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Does Gradient Matter? Marginal Returns and Intergenerational Transmission of Human Capital

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Does The Gradient Matter?
Marginal Returns and the Intergenerational Transmission of Human Capital

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Abstract

Using the education level of in-laws as a control for preferences, this paper investigates the causal relationship between the educational attainment of parents and the education of their children in a lower-income context where there is a high variance of educational attainment and evaluates the importance of the gradient – the marginal effect of parental education on the education of their children. We find that even after controlling for individual and family unobservable characteristics, there is still a strong effect of parent's schooling on the schooling levels of their sons and daughters. Moreover, there is a clear gradient effect. The effect of parent's schooling on children's schooling appears to exhibit diminishing returns under certain range of the schooling cycle.

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It is well established in the literature that more educated parents have children with higher educational attainment. The two most common basic explanations of this relationship are selection and causality. The first posits that this correlation is the result of a selection process in which particular types of parents produce particular types of children. In this setting, parents of the "educated type" produce children who are of the same "educated type." Adding additional years of education to the parent will therefore have no impact on the education of the child, since a child's education is entirely determined by type. The second posits that it is the result of a pure causal relationship in which more education changes a parent's type and makes one a different type of parent. This different type of parent then has children who have higher educational attainments. In this model adding years of schooling to the parent will increase years of schooling of the child.

Received empirical evidence on the intergenerational transmission of human capital is mixed but in general fails to find a strong causal link. One reason for the lack of a strong link may be the fact that most studies examine data from North American and Western European countries where average education is high. It is quite possible that the causal linkage (if one exists) is non-linear and that at lower levels of education the marginal impact of parental education might be quite large. Lower-income countries, where average levels of education are much lower and the variance in education levels is very high, provide an opportunity to examine whether the marginal impact of parental human capital transmission is higher at lower levels of education.

The challenge of this study, and all such similar studies, is in isolating the causal link between parental human capital and children's human capital. Unobservable family characteristics that are correlated with education (preferences) can lead to biased estimates of the linkage. This study uses a novel identification strategy to structurally estimate the effect of parental human capital. We use the fact that the education level of the parents of the spouse, or in-laws, should have no direct causal effect on the human capital accumulation of the individual. The extent to which in-law education and individual education are correlated represents, and is in fact a proxy for, the preferences of the individual reflected through choice of spouse. Controlling for in-law education levels thus allows us to control for unobservable preferences that would bias the estimates and therefore isolate the true causal link between parental education and the education of their children.

The selection and causal theories are not mutually exclusive. Disentangling these two possible stories and evaluating their relative significance are very important from a policy perspective, particularly in the context of developing countries where low levels of schooling are pervasive. The theoretical economics literature has many models of intergenerational links between the human capital of parents and children and the role of those links in explaining poverty traps in the developing world. Learning the correct magnitude of the causal intergenerational transmission of human capital is important for evaluating policy interventions. This is particularly important in an environment in which education is strongly associated with a variety of well-being outcomes. If the causal relationship is of a sizable magnitude, then it suggests that an effort to expand the educational attainment of one generation can have a lasting effect through future generations.

In contrast to the theoretical literature, the empirical economics literature has concentrated on more developed countries, perhaps due to data availability. In general, the empirical economics literature has taken three routes to identify the causal effect of intergenerational transmission of human capital: the use of samples of twins (e.g., Behrman and Rosenzweig (2002, 2005), Antonovics and Goldberg (2005)), the use of samples of adoptees (e.g., Dearden et al. (1997), Bjoerklund et al. (2006), Plug (2004), Sacerdote (2002, 2007)), and the use of instrumental variables (e.g., Black et al. (2005), Chevalier (2004), Oreopolulos et al (2006, 2007), Carneiro et al. (2007), Maurin et al. (2008)). The use of twins attempts to control for family background (including genetics) in order to estimate a causal schooling effect, essentially by using one's sibling as a control. The use of adoptees involves a similar approach. The use of instrumental variables involves a search for possible sources of exogenous variation in parent’s schooling.

As mentioned above, the results are not conclusive. Holmlund et al. (2008) argue that the different results obtained from this literature are due to the use of different identification strategies. In fact, using a Sweden data set capable to be applied by these three methodologies, they are able to replicate the discrepant results for the same country and cohorts. Still, they are not able to account for the discrepant results within methodology. For instance, for twin studies, Behrman and Rosenweig (2002) find positive impact of father´s education on children´s education whereas Antonovics and Goldberg (2005) find no impact. For the IV studies, Black et al. (2005) find no father´s impact whereas Chevalier (2004) finds a negative impact. Finally, most of the adoption studies find positive intergenerational education transmission. However, the magnitudes of the effects differ greatly.[1]

We want to investigate another possible explanation. Most of the studies are for developed countries where the educational levels are higher than the ones in the developing countries. The different methodologies explore variations of parent's education at different points in the distribution, although mostly at the higher end of it. For example, the results from the instrumental variable approach are interpreted as local average treatment effects in which the causal impact depends on the source of variation in the instruments. Most of these studies use as instruments changes in compulsory schooling laws in various developed countries. In the data, these changes occurred at a point in history in which the average schooling level was already substantially greater than the average schooling level in the developing world. Moreover, the schooling changes are only one or two extra years of schooling. It is possible, perhaps even likely, that the intergenerational transmission of human capital exhibits diminishing marginal returns (a 'gradient'). If so, then these IV estimators may be evaluated at a sufficiently high level of years of schooling that the marginal impacts are very small or even no longer significant. This does not necessarily imply that the effects would be small or zero in the context of a developing country with low average educational attainment.

This paper investigates the relationship between the educational attainment of parents and children in a developing country context and evaluates the importance of the gradient.[2] Specifically, it explores three related questions: One, is there a causal effect in the intergenerational transmission of human capital? Two, if yes, does the gradient matter? That is, are there decreasing marginal effects of parent's schooling? Three, do these effects differ by gender? That is, do mothers and fathers affect sons and daughters differently?

These questions are explored using a large household survey data set from Brazil that includes retrospective information on the educational attainment of the adult individual's

[1] For example, Plug (2004) estimates that one extra year of a mother's schooling increases the adopted child years of schooling by 0,28. Bjorklund et al. (2006) using a similar specification estimates the same impact by 0,07, four times smaller.

[2] Holmlund et al. (2008) explores as well the possibility of non-linear effects estimating a quadratic term of parent's schooling in the twin and adoptees samples. They do not find non-linear effects. This result may be due to the range of schooling years in the samples which have a mean of around Eleven years of schooling and a standard deviation of less than Three years of schooling.

parents. The data utilized in this study come from the 1996 *Brazilian Annual Household Survey* from the Brazilian Census Bureau (PNAD/IBGE). Its advantages are twofold. First, it contains information on the final educational attainment of two consecutive generations. Second, it covers generations with low levels of average schooling and higher variance of schooling (in comparison to more developed countries). These two advantages allow for the estimation of the gradient.

This study makes use of a sample of husbands and wives with information on their final educational attainment as well as information on the schooling levels of their parents. We use Generalized Method of Moments (GMM) techniques to estimate structural empirical models that control for unobservable characteristics under reasonable assumptions. We compare those results to those from OLS and SUR estimations.

The results suggest that OLS and SUR estimates of the intergenerational transmission of human capital are biased upward. After controlling for individual and family unobservable attributes, the intergenerational impact is three to four times smaller. More importantly, however, it finds that even after controlling for individual and family unobservable characteristics, there is still a strong effect of parent’s schooling on the schooling levels of their sons and daughters. Moreover, there is a clear gradient effect. The effect of parent's schooling on children's schooling appears to exhibit diminishing returns through a broad range of education levels. Finally, fathers have stronger impacts on sons than on daughters, and mothers have stronger effects on daughters than on sons.

The paper proceeds as follows. Section I presents the data used and the sample selected. Section II discusses a set of stylized facts and evidence about the education distribution among parents and sons and daughters in the sample. Section III introduces the structural model to be estimated and tested and the method of estimation used. Section IV presents a robustness check from an alternative sample. Section V presents the results, and Section VI concludes.

I. The Data

The source of data utilized in this study is the 1996 *Pesquisa Nacional por Amostragem a Domicílio* (PNAD), from *Instituto Brasileiro de Geografia e Estatística* (IBGE), the Brazilian census bureau. The PNAD is a yearly and nationally representative household survey (excepting the rural Amazon region) similar to the Current Population Survey in the U.S. It covers close to one hundred thousand households and includes information on the demographic and labor market characteristics of the households. Additionally, and of particular utility for the present study, the 1996 survey obtains retrospective information from the household head and the spouse about the educational attainment of their parents.

This dataset is very appropriate to estimate the causal relationship between parents' education and sons and daughters' education. First, it has information of complete education of two consecutive generations. Thus, we are able not only to link the parents' education to the sons and daughters' education, but also do so in a point in time when the sons and daughters are no longer in the midst of their formal education / human capital accumulation process. Second, it covers Brazilian generations with low levels of average schooling and higher variance in schooling (in comparison to more developed countries). Thus it allows the estimation of the gradient and discussion of policy responses in an environment where it potentially matters a great deal. Third, due to the nature of the questionnaire, the sons and daughters are the husbands and wives of the households, respectively. Thus, it allows us to explore the correlations between the parents' education and in-laws' education in an attempt to control for individual and family unobservable characteristics.

The sample selected consists of all individuals aged 25 years old and above that are classified as the household head or spouse and are living in households where both a head and a spouse are present. A male head or spouse is considered the husband and a female head or spouse is considered the wife. The sample is restricted to the age 25 and above because we want to consider only those no longer in the midst of their human capital accumulation process. It is very likely that most of the individuals have completed their formal education by the age of 25. 97 is the highest valid age information in the sample. Since we need the education information of the parents, we restrict the sample to heads and spouses.[3] More than 85% of all individuals 25 years old and above are household heads or spouses. Since we wish to explore the correlation of parents' education and in-laws' education, we are required to restrict the sample to households with both heads and spouses. Of all households in the 1996 PNAD, 28% are single head households. Finally, the sample is further restricted to husbands and wives

[3] We could, of course, include the son and daughter living in the household and use the head and spouse education information. However, most of the sons and daughters living in the household are still in the middle of their process of human capital accumulation so for this reason we decided to not include them in this sample.

with valid information on their educational attainment, gender, race/color, and their parent's educational attainment. Note that in this sample, due to the nature of the questionnaire, the adult husband is the 'son' and the adult wife is the 'daughter.'

Table A.1 in the appendix presents the number of observations kept in each step of the sample selection process. The 1996 PNAD encompasses 84,947 households. Of them all, 63 percent are households with heads and spouses aged 25 to 97 years old. Restricting the sample further to only those observations with valid information reduces the final sample to 33,406 observations of husbands and wives. The greatest decrease in the sample size is due to the existence of missing information on the parents' education. Most of the unknown information of parents' education is due to the fact that some heads and spouses declared they did not know their father's or their mother's final educational attainment. A closer inspection of those that declared they did not know their parents' education reveals that they are, in general, illiterate or lower educated. Although we make no attempt to correct to the potential sample selection bias generated by this, it is likely that the bias works against us. Since these husbands (sons) and wives (daughters) are dropped, the final sample likely over-represents the more educated ones. Since there is a steady expansion of educational attainment across generations in Brazil, it is likely that the final sample is more homogenous in education than in the population. Thus, the positive relationship between parents' education and sons and daughters' education is likely to be steeper than the one observed in this sample.

Nonetheless, as robustness check, we also estimate the same models with the alternative sample where the heads and spouses with missing or unknown education information of their parents are included. In this case, indicator variables for missing and unknown parents' education are added. The results are qualitatively the same as the ones for the sample described above. The results from these estimations are discussed in section V and presented in Table A.4 in the appendix.

The basic statistics of the final sample is presented in Table A.2 in the appendix. The final education attainment of husbands and wives is measured in final years of schooling. They average 5.77 and 5.84 years of schooling, respectively. Their average age is 45 and 42 years old, respectively, and around 40 percent of them are non-white. Their parents' educational attainments are reported in categories in 1996 PNAD. They are: no school, incomplete primary, completed primary, incomplete secondary, completed secondary, incomplete high school, complete high school, incomplete college, completed college, master or doctorate. Since the numbers of observations in the incomplete high school, and master and doctorate categories are extremely small, we merged them with completed high school and completed college, respectively. Table A.2 reveals that around 40 percent of fathers have no schooling, and almost 90 percent have at most completed primary education (which encompasses four years of schooling). For the mothers, the figures are very similar and, in fact, they have a higher share of no school (more than 45 percent). Less than seven (six) percent of the fathers (mothers) have at least high school education. Thus, the parents of these husbands and wives have very low education and the rest are relatively more equally distributed over the levels above primary education. The next section presents some stylized facts about the cross-generation education relationships.

II. The Stylized Facts

Table 1 shows the educational attainment distributions of husbands, wives, and their respective parents' education. It also presents the education transition matrices from parents to sons and daughters. Recall that in our data the husbands correspond to the 'sons' and the mothers corresponds to the 'daughters.' To ease the exposition, the education attainment levels are classified into four categories according to the Brazilian educational system. They are up to complete primary education (0 to 4 years of schooling); some or completed secondary (5 to 8); some or completed high school (9 to 11); and some college or above (12 or above). They are labeled primary, secondary, high school, and college, respectively.

The first row of Table 1 shows the education distribution of sons and daughters separately. Around 55 (53) percent of sons (daughters) have up to complete primary education, and less than 11 (10) percent of the sons (daughters) have ate least some college. The first column of Table 1 presents the education distribution of fathers and mothers, respectively. More than 87 (88) percent of fathers (mothers) have at most complete primary education, and 2.84 (1.06) percent of fathers (mothers) have at least some college education. It is very well established in the literature that Brazil has had a very skewed education distribution and the figures of Table 1 are no different. It is also a fact that younger generations have achieved higher schooling attainments (on average). Table 1 also shows this fact even though the figures are in part confounded by cohort effects.

Table 1 also presents the education transition matrices of fathers and mothers, and sons and daughters, separately. The figures are the probability for a son (or a daughter) of having a certain education level, given the education level of the father (or the mother). For instance, the second row in the upper left matrix shows that of all sons who have a father with up to primary education, 61.8 percent have up to primary education, 18.8 percent have some or completed secondary education, 13.2 percent have some or completed high school, and 6.2 percent have at least some college. An inspection of all the four transition matrices reveals clearly that sons and daughters of lower educated parents are more likely to be less educated in comparison to sons and daughters of more educated parents. The results are more marked if one compares the sons and daughters of primary educated parents to sons and daughters of college educated parents. Indeed, of all sons (daughters) who have a father with at least some college education, 71.2 (62.4) percent also have at least some college education. Similar figures arise for sons and daughters with a college educated mother: 72.9 and 72.3, respectively. Thus, in general, parents' education is a good predictor to the sons and daughters' education in Brazil.

The low intergenerational educational mobility in Brazil presented in Table 1 has been documented before (e.g., Veloso e Ferreira (2003)). Whether it is due to some education causality mechanism or some education-type selection process remains an open question. This paper tries to disentangle precisely these two issues. In order to pursue this goal, the paper explores the particular nature of the data, where the sons and daughters are also husband and wives, and that it carries the information about their parents' education. *If one assumes that the assortative mating process in the marriage market is such that the abilities, tastes, and preferences of the individuals are correlated to those of their partner and their relatives, and they are, in turn, correlated with their observable education attainment levels, one can explore the observable correlations among the education attainment levels of sons, daughters, parents, and in-laws in order to control for individuals' unobservable characteristics correlated to education.* This assumption has been explored before. Lam and Schoeni (1993) provide evidence of family background on earnings and returns to schooling in Brazil. They find that the schooling of fathers-in-law has a greater impact on wages than does the schooling of fathers. Based on an assortative mating model, they interpret their result as evidence that parental characteristics are proxies for unobservable workers attributes. We employ a similar assumption. We assume that parents and in-laws education are proxies for individual's unobservable characteristics that are correlated with education. The empirical structural model described in the next section will present these assumptions formally. However, before discussing the model, it is informative to know to what extent the marriage matching is associated with the education correlation of the partners and relatives.

Table 2 shows the cross-tabulations of the education attainment levels between husbands and wives, fathers' husbands and mothers' husbands, and fathers' wives and mothers' wives, separately. The school attainment categories are the same as in Table 1. For each cell in the cross-tabulation, three figures are presented: the overall percentage, the row percentage, and the column percentage. The overall percentage gives the probability of a couple belonging to a given cell. The row percentage gives the probability of a wife of having a certain education level, given her husband's education level. The column percentage gives the probability of a husband having a certain education level, given his wife's education level. For instance, the cross-tabulation in the top of Table 2 refers to husbands and wives' education. It shows that of all couples, 45 percent are composed by husbands and wives with both having at most complete primary education, and 6.1 percent formed by husbands and wives with both having at least some college education. Interestingly, only 0.5 (0.4) percent of them are formed by husbands with primary (college) and wives with college (primary) education. The same cross-tabulation shows that of all wives married with a primary educated husband, 81.6 percent are primary educated, 12.7 are secondary educated, 4.8 are high school educated, and 0.8 are college educated. Similarly, of all husbands married with a primary educated wife, 84.7 percent of them are primary educated, 10.6 are secondary educated, 3.9 are high school educated, and 0.8 are college educated. Thus, there is a positive assortative matching process where more highly educated husbands tend to marry with more highly educated wives and husbands with lower education levels marry with wives with lower education levels.

Qualitatively similar patterns are encountered in the other two cross-tabulations. For instance, of all mothers married to fathers with only a primary education, more than 96 percent have only a primary education as well. So, the fathers and mothers of the husbands and wives appear to engage in positive assortative mating in educational attainment as well. This perhaps reveals that this process has persisted for many generations.

Finally, if parents' education is strongly associated with their sons' and daughters' education, and if husbands' and wives' educations are strongly associated with each other, it is likely that the husbands' parent's educations are positively associated with the wives' parent's educations. Indeed, Table 3 presents the same cross-tabulations of the education levels of father's husbands and fathers' wives, as well as mothers' husband and mothers' wives. Interestingly, there is a strong positive association of their education levels. For instance, of all husband and wife couples, 82.2 (83.9) percent have both parents with only primary educations. Only 0.8 (0.3) have both parents who are college educated. This study explores this positive correlation to control for unobservable individuals' characteristics correlated with their education attainment. The next section introduces the empirical structural model to be estimated and tested.

III. The Structural Model and Estimation Method

Consider the traditional intergenerational human capital transmission model in the literature where the individual's education is an additive function of their parent's education. Specifically in our case, assume that a large number N of households with husbands (h) and wives (w) are observed in a point in time. The equations for a husband's education and a wife's education take the form

$$S_{ij} = \phi_j x_{ij} + \beta_j^f S_{ij}^f + \beta_j^m S_{ij}^m + \varepsilon_{ij}, i = 1, \ldots, N, \; j = h, w. \qquad (1)$$

The husband (or wife) observable characteristics are given by a vector x_{ij} (age, race/color, etc.), the father's (f) education S_{ij}^f, and the mother's (m) education S_{ij}^m. Assume that the disturbance term ε_{ij} takes the following form:

$$\varepsilon_{ij} = c_{ij} + u_{ij.} \qquad (2)$$

Then the model becomes

$$S_{ij} = \phi_j x_{ij} + \beta_j^f S_{ij}^f + \beta_j^m S_{ij}^m + c_{ij} + u_{ij}. \qquad (3)$$

We assume u_{ij} is uncorrelated with x_{ij}, S_{ij}^f, and S_{ij}^m. The term c_{ij} is the unobserved husband (or wife) effect that are correlated with x_{ij}, S_{ij}^f, and S_{ij}^m. For instance, c_{ij} may contain individuals' ability or family-shared tastes for education known by their parents but not observed by the econometrician. These unobservables represented in c_{ij} are very likely to be positively correlated with parents' education. It could be that highly educated parents generate highly educated sons and daughters, and/or that highly educated parents have stronger tastes for education that shape their sons and daughters' tastes as well, and/or even that highly educated parents are wealthier, more informed, or better connected such that the education costs of their sons and daughters are lower. For all cases like those, regressions that do not control for c_{ij} bias upwardly the estimations of β_j^f and β_j^f. Similar strategy was used by Ashenfelter and Zimmerman (1997) to estimate returns to schooling in the U.S.

Assume for simplicity that, conditional on c_{ij}, the sons' and daughters' education depends only on parents' education, so that x_{ij} drops out of (1). Also let the parents' educations S_{ij}^f and S_{ij}^m be scalars. (These assumptions are relaxed in the empirical estimations). Then (3) becomes

$$S_{ij} = \beta_j^f S_{ij}^f + \beta_j^m S_{ij}^m + c_{ij} + u_{ij}. \tag{4}$$

The bias arises because c_{ij} is correlated with S_{ij}^f and S_{ij}^m. If the husband's unobservable characteristic c_{ih} is correlated with his parents' education, then it is also correlated with his in-laws education S_{iw}^f and S_{iw}^m. Likewise, if the wife's unobservable characteristic c_{iw} is correlated with her parents' education S_{iw}^f and S_{iw}^m, then it is also correlated with her in-laws' education S_{ih}^f and S_{ih}^m. We formalize this notion as

$$c_{ij} = \lambda_h^f S_{ih}^f + \lambda_h^m S_{ih}^m + \lambda_w^f S_{iw}^f + \lambda_w^m S_{iw}^m + \xi_{ij}, \tag{5}$$

where $\lambda = (\lambda_h^f, \lambda_h^m, \lambda_w^f, \lambda_w^m)'$ is the vector of partial correlation coefficients and ξ_{ij} is an error orthogonal to $S^p = (S_{ih}^f, S_{ih}^m, S_{iw}^f, S_{iw}^m)$ by construction. Substituting for c_{ij} in (4), we obtain the following system of husband's equation and wife's equation based on observables:

$$S_{ih} = (\beta_h^f + \lambda_h^f)S_{ih}^f + (\beta_h^m + \lambda_h^m)S_{ih}^m + \lambda_w^f S_{iw}^f + \lambda_w^m S_{iw}^m + (\xi_{ih} + u_{ih}) \tag{6.1}$$

$$S_{iw} = \lambda_h^f S_{ih}^f + \lambda_h^m S_{ih}^m + (\beta_w^f + \lambda_w^f)S_{iw}^f + (\beta_w^m + \lambda_w^m)S_{iw}^m + (\xi_{iw} + u_{iw}). \tag{6.2}$$

This system, as it is, is under-identified since there are 12 structural parameters and 8 reduced-form coefficients. However, we want to estimate the gradient of the education effect.

For that, we proceed with two specifications. First, we use indicator variables for the fathers and mother education levels. They are incomplete primary, completed primary, incomplete secondary, complete secondary, some and completed high school, incomplete college, and at least completed college. No school is the omitted category. Second, we construct the continuous variables of years of schooling of the husbands and wives and specify the equations with the variables 'years of schooling' and its square. In both cases the father's (mother's) education S_{ij}^f (S_{ij}^m) becomes a vector with Seven elements in the discrete specification and Two elements in the continuous specification for each j = h or w. Thus, we can make this system identifiable by assuming that the father's (mother's) husband has the same impact of the father's (mother's) wife up to a scale. That is, we assume that $\beta^f = \beta_h^f = \beta_w^f$ and $\beta^m = \beta_h^m = \beta_w^m$, and add two wife's parents factor loads γ and δ. Recalling that S_{ij}^f and S_{ij}^m are vectors now (and so $\beta's$ and $\lambda's$ are vectors as well), the system becomes

$$S_{ih} = (\beta^f + \lambda_h^f)S_{ih}^f + (\beta^m + \lambda_h^m)S_{ih}^m + \lambda_w^f S_{iw}^f + \lambda_w^m S_{iw}^m + (\xi_{ih} + u_{ih}) \qquad (6.1')$$

$$S_{iw} = \lambda_h^f S_{ih}^f + \lambda_h^m S_{ih}^m + (\gamma\beta^f + \lambda_w^f)S_{iw}^f + (\delta\gamma\beta^m + \lambda_w^m)S_{iw}^m + (\xi_{iw} + u_{iw})\,. \qquad (6.2')$$

The factor load γ gives the 'level effect' of the wife's parents' education in relation to the husband's parents' education. The factor load δ gives the wife's mother's education 'level effect' over the wife's father's education. Under the assumptions above, the system is over-identified. For instance, in the discrete variable model, there would be 56 reduced-form coefficients and 44 structural parameters (14 $\beta's$, 28 $\lambda's$, and 2 factor loads γ and δ). The system (6') projects the husband and wives' education S_{ij} (which in this case they are sons and daughters) over their parents' education $S^p = (S_{ih}^f, S_{ih}^m, S_{iw}^f, S_{iw}^m)$. The unrestricted reduced form model is

$$S_i = \Pi S^p + e_i\ , \qquad (7)$$

where $S_i = (S_{ih}, S_{iw})$, Π is the matrix of projection coefficients, and e_i is the 2N elements vector of disturbances. The model (7) implies the nonlinear restrictions

$$\Pi = diag\{\beta^h, \beta^w\} + \lambda'\,, \qquad (8)$$

where $\beta^h = (\beta^f, \beta^m)$ and $\beta^w = (\gamma\beta^f, \delta\gamma\beta^m)$. We can estimate the parameters $\beta's, \lambda's, \gamma$ and δ, and test the implied restrictions. First, we estimate the reduced form Π. The reduced form coefficients are estimated through a system of two equations (the husband equation and the wife equation) where the errors terms are allowed to be freely correlated. Then we use a method of moment estimator to obtain $\beta's, \lambda's, \gamma$ and δ using (8). These structural parameters are recovered using the optimal minimum distance estimator where the variance-covariance matrix of the reduced form coefficients is used as the weighting matrix (Chamberlain, 1982, 1984; Jakubson, 1991). Finally, we test the validity of the model by testing the over-identifying restrictions. The test is an omnibus test in that the rejection does not imply a specific alternative, since the test is against an unrestricted reduced form (Chamberlain, 1982, 1984). The test of the null hypothesis that the unobserved individuals' effect is uncorrelated with his or her parents' education is a test of $\lambda = 0$. The test of the null hypothesis that the effect of the husband's father's education is equal to the effect of the wife's father's education is a test of $\gamma = 1$. The test of the null hypothesis that the effect of the husband's mother's education is equal to the effect of the wife's mother's education is a test of $\delta\gamma = 1$. And the test of the null hypothesis that the effect of the husband's (wife's) father's education is equal to the effect of the husband's (wife's) mother's education is a test of $\beta^f = \beta^m$.

IV. The Results

This section presents the results of two empirical specifications. The first one is the education discrete variable model and the second one is the education continuous variable model.

4.1. The Education Discrete Variable Model

In this model we specify the parents' education with seven education indicator variables for fathers and mothers separately. They are: incomplete primary, completed primary, incomplete secondary, complete secondary, some and completed high school, incomplete college, and at least completed college. No school is the omitted category. Also, the husband's and the wife's age variables and non-white indicator variables are added. It is important to note that the variables age and nonwhite are also used in the specification of the person and family's effect,

c_{ij}. Thus, we explore the correlations of age and race/color with the parents' education as well in order to control for the unobservable individual and family's effect. Finally, since most of the parents are in the very low end of the education distribution (no school and incomplete primary), we add an extra factor load ρ for the incomplete primary indicator variables of the father and of the mother of the daughter (wife). This allows the gender effect to differ across the education distribution.

Before we show the results of the structural model, it is informative to look at the OLS and SUR estimations. This comparison can give us an idea of the bias that can occur if one does not control for person and family effects. Table 4 presents the results for both OLS and SUR regressions. Recall that the dependent variables are the years of schooling completed by the husbands (sons) and wives (daughters). The second and fourth columns of Table 4 show the OLS coefficients for husbands and wives, respectively. The sixth and eighth columns present the SUR coefficients for husbands and wives, respectively. The results exhibit the expected patterns. First, there is a strong positive association between parents' education and sons' and daughters' education. Second, older generations have lower education attainment levels than do younger ones. Third, non-white individuals have lower schooling than white individuals. Fourth, the father's (mother's) education point estimates are greater for sons (daughters) than for daughters (sons) in both OLS and SUR regressions. Finally, SUR point estimates are lower than OLS point estimates. This suggests that if we do not control for correlation of the error terms we bias upward the parental education effect.

The parameter estimates of the structural model (6') with the factor load ρ for the incomplete primary indicator variables of the father and of the mother are presented in Table 5. For expositional convenience we present the education parameters, $\beta's$, and factor loads, γ, δ and ρ, only. The $\lambda's$ are presented in Table A.3 in the appendix. We do not estimate the structural parameters for age and non-white variables since we are interested in the education effects only. Age and non-white are used solely as controls.

The father's education effect on the son's education is given by the set of parameters β_2 to β_8. The mother's education effect on the son's education is given by the set of parameters β_{10} to β_{16}. (For the case of incomplete primary, the father and mother's corresponding parameters should be multiplied by the factor load ρ). The father's education effect on the daughter's education is given by the set of parameters β_2 to β_8, multiplied by the factor load γ. The mother's education effect on the daughter's education is given by the set of parameters β_{10} to β_{16}, multiplied by both factor loads γ and δ. (Again, for the case of incomplete primary, their corresponding parameters should be further multiplied by the factor load ρ).[4]

The effects of the father and mother's education on son and daughter's education are presented in Figure 1 and 2, respectively. Both Table 5 and Figures 1 and 2 show that there is a positive effect of parent's education on their sons' and daughters' education, even after the unobservable person and family effects are controlled for. As expected, once the unobservable person and family effects are controlled for, the parents' education effect becomes three to four times smaller than those estimated by OLS. For instance, according to the OLS estimates, a father that completes primary education increases his son's schooling by 3.11 years in comparison with a father that has no schooling. The SUR model estimates this effect as by 2.74 years. The structural model 1 in Table 5 estimates this effect to be 1.10 years. Similar patterns can be observed for any other education level and they hold for the mothers as well. Thus, these results suggest that there is a positive correlation between the unobservable person and family effects and the parents' education. The failure to control for it will bias the education effect upward.

The parameter estimates from model 1, presented in Table 5, show that the positive effect of parents' education on their sons' education still survive after we take the unobservable person and family effects into account. Moreover, it shows that the effects differ at different levels of parental education. Indeed, there seems to be gradient effects for a range of education levels. More precisely, Figures 1 and 2 depict the pattern that the father's effect increases at

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[4] The full discrete education variable model is:

$$S_{ih} = \phi_h x_{ih} + \rho\beta_2 S^f_{ih_2} + \sum_{k=3}^{8}\beta_k S^f_{ih_k} + \rho\beta_{10} S^m_{ih_{10}} + \sum_{k=11}^{16}\beta_k S^m_{ih_k} + c_{ih} + u_{ih}$$

$$S_{iw} = \phi_w x_{iw} + \rho\gamma\beta_2 S^f_{iw_2} + \sum_{k=3}^{8}\gamma\beta_k S^f_{iw_k} + \rho\theta\gamma\beta_{10} S^m_{iw_{10}} + \sum_{k=11}^{16}\theta\gamma\beta_k S^m_{iw_k} + c_{iw} + u_{iw}$$

$$c_{ij} = \sum_{k=2}^{8}\lambda^h_k S^f_{ih_k} + \sum_{k=10}^{16}\lambda^h_k S^m_{ih_k} + \sum_{k=2}^{8}\lambda^w_k S^f_{iw_k} + \sum_{k=10}^{16}\lambda^w_k S^m_{iw_k} + \sum_{k=17}^{18}\lambda^h_k x_{ih_k} + \sum_{k=17}^{18}\lambda^w_k x_{iw_k} + \xi_{ij}$$

decreasing rates up to high school level, when it jumps up and levels off later again. Similarly, the mother's effect increases at decreasing rates up to incomplete college, when it jumps up and levels off again. Moreover, the factor loads γ, δ and ρ are all statistically different from 1. The father's education effect on the daughter's education is 0.317 the effect on the son's education, except for incomplete primary education that becomes 1.414 x 0.317 = 0.448. The mother effect on the daughter's education is 4.225 x 0.317 = 1.338 the effect on the son's education except, again, for incomplete primary education which becomes 1.414 x 4.225 x 0.317 = 1.891. This result suggests that the gender effect also presents a 'gradient'. Finally, the last row of Table 5 presents the omnibus test based on the unrestricted reduced form. It is a Chi-squared test with 11 degrees of freedom. There are 56 reduced form education coefficients (7 education indicator variables, 2 parents, 2 in-laws, and 2 equations) and 45 structural parameters (14 $\beta's$, 28 $\lambda's$, and 3 factor loads γ, δ and ρ). The test does not reject the model at 5% confidence interval. Thus, the structure imposed by the model is not rejected by the data.

We further proceed to test if the gradients presented in the Figures 1 and 2 are indeed statistically different from each other. We do this by imposing additional restrictions on the structure of the model. The test is a chi-squared test with degrees of freedom equal to the difference of the degrees of freedom between the more and less restrictive models. Table 6 presents the sequences of models that impose different restrictions to the $\beta's$. All of them are compared to the less restrictive model 1. Model 2 tests if complete college has no additional impact relative to incomplete college (β_7=β_8, β_{15}=β_{16}). This is not rejected. Model 3 tests if some college and college has some impact over high school (β_6=β_7=β_8, β_{14}=β_{15}=β_{16}). This is s is rejected. Model 4 adds to model 2 the assumption that complete secondary has no extra effect over incomplete primary (β_4=β_5, β_7=β_8, β_{12}=β_{13}, β_{15}=β_{16}). It is not rejected . Models 5, 6, and 7 test if high school adds to secondary (β_3=β_4=β_5, β_7=β_8, β_{11}=β_{12}=β_{13}, β_{15}=β_{16}), if secondary adds to primary (β_4=β_5=β_6, β_7=β_8, β_{12}=β_{13}=β_{14}, β_{15}=β_{16}), and if completed primary adds to incomplete primary (β_2=β_3, β_4=β_5, β_7=β_8, β_{10}=β_{11}, β_{12}=β_{13}, β_{15}=β_{16}), respectively. All of them are rejected. In conclusion, model 4 is the most restrictive model that is not rejected by the Omnibus test. It suggests that the impacts by education levels are different except that complete secondary has no additional impact relative and incomplete secondary, and that completed college has no marginal impact over incomplete college.

Most of the empirical studies that have evaluated the effects of changes in parents' education have done so at relatively high levels of education compared to less developed countries. Some have found a positive effect, others have found no effects at all, and one has even found a negative effect. Our findings suggest that these different results may be due to the fact that they evaluate these effects off of a small change of education level, one or two years of schooling, and at an education level already high, e.g., eight or nine years of schooling. Looking only in a specific point may miss a large part of the story, and extrapolating from these previous findings may be problematic. For instance, if one looks only at a change between incomplete secondary and completed secondary, which it would entail a move from seven to eight years of schooling in Brazil, one would conclude that there is no effect at all. Similar conclusions would be reached if one examines the change from incomplete college to complete college. On the other hand, if one looks at the change from complete secondary to complete high school, one would conclude that the effect is positive and sizeable. The same findings would be obtained if one compares incomplete primary with completed primary. Moreover, our findings also suggest that the effect of gender varies across the education distribution and the relative impact of fathers and mothers on sons and daughters is different at different levels of their education. If this is true elsewhere, it may also explain why some studies have found that sometimes the mother has a positive effect and the father not, and others have found the opposite.

4.2. The Education Continuous Variable Models

In order to compare our results more closely with those from the received literature we also estimate the model (6') using the parents' education continuous variable years of schooling. The advantage from doing so is that we can estimate the marginal effect of one extra year of schooling. The parent's years of schooling variable is constructed according to the Brazilian education system. Those with an incomplete level we assign the mid-point. The number of completed years of schooling is thus assigned as follows: no school (0 years of schooling); incomplete primary (2 years of schooling); completed primary (4 years of schooling); incomplete secondary (6 years of schooling); completed secondary (8 years of schooling); incomplete high school (10 years of schooling); completed high school (11 years of schooling); incomplete college (13 years of schooling); complete college (15 years of schooling); and masters or doctorate (17 years of schooling).

We first estimate a non-linear model similar to the models 1 to 7 above. The only difference is that the education indicator variables are replaced by the variables years of schooling and its squared term. Table 8.a presents the results for the entire sample; for the sample with all parents having their years of schooling between 5 and 11; and for the sample of parents that have their years of schooling between 0 and 4. The results for the overall sample (first column) show that parents' education has a concave relationship with their sons and daughters' education. The effects show diminishing returns. They reach their peak at 14 years of schooling for the father, and around 11 years of schooling for the mother. Moreover, there is the same gender effect as above and revealed by the parameter estimates γ and δ. On the other hand, the results for those parents with 5 to 11 years of schooling only (as shown in column 3 of Table 7.a) are statistically insignificant. Conversely, the results for those parents with 0 to 4 years of schooling only (as shown in column 5 of Table 7.a) are strongly significant. Thus, the results of table 7.a suggests that in fact there is a gradient effect of parent's education on sons and daughters' education and these effects seem to diminish as parental education increases. The strongest effect occurs at very low levels of schooling when the parents' move from illiterate to literate. Perhaps the change from illiterate to literate is when the change of 'parenthood type' occurs.

Finally, Table 7.b shows the results for the education continuous variable models where the squared terms of the years of schooling are dropped for the same three samples of Table 7.a. These linear models does not have a very good 'fit' if one looks at the chi-squared statistics but still reveals the same patterns of the previous models. The interesting result is that the schooling impact on the 0 to 4 years of schooling sample is stronger than those in the 5 to 11 years of schooling sample. Moreover, father's education has no effect and mother's education has some effect in the 5 to 11 years of schooling sample. Thus, the results start to not be very consistent when one use a more narrow sample of relative higher schooling range and this perhaps explain the discrepancies found the literature so far.

V. Robustness Check

The sample used in these exercises includes all husbands and wives with valid information about their parents' education. As discussed earlier and shown in Table A.1, there are many who have declared they do not know their parents' education or some for whom the information is missing. A closer inspection of these individuals reveals that they have lower schooling on average. If their parents have lower education compared to other parents (as we would expect), the actual functional relationship of intergenerational education would be steeper than the one we estimate with our sample and thus the bias would go against us.

However, it is not completely guaranteed that this is indeed the case. For instance, it is possible that the parents of lower educated individuals are younger (compared to other parents). Given the schooling expansion across generations in Brazil, it would imply that they would be, on average, more educated (compared to the other parents). Since we do not observe the parents' age, we cannot control for parents' cohort. Dropping from the sample the husbands and wives without parents' schooling information would create a sample selection bias that overestimates the relationship of intergenerational education.

In order to check the severity of this issue, we replicate the exercises of model 1 to model 7 to an alternative sample. This new sample includes all husbands and wives with unknown or missing information on their parent's education. As shown in Table A.1, this sample encompasses 52,550 households. Now, the first stage reduced form equations further include as controls an indicator variable for unknown father's education, an indicator variable for unknown mother's education, an indicator variable for missing father's education, and an indicator variable for missing mother's education. The results are presented in Table A.4 in the appendix. These results compare directly to the results of Table 6. (Note that we present the structural coefficients for education only, the other variables are simply used as controls in the first stage).

The results of Table A.4 are qualitatively the same as the ones of Table 6. There is a decreasing positive effect of parents' schooling on son and daughter's schooling. The marginal impact ceases around secondary education. Moreover, father's schooling has a stronger impact on son's education than on daughter's education and mother's schooling have stronger effect on daughter's education than on son's education. Although the chi-square statistics reject some of the models, the additional restrictions of model 4 are not rejected (similar to the previous results).

VI. Conclusion

This paper investigates the relationship between the educational attainment of parents and children in a developing country context and evaluates the importance of the gradient. The results suggest that OLS and SUR estimates of the intergenerational transmission of human capital are biased upward. After controlling for individual and family unobservable attributes, the intergenerational impact is three to four times smaller. More importantly, however, it finds that even after controlling for individual and family unobservable characteristics, there is still a strong effect of parent’s schooling on the schooling levels of their sons and daughters. Moreover, there is a clear gradient effect. The effect of parent's schooling on children's schooling appears to exhibit diminishing returns under certain range of the schooling cycle. Finally, fathers have stronger impacts on sons than on daughters, and mothers have stronger effects on daughters than on sons.

VII. References

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VIII. Tables

Table 1: Education Distribution and Transition Matrix (%)

		Son's Education				Daughter's Education			
		Primary	Secondary	High School	College	Primary	Secondary	High School	College
	Total	55.16	18.31	15.56	10.98	53.15	19.79	17.33	9.73
Father's Education									
Primary	87.83	61.8	18.8	13.2	6.2	59.5	20.5	14.7	5.4
Secondary	5.28	11.9	23.0	35.7	29.4	15.3	21.6	37.5	25.7
High School	4.05	4.7	9.5	36.6	49.3	5.6	10.9	39.2	44.4
College	2.84	2.6	5.9	20.2	71.2	2.4	8.1	27.2	62.4
Mother's Education									
Primary	88.9	61.2	19.0	13.5	6.4	58.9	20.5	14.9	5.6
Secondary	5.57	9.3	18.9	36.7	35.1	10.8	20.2	38.6	30.5
High School	4.46	4.7	7.8	29.2	58.3	3.1	8.3	38.1	50.6
College	1.06	3.1	5.4	18.6	72.9	2.9	3.4	21.5	72.3

Table 2: Cross Tabulations of Husbands' and Wives' Education

Percent Row Pct Col Pct		Primary	Secondary	High School	College
		Wives			
Husbands	**Primary**	45.0	7.0	2.7	0.5
		81.6	12.7	4.8	0.8
		84.7	35.5	15.4	4.7
	Secondary	5.6	8.1	3.9	0.8
		30.7	44.0	21.0	4.3
		10.6	40.7	22.2	8.1
	High School	2.1	3.9	7.2	2.4
		13.4	24.8	46.3	15.6
		3.9	19.5	41.5	25.0
	College	0.4	0.9	3.6	6.1
		4.0	7.9	32.9	55.2
		0.8	4.4	20.9	62.3
		Mothers' Husbands			
Fathers' Husbands	**Primary**	84.8	1.8	1.0	0.2
		96.6	2.0	1.2	0.2
		95.4	31.7	23.3	16.4
	Secondary	2.4	2.3	0.4	0.1
		46.1	44.2	7.9	1.8
		2.7	41.9	9.4	8.8
	High School	1.1	1.0	1.7	0.2
		27.3	24.8	42.6	5.2
		1.3	18.1	38.7	20.1
	College	0.5	0.5	1.3	0.6
		18.3	16.3	44.9	20.4
		0.6	8.3	28.6	54.8
		Mothers' Wives			
Fathers' Wives	**Primary**	84.2	2.0	1.1	0.2
		96.4	2.2	1.2	0.2
		94.8	33.9	25.0	15.0
	Secondary	2.8	2.4	0.5	0.1
		47.6	41.2	9.0	2.2
		3.1	41.3	12.4	10.9
	High School	1.3	1.0	1.6	0.2
		32.2	24.1	38.3	5.4
		1.5	17.2	37.4	19.2
	College	0.5	0.4	1.1	0.6
		19.9	16.4	40.0	23.7
		0.6	7.6	25.3	54.9

Table 3: Cross Tabulations of Parent's and In-Law's Education

Percent / Row Pct / Col Pct

			Primary	Secondary	High School	College
			Fathers' Wives			
Fathers' Husbands	**Primary**	Percent	82.2	3.1	1.7	0.9
		Row Pct	93.5	3.5	1.9	1.0
		Col Pct	94.0	53.4	41.3	32.6
	Secondary	Percent	2.8	1.6	0.5	0.3
		Row Pct	53.7	30.2	9.9	6.3
		Col Pct	3.2	27.5	12.6	12.4
	High School	Percent	1.6	0.7	1.2	0.6
		Row Pct	38.2	18.3	29.0	14.5
		Col Pct	1.8	12.8	28.5	22.0
	College	Percent	0.9	0.4	0.7	0.9
		Row Pct	30.5	12.9	25.6	31.1
		Col Pct	1.0	6.3	17.6	33.0
			Mothers' Wives			
Mothers' Husbands	**Primary**	Percent	83.9	3.0	1.7	0.4
		Row Pct	94.4	3.4	1.9	0.4
		Col Pct	94.4	51.5	39.3	32.6
	Secondary	Percent	2.8	1.9	0.7	0.2
		Row Pct	50.5	33.2	12.8	3.4
		Col Pct	3.2	32.0	16.9	16.6
	High School	Percent	1.7	0.8	1.6	0.3
		Row Pct	38.8	17.8	35.8	7.7
		Col Pct	2.0	13.8	37.7	29.5
	College	Percent	0.4	0.2	0.3	0.3
		Row Pct	37.3	15.0	24.6	23.2
		Col Pct	0.4	2.7	6.2	21.2

Table 4: OLS and SUR Regressions - Education Discrete Variable Model

	OLS				SUR			
	Husbands		Wives		Husbands		Wives	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Intercept	5.777	0.085	6.305	0.081	6.036	0.082	6.685	0.078
Father's Education								
Incomplete Primary	1.420	0.053	1.206	0.051	1.274	0.049	1.040	0.047
Complete Primary	3.113	0.068	2.462	0.064	2.736	0.062	2.120	0.058
Incomplete Secondary	3.802	0.148	2.881	0.133	3.306	0.135	2.378	0.122
Complete Secondary	4.405	0.129	3.843	0.121	3.840	0.118	3.209	0.111
Some and Complete High School	5.290	0.124	4.520	0.117	4.729	0.114	3.710	0.107
Incomplete College	5.491	0.389	4.657	0.362	4.909	0.355	3.952	0.329
Complete College	6.359	0.152	5.409	0.151	5.699	0.139	4.455	0.138
Mother's Education								
Incomplete Primary	1.368	0.054	1.617	0.052	1.144	0.050	1.419	0.047
Complete Primary	2.653	0.069	2.882	0.064	2.251	0.063	2.481	0.059
Incomplete Secondary	3.085	0.143	3.387	0.130	2.669	0.130	2.905	0.118
Complete Secondary	4.130	0.131	4.274	0.127	3.492	0.120	3.836	0.116
Some and Complete High School	4.707	0.123	5.099	0.118	4.024	0.113	4.456	0.108
Incomplete College	4.735	0.592	5.880	0.560	3.866	0.539	5.094	0.510
Complete College	5.002	0.221	5.443	0.207	4.222	0.201	4.920	0.189
Age	-0.053	0.001	-0.069	0.002	-0.051	0.001	-0.070	0.002
Non-white	-1.073	0.041	-0.833	0.040	-1.020	0.038	-0.741	0.038
R-Squared	0.475		0.462					

Table 5: Structural Model
Education Discrete Variable Model

	Structural Parameters	Model 1 Coeff.	Std. Error
	Father's Education		
β_2	Incomplete Primary	0.576	0.005
β_3	Complete Primary	1.099	0.007
β_4	Incomplete Secondary	1.360	0.014
β_5	Complete Secondary	1.360	0.013
β_6	Some and Complete High School	1.723	0.012
β_7	Incomplete College	2.025	0.031
β_8	Complete College	2.074	0.015
	Mother's Education		
β_{10}	Incomplete Primary	0.348	0.005
β_{11}	Complete Primary	0.603	0.006
β_{12}	Incomplete Secondary	0.735	0.010
β_{13}	Complete Secondary	0.841	0.011
β_{14}	Some and Complete High School	0.941	0.011
β_{15}	Incomplete College	1.172	0.032
β_{16}	Complete College	1.207	0.016
	Daughter's Factor Loads		
γ	Father and Mother's Education	0.325	0.004
δ	Mother's Education	4.067	0.085
	Incomplete Primary Factor Load		
ρ	Father and Mother's Education	1.425	0.013
Chi-Squared (DF)		16.641 (11)	

Note: Additional controls in the first-stage reduced-form estimations are age and non-white indicator variables.

Table 6: Strutural Models and Tests
Education Discrete Variable Models

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	Coeff.	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
Father's Education														
β_2	0.576	0.005	0.576	0.005	0.573	0.005	0.576	0.005	0.575	0.005	0.572	0.005	0.692	0.005
β_3	1.099	0.007	1.099	0.007	1.093	0.007	1.098	0.007	1.152	0.007	1.089	0.007		
β_4	1.360	0.014	1.360	0.014	1.357	0.014	1.355	0.011			1.496	0.010	1.291	0.010
β_5	1.360	0.013	1.359	0.013	1.355	0.013								
β_6	1.723	0.012	1.722	0.012	1.849	0.011	1.723	0.012	1.699	0.012			1.653	0.012
β_7	2.025	0.031	2.067	0.014			2.066	0.014	2.047	0.014	2.021	0.014	1.982	0.014
β_8	2.074	0.015												
Mother's Education														
β_{10}	0.348	0.005	0.349	0.005	0.352	0.005	0.350	0.005	0.356	0.005	0.351	0.005	0.469	0.005
β_{11}	0.603	0.006	0.603	0.006	0.610	0.006	0.602	0.006	0.651	0.006	0.607	0.006		
β_{12}	0.735	0.010	0.735	0.010	0.744	0.010	0.786	0.009			0.848	0.009	0.714	0.009
β_{13}	0.841	0.011	0.842	0.011	0.853	0.011								
β_{14}	0.941	0.011	0.941	0.011	1.017	0.011	0.929	0.011	0.901	0.011			0.853	0.011
β_{15}	1.172	0.032	1.204	0.015			1.194	0.015	1.170	0.015	1.181	0.015	1.136	0.015
β_{16}	1.207	0.016												
Daughters' Factor Loads														
γ	0.325	0.004	0.325	0.004	0.326	0.005	0.328	0.004	0.341	0.004	0.330	0.004	0.303	0.005
δ	4.067	0.085	4.062	0.085	3.999	0.084	4.019	0.084	3.798	0.077	3.887	0.081	4.336	0.096
Incomplete Primary Factor Load														
ρ	1.425	0.013	1.425	0.013	1.431	0.013	1.419	0.013	1.404	0.012	1.448	0.013	1.166	0.008
Chi-Squared (DF)	16.641	(11)	16.677	(13)	29.042	(15)	17.690	(15)	34.499	(17)	30.595	(17)	125.552	(17)
Chi-Squared Diff.(DF)			0.037	(2)	12.402	(4)	1.050	(4)	17.858	(6)	13.954	(6)	108.912	(6)

Note 1: Additional controls in the first-stage reduced-form estimations are age and non-white indicator variables.

Note 2: The models test the following assumptions:

Model 2:	$\beta_7=\beta_8$, $\beta_{15}=\beta_{16}$
Model 3:	$\beta_6=\beta_7=\beta_8$, $\beta_{14}=\beta_{15}=\beta_{16}$
Model 4:	$\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$
Model 5:	$\beta_3=\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{11}=\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$
Model 6:	$\beta_4=\beta_5=\beta_6$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}=\beta_{14}$, $\beta_{15}=\beta_{16}$
Model 7:	$\beta_2=\beta_3$, $\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{10}=\beta_{11}$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$

Table 7.a: Structural Model and Tests

Education Continuous Variable Non-Linear Models

	All Sample		2 <= Education <= 11		5 <= Education <= 11		0 <= Education <= 4	
Parameters	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
β_1	0.280	0.002	0.377	0.006	-0.259	0.046	0.262	0.005
β_2	-0.010	0.000	-0.019	0.000	0.019	0.003	0.006	0.001
β_3	0.177	0.002	0.099	0.004	0.231	0.016	0.277	0.004
β_4	-0.008	0.000	-0.004	0.000	-0.006	0.001	-0.041	0.001
λ^h_1	0.317	0.002	0.427	0.007	0.076	0.085	0.177	0.005
λ^h_2	-0.012	0.000	-0.021	0.001	0.001	0.005	0.025	0.001
λ^h_3	0.349	0.002	0.326	0.007	0.156	0.071	0.333	0.005
λ^h_4	-0.014	0.000	-0.011	0.001	-0.010	0.004	-0.005	0.001
λ^w_1	0.347	0.002	0.333	0.006	0.732	0.070	0.279	0.004
λ^w_2	-0.009	0.000	-0.010	0.000	-0.038	0.004	0.005	0.001
λ^w_3	0.372	0.002	0.340	0.004	0.092	0.010	0.250	0.005
λ^w_4	-0.015	0.000	-0.011	0.000	0.005	0.001	0.013	0.001
γ	0.286	0.005	0.017	0.004	1.015	0.066	0.391	0.006
δ	4.776	0.117	138.367	38.267	0.599	0.059	4.414	0.107
Chi-Squared (DF)	8.705	(2)	0.580	(2)	2.402	(2)	7.319	(2)

Note: Additional controls in the first-stage reduced-form estimations are age and non-white indicator variables.

Table 7.b: Structural Model and Tests

Education Continuous Variable Linear Models

	All Sample		2 <= Education <= 11		5 <= Education <= 11		0 <= Education <= 4	
Parameters	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
β_1	0.128	0.001	0.107	0.002	0.094	0.006	0.223	0.002
β_2	0.124	0.001	0.099	0.002	0.122	0.005	0.200	0.002
λ^h_1	0.179	0.001	0.193	0.002	0.085	0.006	0.289	0.002
λ^h_2	0.202	0.001	0.176	0.002	-0.003	0.006	0.288	0.002
λ^w_1	0.218	0.001	0.189	0.002	0.070	0.006	0.262	0.002
λ^w_2	0.248	0.001	0.247	0.001	0.164	0.003	0.339	0.002
γ	0.635	0.003	0.626	0.006	0.788	0.028	0.758	0.004
Chi-Squared (DF)	58.911	(1)	31.941	(1)	0.126	(1)	31.698	(1)

Note: Additional controls in the first-stage reduced-form estimations are age and non-white indicator variables.

IX. Figures

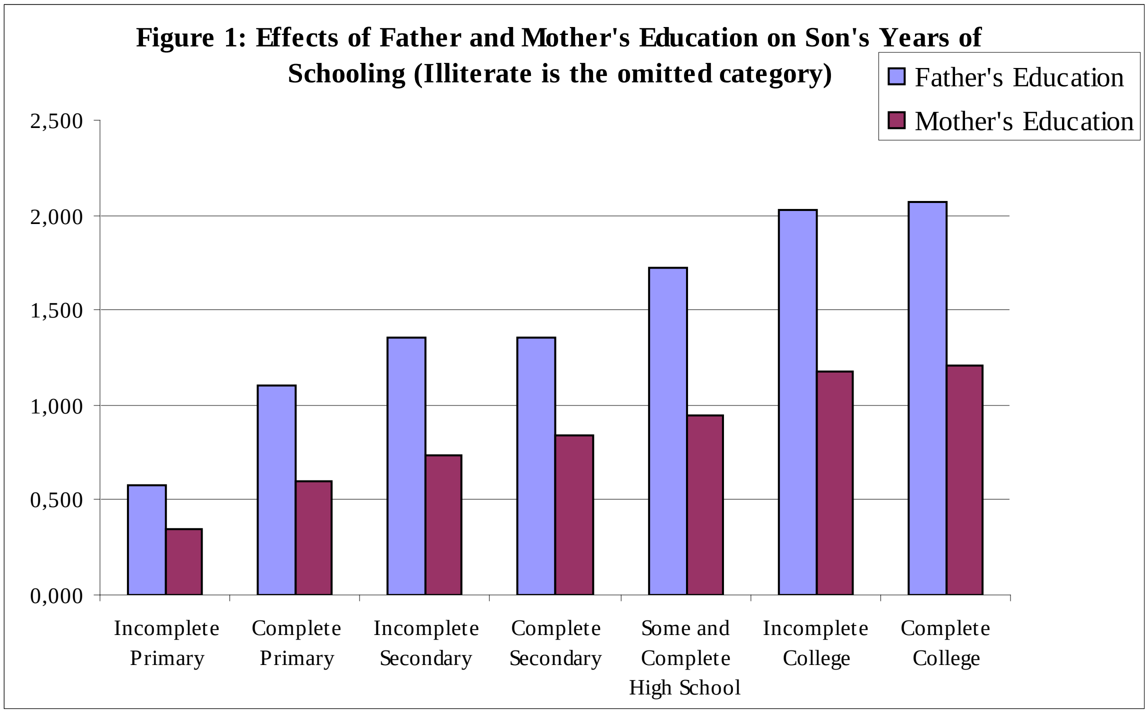


Figure 1: Effects of Father and Mother's Education on Son's Years of Schooling (Illiterate is the omitted category)
Father's Education
Mother's Education
2,500
2,000
1,500
1,000
0,500
0,000
Incomplete Primary
Complete Primary
Incomplete Secondary
Complete Secondary
Some and Complete High School
Incomplete College
Complete College

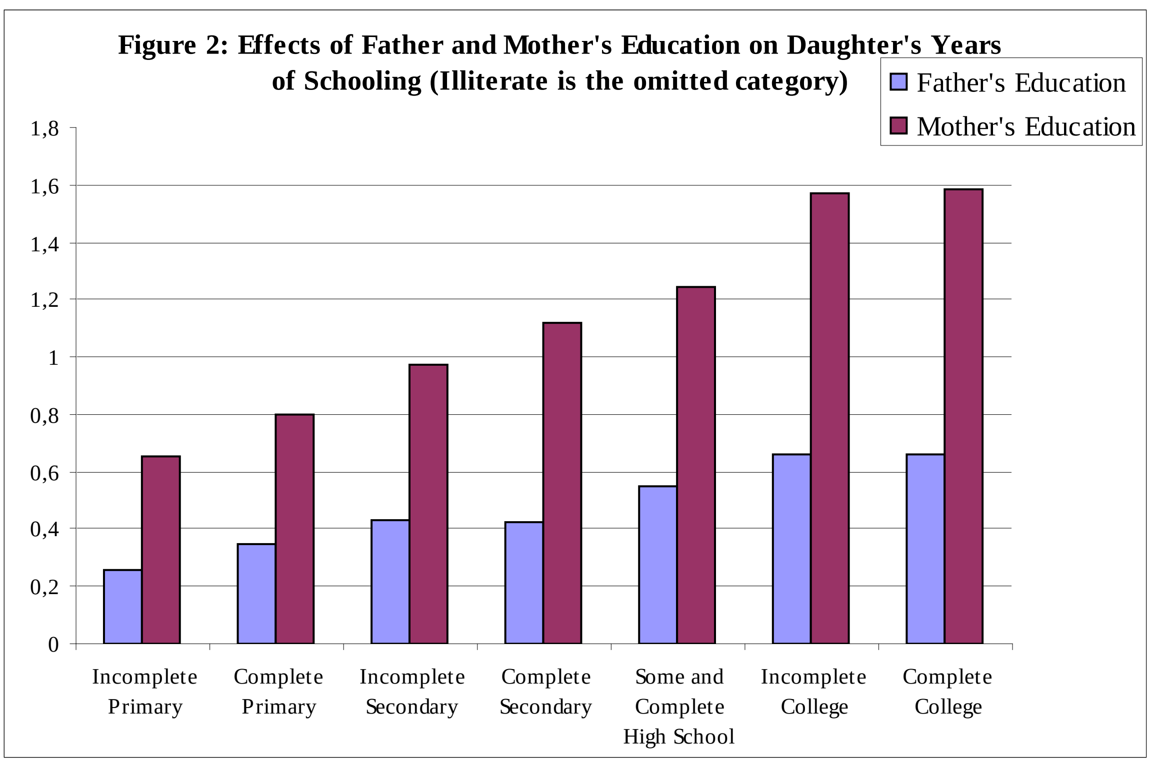


Figure 2: Effects of Father and Mother's Education on Daughter's Years of Schooling (Illiterate is the omitted category)
Father's Education
Mother's Education
1,8
1,6
1,4
1,2
1
0,8
0,6
0,4
0,2
0
Incomplete Primary
Complete Primary
Incomplete Secondary
Complete Secondary
Some and Complete High School
Incomplete College
Complete College

Figure 3: Marginal Effects of Father and Mother's Education on Son's Years of Schooling (Illiterate is the omitted category)

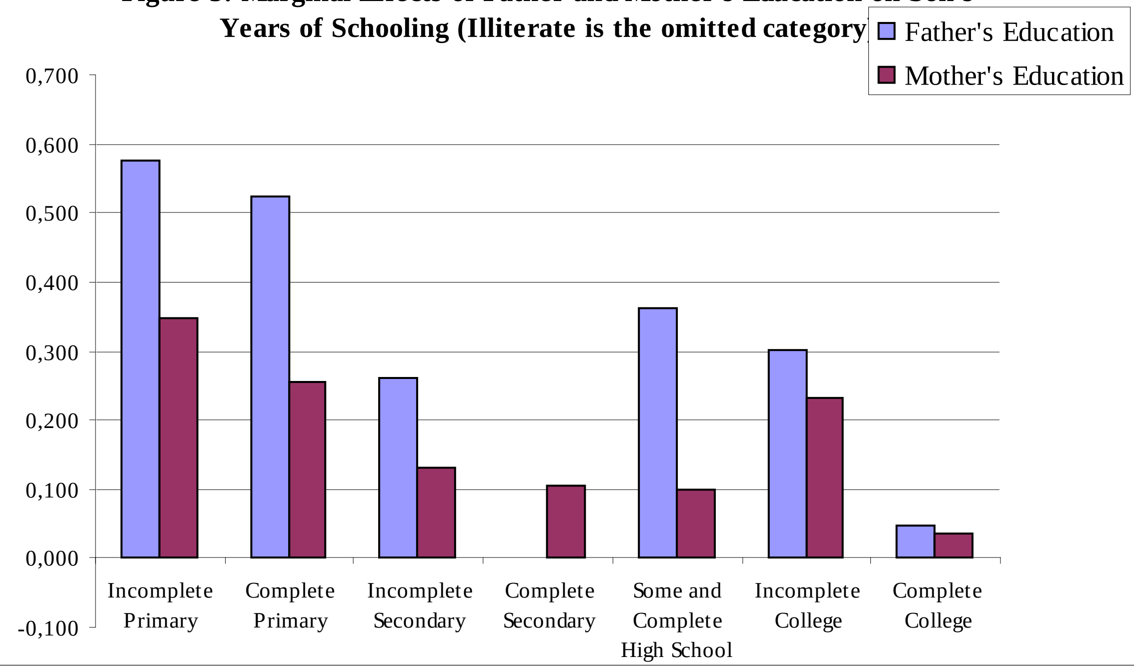


Figure 4: Marginal Effects of Father and Mother's Education on Daughter's Years of Schooling (Illiterate is the omitted c

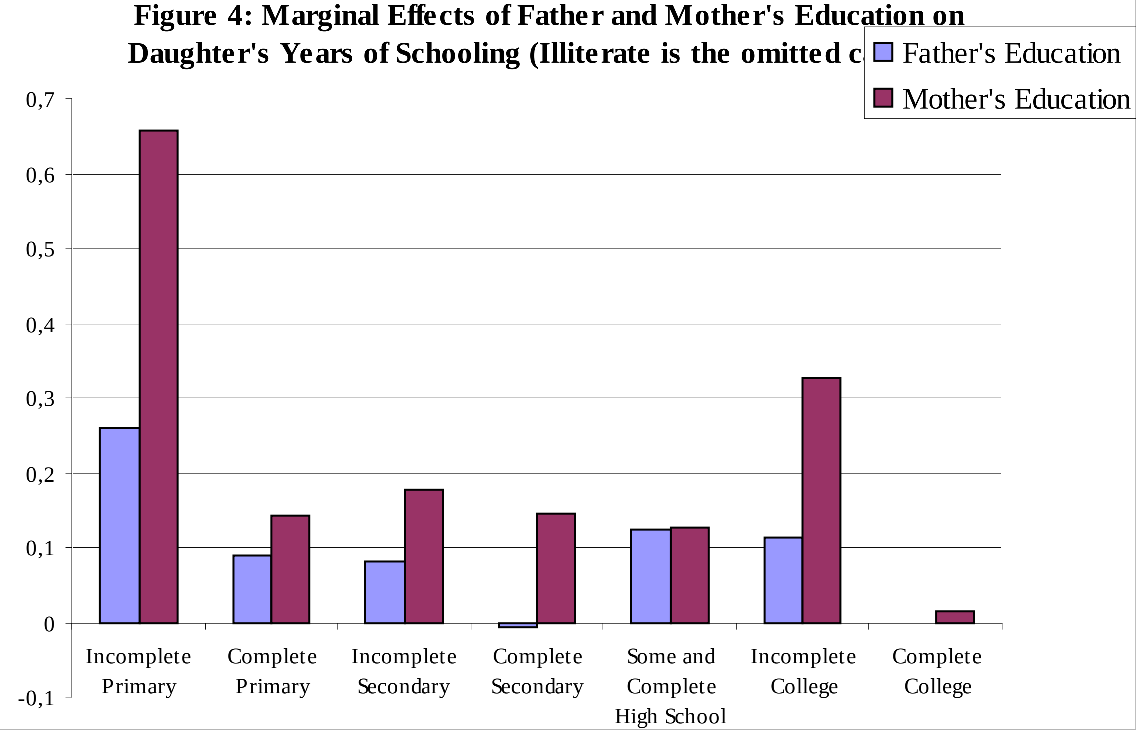
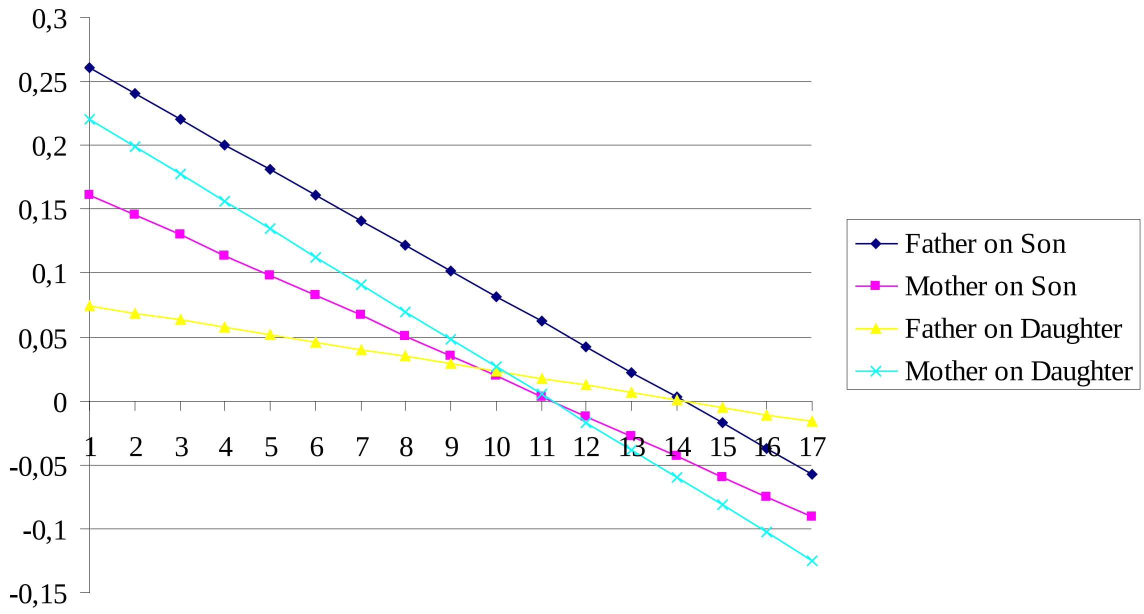


Figure 5: Marginal Effects of Parent's Education



X. Appendix

Table A.1: Sample Slection - 1996 PNAD

Restrictions	Number of Observations	%
Number of Households	84.947	100%
With Spouses	61.027	72%
With Heads and Spouses Aged 25 to 97	53.092	63%
With Valid Information on Their Education,and Race/Color	52.550	62%
With Valid Information on Their Parents' Education	33.406	39%

Table A.2: Sample Basic Statistics

Variable	N	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
		Husbands (Sons)				Wives (Daughters)			
Years of Schooling	33,406	5.772	4.830	0	18	5.843	4.634	0	18
Age	33,406	45.980	13.181	25	96	42.234	12.253	25	91
Non-White	33,406	0.402	0.490	0	1	0.377	0.485	0	1
Father's Education									
No School	33,406	0.409	0.492	0	1	0.393	0.488	0	1
Incomplete Primary	33,406	0.286	0.452	0	1	0.289	0.453	0	1
Completed Primary	33,406	0.183	0.387	0	1	0.193	0.394	0	1
Incomplete Secondary	33,406	0.020	0.142	0	1	0.024	0.153	0	1
Complete Secondary	33,406	0.032	0.177	0	1	0.034	0.181	0	1
Some and Completed High School	33,406	0.041	0.197	0	1	0.041	0.199	0	1
Incomplete College	33,406	0.003	0.050	0	1	0.003	0.052	0	1
Completed College or More	33,406	0.026	0.159	0	1	0.024	0.153	0	1
Mother's Education									
No School	33,406	0.470	0.499	0	1	0.455	0.498	0	1
Incomplete Primary	33,406	0.250	0.433	0	1	0.256	0.436	0	1
Completed Primary	33,406	0.169	0.375	0	1	0.177	0.382	0	1
Incomplete Secondary	33,406	0.023	0.149	0	1	0.026	0.158	0	1
Complete Secondary	33,406	0.033	0.179	0	1	0.032	0.176	0	1
Some and Completed High School	33,406	0.045	0.206	0	1	0.042	0.201	0	1
Incomplete College	33,406	0.001	0.033	0	1	0.001	0.034	0	1
Completed College or More	33,406	0.010	0.097	0	1	0.010	0.102	0	1

Table A.3: Strucutral Models 1 to 7 - Education Discrete Variable Models

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Parameters	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
β_2	0.576	0.005	0.576	0.005	0.573	0.005	0.576	0.005	0.575	0.005	0.572	0.005	0.692	0.005
β_3	1.099	0.007	1.099	0.007	1.093	0.007	1.098	0.007	1.152	0.007	1.089	0.007		
β_4	1.360	0.014	1.360	0.014	1.357	0.014	1.355	0.011			1.496	0.010	1.291	0.010
β_5	1.360	0.013	1.359	0.013	1.355	0.013								
β_6	1.723	0.012	1.722	0.012	1.849	0.011	1.723	0.012	1.699	0.012			1.653	0.012
β_7	2.025	0.031	2.067	0.014			2.066	0.014	2.047	0.014	2.021	0.014	1.982	0.014
β_8	2.074	0.015												
β_{10}	0.348	0.005	0.349	0.005	0.352	0.005	0.350	0.005	0.356	0.005	0.351	0.005	0.469	0.005
β_{11}	0.603	0.006	0.603	0.006	0.610	0.006	0.602	0.006	0.651	0.006	0.607	0.006		
β_{12}	0.735	0.010	0.735	0.010	0.744	0.010	0.786	0.009			0.848	0.009	0.714	0.009
β_{13}	0.841	0.011	0.842	0.011	0.853	0.011								
β_{14}	0.941	0.011	0.941	0.011	1.017	0.011	0.929	0.011	0.901	0.011			0.853	0.011
β_{15}	1.172	0.032	1.204	0.015			1.194	0.015	1.170	0.015	1.181	0.015	1.136	0.015
β_{16}	1.207	0.016												
λ^h_2	0.461	0.005	0.461	0.005	0.465	0.005	0.461	0.005	0.462	0.005	0.460	0.005	0.410	0.005
λ^h_3	1.165	0.007	1.165	0.007	1.170	0.007	1.166	0.007	1.138	0.007	1.172	0.007	1.347	0.007
λ^h_4	1.452	0.015	1.451	0.015	1.452	0.015	1.454	0.014	1.544	0.014	1.391	0.014	1.491	0.014
λ^h_5	1.747	0.013	1.748	0.013	1.747	0.013	1.752	0.013	1.836	0.012	1.688	0.012	1.767	0.013
λ^h_6	1.835	0.013	1.834	0.013	1.769	0.012	1.835	0.013	1.843	0.013	1.943	0.012	1.872	0.013
λ^h_7	1.828	0.034	1.810	0.032	1.902	0.031	1.810	0.032	1.782	0.032	1.840	0.032	1.862	0.032
λ^h_8	2.168	0.015	2.170	0.015	2.263	0.014	2.171	0.015	2.173	0.015	2.190	0.015	2.208	0.015
λ^h_{10}	0.645	0.005	0.645	0.005	0.641	0.005	0.644	0.005	0.638	0.005	0.646	0.005	0.602	0.005
λ^h_{11}	1.228	0.007	1.227	0.007	1.224	0.007	1.228	0.007	1.212	0.007	1.225	0.007	1.293	0.007
λ^h_{12}	1.317	0.014	1.317	0.014	1.310	0.014	1.291	0.014	1.351	0.014	1.267	0.014	1.339	0.014
λ^h_{13}	1.959	0.013	1.959	0.013	1.962	0.013	1.983	0.013	2.062	0.012	1.950	0.013	2.020	0.013
λ^h_{14}	2.119	0.013	2.120	0.013	2.091	0.013	2.124	0.013	2.141	0.013	2.160	0.012	2.160	0.012
λ^h_{15}	2.330	0.046	2.310	0.042	2.442	0.042	2.315	0.042	2.336	0.042	2.360	0.042	2.449	0.042
λ^h_{16}	2.284	0.021	2.286	0.021	2.352	0.020	2.291	0.021	2.301	0.020	2.310	0.020	2.319	0.020
λ^w_2	0.580	0.005	0.579	0.005	0.578	0.005	0.579	0.005	0.577	0.005	0.577	0.005	0.588	0.005
λ^w_3	1.242	0.007	1.242	0.007	1.242	0.007	1.239	0.007	1.223	0.007	1.239	0.007	1.326	0.006
λ^w_4	1.566	0.014	1.566	0.014	1.562	0.014	1.561	0.014	1.599	0.014	1.538	0.014	1.608	0.014
λ^w_5	2.127	0.012	2.127	0.012	2.124	0.012	2.125	0.012	2.150	0.012	2.108	0.012	2.162	0.012
λ^w_6	2.634	0.012	2.634	0.012	2.600	0.012	2.629	0.012	2.621	0.012	2.678	0.012	2.675	0.012
λ^w_7	2.667	0.031	2.657	0.030	2.712	0.030	2.661	0.030	2.628	0.030	2.690	0.030	2.703	0.030
λ^w_8	3.143	0.015	3.144	0.015	3.189	0.014	3.139	0.015	3.132	0.015	3.140	0.015	3.210	0.015
λ^w_{10}	0.617	0.005	0.617	0.005	0.616	0.005	0.618	0.005	0.617	0.005	0.624	0.005	0.583	0.005
λ^w_{11}	1.318	0.007	1.318	0.007	1.314	0.007	1.320	0.007	1.289	0.007	1.331	0.007	1.415	0.007
λ^w_{12}	1.579	0.014	1.580	0.014	1.576	0.014	1.552	0.014	1.629	0.013	1.538	0.014	1.588	0.014
λ^w_{13}	1.777	0.014	1.776	0.014	1.777	0.014	1.824	0.013	1.936	0.012	1.793	0.013	1.864	0.013
λ^w_{14}	2.414	0.013	2.415	0.013	2.365	0.013	2.427	0.013	2.448	0.013	2.522	0.012	2.488	0.013
λ^w_{15}	2.855	0.057	2.822	0.049	3.063	0.048	2.834	0.049	2.905	0.049	2.877	0.049	2.814	0.049
λ^w_{16}	2.224	0.019	2.228	0.019	2.350	0.018	2.235	0.019	2.253	0.019	2.286	0.019	2.250	0.019
γ	0.325	0.004	0.325	0.004	0.326	0.005	0.328	0.004	0.341	0.004	0.330	0.004	0.303	0.005
δ	4.067	0.085	4.062	0.085	3.999	0.084	4.019	0.084	3.798	0.077	3.887	0.081	4.336	0.096
ρ	1.425	0.013	1.425	0.013	1.431	0.013	1.419	0.013	1.404	0.012	1.448	0.013	1.166	0.008
Chi-Squared (DF)	16.641	(11)	16.677	(13)	29.042	(15)	17.690	(15)	34.499	(17)	30.595	(17)	125.552	(17)
Chi-Squared Difference(DF)			0.037	(2)	12.402	(4)	1.050	(4)	17.858	(6)	13.954	(6)	108.912	(6)

Note 1: Additional controls in the first-stage reduced-form estimations are age and non-white indicator variables.

Note 2: The models test the following assumptions:

Model 2:	β_7=β_8, β_{15}=β_{16}
Model 3:	β_6=β_7=β_8, β_{14}=β_{15}=β_{16}
Model 4:	β_4=β_5, β_7=β_8, β_{12}=β_{13}, β_{15}=β_{16}
Model 5:	β_3=β_4=β_5, β_7=β_8, β_{11}=β_{12}=β_{13}, β_{15}=β_{16}
Model 6:	β_4=β_5=β_6, β_7=β_8, β_{12}=β_{13}=β_{14}, β_{15}=β_{16}
Model 7:	β_2=β_3, β_4=β_5, β_7=β_8, β_{10}=β_{11}, β_{12}=β_{13}, β_{15}=β_{16}

Table A.4: Strucutral Models 1 to 7 - Education Discrete Variable Models
Alternative Sample

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
Parameters	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
β_2	0.551	0.004	0.551	0.004	0.549	0.004	0.551	0.004	0.551	0.004	0.548	0.004	0.666	0.004
β_3	1.015	0.006	1.015	0.006	1.009	0.006	1.013	0.006	1.067	0.006	1.007	0.006		
β_4	1.278	0.012	1.276	0.012	1.270	0.012	1.244	0.009			1.361	0.008	1.216	0.009
β_5	1.225	0.012	1.224	0.012	1.222	0.012								
β_6	1.555	0.011	1.554	0.011	1.688	0.010	1.559	0.011	1.554	0.011			1.536	0.011
β_7	1.873	0.031	1.897	0.013			1.897	0.013	1.888	0.012	1.868	0.012	1.867	0.012
β_8	1.904	0.013												
β_{10}	0.359	0.004	0.359	0.004	0.361	0.004	0.360	0.004	0.363	0.004	0.360	0.004	0.501	0.004
β_{11}	0.648	0.005	0.649	0.005	0.653	0.005	0.647	0.005	0.684	0.005	0.651	0.005		
β_{12}	0.713	0.009	0.715	0.009	0.718	0.009	0.798	0.008			0.862	0.007	0.733	0.007
β_{13}	0.888	0.010	0.890	0.010	0.891	0.010								
β_{14}	0.965	0.010	0.966	0.010	1.020	0.009	0.951	0.010	0.928	0.009			0.883	0.009
β_{15}	1.313	0.033	1.163	0.014			1.151	0.014	1.125	0.014	1.139	0.014	1.084	0.013
β_{16}	1.143	0.014												
λ^h_2	0.506	0.004	0.505	0.004	0.505	0.004	0.506	0.004	0.504	0.004	0.507	0.004	0.459	0.004
λ^h_3	1.189	0.006	1.189	0.006	1.191	0.006	1.190	0.006	1.160	0.006	1.198	0.006	1.352	0.006
λ^h_4	1.425	0.013	1.427	0.013	1.428	0.013	1.442	0.012	1.517	0.012	1.391	0.012	1.459	0.012
λ^h_5	1.813	0.012	1.814	0.012	1.813	0.012	1.808	0.011	1.884	0.011	1.755	0.011	1.820	0.011
λ^h_6	1.998	0.011	1.999	0.011	1.921	0.011	1.995	0.011	1.999	0.011	2.097	0.011	2.023	0.011
λ^h_7	1.774	0.030	1.761	0.028	1.835	0.027	1.759	0.028	1.742	0.028	1.771	0.028	1.796	0.028
λ^h_8	2.344	0.014	2.347	0.013	2.434	0.013	2.348	0.013	2.341	0.013	2.365	0.013	2.367	0.013
λ^h_{10}	0.638	0.004	0.638	0.004	0.638	0.004	0.638	0.004	0.635	0.004	0.640	0.004	0.577	0.004
λ^h_{11}	1.267	0.006	1.267	0.006	1.267	0.006	1.267	0.006	1.251	0.006	1.263	0.006	1.336	0.006
λ^h_{12}	1.487	0.012	1.487	0.012	1.483	0.012	1.444	0.012	1.501	0.012	1.412	0.012	1.485	0.012
λ^h_{13}	2.044	0.011	2.043	0.011	2.044	0.011	2.083	0.011	2.138	0.011	2.052	0.011	2.115	0.011
λ^h_{14}	2.196	0.011	2.195	0.011	2.177	0.011	2.201	0.011	2.210	0.011	2.239	0.011	2.229	0.011
λ^h_{15}	2.379	0.045	2.473	0.041	2.569	0.041	2.484	0.041	2.501	0.041	2.490	0.041	2.584	0.041
λ^h_{16}	2.475	0.019	2.464	0.019	2.522	0.018	2.468	0.019	2.479	0.019	2.479	0.019	2.499	0.019
λ^w_2	0.566	0.004	0.565	0.004	0.564	0.004	0.564	0.004	0.563	0.004	0.564	0.004	0.568	0.004
λ^w_3	1.299	0.006	1.299	0.006	1.298	0.006	1.296	0.006	1.284	0.006	1.297	0.006	1.361	0.005
λ^w_4	1.560	0.012	1.560	0.012	1.556	0.012	1.560	0.012	1.596	0.011	1.541	0.012	1.584	0.012
λ^w_5	2.135	0.010	2.134	0.010	2.126	0.010	2.128	0.010	2.156	0.010	2.114	0.010	2.140	0.010
λ^w_6	2.598	0.010	2.597	0.010	2.560	0.010	2.592	0.010	2.589	0.010	2.640	0.010	2.599	0.010
λ^w_7	2.656	0.028	2.648	0.028	2.684	0.028	2.650	0.028	2.632	0.028	2.665	0.028	2.649	0.028
λ^w_8	3.049	0.013	3.050	0.013	3.090	0.013	3.049	0.013	3.048	0.013	3.050	0.013	3.081	0.013
λ^w_{10}	0.627	0.004	0.627	0.004	0.629	0.004	0.629	0.004	0.628	0.004	0.631	0.004	0.598	0.004
λ^w_{11}	1.336	0.006	1.336	0.006	1.337	0.006	1.340	0.006	1.318	0.006	1.345	0.006	1.425	0.006
λ^w_{12}	1.581	0.012	1.581	0.012	1.588	0.012	1.539	0.011	1.594	0.011	1.520	0.011	1.571	0.011
λ^w_{13}	1.961	0.012	1.961	0.012	1.978	0.012	2.032	0.011	2.114	0.011	1.996	0.011	2.058	0.011
λ^w_{14}	2.524	0.011	2.525	0.011	2.502	0.011	2.538	0.011	2.547	0.011	2.618	0.010	2.577	0.011
λ^w_{15}	2.944	0.052	3.092	0.043	3.270	0.042	3.101	0.043	3.126	0.043	3.141	0.043	3.119	0.043
λ^w_{16}	2.552	0.017	2.541	0.017	2.632	0.016	2.547	0.017	2.559	0.017	2.587	0.017	2.562	0.017
γ	0.342	0.004	0.343	0.004	0.345	0.004	0.347	0.004	0.356	0.004	0.344	0.004	0.334	0.004
δ	3.381	0.060	3.358	0.059	3.300	0.058	3.307	0.058	3.208	0.056	3.277	0.058	3.491	0.064
ρ	1.485	0.012	1.485	0.012	1.489	0.012	1.477	0.012	1.470	0.011	1.503	0.012	1.153	0.007
Chi-Squared (DF)	21.897	(11)	22.173	(13)	32.823	(15)	25.111	(15)	39.926	(17)	37.295	(17)	149.174	(17)
Chi-Squared Difference(DF)			0.276	(2)	10.927	(4)	3.215	(4)	18.029	(6)	15.399	(6)	127.277	(6)

Note 1: Additional controls in the first-stage reduced-form estimations are, non-white indicator variables, unknown parents' education indicator variables, and missing parents' education indicator variables.

Note 2: The models test the following assumptions:

Model 2: $\beta_7=\beta_8$, $\beta_{15}=\beta_{16}$

Model 3: $\beta_6=\beta_7=\beta_8$, $\beta_{14}=\beta_{15}=\beta_{16}$

Model 4: $\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$

Model 5: $\beta_3=\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{11}=\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$

Model 6: $\beta_4=\beta_5=\beta_6$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}=\beta_{14}$, $\beta_{15}=\beta_{16}$

Model 7: $\beta_2=\beta_3$, $\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{10}=\beta_{11}$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$

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