Does The Gradient Matter?
Further Understanding the Intergenerational Transmission of Human Capital

Abstract

This paper investigates the relationship between the educational attainment of parents and children in a developing country context and evaluates the importance of the gradients. Specifically, it explores three related questions: (i) Is there a causal effect in the intergenerational transmission of human capital? (ii) if yes, does the gradient matter? That is, are there decreasing marginal effects of parent's schooling? And (iii) do these effects differ across genders? 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 adult individual's parents' educational attainments. The data set is the 1996 *Brazilian Annual Household Survey* from the Brazilian Census Bureau (PNAD/IBGE). 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 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. These results shed some new light in understanding the intergeneration transmission of human capital. First, it suggests that there is a causal relationship from parent's education to the education of sons and daughters. Second, the impact is larger at lower levels of schooling, and diminishes as schooling attainment increases for a given cycle of the formal education. Third, there appears to be a strong gender component in the intergenerational transmission mechanism.

(**JEL classification numbers:** J24, J62, O15)

(**Keywords:** Human Capital, Intergenerational Transmission, Developing Countries)

Introduction

It is well established in the literature that more educated parents have children with higher educational attainment. There are two generic explanations of this relationship.

On the one hand, this can be 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 have no impact on the education of the child, since child's education is entirely determined by type.

On the other hand, this can be 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.

Of course, the two explanations 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 the 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), Antonovics and Goldberg (2003)), the use of samples of adoptees (e.g., Bjoerklund et al. (2006), Plug (2004), Sacerdote (2002)), and the use of instrumental variables (e.g., Balck et al. (2005), Chevalier (2004), Oreopolulos et al (2004)). 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.

The results are not conclusive. Some studies have found positive effects of parent's schooling on the educational attainment of the child, while most of the others have found no effect and one has even found negative effects. In addition, the findings are difficult to interpret given the limitations of the samples used and the identification assumptions for the instruments selected.

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 gradients. Specifically, it explores three related questions: (i) Is there a causal effect in the intergenerational transmission of human capital? (ii) if yes, does the gradient matter? That is, are there decreasing marginal effects of parent's schooling? And (iii) do these effects differ across genders? 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 adult individual's parents' educational attainments. The data set is 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). Thus it allows the estimation of the gradient effects.

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 (we think) 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 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.

These results shed some new light in understanding the intergeneration transmission of human capital. First, it suggests that there is a causal relationship from parent's education to the education of sons and daughters. Second, the impact is larger at lower levels of schooling, and diminishes as schooling attainment increases for a given cycle of the formal education. Third, there appears to be a strong gender component in the intergenerational transmission mechanism.

The paper proceeds as follows. Section II presents the data used and the sample selected. Section III shows the stylized facts and evidences of the education distribution among parents and sons and daughters in the sample. Section IV introduces the structural model to be estimated and tested and the method of estimation used. 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 it 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 of schooling (in comparison to more developed countries). Thus it allows the estimation of the gradient effects and the discussion of policy responses in an environment where it matters the most. 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 to 97 years old that are household head or spouse living in households where there are head and spouse. A male head or spouse is considered the husband and a female head or spouse is considered wife. The sample is restricted to the age 25 to 97 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 attainment at the age 25 and above. The age 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.[1] Note that more than 85% of all individuals 25 years old and above are household heads or spouses. In fact, if we consider age 30 and above, more than 92% of them are heads or spouses. Moreover, since we will explore the correlation of the parents' education and in-laws' education, we further restrict the sample to households with heads and spouses. Thus households with no spouses are automatically excluded from the sample. Of all households in 1996 Pnad, 28% are single head households. Finally the sample is further restricted to husbands and wives with valid information on their education attainment, gender, race/color, and their parent's education attainment. Note that in this sample, due to the nature of the questionnaire, the husband is the son and the wife is the daughter. The Table A.1 in the appendix presents the number of observations kept in each step of the sample selection.

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 further to

[1] 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.

observations with valid information only the final sample consists of 33,406 observations of husbands and wives. The greatest decrease in the sample size is due to the existence of no information on 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 or mother final education attainment. A closer inspection of those that declared they did not know their parents' education showed 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 goes against us. Since these husbands (sons) and wives (daughters) are dropped, the final sample may over-represent the more educated ones. Since there is a steady expansion of education attainment across generations in Brazil, it is likely that the final sample is more homogenous in education than otherwise. Thus, the positive relationship between parents' education and sons and daughters' education is likely to be steeper than the one observed in this sample.

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' education attainments are reported in categories in 1996 PNAD. They are illiterate, 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 shows that around

40 percent of the fathers are illiterate, 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 illiterates (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 are very low educated and the rest are relatively more equally distributed over the levels above primary education. The next section presents some stylized facts of the cross-generation education relationships.

II. The Stylized Facts

Table 1 shows the education 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 attainments 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 to right education distribution and the figures of Table 1 are no different.   It is also a fact that the younger generations have obtained 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. Their figures are the probability of a son (or a daughter) to have a certain education level, given the education level of the father (or the mother). For instance, the second row in the up/left matrix shows that of all sons from 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 of sons and daughters of more educated parents. The results are 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) of at least some college educated father, 71.2 (62.4) percent have at least some college education. Similar figures for sons and daughters with a college educated mother: 72.9 and 72.3, respectively. Thus, the parents' education is a good predictor to the sons and daughters' education in Brazil.

The low intergenerational education mobility in Brazil presented in Table 1 has been documented before (e.g., Veloso e Ferreira (2003)).   The still open question is that if it is due to some education causality mechanism or some education-type selection process. This paper tries precisely to disentangle these two issues. In order to pursue this goal, the paper explores the particular nature of the data that the sons and daughters are husband and wives, respectively, and that it carries the information about their parents' education. If one assumes that the assortative matching 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, one can explore the observable correlations among the education attainments of sons, daughters, parents, and in-laws in order to control for individuals' unobservable characteristics correlated to 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 at 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 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 to belong to a given cell. The row percentage gives the probability of a wife to have a certain education level, given a husband's education level. The column percentage gives the probability of a husband to have a certain education level, given a 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 higher educated husbands marry higher educated wives and lower educated husbands marry lower educated wives. Qualitatively similar patterns are encountered in the other two cross-tabulations. For instance, of all mothers married to primary educated fathers, more than 96 percent are primary educated as well. So, the fathers and mothers of the husbands and wives also present this positive assortative matching in education attainments revealing, perhaps, 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' education are strongly associated to each other, it is likely that the husbands' parent's education be positively associated with the wives' parent's education. 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 their fathers (mothers) primary educated. Only 0.8 (0.3) 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.

IV. 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

$$S_{ij} = \phi_j x_{ij} + \beta_j^f S_{ij}^f + \beta_j^m S_{ij}^m + \varepsilon_{ij}, i = 1,..., N, j = h, w. \tag{1}$$

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:

$$\varepsilon_{ij} = c_{ij} + u_{ij}. \tag{2}$$

Then the model becomes

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

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 positive correlated with parent's education. It can be that high-educated type parents generate high-educated type sons and daughters, and/or that high-educated parents have stronger tastes for education that shape their sons and daughters' tastes as well, and/or even that high-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, the regression that do not control for c_{ij} bias upwardly the estimations of β_j^f and β_j^f.

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

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

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

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

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:

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

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

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. Illiterate 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 squared terms. In both cases the fathers' (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-identifiable. For instance, in the discrete variable model, there would be 56 reduced-form coefficients and 44 structural parameters (14 β ' s , 28 λ ' 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 $S^p = (S^f_{ih}, S^m_{ih}, S^f_{iw}, S^m_{iw})$. The unrestricted reduced form model is

$$S_i = \Pi S^p + e_i \ , \tag{7}$$

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

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

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 . Then we use a method of moments estimator to obtain $\beta' s, \lambda' s, \gamma$ and δ using (8). 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. 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 $\beta^f = \beta^m$.

V. 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.

V.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. Illiterate is the omitted category. Also, the husband's and 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 (illiterate 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. The comparison can give us an idea of the bias one can incur if does not control for person and family's effect. 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, the older generations have lower education attainment than younger ones. Third, non-white individuals have lower schooling than white individuals. Fourth, father's (mother's) education point estimates are greater for sons (daughters) than for daughters (sons) in both OLS n SUR regressions. Finally, SUR point estimates are lower than OLS point estimates. It suggests that if we do not control for correlation of the error terms we bias upward the parents' education effect.

The parameters' 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 6. 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.XX 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 as controls solely.

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). The effects of the father and mother's education on son and daughter's education are presented in Figure 1 and 2, respectively. Both the 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 when the unobservable person and family effect are controlled for. As expected, once the unobservable person and family effect is controlled the parents' education effects become Three to Four times smaller than those estimated by OLS. For instance, according to the OLS estimates a father that completes a primary education increases his son's schooling by 3.11 years in comparison with an illiterate father. 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 effect and the parents' education. The failure to control for it will bias the education effect upwardly.

The model 1 in Table 5 shows that the positive effect of parents' education on their sons' education still survive after we take the unobservable person and family effect into account. Moreover, it shows that the effects differ at different levels of parents' education. Indeed, there seems to be gradient effects for certain range of education levels. More precisely, Figures 1 and 2 depict the pattern that the father's effect increases at decreasing rates up to high school level, when it jumps up and level off later again. Similarly, the mother's effect increases at decreasing rates up to incomplete college, when it jumps up and level 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 1.414x0.317 = 0.448. The mother effect on the daughter's education is 4.225x0.317 = 1.338 the effect on the son's education except, again, for incomplete primary education that becomes 1.414x4.225x0.317 = 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 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 to each other. We do this by imposing additional restrictions in 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 ($\beta_7=\beta_8$, $\beta_{15}=\beta_{16}$). This is not rejected. Model 3 tests if some college and college has some impact over high school ($\beta_6=\beta_7=\beta_8$, $\beta_{14}=\beta_{15}=\beta_{16}$). This is s is rejected. Model 4 adds to model 2 the assumption that complete secondary has no extra effect over incomplete primary ($\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$). We do not reject it. Models 5, 6, and 7 test additionally if high school adds to secondary ($\beta_3=\beta_4=\beta_5$, $\beta_7=\beta_8$, $\beta_{11}=\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$), if secondary adds to primary ($\beta_4=\beta_5=\beta_6$, $\beta_7=\beta_8$, $\beta_{12}=\beta_{13}=\beta_{14}$, $\beta_{15}=\beta_{16}$), and if completed primary adds to incomplete primary ($\beta_2=\beta_3$, $\beta_4=\beta_5$,

$\beta_7=\beta_8$, $\beta_{10}=\beta_{11}$, $\beta_{12}=\beta_{13}$, $\beta_{15}=\beta_{16}$), respectively. All of them are rejected. In conclusion, model 4 is the most restrictive model that are 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 evaluate the effects of changes in parents' education at levels relatively higher comparatively to less developed countries. Some obtained a positive effect, others 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 of a small change of education level, one or two years of schooling, at an education level already high, e.g., eight or nine years of schooling. Looking only in a specific point may miss the whole story and extrapolating their findings may turn out to wrong. 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 'gender effect' varies across the education distribution and the relative impact of fathers and mothers on sons and daughters are different at different levels of their education. If this is true elsewhere, it may also explain why some studies found that sometimes the mother has a positive effect and the father not, and others found the opposite.

IV.2. The Education Continuous Variable Models

In order to compare our results more closely with those more common in the literature we also estimate the model (6') using the parents' education continuous variable years of schooling. The advantage 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: illiterate (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 present 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 8.a) are statistically insignificant. However, the results for those parents with 0 to 4 years of schooling only (as shown in column 5 of Table 8.a) are strongly significant. Thus, the results of table 8.a suggests that in fact there is a gradient effect of parent's education on sons and daughters' education and these effects seem to peter out as parents' education increases. The strongest effect occurs at very low level 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 8.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 8.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.

VI. Conclusions

This paper investigates the relationship between the educational attainment of parents and children in a developing country context and evaluates the importance of the gradients. Specifically, it explores three related questions: (i) Is there a causal effect in the intergenerational transmission of human capital? (ii) if yes, does the gradient matter? That is, are there decreasing marginal effects of parent's schooling? And (iii) do these effects differ across genders? That is, do mothers and fathers affect sons and daughters differently?

This study makes use of a sample of Brazilian 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 (we think) 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 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.

These results shed some new light in understanding the intergeneration transmission of human capital. First, it suggests that there is a causal relationship from parent's education to the education of sons and daughters. Second, the impact is larger at lower levels of schooling, and diminishes as schooling attainment increases for a given cycle of the formal education. Third, there appears to be a strong gender component in the intergenerational transmission mechanism.

VII. References

Antonovics, Kate, and Arthur S. Goldberger. “Does Increasing Women’s Schooling Raise the Schooling of the Next Generation? Comment,” American Economic Review, December 2005.

Behrman Jere R., and Mark R. Rosenzweig “Does Increasing Women’s Schooling Raise the Schooling of the Next Generation?” American Economic Review, 92:1, March 2002, 323-334.

Behrman, J. R. & Rosenzweig, M. R. “Does Increasing Women’s Schooling Raise the Schooling of the Next Generation? Reply.” The American Economic Review 95(5), 2005.

Bjoerklund, Anders, Markus Jantti, and Gary Solon. “Nature and Nurture in the Intergenerational Transmission of Socioeconomic Status: Evidence from Swedish Children and Their Biological and Rearing Parents.” May 2006, Mimeo.

Bjoerklund, A., M. Lindahl, and E. Plug. “The origins of intergenerational associations: Lessons from swedish adoption data.” The Quarterly Journal of Economics, 2006 .

Black, Sandra, Paul J. Devereux, and Kjell G. Salanes. “Why the Apple Doesn’t Fall Far: Understanding the Intergenerational Transmission of Education.” American Economic Review, March 2005.

Chevalier, Arnaud. “Parental Education and Child’s Education: A Natural Experiment.” IZA Discussion Paper No. 1153, May 2004.

Oreopoulos, Philip, Marianne E. Page, Anne Huff Stevens. “The Intergenerational Effects of Compulsory Schooling.” University of Toronto, 2004. Mimeo.

Pastore, J., and N. do Valle Silva. Mobilidade Social no Brasil. Makron Books, São Paulo, 2000.

Plug, Erik. “Estimating the Effect of Mother’s Schooling on Children’s Schooling Using a Sample of Adoptees.” American Economic Review (94) 2004.

Sacerdote, Bruce. The Nature and Nurture of Economic Outcomes. American Economic Review, May 2002.

Veloso, Fernando A., and S. G. Ferreira . Mobilidade Intergeracional de Educação no Brasil. Pesquisa e Planejamento Econômico, Rio de Janeiro, RJ - Brasil, v. 33, n. 3, p. 481-513, 2003.

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					

	Structural Parameters	Model 1 Coeff.	Std. Error
	Father's Education		
β_2	Incomplete Primary	0,580	0,049
β_3	Complete Primary	1,103	0,064
β_4	Incomplete Secondary	1,358	0,134
β_5	Complete Secondary	1,340	0,118
β_6	Some and Complete High School	1,729	0,115
β_7	Incomplete College	2,089	0,344
β_8	Complete College	2,085	0,140
	Mother's Education		
β_{10}	Incomplete Primary	0,347	0,045
β_{11}	Complete Primary	0,597	0,058
β_{12}	Incomplete Secondary	0,729	0,094
β_{13}	Complete Secondary	0,837	0,098
β_{14}	Some and Complete High School	0,930	0,098
β_{15}	Incomplete College	1,174	0,335
β_{16}	Complete College	1,185	0,152
	Daughter's Factor Loads		
γ	Father and Mother's Education	0,317	0,043
δ	Mother's Education	4,225	0,862
	Incomplete Primary Factor Load		
ρ	Father and Mother's Education	1,414	0,123
Chi-Squared (DF)		19,657 (11)	

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	0,580	0,049	0,580	0,049	0,578	0,049	0,580	0,049	0,576	0,049	0,577	0,049	0,736	0,047
β_3	1,103	0,064	1,103	0,064	1,098	0,064	1,102	0,064	1,151	0,062	1,091	0,064		
β_4	1,358	0,134	1,358	0,134	1,351	0,134	1,345	0,098			1,488	0,087	1,296	0,096
β_5	1,340	0,118	1,340	0,118	1,334	0,118								
β_6	1,729	0,115	1,729	0,115	1,856	0,104	1,730	0,115	1,721	0,113			1,674	0,112
β_7	2,089	0,344	2,086	0,135			2,085	0,135	2,072	0,133	2,053	0,133	2,024	0,133
β_8	2,085	0,140												
Mother's Education														
β_{10}	0,347	0,045	0,347	0,045	0,350	0,045	0,349	0,045	0,352	0,045	0,351	0,045	0,479	0,044
β_{11}	0,597	0,058	0,597	0,058	0,602	0,058	0,598	0,058	0,644	0,059	0,606	0,058		
β_{12}	0,729	0,094	0,729	0,094	0,735	0,095	0,786	0,083			0,856	0,081	0,752	0,080
β_{13}	0,837	0,098	0,836	0,098	0,841	0,099								
β_{14}	0,930	0,098	0,930	0,098	0,993	0,099	0,925	0,098	0,901	0,096			0,877	0,094
β_{15}	1,174	0,335	1,183	0,147			1,179	0,147	1,156	0,146	1,178	0,147	1,126	0,143
β_{16}	1,185	0,152												
Daughters' Factor Loads														
γ	0,317	0,043	0,317	0,043	0,317	0,043	0,320	0,043	0,332	0,043	0,322	0,043	0,289	0,045
δ	4,225	0,862	4,226	0,862	4,162	0,851	4,162	0,846	3,944	0,785	4,036	0,818	4,620	1,010
Incomplete Primary Factor Load														
ρ	1,414	0,123	1,414	0,123	1,418	0,123	1,412	0,122	1,409	0,119	1,431	0,122	1,130	0,068
Chi-Squared (DF)	19,657 (11)		19,658 (13)		31,830 (15)		20,867 (15)		40,663 (17)		36,239 (17)		153,880 (17)	
Chi-Squared Diff.(DF)			0,001 (2)		12,173 (4)		1,210 (4)		21,006 (6)		16,582 (6)		134,223 (6)	

Note: 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 8.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	0,281	0,018	0,382	0,063	-0,259	0,460	0,260	0,046
β_2	-0,010	0,001	-0,019	0,005	0,019	0,026	0,006	0,012
β_3	0,176	0,017	0,100	0,038	0,231	0,164	0,276	0,038
β_4	-0,008	0,001	-0,004	0,002	-0,006	0,009	-0,040	0,008
λ^h_1	0,317	0,018	0,425	0,070	0,076	0,846	0,177	0,048
λ^h_2	-0,012	0,001	-0,021	0,005	0,001	0,048	0,024	0,012
λ^h_3	0,350	0,018	0,326	0,065	0,156	0,712	0,334	0,048
λ^h_4	-0,014	0,001	-0,011	0,005	-0,010	0,040	-0,005	0,012
λ^w_1	0,348	0,017	0,325	0,062	0,732	0,703	0,281	0,043
λ^w_2	-0,009	0,001	-0,009	0,005	-0,038	0,040	0,005	0,011
λ^w_3	0,372	0,019	0,341	0,036	0,092	0,104	0,251	0,049
λ^w_4	-0,015	0,001	-0,011	0,003	0,005	0,006	0,013	0,013
γ	0,279	0,046	0,055	0,101	1,015	0,662	0,374	0,057
δ	4,959	1,148	41,424	81,498	0,599	0,588	4,583	1,074
Chi-Squared (DF)	9,712	(2)	0,436	(2)	2,402	(2)	9,060	(2)

14,05	9,97		
11,23	11,55		3,44

Table 8.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	0,007	0,106	0,015	0,094	0,055	0,221	0,002
β_2	0,125	0,008	0,100	0,015	0,122	0,050	0,203	0,002
λ^h_1	0,181	0,008	0,194	0,017	0,085	0,063	0,293	0,002
λ^h_2	0,200	0,009	0,176	0,018	-0,003	0,061	0,283	0,002
λ^w_1	0,218	0,008	0,188	0,017	0,070	0,057	0,263	0,002
λ^w_2	0,246	0,009	0,247	0,014	0,164	0,033	0,335	0,002
γ	0,635	0,025	0,627	0,067	0,788	0,276	0,769	0,004
Chi-Squared (DF)	71,411	(1)	33,460	(1)	0,126	(1)	36,278	(1)

IX. Figures

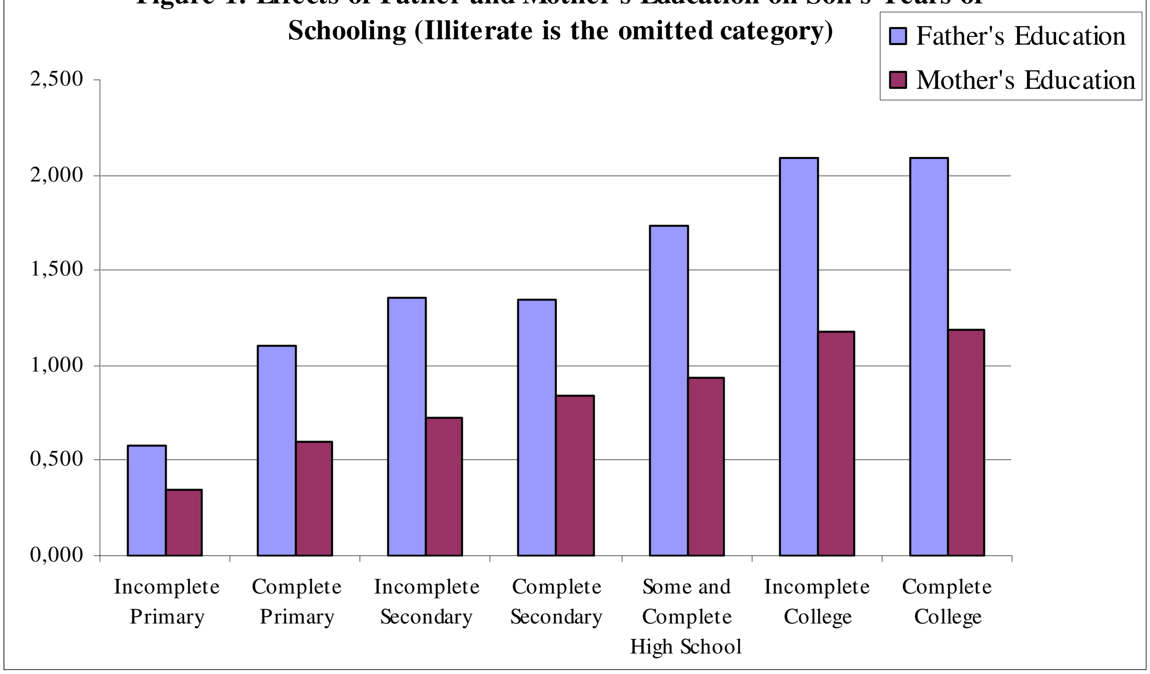


Figure 1: Effects of Father and Mother's Education on Son's Years of Schooling (Illiterate is the omitted category)

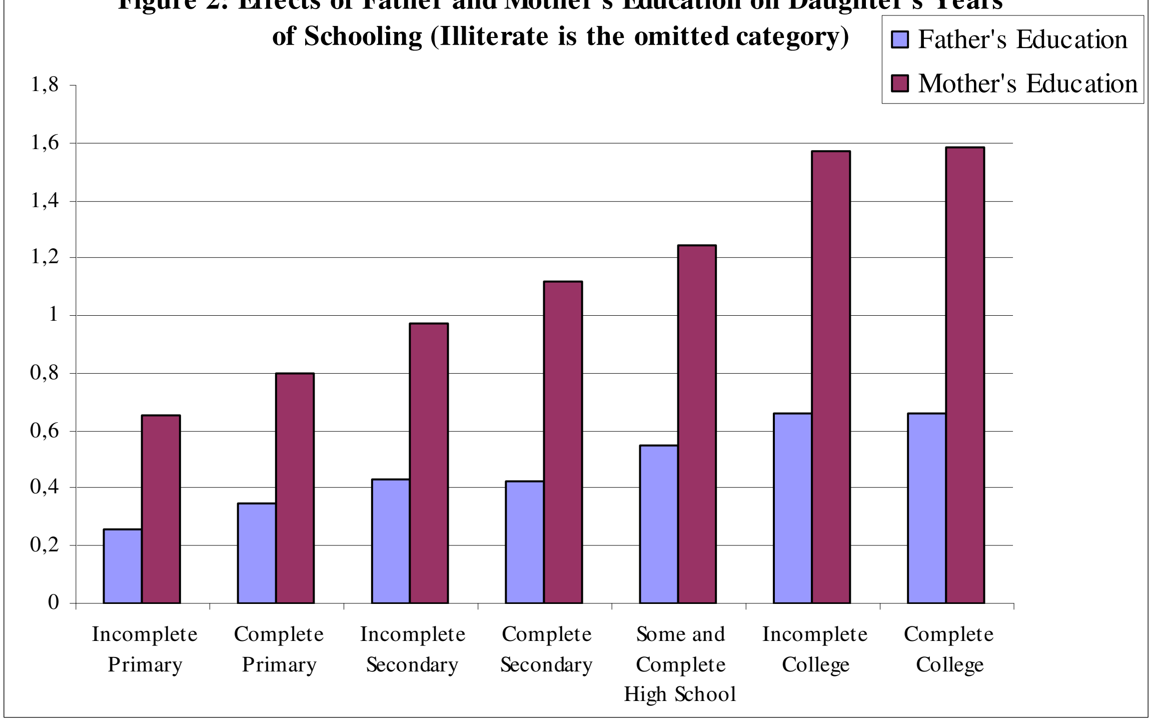
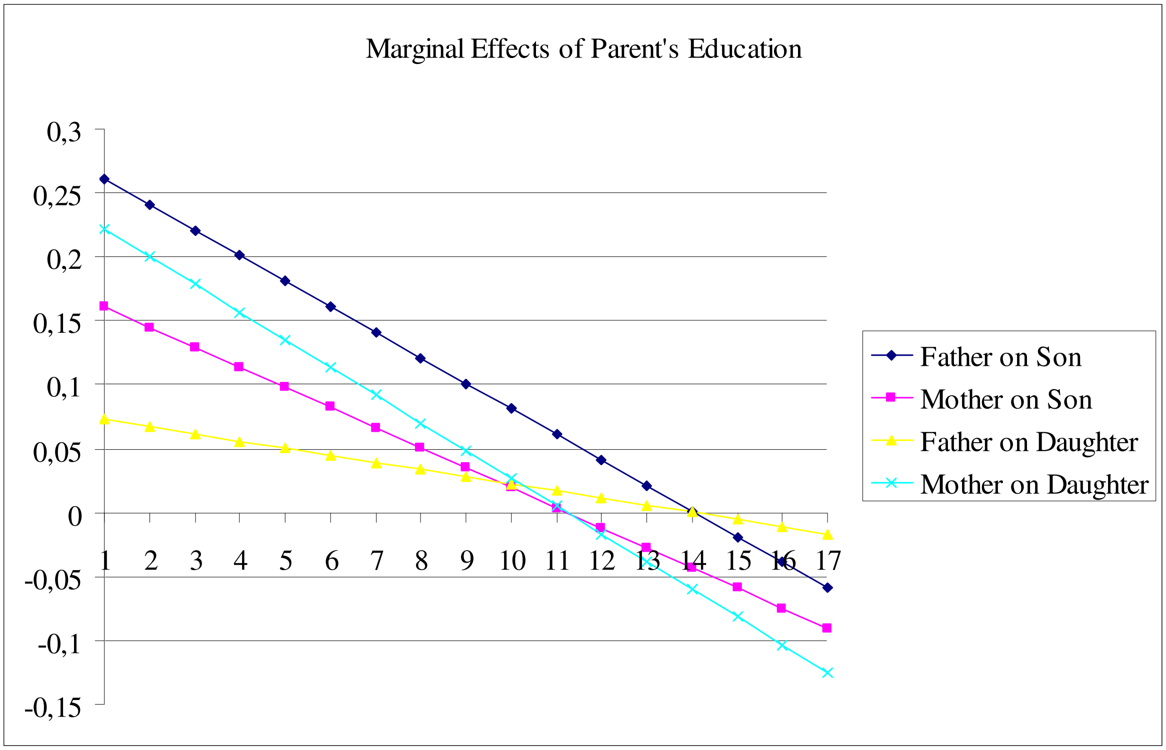


Figure 2: Effects of Father and Mother's Education on Daughter's Years of Schooling (Illiterate is the omitted category)


Marginal Effects of Parent's Education
0,3
0,25
0,2
0,15
0,1
0,05
0
-0,05
-0,1
-0,15
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17
Father on Son
Mother on Son
Father on Daughter
Mother on Daughter

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									
Illiterate	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									
Illiterate	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.XX: 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	0,580	0,049	0,580	0,049	0,578	0,049	0,580	0,049	0,576	0,049	0,577	0,049	0,736	0,047
β_3	1,103	0,064	1,103	0,064	1,098	0,064	1,102	0,064	1,151	0,062	1,091	0,064		
β_4	1,358	0,134	1,358	0,134	1,351	0,134	1,345	0,098			1,488	0,087	1,296	0,096
β_5	1,340	0,118	1,340	0,118	1,334	0,118								
β_6	1,729	0,115	1,729	0,115	1,856	0,104	1,730	0,115	1,721	0,113			1,674	0,112
β_7	2,089	0,344	2,086	0,135			2,085	0,135	2,072	0,133	2,053	0,133	2,024	0,133
β_8	2,085	0,140												
β_{10}	0,347	0,045	0,347	0,045	0,350	0,045	0,349	0,045	0,352	0,045	0,351	0,045	0,479	0,044
β_{11}	0,597	0,058	0,597	0,058	0,602	0,058	0,598	0,058	0,644	0,059	0,606	0,058		
β_{12}	0,729	0,094	0,729	0,094	0,735	0,095	0,786	0,083			0,856	0,081	0,752	0,080
β_{13}	0,837	0,098	0,836	0,098	0,841	0,099								
β_{14}	0,930	0,098	0,930	0,098	0,993	0,099	0,925	0,098	0,901	0,096			0,877	0,094
β_{15}	1,174	0,335	1,183	0,147			1,179	0,147	1,156	0,146	1,178	0,147	1,126	0,143
β_{16}	1,185	0,152												
λ^h_2	0,461	0,051	0,461	0,051	0,462	0,051	0,461	0,051	0,463	0,051	0,463	0,051	0,386	0,051
λ^h_3	1,162	0,066	1,162	0,066	1,165	0,066	1,163	0,066	1,139	0,066	1,168	0,066	1,338	0,063
λ^h_4	1,451	0,139	1,451	0,139	1,454	0,139	1,457	0,132	1,550	0,127	1,389	0,130	1,481	0,131
λ^h_5	1,760	0,122	1,760	0,122	1,763	0,122	1,758	0,118	1,851	0,112	1,690	0,116	1,781	0,118
λ^h_6	1,835	0,119	1,835	0,119	1,774	0,117	1,834	0,119	1,839	0,119	1,950	0,114	1,861	0,118
λ^h_7	1,811	0,360	1,813	0,327	1,922	0,324	1,813	0,327	1,819	0,327	1,829	0,327	1,842	0,327
λ^h_8	2,166	0,146	2,166	0,145	2,276	0,139	2,166	0,145	2,173	0,145	2,182	0,145	2,196	0,144
λ^h_{10}	0,649	0,051	0,649	0,051	0,648	0,051	0,648	0,051	0,646	0,051	0,647	0,051	0,586	0,050
λ^h_{11}	1,231	0,065	1,231	0,065	1,229	0,065	1,231	0,065	1,208	0,065	1,227	0,065	1,287	0,062
λ^h_{12}	1,314	0,127	1,314	0,127	1,311	0,127	1,287	0,125	1,354	0,122	1,254	0,125	1,303	0,125
λ^h_{13}	1,959	0,120	1,959	0,120	1,957	0,120	1,983	0,118	2,051	0,114	1,950	0,117	2,000	0,117
λ^h_{14}	2,121	0,115	2,121	0,115	2,091	0,115	2,123	0,115	2,135	0,115	2,156	0,112	2,146	0,115
λ^h_{15}	2,327	0,512	2,322	0,491	2,413	0,489	2,324	0,491	2,335	0,491	2,324	0,491	2,349	0,491
λ^h_{16}	2,293	0,198	2,294	0,197	2,385	0,190	2,296	0,197	2,307	0,197	2,296	0,197	2,322	0,197

	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**
(cont.)														
λ^w_2	0,584	0,050	0,584	0,050	0,584	0,050	0,583	0,050	0,579	0,050	0,582	0,050	0,595	0,050
λ^w_3	1,252	0,062	1,252	0,062	1,252	0,062	1,250	0,062	1,235	0,063	1,251	0,062	1,323	0,059
λ^w_4	1,586	0,120	1,586	0,120	1,586	0,120	1,585	0,119	1,611	0,118	1,560	0,120	1,614	0,119
λ^w_5	2,146	0,112	2,146	0,112	2,146	0,112	2,143	0,111	2,168	0,109	2,118	0,112	2,172	0,111
λ^w_6	2,657	0,111	2,657	0,111	2,636	0,111	2,654	0,111	2,645	0,111	2,693	0,108	2,691	0,111
λ^w_7	2,576	0,315	2,577	0,310	2,614	0,309	2,574	0,310	2,563	0,310	2,577	0,310	2,616	0,310
λ^w_8	3,166	0,142	3,166	0,142	3,203	0,140	3,162	0,142	3,152	0,142	3,166	0,142	3,205	0,142
λ^w_{10}	0,618	0,052	0,618	0,052	0,619	0,052	0,619	0,052	0,622	0,052	0,620	0,052	0,584	0,052
λ^w_{11}	1,319	0,065	1,319	0,065	1,322	0,065	1,321	0,065	1,296	0,064	1,326	0,065	1,402	0,062
λ^w_{12}	1,581	0,125	1,581	0,125	1,584	0,125	1,544	0,120	1,650	0,115	1,511	0,119	1,566	0,120
λ^w_{13}	1,766	0,125	1,766	0,125	1,771	0,125	1,804	0,120	1,910	0,115	1,771	0,118	1,826	0,120
λ^w_{14}	2,405	0,118	2,405	0,118	2,371	0,117	2,413	0,118	2,440	0,117	2,476	0,112	2,444	0,117
λ^w_{15}	2,820	0,526	2,813	0,482	2,956	0,477	2,821	0,482	2,851	0,482	2,842	0,482	2,855	0,482
λ^w_{16}	2,219	0,201	2,220	0,199	2,363	0,186	2,228	0,199	2,258	0,199	2,248	0,199	2,262	0,199
γ	0,317	0,043	0,317	0,043	0,317	0,043	0,320	0,043	0,332	0,043	0,322	0,043	0,289	0,045
δ	4,225	0,862	4,226	0,862	4,162	0,851	4,162	0,846	3,944	0,785	4,036	0,818	4,620	1,010
ρ	1,414	0,123	1,414	0,123	1,418	0,123	1,412	0,122	1,409	0,119	1,431	0,122	1,130	0,068
Chi-Squared (DF)	19,657	(11)	19,658	(13)	31,830	(15)	20,867	(15)	40,663	(17)	36,239	(17)	153,880	(17)
Chi-Squared Difference(DF)			0,001	(2)	12,173	(4)	1,210	(4)	21,006	(6)	16,582	(6)	134,223	(6)

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