *inter*generational 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 (2024), 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 between different developing countries. The rationale is that certain structural conditions that shape intergenerational transmission and differ in low-income countries, such as financial constraints or marital customs, have distinct dynamic implications. To support these arguments empirically, we exploit regional variations in marital customs and sudden shifts in economic conditions in Indonesia.

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 are directly involved in selecting their children's spouses – as is customary in some developing countries, where marriages are arranged by family members, a practice that has become exceedingly rare in high-income countries (Averett, Hoffman et al. 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 fact, 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 2024).

In our theoretical discussion, we also compare the multigenerational patterns generated by different models of intergenerational transmission. We show that the classic framework developed by Becker and Tomes (1979, 1986) can generate either a negative or positive grandparent coefficient, depending on parameterization. This contrasts with earlier discussions, as Solon (2014) describes a popular variant of the Becker-Tomes model (also considered by 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 Becker and Tomes' stochastic version with a deterministic one. While this simplification has little impact on other aspects, it greatly affects its multigenerational implications. As we show, the original Becker-Tomes model can rationalize different multigenerational patterns, and also nests a simple latent factor model that has been used to rationalize positive grandparent coefficients in recent multigenerational studies. Specifically, the sign of the grandparent coefficient depends on the relative importance of "direct" income effects and – when extending the Becker-Tomes model to two parents – the structure of the assortative process.

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. Our findings show that 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 the 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 some interesting empirical "facts", particularly 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 show 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. Indonesia is an interesting context to study due to its ethnic diversity and the government's substantial investments in education. In the 1970s, Indonesia undertook a large-scale primary school construction program, which significantly improved educational attainment and labor market outcomes for boys (Ashraf et al. 2020; Duflo 2001) and also had positive effects for girls, especially among specific ethnic groups (Ashraf et al. 2020, Akresh, Halim and Kleemans 2022). The program particularly benefited children of poorly educated parents, raising social mobility (Hertz, Jayasundera et al. 2007), and also had positive spillovers on 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 contributes to this literature by highlighting the effects of marital customs and financial constraints 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-

[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).

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

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 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 (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 2024), 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,

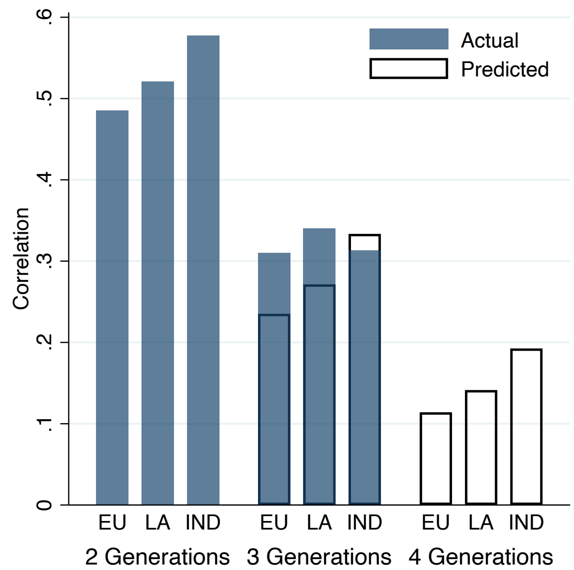
[3]These are the most common measures of multigenerational mobility, but other measures are in use; see in particular the "dynastic" regressions in Adermon, Lindahl and Palme (2021) and name-based measures in Clark (2014) and Barone and Mocetti (2020).

[4]See Braun and Stuhler (2018). The stationarity assumption simplifies the presentation but is not necessary for the result (see Appendix A1).

[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 2024), and Indonesia (IFLS, own estimates). The hollow bars show naive extrapolations from the parent-child correlations (see text).

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 naive predictions. For the European and Latin American regions, the correlations between three generations are much larger than a naive iteration of 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.

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

[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).

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 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 equation (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 a higher grandparent income, 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 we normalize the steady-state variances of both e and y to one, we have

$$\begin{aligned} \beta_{-1} \equiv \frac{Cov(y_{it}, y_{it-1})}{Var(y_{it-1})} &= Cov(\rho e_{it} + u_{it}, \rho e_{it-1} + u_{it-1}) \\ &= \rho^2 \lambda \qquad (9) \\ \beta_{-2} \equiv \frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} &= \rho^2 \lambda^2. \qquad (10) \end{aligned}$$

Because λ must be below one, the grandparent-child correlation is greater than 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.

[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.

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 (7). In this model, regression (2) does not yield $\beta_{gp} = -\gamma\lambda$.[9] Instead, if we normalize the variances of e and y to one, the coefficient can be expressed as (see Appendix A2)

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

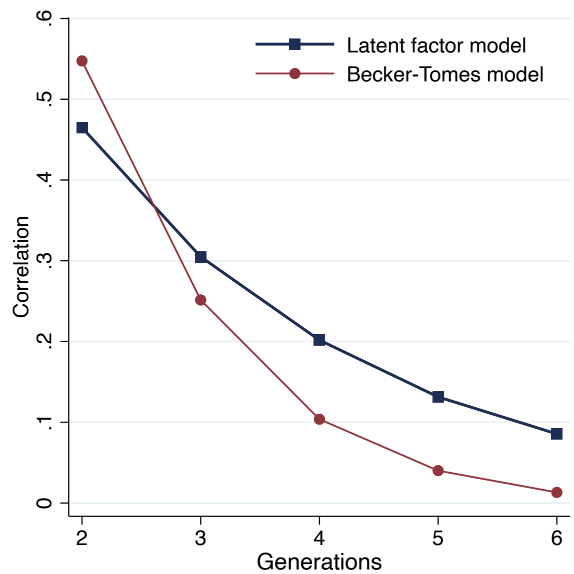
where the denominator is positive, and the sign of the numerator is ambiguous and depends on the relative sizes of γ and λ. If parental status y_{it-1} has a comparatively large direct effect on child status, that is $\gamma > \lambda$, coefficient estimates of β_{gp} will be negative. Notably, this 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.[10]

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.

[9] 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 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.

[10] 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.[11] 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

[11] 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 empirical evidence.

more salient for parental investments in child education in developing 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 A2, 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. From the "duality" in eq. (3), it follows that the ratio between multi- and intergenerational correlations β_{-k}/β_{-1} would be comparatively low. 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 that might be of particular relevance in the developing world. 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. And in Section 6, we highlight the potential role of marital customs and assortative mating as another distinct factor shaping multigenerational transmission patterns.

4 Data and empirical results

4.1 Data

Our main data source is the Indonesian Family Life Surveys (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 and Karoly 1995).[12] 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 registered as children in the first wave and they report their completed education in the following waves. We assume individuals complete their education by age 25. 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, were born between 1952 and 1957, on average; (3) the grandparents *G3* of G1 and thus parents of G2, were born between 1913 and 1927, on average.

Our outcome of interest is educational attainment, which we primarily measure with the highest level of education obtained by an individual by age 25.[13]. In the IFLS, individuals are asked about the different levels of schools they have completed. We translate the different answers into years of education according to the number of years 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 should 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.[14]

In our analysis, we also use information from the IFLS on provinces of birth, migration, marital traditions, education expenditures and earnings. Section A3 in the Appendix provides more details

[12] 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).

[13] More details on the education measure and steps for validation with the census data are available in A5.

[14] For some household members, education is reported differently. This happens when there is a part of the questionnaire which is filled by the head of the household and another part which is filled by the household members themselves. Head of households are also asked about their parents' and their in-laws' educational attainment, even if they are not part of the household, for example, if they have deceased or because they were living elsewhere.

on the construction of these variables. Our estimation sample includes observations for which we observe the education of all four grandparents and both parents, totaling 8,277 individuals. [15]

4.2 Descriptive statistics

Table 1 reports descriptive statistics by generation. We see that the average years of education increased dramatically over the three generations. The increase is more pronounced for women than men, reflecting a significant decrease in the proportion of individuals with zero education over generations. Figure A1 shows that 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. Moreover, this shift towards the right of the educational distribution is gradual: while the distribution for grandparents is quite compressed, the parental distribution is more dispersed and the distribution of the third generation (G1) is less scattered (see Figure A7). This reflects a concentration around zero for the G3 generation, more dropouts during primary school for the parents and more concentration around six years of schooling (equivalent to primary school completion), nine years of schooling (completed middle school) and 12 years (completed high school) for the third generation.

In terms of income, men earn more and have more "prestigious" jobs than women in the second generation. 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 the restricted sample report that the parents selected the spouse for them. This fraction is similar in the sample where we do not restrict to the individuals for whom we have information about all the four grandparents. Provinces where more than 40% of the women in our restricted sample 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%).

[15] On average, the education of paternal grandmother and grandfather are both lower in the restricted sample compared to the full sample. Since the total number of observations do not differ much across the samples, we do not a-priori have strong suspicion that results would differ when we use one sample instead of another.

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	39.6	31.1	38.3	30.7
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 a selected fraction of individuals born between 1975 and 1988 report earnings and occupation by 2014, hence we do not report the statistics about these variables for them. Age at child birth is measured as the average for all children within a household.

4.3 Intergenerational correlations

We begin the analysis by estimating the intergenerational transmission of education in Indonesia using the restricted sample of about 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 Indonesia has relatively low intergenerational mobility compared to developed contexts (Hertz et al. 2008, van der Weide et al. 2024).[16]

[16]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 slightly smaller than the actual three-generation correlation considering individual lineages (rows 1-4), but 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 suggested by intergenerational correlations (Anderson, Sheppard and Monden 2018). Therefore, while *inter*generational correlations are comparatively high in Indonesia, *multi*generational correlations do not appear particularly high.

To probe these patterns further, Table 3 reports estimates from three-generation regressions based on eq. (2). Our main finding 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). Interestingly, this negative grandparent coefficient 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 from China, which shows a positive coefficient among co-resident grandparents and zero effects from non-co-resident grandparents (Zeng and Xie, 2014).

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		
R^2	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.[17] 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 existing evidence (e.g. Anderson, Sheppard and Monden 2018, Colagrossi, d'Hombres and Schnepf 2020). Interestingly, when the education

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

of fathers is included as G2, the grandparental coefficient is more positive if the outcome of the *maternal* grandparents is considered. This observation likely reflects the omitted variable bias from excluding the corresponding parent of the grandparents' lineage, which we formalize in Section 6.1.

5 Evidence on financial constraints and direct income effects

The "direct" income effects represented by the parameter γ is the main mechanism that could explain why (two-generation) inter-generational correlations are larger in development countries in the Becker-Tomes model. As we show in in section 3, the direct income effect also has implications for multigenerational correlation: the higher the γ, the more negative the coefficient β_{gp}.

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.[18] The strength of this income effect may also depend on the parents' ability to borrow. The stronger the credit constraints, the stronger the link between parental income and parental investments which affect child outcomes (Becker and Tomes 1986).

In this section, we bring two pieces of evidence to test the implication of the Becker-Tomes model about the relationship between γ and the strength of the multigenerational coefficient β_{gp}. Importantly, 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 and to do so with a higher probability if the child was female rather than male (Cameron and Worswick 2001). Parental lower propensity to invest in daughters may be caused by 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 labour market returns to education. The

[18] Another extensively deployed 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.

latter is supported by empirical studies showing that factors which improve the job prospects for women, 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.

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 prioritise 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 0.3, with a standard deviation of 0.16.[19]

Column (1) reveals that in districts with higher educational spending, the grand parental coefficient in the multigenerational regression (equation (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. A lower relevance of the family endowment channel in these areas could in principle also explain the smaller estimate for the parental coefficient in the multigenerational regression (second row of column (1)).

[19]We use the expenditure in education as reported by IFLS respondent, see Section 4. For a more detailed description of the result in Table 4, see Appendix A6. 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).

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: The table above reports estimates of eq. (2) interacted with the average households' expenditure shares in education at the district level. It also controls for the main effect of the expenditure shares in education. Standard errors are clustered at the family level. 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 34 districts that 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 – corresponding to 34 districts.) *** 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 grandparental coefficient is positive in regions with low educational expenditures, but it significantly diminishes in areas with higher spending. For daughters, neither the coefficient on β_{gp} nor its interaction with the average share of household income spent on educational resources in the area are economically or statistically significant. This pattern suggests that the direct investment channel is particularly relevant for boys. For this group, the negative coefficient on the interaction between β_{gp} and the expenditure share is again in line with the implications of the model.

5.2 Income shocks and financial constraints

The average share of household income spent on educational expenditures is an imperfect proxy for credit constraints and could reflect a host of other area-level factors determining the demand and supply of educational inputs. We therefore present a second piece of analysis, this time aiming to further isolate variation in credit constraints across area. To do this, we leverage geographical variation in the effects of the Indonesian economic crisis of 1997 on local economic conditions and in particular in the tightening of 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. 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.

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 1978 or before and who were 18 or older when the crisis hit were too old to see their education affected by the crisis.[20] In contrast, children born before that could have seen parental investments in their education affected.

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

[20] 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).

fixed effects:

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

where Y_{icp} is individual i's years of education, P_{icp} their parents' average education and P_{icp} their grandparents' average education; ρ_c are birth cohort fixed effects, δ_p are province fixed effects; $Post_{icp}$ is a dummy indicating whether individual i was born after 1978, and Exp_p is province p-level measure of exposure to the crisis, which we measure as the proportional change in unemployment between 1996 and 1997 in province p. In the model above, the coefficient of interest is β_9, which indicates 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: The table above reports OLS estimates of eq. (13) where the dependent variable is measured as years of education, and exposure to the crisis is measured as the proportional change in province-level unemployment rate between 1996 and 1998 relative to the unemployment rate in 1996. The "Treated" sets of cohorts are defined as cohorts born after 1979, and therefore who were aged 17 or younger when the crisis hit, and the "Control" sets of cohorts are defined as cohorts born before 1979, who therefore were too old to see their education affected by the crisis. The specification controls for province of birth and year of birth (cohort) fixed effects, the 1996-98 proportional change in unemployment in that province ("Exp"), the interaction between that variable and a "Post" dummy taking the value 1 for cohorts born after 1979, interactions between parental average education and each of "Exp", "Post", and the interaction of the two. *** 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 grandparental coefficient becomes statistically more negative in areas and cohorts that are more exposed to the crisis (and presumably where financial constraints became tighter) 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 link between financial constraints and the strength of multigenerational transmission but this link is much more pronounced for boys than for daughters in the context of Indonesia.

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 verified the validity of this theoretical prediction in our Indonesia context in Table 3 and Appendix Table A2, also showing that the grandparental coefficient tends to be larger when including the grandparent of the omitted lineage, e.g. when controlling for the father's education and that of maternal grandparents only. More generally, the degree to which the education of grandparents captures the intergenerational correlation between the omitted parent and the offspring depends on the degree of assortative mating.

The observation that the assortative mating process can affect the long run transmission in education also matters when comparing multigenerational estimates across countries, as the heterogeneity in these estimates might reflect heterogeneity in the structure and degree of assortative matching, in addition to differences in the intergenerational transmission processes. Indeed, 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, for example, 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 has a clear gradient in terms of socioeconomic background: for example, 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. 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 variation in the share of women whose spouses were chosen by the family partly reflects the differential ethnic composition across provinces (Ashraf et al. 2020).

6.1 The role of assortative processes in multigenerational transmission

To understand the implications of different *structures* for the assortative process, consider a version of the latent factor model with assortative mating. Specifically, let us assume that endowments are determined by the average of father's and mother's endowment

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

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

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, or mother and maternal grandparent)

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

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),

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

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,

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

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

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

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, assume that this "family-based" assortative matching can be represented by the linear projections

$$e^p_{i,t-1} = m e^{m,m}_{i,t-2} + v_{i,t-1} \quad (23)$$

$$e^m_{i,t-1} = m e^{p,m}_{i,t-2} + w_{i,t-1} \quad (24)$$

i.e. we assume that the mothers of each spouse "choose" the respective partner for their child. This assortative process implies the spousal correlation[21]

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

[21] 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 $Cov(e^p_{it-1}, e^m_{it-1}) = Cov(e^{m,m}_{i,t-2}, e^{m,p}_{i,t-2})$.

where $\lambda_I = \frac{\tilde{\lambda}}{2-m\tilde{\lambda}}$. Note that for a given matching parameter m, the spousal correlations 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[22]

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

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 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. The ratio

$$\frac{\beta_{-2}}{\beta_{-1}} = \frac{\tilde{\lambda} + m\left(2 - m\tilde{\lambda}\right)}{2}$$

is therefore necessarily (unless $m = \tilde{\lambda} = 1$) 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 the multivariate regression (2)? 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

$$\beta_{gp} = \frac{\beta_{-2} - \beta_{-1}^2}{1 - \beta_{-1}^2} = \frac{\rho^2 \tilde{\lambda} \frac{\lambda_I + m}{2} - \rho^4 \lambda_I^2}{1 - \rho^4 \lambda_I^2} \tag{25}$$

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 parent-based assortative mating considered here therefore implies *stronger* multigenera-

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

tional transmission. The intuition is that with family-based matching, the characteristics of a child's spouse is a function not only of the child's own but also the parents' traits. This adds another source of multigenerational persistence that is not fully captured by conventional parent-child correlations. However, this prediction hinges on the specific structure of the assortative process. We assumed that the parents of prospective spouses are matched on their endowments e, but alternative structures are also plausible. The broader takeaway from our discussion, therefore, is not a specific prediction about the sign of β_{gp}, but rather the understanding that this coefficient – and the relative strength of inter- and multigenerational correlations – depends on the structure of the assortative process, and will therefore differ between countries or groups that follow different marital norms.

6.2 Evidence on assortative matching and multigenerational transmission

To empirically assess whether the peculiarity of the marriage market in Indonesia impacts the multigenerational transmission process, we exploit the rich information in the IFLS. 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. However, the way parents select spouses, and the implied consequences on multigenerational transmission process, in a family-based assortative mating system are not clear. We thus first investigate whether observed assortative mating is different depending on who selected the spouse, and then compare the estimated inter- and multigenerational parameters for different groups.

Table 6 shows the estimated parameters of different regressions, where the outcomes are the years of education of one individual and the independent variables are the years of education of the spouse (Column 1) and the parents of the spouse (Columns 2-3). Each variable is interacted with a dummy which equals 1 if the wife of the couple declares that her husband was selected by her parents.[23] Column 1 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). Hence, in families where the parents select the spouse for

[23] 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.

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: 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 education of the wife and the father of the wife (column 2), or the education of the husband and the mother of the husband (column 3). The indicator *FamilyChoice* equals 1 if the wife declares that her husband was selected by her family. Each regression controls for the 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

their child, the spouses are more different to each other but more similar to their respective in-laws.

In Section 6.1, we showed that this pattern 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.[24] Table 7 reports the estimates of the baseline coefficients and of the coefficients for this interaction. The outcome 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

[24]In Table 6 we use the wife's answer about whether the husband was selected by her family as the proxy for traditional marital practice. The results also hold when we instead use as a proxy the answer of the husbands who declare that the wife was selected by his parents.

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 dummy variable *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 the birth cohort of the wife fixed effects, standard errors are clustered at the family level. *** p<0.01, ** p<0.05, * p<0.1.

we consider the average education of the two parents and the average education of all grandparents. Conditional on grandparental education, the education of parents is less predictive of their children's education when the mother's family is involved in the choice of the spouse. In contrast, we find that the education of grandparents is more predictive of grandchildren's education when the parents were matched by the grandparents. In fact, the coefficient on grandparental education is negative and highly 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 $1(FamilyChoice)$). All these results are in line with the "family-based" model, where the match is based on the correlation between the endowment of one spouse and the endowment of the parents of the other spouse.

While we cannot exclude other mechanisms at play within the assortative mating process, this evidence suggests that one of the most widespread practices in the context of household formation in Indonesia, that is parents selecting the spouse for their children, may affect the long term persistence in education across generations. Declines in the use of 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

Understanding the reasons for the persistence in economic status across generations has important policy implications, particularly for developing countries where mobility is relatively low. But while we have much evidence on *inter*generational mobility from one generation to the next, we still know little about the long-run persistence of socioeconomic advantages across multiple generations. Our key argument is that these multigenerational dynamics are bound to differ between the developing and developed world, as well as between different developing countries. High intergenerational persistence in developing countries does therefore not necessarily imply high long-run persistence.

We first showed that multigenerational correlations in education decay more quickly in Indonesia than in high-come countries. To understand why, we then compared the multigenerational implications of different transmission mechanisms in standard models of intergenerational mobility. 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 dataset from Indonesia spans three generations, allowing us to study the strengths of these mechanisms, as well as their implications for the transmission process across multiple generations. 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 show that the"grandparent coefficient" is more negative for boys in areas where education is more expensive. Going beyond descriptive associations, we leverage the plausibly-exogenous variation in credit constraints induced by the 1997 Asian Financial Crisis to show that the coefficient is also 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 particular multigenerational pattern observed in Indonesia.

Marital customs are another key factor influencing multigenerational persistence. Recognizing that approximately 28% of women and 19% of men in our sample reported having their spouses chosen by their parents, we first 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 regional variations in marital customs across Indonesia, we found support for all three predictions.

Overall, these results underscore the complexity of multigenerational transmission, which depends on the relative strengths of different mechanisms. Our work is of course far from conclusive in identifying the factors that shape long-run persistence. Our empirical analysis also comes with the caveat that the sample of individuals with complete information on education of all parents and all grandparents is not necessarily representative for developing countries more generally. Our results may therefore not immediately translate to other contexts. Still, our findings illustrate why the persistence of economic status in developing countries is bound to follow distinct patterns, and points to potentially important mechanisms to understand these dynamics.

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Appendix

A1 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)

$$\beta_{gp} = \frac{Cov(y_{it}, \tilde{y}_{it-2})}{Var(\tilde{y}_{it-2})}, \tag{26}$$

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

$$\begin{aligned}\beta_{gp} &= \left(\frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} - \frac{Cov(y_{it-1}, y_{it-2})}{Var(y_{it-1})} \frac{Cov(y_{it}, y_{it-1})}{Var(y_{it-2})} \right) \frac{Var(y_{it-2})}{Var(\tilde{y}_{it-2})} \\ &= \left(\beta_{-2} - \beta_{-1}^{gp \to p} \beta_{-1}^{p \to c} \right) \frac{Var(y_{it-2})}{Var(\tilde{y}_{it-2})}, \end{aligned} \tag{27}$$

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 $\beta_{-2} > \beta_{-1}^{gp \to p} \beta_{-1}^{p \to c}$.

A2 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

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

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 same argument implies $Var(y_{it-1}) = (\rho^2 + \sigma^2 + 2\gamma\rho^2\lambda/(1-\gamma\lambda))/(1-\gamma^2)$.

The grandparent-child correlation equals

$$\begin{aligned}\beta_{-2} &= \frac{Cov(y_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \frac{Cov(\gamma y_{it-1} + \rho e_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \gamma \frac{Cov(y_{it-1}, y_{it-2})}{Var(y_{it-2})} + \rho \frac{Cov(e_{it}, y_{it-2})}{Var(y_{it-2})} \\ &= \gamma \beta_{-1} + \frac{\rho^2 \lambda^2}{(1-\gamma\lambda) Var(y_{it-2})} \end{aligned} \tag{29}$$

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

$$\begin{aligned}\beta_{gp} &= \frac{\gamma \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right) + \frac{\rho^2\lambda^2}{1-\gamma\lambda} - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \\ &= \frac{\gamma \frac{\rho^2\lambda}{1-\gamma\lambda} + \frac{\rho^2\lambda^2}{1-\gamma\lambda} - 2\gamma \frac{\rho^2\lambda}{1-\gamma\lambda} - \left(\frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \\ &= \frac{\frac{\rho^2\lambda}{1-\gamma\lambda}\left(\lambda - \gamma - \frac{\rho^2\lambda}{1-\gamma\lambda}\right)}{1 - \left(\gamma + \frac{\rho^2\lambda}{1-\gamma\lambda}\right)^2} \end{aligned} \tag{30}$$

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 (30) 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 find the derivative of β_{gp} with respect to γ, we however cannot normalize the variance of y, as this variance depends itself on γ. In this case, the grandparent coefficient is given by (the following steps have been derived using the software *Mathematica*)

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

Its derivative with respect to γ is

$$\frac{\partial \beta_{gp}}{\partial \gamma} = \frac{-\lambda\rho^2\left(\rho^2\sigma^4\left(\gamma^2\left(\lambda^4+\lambda^2\right)-4\gamma\lambda-\lambda^2+3\right)+\left(\lambda^2-1\right)\rho^4\sigma^2\left(2\gamma\lambda-\lambda^2-3\right)\right)}{\left(2\rho^2\sigma^2(\gamma\lambda-1)-\sigma^4(\gamma\lambda-1)^2+\left(\lambda^2-1\right)\rho^4\right)^2}$$
$$+\frac{\lambda\rho^2\left(\left(\lambda^2-1\right)\sigma^6(\gamma\lambda-1)^2+\left(\lambda^2-1\right)^2\rho^6\right)}{\left(2\rho^2\sigma^2(\gamma\lambda-1)-\sigma^4(\gamma\lambda-1)^2+\left(\lambda^2-1\right)\rho^4\right)^2}, \quad (32)$$

which is negative (if $\lambda > 0$, $\rho > 0$).

A3 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.

A4 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.

A5 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.

A6 Multigenerational regression by quartiles of expenditure in education at the district level

As mentioned in Section 4 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 grandparental 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

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. The mean expenditure share across the 34 districts we consider is 0.3. 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 0.6. 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:

$$y_{it,k} = \beta_p y_{it-1} + \beta_{p,exp} ExpSh_k \times y_{it-1} + \beta_{gp} y_{it-2} + \beta_{gp,exp} ExpSh_k \times y_{it-2} + \beta_{exp} ExpSh_k + \varepsilon_{it,k}. \quad (33)$$

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).

$$y_{it,k} = \sum_{b=1}^{2} \beta_{p,b} ExpSh_{k,b} \times y_{it-1} + \sum_{b=1}^{2} \beta_{gp,b} ExpSh_{k,b} \times y_{it-2} + \sum_{b=1}^{2} \beta_b ExpSh_{k,b} + \varepsilon_{it,k}. \quad (34)$$

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

parental education and own willingness to spend in children's education (for example, it is possible that more educated parents are more willing to invest in their children).

A7 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

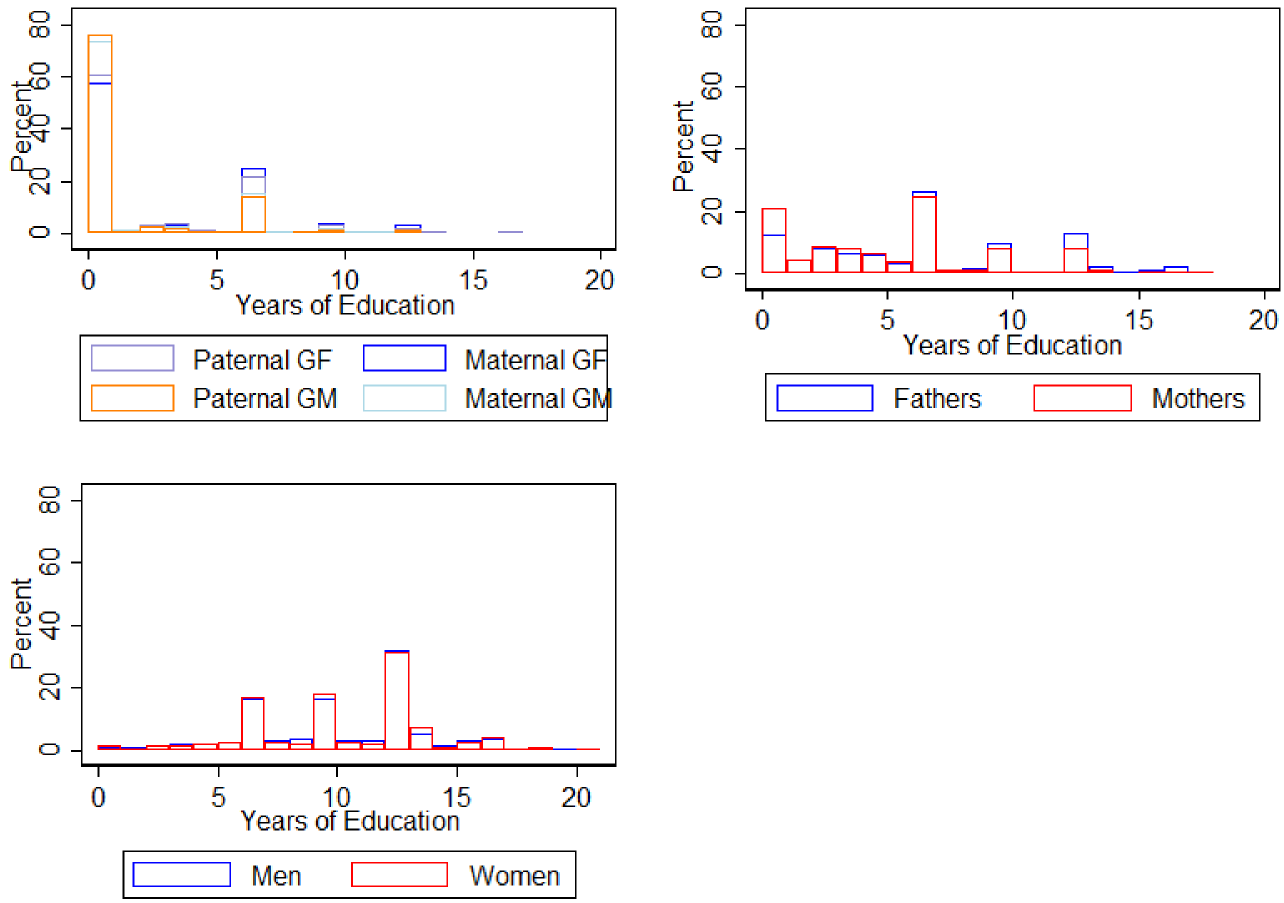
Note: The table above reports the estimates of multigenerational correlations in education from eq. (2) for different combinations of parents and grandparents education. The dependent variable is the child's years of education (G1). Standard errors are clustered at the family level (all children with 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	Male	Female	All Children	Male	Female
	(1)	(2)	(3)	(4)	(5)	(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

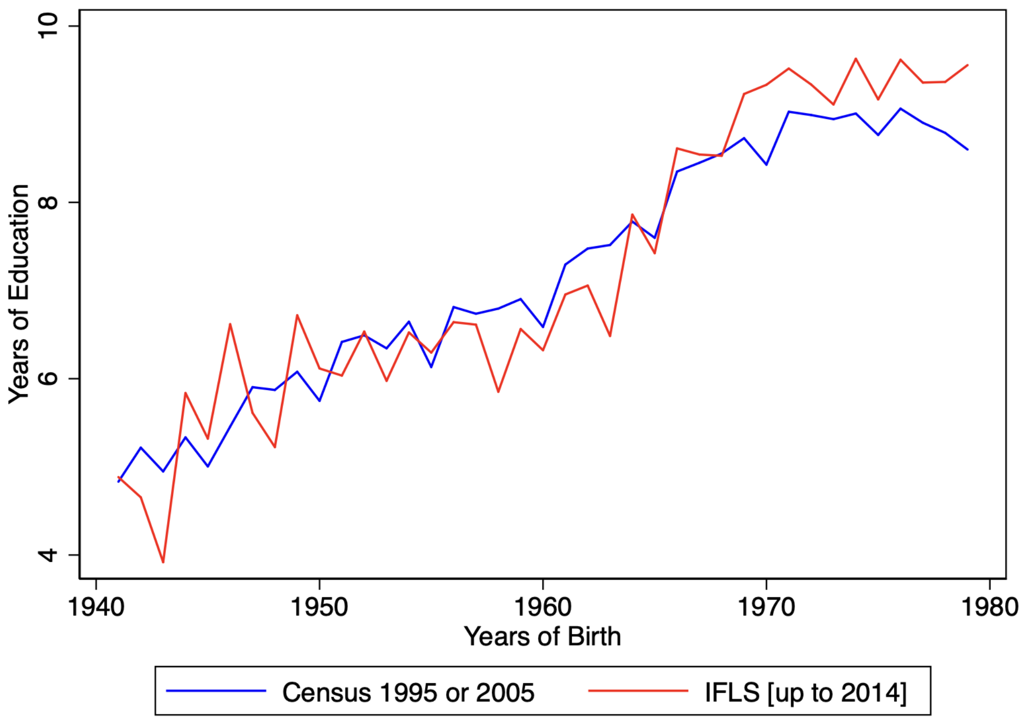
Note: The table above reports the estimates of eq.(2) interacted with measures of households' expenditure shares in education at the district level (Columns (1)–(3) use a continuous measure of the average expenditure share at the district level, Columns (4)–(6) use two dummies indicating whether the 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.

Figure A1: Years of Education, Separately for Three Generations



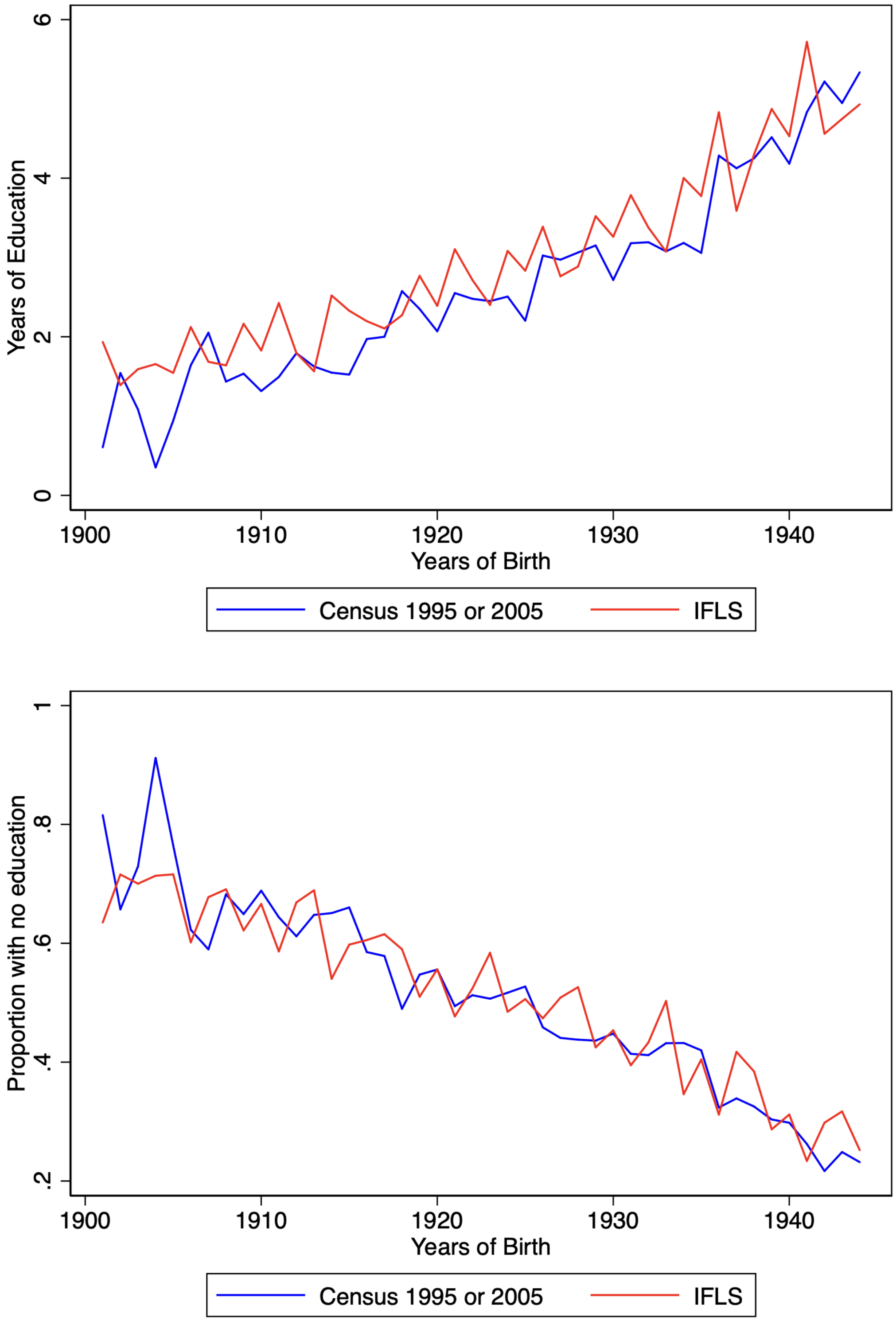
Note: The panels show the distribution of education among the grandparents, parents, and the grandchildren in the IFLS sample.

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



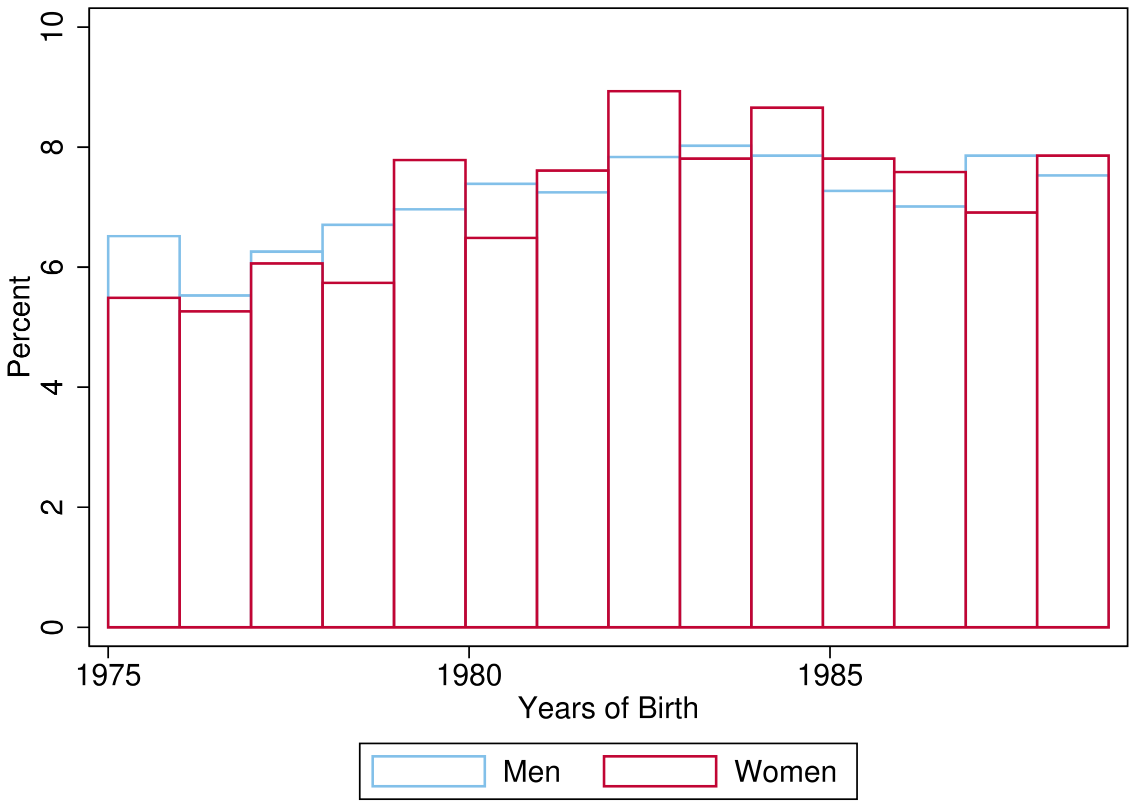
Note: The figure plots the average years of education per cohort (born between 1940 to 1980) in the 1995 or 2005 Census and in the IFLS panel.

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



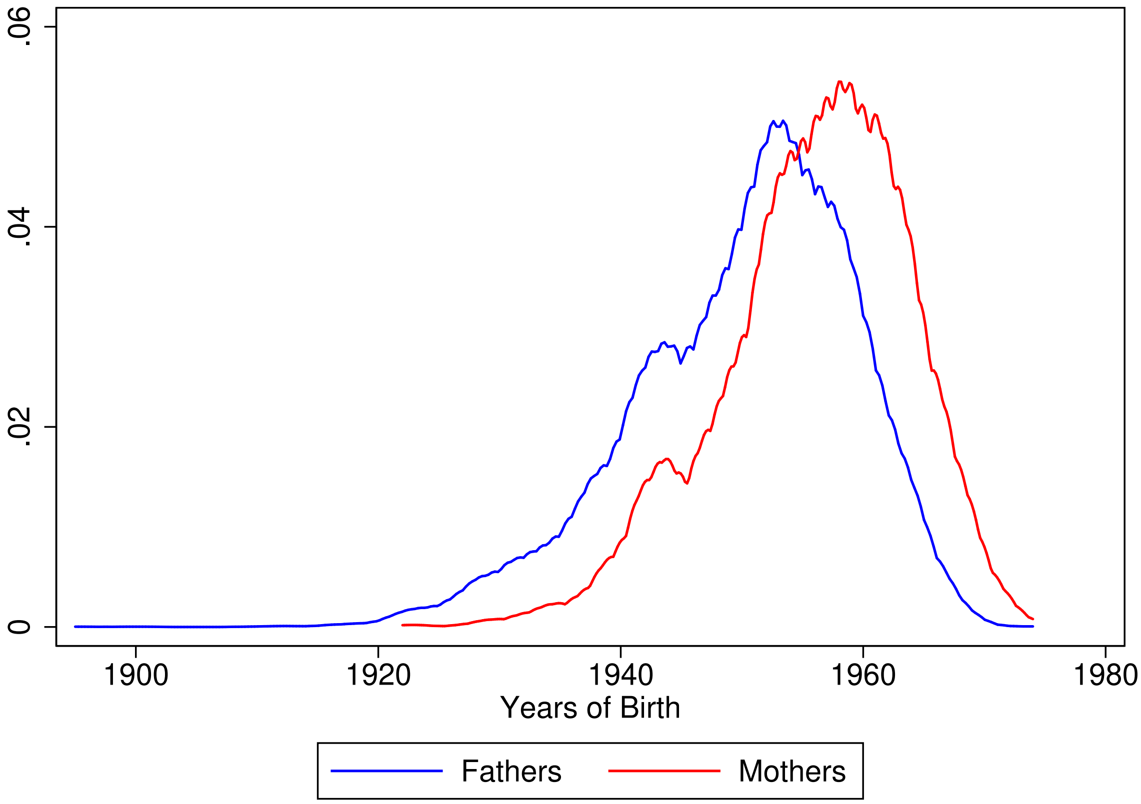
Note: The top panel plots the average years of education per cohort (born between 1900 to 1940) in the 1995 or 2005 Census and in the IFLS panel. The bottom panel plots the proportion of respondents with no education per cohort (born between 1900 to 1940) in the 1995 or 2005 Census and in the IFLS panel.

Figure A4: Years of Birth, Cohorts 1975-1988



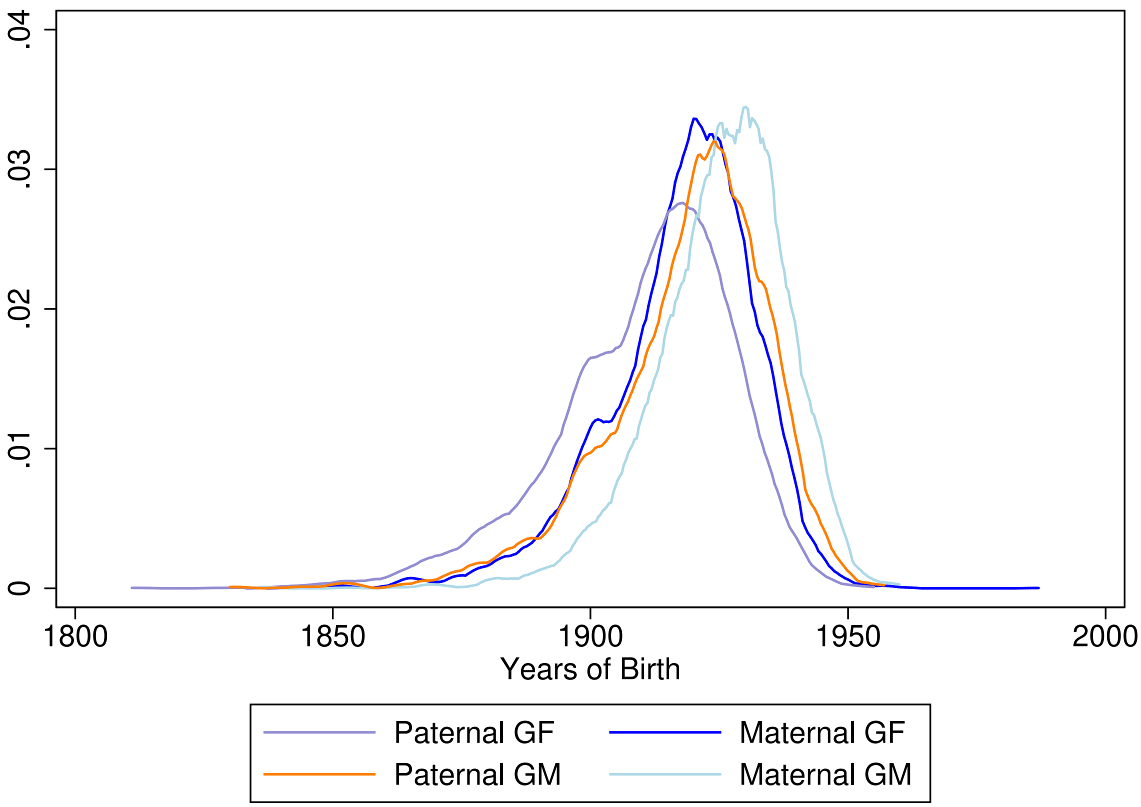
Notes: The figure plots the distribution of birth cohorts in our grandchildren sample by gender.

Figure A5: Distribution of Years of Birth, Parents



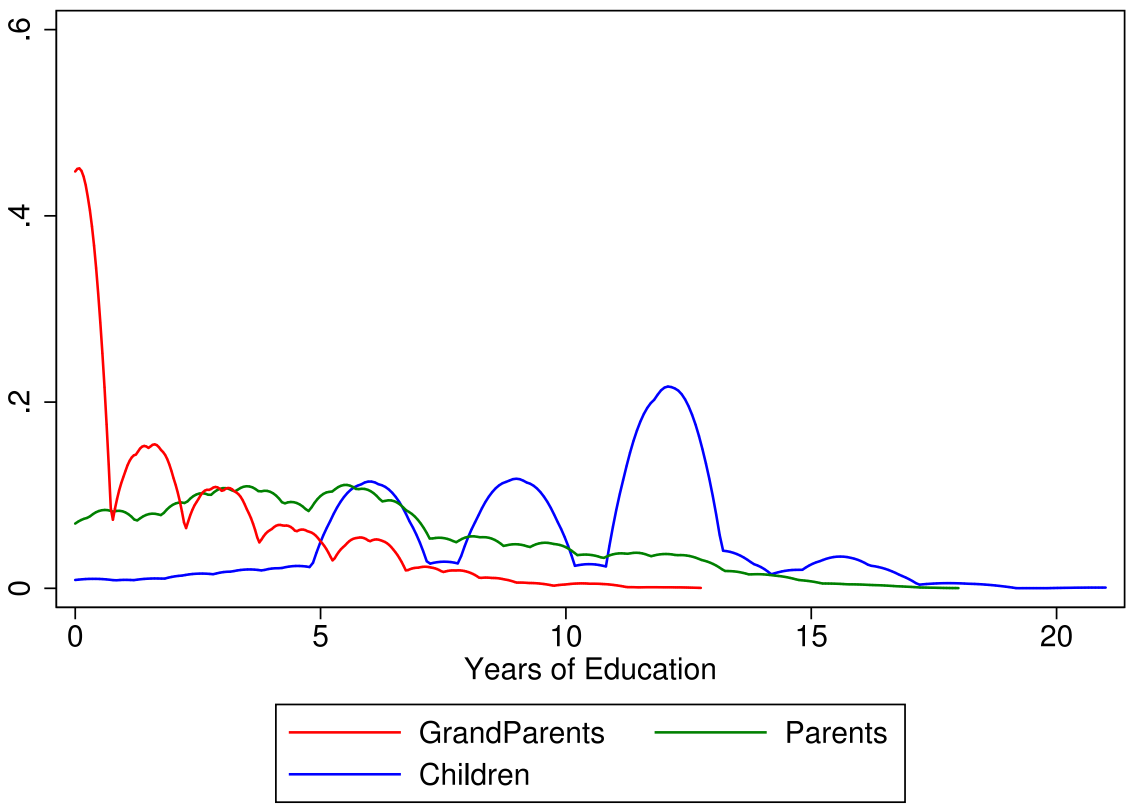
Note: Kernel density estimation for the distribution of years of birth of fathers and mothers of individuals born between 1975 and 1988.

Figure A6: Distribution of Years of Birth, Grandparents



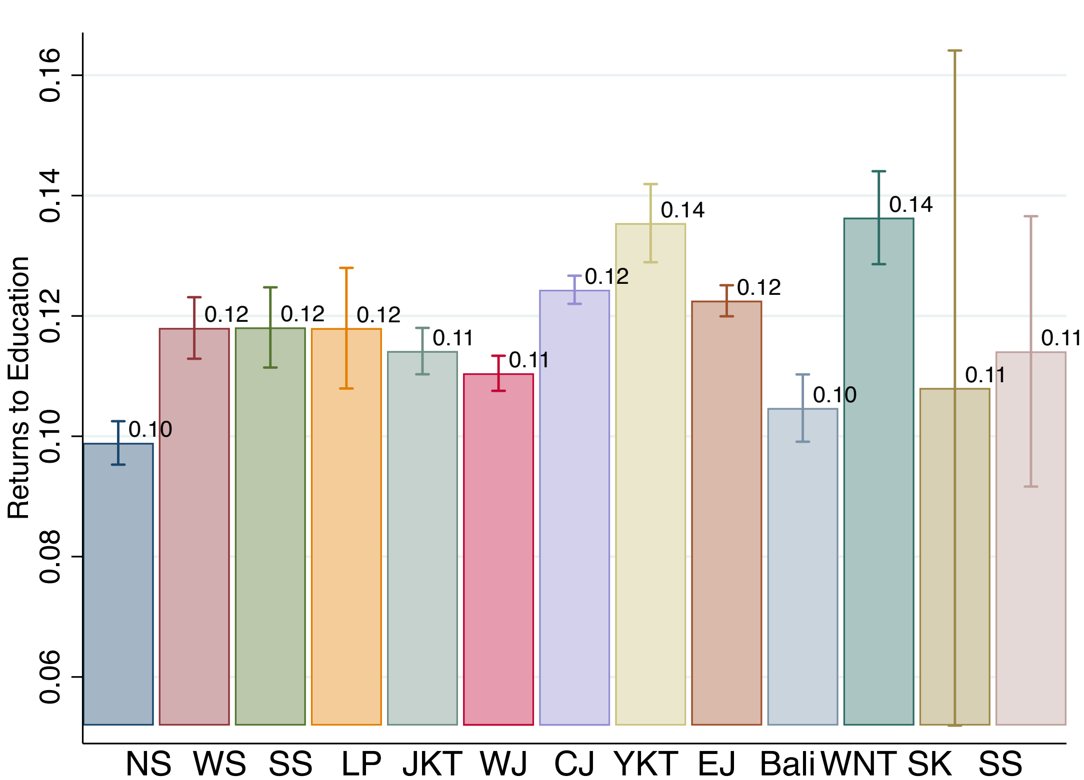
Note: Kernel density estimation for the distribution of years of birth of grandfathers and grandmothers by lineage.

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.