What is the Source of the Intergenerational Correlation in Earnings?

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Abstract

A dynastic model of household behavior is used to estimate and decompose the correlations in earnings across generations. The estimated model can explain 75% to 80% of the observed correlation in lifetime earnings between fathers and sons, mothers and daughters, and families across generations. We find that human capital accumulation in the labor market, the nonlinear return to part- versus full-time work, and the return to parental time investment in children are the main forces driving the intergenerational correlation in earnings through their effects on fertility and the division of labor within the household. Assortative mating magnifies these forces.

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1 Introduction

The intergenerational correlation of income (IGC) is an important measure of mobility. However, aside from a handful of papers, the source of intergenerational transmission of income remains to be explored. How much of the IGC can be attributed directly to parental human capital and how much is because of differences in investment of parents? What role do labor markets and assortative mating in the marriage market play in the observed persistence of earnings? The impact of policies on intergenerational mobility critically relies on the answers to these questions. We address these questions by developing and estimating a dynastic model in which fertility, time, and monetary investment in children are endogenous. We then use the estimated model to quantify the relative importance of several factors that can generate persistence in earnings across generations.

A small but growing literature has placed increased emphasis on estimating the causal relationship and analyzing the mechanisms that drive the relationship between parental and children income. However, papers that estimate a causal relationship typically do not consider households, parental investment, and fertility decisions.[1] While there is a large literature on the importance of family structure in children's outcomes,[2] most papers that account for the role of investment decisions in the intergenerational correlation of earnings do not take into account fertility, assortative mating, and household decisions.[3]

[1]Lefgren, Lindquist, Sims (2012) use instrumental variables technique to separate the impact of human capital and paternal income on their sons' income. They do not analyze household behavior, and do not consider the role of mothers or parental choices in the persistence of income. See Black and Devereux (2011) for a survey on the literature using instrumental variabless and natural experiments to estimate causal effects.

[2]For a comprehensive survey on the literature on family and children's skill and human capital development, see Heckman and Mosso (2014).

[3]Lee and Shesadri (2015) is the only study we are aware of that analyzes and quantifies the mechanism underlying the IGC accounting for parental investment. They develop a lifecycle dynastic model in which parents tradeoff their own and their offsprings human capital and also make bequests decisions. In the paper, however, fertility is exogenous and each parent has one child. Several other papers consider the role of assortative mating, see Chadwick and Solon (2002), Ermisch, Francesconi and Seidler (2005) and Holmlund (2008). These papers do not analyze the underlying mechanism of transmission of income.

Our paper explicitly models the life-cycle sequential decision of time investment, labor supply, and fertility and estimates the impact of income, parental characteristics, and assortative mating on the IGC of income.

Our model builds on dynastic models with endogenous fertility pioneered by Barro and Becker (1988, 1989) and models of transmission of human capital with exogenous fertility such as Loury (1981). Our goal is to capture the impact of parental characteristics and their resource constraints on their decisions and on the IGC of earnings. We therefore extend the dynastic model to incorporate the life-cycle. This extension allows us to study the choices of number and spacing of children. Our framework is a unitary household, which is the simplest way to capture variation in resources, trade-offs, and decisions of couples with different education levels and skills. In our model, the main economic mechanism that generates correlation in earnings across generations is transmission of human capital through income and time investment; in addition, there is direct transmission of human capital from parents to children.

This framework allows us to separate the effect of parental human capital from income and time investment on the IGC. In addition, we account for the impact of assortative mating patterns and the labor market structure on the IGC. Assortative mating affects investment in children by its influence on the level and allocation of available resources – time and money – within the household. It also affects the outcomes and earnings of the children's households. For these reasons, assortative mating can increase IGC.[4] The non-linear nature of earnings (i.e. the returns to experience) and the non-linear returns to full-time versus part-time work can potentially affect labor supply decision and specialization patterns in different types of households. Moreover, through its effect on the labor supply (especially that of females), it can potentially impact fertility decisions.

We estimate our dynastic life-cycle model on data from the Panel Study of

[4]See Fernandez and Rogerson (2001) and Fernandez et al. (2005) and Greenwood et al. (2014) on the role of assortative mating in educational attainnment and cross-sectional inequality. These papers did not explicitly model time investment decisions or fertility and mainly relate the impact of assortative mating on cross- sectional inequality.

Income Dynamics (PSID) and show that it can replicate the intergenerational elasticity of earnings observed in the data. We then perform counterfactual exercise to decompose the persistence of earnings across generations into the effect of (i) assortative mating, (ii) the age-earnings profile, (iii) human capital accumulation in the labor market (iv), the nonlinearity in the return to part-time versus full-time work (v) the direct cost of children depending on parental education, and (vi) the effect of nature — the automatic transmission of economic status across generations.

Our first major finding is that the labor market is the main source of the IGC. We find that the source that generates the largest correlation is the returns to experience in the labor market; it accounts for roughly 42% of the observed persistence in earnings across generation. The returns to experience increase the labor supply of more educated females disproportionately, and decrease the total time they spend with their children relative to the time spent by less educated women; however, the time spent with each child of the more educated women increases. There are several forces driving this result: As household income rises, the demand for both the number of children and their "quality" increases. However, the opportunity cost of time introduced by the returns to experience is higher for more educated women. This reduces fertility and the total time spent with children in households with more educated females. However, in households with more educated females, the reduction in fertility is significantly greater than the reduction in total time spent with children, and therefore, time spent with each child increases. This relative decrease in the number of children and the rise in parental time spent with each child in more educated households increases the intergenerational persistence in earnings. Introducing the non-linear return to part-time versus full-time work further increases the correlation to a level above the one observed in the data; the mechanism is similar to the one in the returns to experience counterfactual.

The second major finding is that assortative mating by itself can account for less than 13% of observed persistence in earnings across generation. The third main finding is that the utility costs estimated capture the increased demand for children of more educated households and therefore acts to mute the persistence in earnings across generations. This is consistent with the prediction by Barro and Becker (1989), that wealthier parents have more children which reduces the correlation in wealth across generation.[5] Our estimates therefore emphasize the tension between the different factors that affect persistence: On one hand, the demand for children rises with income. On the other hand, the opportunity cost of time of more educated people is higher. Because parental time with children has a large impact on their human capital, the (opportunity) cost of "quality" (measured as educational attainment) is higher the higher the parents' potential income. Since the demand for quality of children also rises with income, assessing the impact of the different factor is an empirical question. Finally, overall parental characteristics transmitted regardless of behavior account for a significant fraction of the observed persistence in earnings.

The rest of the paper is organized as follows. Section 2 presents out theoretical model. Section 3 presents the data, empirical strategy, and estimation results. Section 4 presents the counterfactual decomposition. ,Section 5 concludes while the Appendices contain estimation details along with additional tables and results.

2 Model

This section develops a partial equilibrium model of altruistic parents who make transfers to their children. We build on previously developed dynastic models that analyze transfers and intergenerational transmission of human capital. In some models, such as those of Loury (1981) and Becker and Tomes (1986), fertility is exogenous, while in others, such as the models of Becker and Barro (1988) and Barro and Becker (1989), fertility is endogenous. The Barro-Becker framework is extended in our model by incorporating a life-cycle model.

[5] In their model, there is no persistence. As shown by Alvarez (1999), relaxing several assumptions in their framework can lead to persistrence. The main assumption relaxed in our paper is the non-separability of budget sets across generations.

Life-cycle is important to understanding fertility behavior, spacing of children, and timing of different types of investments. The aim of the model is to capture the impact of fertility, labor supply, and time spent with children on human capital of children and persistence of income across generation. We extend the basic dynastic model of a single decision-maker to a unitary household to capture the importance of the household type and patterns of specialization within the household on the intergenerational correlation of earnings.[6]

2.1 Environment and Choices

Consider an economy populated with two groups of agents, females (f) and males (m). Each is indexed by a vector of life-time invariant characteristics. Let x_f denote the type of female and x_m denote the type of male. Assume that the supports of x_f and x_m are finite. An adult lives for T periods. Adults may have children during their life. A child can be either female or male. Let ζ, a dummy variable, denote whether or not a child is a female. Children becomes adults after being raised by both parents for T^e periods.

Children (ages 0 to T^e) do nothing. This childhood period is divided into the early childhood period ages 0 to 5 years of age, and the later childhood period (ages 6 to T^e). Parents make active investments in the early childhood years and passive investments in later childhood years. At age $T^e + 1$ young adults form households and are matched according to a marriage matching function $G(x_m,\ x_f)$. Between periods T^e and $T^e + T^f$, households supply labor, have children, spend time raising young children, and consume. From age $T^e + T^f + 1$ to T, old households supply labor, spend time raising existing young children, and consume but are infertile.

Consider a couple of type (f, m). Each period of their adult life they jointly choose a discrete choice vector a and a continuous choice c. The discrete choice vector is given by $a = (h_f, h_m, d_f, d_m, b)$ which consists of household market work time $h = (h_f, h_m)$, household time with children $d = (d_f, d_m)$, and whether to have a child or not b. We denote the feasible set of action

[6] See Gayle, Golan, and Soytas 2015.

vectors A, whose elements depend on whether the household is a young or old. For each period, t, in their adult life couples have a vector of state variables z_t, which is given by $z_t = (a_{T^e+1}, ..., a_{t-1}, \zeta_{T^e+1}, .., \zeta_{t-1}, x_f, x_m)$. It includes the history of past choices, time invariant characteristics, and the gender of each child.

Budget Constraint Raising children requires parental time, d, and market expenditure. There is a per-period cost of the expenditures of raising a child, which is assumed to be proportional to the household's current earnings and the number of children. The budget constraint is described by the following equation:

$$c_t + \alpha(z_t)(N_t + b_t)w_t(z_t, h_t) \leq w_t(z_t, h_t) \tag{1}$$

where $w_t(z_t, h_t)$ is total household earnings which is the sum of the earnings of the female, $w_{ft}(z_{ft}, h_{ft})$, and the earnings of the male, $w_{mt}(z_{mt}, h_{mt})$. $N_t + b_t$ is the total number of children at the end period t in an adult life-cycle. Thus, N_t is the number of children at the beginning of period t, and b_t is the decision variable of whether or not to have a child in period t. $\alpha(z_t)$ is the proportion of household earnings spent per child.[7]

Preferences and Household Optimization Adult households care about consumption, leisure, the number of children, and the future household utility of their children. Extending the original Barro Becker (1989) formulation to unitary households, we assume that the life-time utility for a type-(f, m) household at age $T^e + 1$ is as follows:

$$U^i(f, m) = V^i(f, m) + \beta^{T-T^e-1}\lambda E_{T^e+1}\left[N_{T^f}^{1-v}\overline{U}^{i+1}|f, m\right], \tag{2}$$

[7] This assumption is made because we do not observe expenditures on children in the data. Letting α be a function of z allows us to capture the differential expenditures on children made by households with different incomes and characteristics.

where $U^i(f,m)$ represents the full value of the utility of a household at age T^e+1 in generation i from that point forward; $V^i(f,m)$ is the utility the household derives from its own path of consumption and discrete actions; N_{Tf} is the number of children in the household at the end of the fertile period ,and $\overline{U}^{i+1}$ is the expected utility of the household to which their typical child will be assigned.

Let $I^o_{a_t}$ be the indicator variable of the optimal discrete choice of a type-(f,m) household of age T^e+1+t. We assume that the utility from the life-time of own action and consumption is of the form

$$V^i(f,m) = E_{T^e+1}\left[\sum_{t=T^e+1}^{T} \beta^{t-T^e-1} \sum_{a_t \in A_t} I^o_{a_t}\{u_{a_t}(z_t) + \varepsilon_{a_t}\}\right]. \tag{3}$$

We distinguish between the time preference, β, and the degree of altruism between generations, λ. Thus, $\lambda = 1$ means that a household cares as much about their children's household utility as they care about their own. Also, households discount the utility of each additional child by a factor of $1 - v$, where $0 < v < 1$ because we assume diminishing marginal returns from children. The within- generation utility, $u_{a_t}(z_t)$, can be written as a function of only the discrete actions by substituting the binding budget constraint for consumption. This is described by the following equation:

$$u_{a_t}(z_t) = \theta_{a_t}(z_t) + u_t[w_t(z_t,h_t)(1-\alpha(z_t)(N_t+b_t)), z_t]$$

where $\theta_a(z)$ is dis/utility from taking discrete action a and $u_t[., z_t]$ is the utility from consumption. Associated with each possible discrete action is a per-period additive state specific error ε_a.

Similar to equation (2), we can define expected future utility for a young adult in generation $i+1$ at age T^e+1. Therefore, recursively $\overline{U}^{i+1}$ is described by the following equation:

$$\overline{U}^{i+1}(f,m) = \frac{1}{N_{Tf}} \sum_{n=1}^{N_{Tf}} \sum_{f'=1}^{F} \sum_{m'=1}^{M} G(f',m') U_n^{i+1}(f',m'), \tag{4}$$

where N_{Tf} is total number of children in the household during the fertile period, and $U_n(f', m')$ is the expected utility of the household of child n.

Human Capital and Earnings Life-Cycle Dynamics The earnings process depends on education, experience, and innate ability and is determined by the following set of equations:

$$\ln w_{f(m)t} = W_{f(m)t}(e, h_{f(m)t}) + H_{f(m)t}(h_{f(m)T^e+1}, ..., h_{f(m)t-1}) + \eta_{f(m)} + \epsilon_{f(m)t}. \quad (5)$$

$W_{f(m)}(x, h_{f(m)t})$ is the market earnings for an adult of gender $f(m)$, age t, education level e, and market work hours $h_{f(m)t}$. It captures the labor market returns to education and hours worked and is gender- and age-specific. An important feature of $W_{f(m)}(x, h_{f(m)t})$ is that is may depend on $h_{f(m)t}$ in a nonlinear manner, for example, full-time work pays more than twice as such as part-time work.[8] Experience, $H_{f(m)}(h_{f(m)T^e+1}, ..., h_{f(m)t-1})$, is accumulated while adults work, and its return in the labor market depends on the type of experience – part-time versus full-time – and how recent the experience was obtained. Thus, this specification captures both depreciation of human capital and differential returns to part-time versus full-time, both of which are gender-specific. Innate ability, $\eta_{f(m)}$, is rewarded in the labor market and $\epsilon_{f(m)t}$ is an i.i.d. idiosyncratic error term.

The earnings dynamics specified above distinguish between endogenous state dependence through the return to experience and persistent productivity heterogeneity, $x \equiv (e, \eta)$, via education and innate ability. The process of experience accumulation is central to our analysis because it captures the potential gender differences in the career interruptions and the effect of fewer labor market hours on the earnings of women and men. This may help rationalize some of the specialization patterns observed in the data.

Children Outcomes The characteristics of children, $x' \equiv (e', \eta')$, are affected by their parents' characteristics, early childhood monetary investments, early childhood time investments, and the presence and timing of siblings in

[8] See Altug and Miller (1998), Gayle and Golan (2012), and Gayle and Miller (2013), who document these features of the modern labor market.

early childhood. This intergenerational production function is determined by the following sets of equations

$$
\begin{aligned}
e'_{f(m)} &= \Gamma_{f(m)}[x, d^{(0)}, ..., d^{(5)}, w^{(0)}, ..., w^{(5)}, S_{-5})] + \omega'_{f(m)} && \text{(6a)} \\
\eta'_{f(m)} &= \Gamma_{f(m)\eta}(e') + \widetilde{\eta}'_{f(m)} && \text{(6b)} \\
\Pr(\widetilde{\eta}' &= \widetilde{\eta}_i) = F_{f(m)}(e_f, e_m, \eta_f, \eta_m), && \text{(6c)}
\end{aligned}
$$

where $d^{(j)} = (d_f^{(j)}, d_m^{(j)})$ is the parental time investment at age j of the child, $w^{(j)}$ is the household earnings at age j of the child, S_{-5} is the gender-adjusted number of young siblings present in the household during early childhood, and $\omega_{f(m)}$ is the gender-specific luck component that determines the educational outcome of offspring. A child's innate ability, $\eta'_{f(m)}$, is determined once the education level is determined as the sum of systematic, $\Gamma_{f(m)\eta}(e')$, and random, $\widetilde{\eta}'_{f(m)}$, components. The random component, $\widetilde{\eta}'_{f(m)}$, is assumed to have finite support and to be independent of $\omega'_{f(m)}$ with probability distribution function, $F_{f(m)}(e_f, e_m, \eta_f, \eta_m)$. An important feature of this specification is that it divides the child's ability into a component determined by parental inputs through the effect of the educational outcome, innate ability, and a separable component that is directly transmitted through the parents' innate ability.

2.2 Discussion

In Barro and Becker (1989) model with endogenous fertility there is no persistence in income. However, several features of our model can lead to intergenerational persistence in income. These are (i) the nonlinearity in the cost of transferring human across generations, (ii) non-seperability in the feasible set across generations, (iii) specialization in housework and labor market work within households, and (iv) assortative mating.[9]

The per-period cost of raising children and transferring human capital across generations is described in the budget constraint in equation (1) as

[9] See Alvarez (1999) for similar conditions that can generate persistence in income and wealth across generations in dynastic models with endogenous fertility. Also see Doepke (2005) and Jones, Schoonbroodt and Tertilt (2008) for other discussion of these conditions.

well as the opportunity cost of time investment input in children, which is the forgone earnings. Time investment and labor supply are modeled as discrete choices which introduces nonlinearity in the cost of raising children and transferring human capital. Specifically, the fact that labor supply is discrete and that the returns to part- and full-time work are nonlinear allows for the cost of transferring human capital to each child to be increasing in the number of children. As a result it can generate persistence in income across generations.

We incorporate the dynamic elements of the life-cycle, which involve age effect and experience. The opportunity cost of time with children therefore incorporates returns to experience, which are also nonlinear (depends on the level of labor supply). The nonlinearity involved in labor supply is realistic; parents' labor market time is often not proportional to the number of children they have and hours in the labor market. For a given wage rate, these are not always flexible and depend on the occupation and type of job. Furthermore, fertility decisions are made sequentially, and due to age effects, the cost of a child varies over the life-cycle. Mookherjee, Prina, and Ray (2012) develop a model with most of these characteristics. They show that by incorporating a dynamic analysis of the return to human capital can help generate persistence in a dynastic Barro-Becker model.

The feasible set across generations is non-separable in our model because the wages of the children (and therefore, their opportunity cost of time) depend on their education and labor market skills. However, education and labor market skills of children are linked to their parents' skills and education through the production function of education. This is one of the most natural ways of generating persistence in the standard dynastic model.

Incorporating two household members into the model captures important issues of the degree of specialization in housework and labor market work in households with different composition of education. The importance of which spouse spends time with the children (and the levels of time) depends on the production function of education of children and whether the time of spouses is complement or substitute. To the best of our knowledge, ours is the first paper to explicitly analyze this mechanism as a potential source of intergenerational persistence in earnings.

Finally, patterns of assortative mating may amplify the persistence of income across generations relative to a more random matching pattern. In our model, there is potential correlation of the cost of transfers to children (time input) with both parents' characteristics and assortative mating patterns. This implies that if children of more educated parents are more likely to be more educated, they are also more likely to have a more educated spouse, which increases the family resources and their children's educational outcomes. Several recent papers have highlighted the importance of this mechanism for explaining cross-sectional inequality. For example, Fernandez and Rogerson (2001); Fernandez, Guner, and Knowles (2005); and Geenwood, Guner, Kocharkov, and Santas, (2014, 2016). While these papers do not directly analyze intergenerational persistence of earnings, they do use dynastic models with household behavior which similar to the one used here.

3 Data and Estimation

3.1 Estimation

A multistage estimation technique developed by Gayle, Golan, and Soytas (2015) is used to estimate the model using data from the PSID. The estimation method combines forward simulation (see Hotz et al., 1994), an alternative value function representation for stationary dynastic models (see Gayle, Golan, and Soytas, 2015), and the Hotz and Miller (1993) inversion and proceeds in four steps. In step 1 the (i) earnings equation, (ii) intergenerational education production function, and (iii) the marriage market matching function at age 25 are estimated. In step 2, conditional choice probabilities (CCPs) of household decisions are estimated. In step 3, the alternative value functions representation, the estimates from steps 1 and 2 and Hotz et al.'s 1993 forward simulation technique are used to estimate the household continuation value for each age in the life-cycle. Finally, in step 4, the Hotz-Miller inversion is used to form moment conditions for a generalized method of moments (GMM) estimation of the utility function parameters and the discount factors. The theoretical framework has several features that could generate earnings persistence across generations. Of these features, only the direct monetary costs of raising children are estimated in step 4. The other important features - the earnings structure, education production function, the relative importance of "nature versus nurture", and the marriage market matching function— are estimated outside of model. The preference parameters, the monetary costs of raising children, and the discount factor are estimated using revealed preferences of households to have children and the division of labor within the households. This implies that the intergenerational correlation in earnings is not targeted at any time during estimation of the model. This allows us to validate the model by accessing how well it is able to replicate the observed correlation in earnings across generations.

The conditions under which this general class of models are semi-parametrically identified are established in Magnac and Thesmar (2002) and Pesendorfer and Schmidt-Dengler (2008). The critical assumption for achieving identification in our model is that the economic environment is stationary over generations. This assumption is standard in intergenerational models and is used both in the estimation and the identification of the intergenerational discount factors. Gayle, Golan, and Soytas (2014) offer a more detailed discussion of identification in a more general setting.

3.2 Data

We use data from the Family-Individual File of the PSID. We select individuals from 1968 to 1996. The initial sample consists of 12,051 males and 17,744 females; these individuals were observed for at least one year during our sample period. The sample is restricted to white individuals between the ages of 17 and 55. The earnings equation requires the knowledge of the last four labor market employment history. This immediately eliminates individuals with fewer than 5 years of sequential observations. To track parental time input throughout a child's early life, we excluded parents observed after their children reached 16 years of age. We also excluded parents with missing observations during the first 16 years of their children's lives. Furthermore, if there are missing observations for the spouse of a married individual, then that individual is excluded from our sample. After imposing these restrictions, the main sample contains 89,538 individual-year observations.

The theoretical model is a unitary model without divorce. This is a convenient and straightforward way of introducing household decisions and marital sorting into the dynastic model.[10] Consistent with the model, we use data on married couples. Ideally, the estimation should be done using lifelong married couples. however, this would significantly reduce the number of observations in our sample, thereby making it non-representative of the overall population. To mitigate this issue we use two subsamples in the model estimation. The first sample consist of all individuals (who meet the restrictions described in paragraph above) who were married for at least one year in our sample period. This sample contains 41,448 individual-year observations and is used in all the estimations in steps 1 and 2 (i.e., earnings equation, intergenerational education production function, the marriage market matching function at age 25, and the household choice probabilities). The second sample consists of married couples who remained married over the years observed in the PSID. This sample contains 32,144 individual-year observations and is used to estimate the preference parameters and the discount factors.

The summary statistics of the two samples are presented in Table 1. It shows that the life-time married sample is on average about the same age as the eve- married sample. By construction all individuals in both samples are married. The female-to-male ratio is 60% in the ever-married sample and is equal to 50% by construction in the life-long married sample (we observe the same couple family over years). The life-long married sample have on average one extra year of education, but this is not statistically significant. Individuals in the ever-married sample have more children; however, in the life-long mar-

[10] See, for example, Fernandez, and Rogerson (2001) and Fernandez, Guner and Knowles (2005) for theoretical and empirical models that use the unitary household formulation to introduce marital sorting in a dynastic model. For a dynastic model with a non-unitary household, see Gayle, Golan, and Soytas (2014).

ried sample, we observe higher annual labor income and labor market hours for individuals. This is consistent with the fact that child-bearing potentially reduces labor market participation, especially that of women. Again consistent with the higher number of children in the ever-married sample, on average adults in this group have higher housework hours and time spent with children. However, we note that none of these differences are statistically significant. A similar pattern holds for the children's generation as well.[11]

3.3 Estimates of Earnings Dynamics and Innate Ability

Table 2-C in the online appendix C presents the estimates of our earnings and the innate ability equation. Figure 1 presents a graphical depiction of the main features of the estimates that will play a prominent role in generating persistence in earnings across generations. The specification of $W_{f(m)}(e, h_{f(m)t})$ is quadratic in age and differs by education level; however, we parsimoniously restrict this to be the same for females and males. There is a different market price per unit for part-time hours versus full-time hours and this price per unit differs by gender. For the return to experience, we adopt the learning-by-doing specification of Gayle and Golan (2012).[12] The basic feature of this specification is that the return to experience differs by the type of experience (full-time versus part-time), gender, and how long ago this experience was obtained (depreciation). The earnings equation was estimated using a standard GMM. Past labor market histories, age, and education are used as instruments.[13]

Table 2-C and the top panel of Figure 1 show that the age-earnings profile steepens with more education. This is potentially important for the persistence of income across generations. Parents with different age-earnings profiles will choose a different timing of having children, as documented in Carneiro et al. (2013); therefore, the timing of income in early childhood can affect the outcome of the child. All else being equal, low educated households would

[11] Note that because of the stationarity asssumption of the model the children's generation is needed only to estimate the education production function.

[12] Gayle and Golan (2012) show how the estimate of this specification can be rationalized by a simple labor demand model.

[13] See Altug and Miller (1998), Blundell and Bond (1998), among others for details.

delay having children relative to high educated households. Given the fixed fertile period of life, high educated households would have more children and we would possibly observe less persistence in earnings across generations.

Table 2-C shows that working full-time pays 2.6 times more than working part-time for males and 2.3 times for females. Coupled with the education gender gap displayed in the bottom panel of Figure 1, it provides an incentive for females to specialize less in market work. The gender gap increases with education, which all else equal, would have more specialization in assortatively matched couples with high education, possibly leading to more persistence in earnings across generations.

Finally, Table 2-C and the middle panel of Figure 1 show that the return to experience is highly nonlinear in part- and full-time work, with higher returns to full-time experience than part-time experience. This specification includes a depreciation of human capital, and the results show that part-time work may not generate enough returns to offset the estimated rate of depreciation. Moreover, the part-time penalty in the return to experience (see the middle panel of Figure 1) increases over time but the increase is less for females than males.[14] In general, both the nonlinearity in current hours and the return to experience introduce nonlinearity into the opportunity cost of spending time with children, which in our model could be a source of persistence in earnings across generations.

3.4 Intergenerational Education Production Function

Equations (6a) to (6c) specify the intergenerational production function. In the empirical implementation, $\Gamma_{f(m)}$ and $\Gamma_{f(m)\eta}$ are both linear functions. The linearity assumptions are used for two reasons. First, nonlinearity in the intergenerational production function itself can generate persistence in earnings across generations. We wanted to focus on the economic mechanism that generates persistence of earnings across generations. Second, the intergenera-

[14] This feature of the labor market was found by other authors. Gayle and Golan (2012) and Gayle and Miller (2004) pointed out a similar structure for the USA, and Blundell, Dias, Meghir, and Shaw (2016) document a similar feature in the British labor market.

tional production function is one of the central components in the estimation of the dynastic models. Hence, to boost the credibility of our results we used an instrumental variable identification strategy with a linear probability model (IV-LPM). There are three other methods of estimating discrete choice models with endogenous regressors: maximum likelihood, control variable, and special regressor approaches.[15] However, given the other issues (discussed below) in estimating the intergenerational production functions, the IV-LPM is the most straightforward method for simultaneously dealing with all these issues.

There is a large literature on the estimation of the direct effect of parental traits and investment on children's income (Behrman, 1997; Behrman and Rosenzweiz, 2002; and Lee, Roys, and Seshadri, 2015). There are two well-known fundamental problems with estimating the causal intergenerational schooling effect of parents' education. The first is the standard ability "bias" from the literature on the estimation of the returns to education. That is, more "able" mothers may obtain more schooling: If schooling or earnings ability is genetically transmitted to their children, the intergenerational education correlation between children and parents may merely reflect, that more able parents, who have more schooling, have more able children, who obtain more schooling. The second problem is that the relationship among parental traits, investment, and children's outcomes is normally estimated for mothers-children only. Thus, even among mothers with the same abilities, those with higher education may have children with greater educational and labor market performances because of assortative mating.

The specification of the education production function in our model, equations (6a) to (6c), internalizes all these concerns which are accounted for in the estimation as follows. First, in the theoretical model we assumed that observed ability in the labor market is a monotonic transformation of academic ability; therefore by using the panel structure of our data we are able to estimate fixed effects for both parents and children using data on earnings. This estimated fixed effect is then used in the estimation of the education production function to mitigate the ability bias. Second, we include fathers'

[15] See Lewbel, Dang, and Yang (2012) for a comparison of the different approaches.

education and home time in the education production function while explicitly accounting for household interactions implied by our model.

However, this leads to a third problem: the simultaneity of the inputs of both fathers and mothers and the endogeneity of which parent and type of parent spends time with a given child. The output of the intergenerational education production function (i.e., completed education level) is determined across generations, while the inputs, such as parental time investment, are determined over the life-cycle of each generation. Therefore, we treat these inputs as predetermined and use instruments from within the system to estimate the production function. This leads to a system of equations that need to be estimated simultaneously. The system of equations is the education production function in equations (6a) to (6c), as well as labor supply, income, time spent with children, and subsequent fertility equations.

To estimate our system we need a number of exclusion restrictions, which are motivated by our theoretical model. The first is the sex composition of siblings; it enters the education production function but not the labor supply and parental time equations. It is similar to the siblings-sex ratio first used by Angrist and Evans (1998) and is justified on the basis that the direct cost does not depend on the sex of the children but the number of children, while the outcomes of children (i.e., education and earnings) differ by the gender of the children. This set of instruments therefore provides quasi-experimental variation in parental time and subsequent fertility. The second set of instruments – the difference in the age-earnings profile by education – is used to provide quasi-experimental variation in income, labor hours, and subsequent fertility. See Appendix C for details on how we operationalized these two sets of instruments within a three stage least squares (3SLS) framework.

Table 2 presents results of a 3SLS estimation of the system of individual educational outcomes; the estimates of the rest of the system of equations are in Table 3-C in Appendix C. Parental time investment is the sum of the parental time investment over the first 5 years of the child's life. The total time investment is a variable that ranges between 0 and 10 since low parental investment is coded as 1 and high parental investment is coded as 2. The estimation results show that controlling for all inputs, a child whose mother has a college education has a higher probability of obtaining at least some college education and a significantly lower probability of not graduating from high school relative to a child with a less educated mother; while the probability of graduating from college is also larger, it is not statistically significant. If a child's father, however, has some college or college education, the child has a higher probability of graduating from college.

Table 2 also shows that while a mother's time investment significantly increases the probability of a child graduating from college or having some college education, a father's time investment significantly increases the probability of the child graduating from high school or having some college education. These estimates suggest that while a mother's time investment increases the probability of a high educational outcome, a father's time investment truncates low educational outcome. However, the time investment of both parents is productive in terms of their children's education outcomes.

It is important to note that hours spent with children by mothers and fathers are at different margins, with mothers providing significantly more hours with their children than fathers. Thus, the magnitudes of the discrete levels of time investment of mothers and fathers are not directly comparable since what constitutes low and high investment differs across genders. Figure 1-C highlights the relative magnitudes. It shows that fathers' time investment does have a significant impact on the education outcome of their children. For example, in a household consisting of two high school dropout parents, a daughter would have a 2 percent chance of graduating from college if the mother has the sample average amount of time investment and the father has a low time investment for the first 5 years of the child's life. However, the chance of graduating from college increases to 15 percent if the father increases his time investment to high while the mother's time investment remains at the sample average. A similar pattern holds for all other household types.

Figure 2-C highlights the relative importance of parental time investments versus the automatic transmission of education status from parents to children. It highlights the role of both "nature" (education status is automatically

transferred from parents to children) and "nurture" (more parental time with children increases the probability of the children having a higher educational outcome). The relative importance of nature versus nurture in accounting for the persistence of earnings across generations is a quantification question that needs to be answered with an optimizing behavioral framework, and parents may take actions that either enhance or diminish the relative effect of nature versus nurture.

3.5 The Empirical Marriage Matching Function

The empirical marriage matching function assigns household formation at age 25 for both the parents' and children's generations. It is a multidimensional matching that assigns the spouse characteristics in terms of education, work history, and pervious fertility. The details of the estimation of this matching function and its results are presented in Appendices A and C. Figure 3-C summarizes the main elements of this matching function over spousal education. It shows what is well known in the literature: Household matching with respect to education is highly assortative. This is the average matching rate for the parents' and children's samples. Assortative matching in the marriage market has increased over time; however, in estimation we will be entering the average matching rate over the sample period. This is necessary because of the stationarity assumption needed in the theoretical analysis.

3.6 Discount Factors and the Direct Costs of Raising Children

This section presents estimates of the intergenerational and intertemporal discount factors, the preference parameters, and child care cost parameters. Table 3 describes the utility function estimates including the discount factors. It shows that the intergenerational discount factor, λ, is 0.795 (for complete table of the estimates see table B-1). This implies that in the second to last period of a parent's life, the parent's valuation of their child's utility is 79.5% of their own utility. The estimated value is in the same range of values obtained in the literature calibrating dynastic model (Rios-Rull and Sanchez-Marcos, 2002; Greenwood, Guner, and Knowles, 2003). However, these models do not the include life-cycle. The estimated discount factor, β, is 0.813. The discount factor is smaller than typical calibrated values; however, few papers that estimate it find lower values (for example, Arcidiacono, Sieg, and Sloan, 2007, find it to be 0.8).[16] Lastly, the discount factor associated with the number of children, υ, is 0.111. This implies that the marginal increase in value from the second child is 0.68 and of the third child is 0.60.

Table 3 also presents the marginal utility of income. Utility from income declines in the number of children; for a person with less than a high school diploma and a spouse with less than a high school diploma, the coefficient on the interaction of children and family income is -0.309, implying that the net costs of raising children increase with the number of children as well as the family income[17]. The costs decline with own and spouse education. However, for all households the net utility from children is negative and declining in family income, capturing the increase in spending on children for wealthier families. For families with the same income and number of children, the costs of children increase in income for all types of households. In our model, fertility decisions depend, therefore, on education and income through the costs in the utility function. The costs of children are lower in households with higher education; however, these costs increase in income and income is higher for more educated households. The earnings equations capture the increase in earnings and, therefore, the increase in opportunity costs of time for more educated households. In the Barro-Becker model, the neutrality result holds - that is, wealthier people have more children, so the investment per child is the same and there is no intergenerational persistence. In our model, however, several other channels are correlated with education creating persistence. Whether wealthier households have more or fewer children and whether investment per child increases in more educated households is an empirical question.

[16] We are not aware of dynastic models in which the time discount factor is estimated.

[17] Note that the coefficients on children in the utility represent net utility because we cannot observe expenditure on children directly.

3.7 Model Fit and Explanatory Power

There are many criteria for assessing the fit of a model; in this paper we used three such criteria. The first is the statistical overidentifying J-test. We cannot reject the overidentifying test at the 5% level. The other two criteria require us to solve the model numerically. As such, we numerically solve the model and simulate 10,000 synthetic generations. The second criterion computes the unconditional choice probabilities of household labor supply, fertility, and parental time with children from these synthetic generations and compares them to the unconditional choice probabilities computed from the data. The comparison shows that our estimated model can replicate the observed choices in the data. This is a visual representation and aggregated summary of the restrictions in the J-test as these are the aggregates of the moments targeted in estimation. Hence, this criterion is not an independent source of model validation (The tables with the result, 1-B and 2-B, are in Appendix B). However, it is a useful benchmark for the counterfactual simulation to follow. Finally, given the synthetic dataset, we calculate the intergenerational correlation of earnings and compare the results to the estimates from the data. This is an independent source of model validation as these correlations are not moments that are targeted in the estimation. Table 4 provides the results of this latter exercise.

4 Source of the Intergenerational Persistence in Earnings

We conduct six counterfactual exercises to quantify the sources of the intergenerational correlation in earnings. The baseline counterfactual (CF0) is computed by eliminating the dispersion of parental education input, with the education level being assigned to high school for all parents. Thus, in the education production function, only gender, parental time input, and siblings account for the variation in educational outcomes. The spouse matching function is set to be uniform with equal probabilities for each person to marry a spouse with each one of the four education categories. The earnings equation is set so compensation does not vary with age and experience (it is set for age 32 and the average experience of a high school graduate). The return to full-time work is set to be twice as large as the return to part-time work, understating the return to full-time work. However, we keep the individual fixed effects that are systematically correlated with education. Lastly, the direct monetary costs of raising children that are a function of education are set to the values of high school graduates; the only variation in the direct monetary costs of raising children is due to gender. Therefore, the only systematic source of correlation in this counterfactual is due to systematic differences in fixed effects in earnings for different education groups. Otherwise, only the variation in idiosyncratic taste shocks may drive additional differences in choices.

Each one of the counterfactuals 1-5 adds back one element at a time to the previous counterfactual.[18] Counterfactual 1 (AM) adds back the *assortative mating* function in the data. It isolates the effect of assortative mating on the observed choices and intergenerational correlations in incomes. Counterfactual 2 (AEP) adds back the estimated *age-earnings* relationship into the earnings equations. Thus, it measures the age effect on earnings in the observed correlation. Counterfactual 3 (RTE) adds to AEP the estimated *returns to labor market experience* in the earnings equation. Counterfactual 4 (FTPT) adds the estimated *returns to full-time versus part-time* work to the earnings equation to RTE. Counterfactual 5 (UC) adds back the direct monetary cost of raising children estimates, which vary by education group, to FTPT. Counterfactual 6 (NA) adds back the effect of education in the education production function -the effect of nature- to FTPT.

Since the order in which we add the different factors matters, we repeat this exercise in a different order. The second set of simulations includes four counterfactuals with the different factors added in a cumulative manner. Counterfactual 1 now adds the effect of the age-earnings profile to the baseline model

[18] Our model is highly nonlinear and therefore, the different factors in the model interact in nontrivial ways and the effects are not additive. To isolate the effect of the different factors affecting the correlation, we also add each factor separately to the baseline counterfactual and report the impacts in Appendix B, Table 5-B.

in counterfactual 0. Counterfactual 2 adds the returns to experience in the earnings equation. Counterfactual 3 adds the estimated returns to part-time and full-time work. And counterfactual 4 adds assortative mating at the end. The reason we chose to run the cumulative counterfactuals in that order is because we wanted to assess the impact of assortative mating and how it interacts with the earnings structure in the labor markets. Therefore, in the first set of cumulative counterfactuals, assortative mating is added before we add the estimated earnings structure. In the second set, we first add the estimated earnings structure and then add the estimated assortative mating function. We discuss this further below. Unless mentioned otherwise, the discussion focuses on the correlation of average income from age 30 to age 40. However, the tables present other measures such as individual income correlations.

4.1 A Cumulative Decomposition

Tables 5A and 5B and Figures 2 and 3 present the results. Table 5 presents labor supply, time with children, and fertility choices along with total and average time input in children for mothers and fathers. Figure 2 presents the decomposition of the intergenerational correlation in average earnings between ages 30 and 40 of fathers and sons, of mothers and daughters, and of the parent and child family incomes. Figure 3 presents the results of the robustness check as outlined above. A complete table with the inputs for Figure 2 is included in Appendix B (table 3-B). In counterfactual 0 the correlations are small, this counterfactual can create less than 6% of the observed correlations in family average incomes between ages 30 and 40. Counterfactual 1 adds assortative mating: it generates about 10% of the observed correlation in earnings for families of fathers and sons and 15% for families of mothers and daughters.

The Effect of Labor Markets Counterfactuals 2-4 measure the effect of the earnings structure on intergenerational mobility. AEP adds the age-earnings profile, and its marginal impact on the intergenerational correlation in earnings is small and accounts for only 4.5%. Figure 1 shows that adding labor market experience into the earnings equations (RTE) increases the persistence in earnings across generations significantly, accounting for about 60% of the observed correlations for families of fathers and sons and mothers and daughters intergenerational pairs.[19]

Looking further into the reasons for the positive effect of the earnings structure on the correlations, we turn to Tables 5A and 5B which show the effects of the different factors on parental choices. Female labor supply increases. The largest increase is in full-time work of the more educated households. This is because the opportunity cost of time rises due to the dynamic effect of current participation on future earnings. Fertility, however, declines. The largest decline is for households in which both spouses have some college or college education. These are the households for which the opportunity cost of time is the highest. Due to the increase in the full-time work of females, there is also an income effect that increases demand for quality of children. Together with an increase in the opportunity cost of time, this demand for quality drives the decline in fertility. As a result, mothers' time per child increases at a higher rate in high education households. Fathers' time per child also increases in high education households. Thus, the decline in fertility and the increase in parental time per child is consistent with quantity-quality trade-off, although in the raw data we do not find a negative correlation between education and fertility. In contrast, average time with children for both mother and father declines in households in which both parents have less than a high school education, mainly because of the more moderate decline in fertility in these households. The relative increase in parental time per child in more educated households creates the large increase in persistence in income - and so the decline in intergenerational mobility.

The introduction of the nonlinear returns to full-time versus part-time work (FTPT) raises the correlation to around 0.351, accounting for 140% of the intergenerational correlation in earnings in all intergenerational pairs. Looking at Table 5 reveals that it increases the full-time work of women (substitution

[19] As shown in Appendix B, Table 5-B, it is the single factor that created the most persistence. It generates about 75% of the correlation in the simulated data (and about 55% of the correlation in the observed data).

effect) and reduces the male labor supply (the income effect of an increase in the wife's earnings). Full-time work increases the most for educated females. Fertility declines the most for educated females married to educated males. This decline increases maternal time per child disproportionately for educated mothers. Fathers' time per child declines but not as much as the increase in maternal time. Nevertheless, the impact of maternal and paternal time on children's outcomes is not symmetric. Overall, the large decline in fertility, stronger in households with college educated fathers, and the increase in mothers' income raise the intergenerational correlation of income. It is important to note the significance of this result: Without any effect of "nature" in the production function of children's education – the automatic transmission of economic status across generations – the dynastic model in the spirit of Barro-Becker (1989) can generate more persistence than what is observed in the data.

Utility Costs of Children Lastly, Figure 2 shows the effect of the cost of children in the utility function by allowing the direct monetary cost of raising children to vary with education. Interestingly, this reduces the correlation to around 0.17, accounting for between 59% and 69% of the intergenerational persistence in earnings depending on the intergenerational pair considered. The result is similar to the one in the model with endogenous fertility in Barro and Becker (1989) in which there is no persistence. In the Barro and Becker (1989) model, wealthier households have more children, so the "quality" of each child is independent of the parents' wealth. In our framework, this effect is captured through the direct monetary cost of raising children that depends on education and income. More educated households have higher marginal utility from children, which increases fertility. In households in which either the women or the men have less than a high school education fertility declines. As a result, maternal time per child declines in households in which females have some college or college education and the males have at least a high school diploma. While fathers' time with children increases in households with more educated females, it is not enough to offset the decline in maternal time per child in these households.

In summary, the structure of the labor market –human capital accumulated through experience and the nonlinear return to part- versus full-time work– can endogenously generate up to 140% of the persistence in earnings observed in the data without any effect of nature. However, this is mitigated by the quality-quantify trade-off which reduces the persistence of earnings across generations. Overall, nurture accounts for between 58% and 68% of the observed persistence in earnings. While we find a small role for assortative mating in the absence of the labor market structure, the mechanism through which the labor structure operates is the division of labor and specialization in the household. As such, we investigate the marginal importance of assortative mating in the presence of the labor market structure.

4.2 The Complementarity of the Earnings Structure and Assortative Mating

Figure 3 (and Table 4-B) presents the results from an alternative counterfactual simulation when we add assortative mating after adding the labor market structure. As before, the impact of the age-earnings profile is small, and the impact of the human capital accumulated through on-the-job experience and the nonlinearity in full-time versus part-time work are significant and large. The main difference between the impacts of the labor market structure in the alternative counterfactual designs is that in the absence of assortative mating, the impact of labor market on mothers to daughters' persistence in earnings is muted. However, when we add assortative mating to the earnings structure in the labor market, the impact is very large and increases the intergenerational persistence in earnings back to the level in the counterfactual UC -highlighting that while assortative mating by itself is not a major source of the correlation in earnings, coupled with the structure of the labor market, it has a larger role.

While assortative mating creates little of the observed persistence, when interacting with the earnings structure, it amplifies its effect substantially. For families of father and sons for example, the correlation of earnings measured as the average income between the ages of 30-40 increases by 66% (from 0.2118 t0 0.3513), and for all families the correlation increases by more than 140% (from 0.135 to 0.33), when we add introduce assortative mating to the model. Greenwood et al. (2014) also noted that assortative mating by itself does not increase the cross-sectional inequality, but plays a large role when women work. In our analysis of the intergenerational persistence in earnings, the mechanism through which assortative mating creates persistence, the female labor supply is the key. Fernandez and Rogerson (2001) show the importance of assortative mating to understanding cross-sectional earnings inequality. Fertility is also important in their mechanism through the decrease in fertility with education.[20] While in our sample fertility does not decline with household education, the quantity-quality trade-off is important. Although we do not find that assortative mating on its own is important, our robustness check shows that interacted with the earnings structure, it amplifies it and creates larger inequality by increasing persistence and reducing mobility.

5 Conclusion

This paper estimates a dynastic model of intergenerational transmission of human capital in which unitary households choose parental time, fertility, and labor supply. We decompose the impact of the following factors on the intergenerational correlation of earnings: assortative mating, earnings structure, heterogeneity in preference of households with different education levels, and the impact of parental education on the "education production function" of children.

We find that accounting for the division of work within the household and endogenous fertility is important for understanding the mechanism of intergenerational transmission of human capital. Parental time with children is an

[20] Our finding that the labor market earnings structure increases persistence of earnings through the decrease in fertility is related to previous findings in the literature. For example, Caucutt, Gunner, and Knowles (2002) find that returns to experience in the labor market delay fertility and decrease total fertility rates. The decline in fertility is central for generating persistence in our model.

important mechanism of transmission of human capital. Earnings structure has the largest impact on the persistence of earnings across generations. It has involved income and substitution effects on the household labor supply and parental time with children. Specifically, the nonlinearity of earnings in the labor market in hours and returns to the labor market experience also affect specialization patterns in households and fertility. The disproportionately larger returns to working full-time relative to part-time and the returns to experience reduce overall maternal time with children but decrease fertility and increase time investment per child in high education households. Therefore, the labor market earnings structure increases the persistence of outcomes across generations. While the role of parental education in reducing mobility across generations is important, much of the observed persistence in earnings across generations can be attributed to the earnings structure in the labor market. Lastly, we find that the impact of parental education in the net (utility) costs of raising children itself reduces the persistence of income. The intuition is in the spirit of Barro and Becker (1989). More educated households are wealthier, which tends to increase demand for children and reduce investment of time per child.

Our findings are related to the quantity-quality trade-off in the literature that often refers to a negative correlation between income and fertility. However, the literature on causal effects often finds that income has a positive effect on fertility (the husband typically); see, for example, Heckman and Walker (1990) and Lindo (2010). Our model predicts (as previously argued in the literature) an ambiguous relationship between fertility and income. On the one hand, if children are a normal good, higher income should increase demand at the same time the opportunity cost of time is higher. To the extent that parental time is important in early childhood, time also affects the quality of children and demand for quality increases with income as well. Our model captures all these elements and identifies and quantifies the causal effects of income and the opportunity cost of time. We find that increased income indeed raises fertility and reduces intergenerational correlation in earnings substantially –without the income effect on demand for children, the correlation would have been substantially larger. However, we find that the observed correlation in earnings across generations is higher due to (i) the increased opportunity cost of time amplified by the earnings structure of returns to experience and full-time work and (ii) increased demand for children when accounting for the substantial contribution of parental time to educational outcome of children.

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Table 1: Summary Statistics

Variable	All N	All Mean	Married N	Married Mean	Lifelong Married N	Lifelong Married Mean
Panel A: Parents' Sample						
Female	68,856	0.55	38,078	0.60	29,474	0.50
Married	68,856	0.55	38,078	1.00	29,474	1.00
Age	68,856	28.59	38,078	31.98	29,474	32.50
		(7.93)		(6.89)		(3.73)
Education (yrs. completed)	68,856	13.70	38,078	13.74	29,474	14.66
		(2.15)		(2.13)		(1.75)
No. of children	68,856	0.79	38,078	1.28	29,474	0.98
		(1.02)		(1.04)		(0.95)
Labor income ($ US 2005)	68,739	22,295	38,003	31,357	28,854	38,217
		(2779)		(2987)		(2043)
Labor market hours	68,790	1182	38,051	1598	28,914	1690
		(1053)		(916.)		(525.)
Housework hours	49,865	729.9	38,078	788.2	29,348	694.8
		(591.1)		(614.2)		(356.7)
Time spent with children	68,856	257.7	38,078	417.0	29,348	215.3
		(487.8)		(570.0)		(295.5)
No. of individuals	5,112		3,431		2,372	
Panel B: Children's sample						
Female	20,682	0.53	3,370	0.82	2,670	0.50
Married	20,682	0.16	3,370	1.00	2,670	1.00
Age	20,682	20.98	3,370	24.60	2,670	29.20
		(3.64)		(3.64)		(2.42)
Education (yrs. completed)	20,682	13.39	3,370	13.05	2,670	14.15
		(2.01)		(1.84)		(1.70)
No. of children	20,682	0.18	3,370	0.85	2,670	0.37
		(0.52)		(0.86)		(0.61)
Labor income ($ US 2005)	20,482	6,926	3293	21,254	2,576	39,181
		(1603)		(2331)		(2274)
Labor market hours	20,476	892	3,290	1467	2,576	1878.1
		(891.7)		(927.1)		(525.8)
Housework hours	6,486	648.8	3,370	785.1	2,662	516.2
		(523.3)		(561.5)		(286.4)
Time spent with children	20,678	72.7	3,370	351.1	2,662	84.50
		(277.8)		(528.6)		(184.1)
No. of individuals	3,778		759		550	

Note: Panel Study of Income Dynamics (PSID), 1968 to 1997. The number of observations of families is 16,072. Table uses both individual and spouse information. Therefore, for samples of married individuals, the total number of observations is two times the number of families. Standard deviations are listed in parentheses.

Table 2: 3SLS System Estimation of the Education Production Function

Variable	High School	Some College	College
High school father	0.084	0.007	-0.005
	(0.034)	(0.054)	(0.044)
Some college father	0.057	0.128	0.052
	(0.024)	(0.038)	(0.031)
College father	-0.038	0.017	0.123
	(0.032)	(0.051)	(0.042)
High school mother	0.110	0.101	-0.011
	(0.042)	(0.066)	(0.053)
Some college mother	0.041	-0.018	0.026
	(0.032)	(0.050)	(0.041)
College mother	0.102	0.128	0.038
	(0.038)	(0.059)	(0.048)
Mother's time	-0.043	0.060	0.053
	(0.021)	(0.034)	(0.027)
Father's time	0.026	0.096	0.028
	(0.019)	(0.029)	(0.025)
Mother's labor income	-0.032	-0.018	0.004
	(0.009)	(0.014)	(0.012)
Father's labor income	0.001	0.001	0.003
	(0.003)	(0.004)	(0.003)
Female	-0.004	0.136	0.086
	(0.017)	(0.027)	(0.022)
Number of siblings under age 3	0.010	-0.106	-0.043
	(0.020)	(0.033)	(0.026)
Number of siblings between age 3 and 6	-0.029	-0.025	0.009
	(0.026)	(0.042)	(0.034)
Constant	0.997	-0.118	-0.288
	(0.109)	(0.172)	(0.140)
Observations	1,332	1,332	1,332

Note: The excluded class is less than high school. Standard errors are listed in parentheses. Instruments: sibling sex composition (i.e., fraction of female siblings under age 3 and between ages 3 and 6) and age-earnings profile (i.e., linear and quadratic terms of mother's and father's age when the child was 5 years old).

Table 3: Discount Factors and the Cost of Children

Marginal Utility of Income and Cost of Children		Discount Factors	
Variable	Estimates	Variable	Estimates
Family labor income	0.373	β	0.813
	(0.054)		(0.008)
Children × Family labor income	-0.309	λ	0.795
	(0.053)		(0.009)
Children × HS × Family labor income	0.055	υ	0.111
	(0.032)		(0.007)
Children × SC × Family labor income	0.082		
	(0.021)		
Children × COL × Family labor income	0.101		
	(0.056)		
Children × HS spouse × Family labor income	0.044		
	(0.046)		
Children × SC spouse × Family labor income	0.058		
	(0.055)		
Children × COL spouse × Family labor income	0.084		
	(0.048)		

Note: Standard errors are listed in parentheses. LHS: individual has less than a high school education. HS: individual has completed high school but not attended college. SC: individual has completed more education than high school but is not a college graduate. COL: individual has at least a college degree.

Table 4: Intergenerational Correlation of Log Labor Earnings

	Individual Earnings		Family Earnings	
	Data	Model	Data	Model
Panel A: Fathers-sons				
Earnings at age 35†	0.251	0.146	0.317	0.159
	(0.099)	(0.033)	(0.094)	(0.035)
Average earnings from age 30 to 40‡	0.356	0.266	0.337	0.251
	(0.091)	(0.060)	(0.086)	(0.056)
Panel B: Mothers-daughters				
Earnings at age 35†	0.001	0.129	0.067	0.129
	(0.122)	(0.036)	(0.087)	(0.029)
Average earnings from age 30 to 40‡	-0.032	0.204	0.286	0.222
	(0.08)	(0.046)	(0.077)	(0.050)
Panel C: All				
Earnings at age 35†	-	-	0.1754	0.143
	-	-	(0.064)	(0.032)
Average earnings from age 30 to 40‡	-	-	0.31	0.236
	-	-	(0.070)	(0.053)

Note: † Uses parent-children pairs at age 35. ‡ Uses the average earnings for parent-children pairs when both are observed continuously between the ages of 30 and 40.

Table 5A: Cumulative Decomposition Choices

VARIABLE			CF0 M. ED 1	CF0 M. ED 2	CF0 M. ED 3	CF0 M. ED 4	AM M. ED 1	AM M. ED 2	AM M. ED 3	AM M. ED 4	AEP M. ED 1	AEP M. ED 2	AEP M. ED 3	AEP M. ED 4	RTE M. ED 1	RTE M. ED 2	RTE M. ED 3	RTE M. ED 4
MALE Home time	F. ED	1	1.67	1.85	0.92	1.37	1.43	1.58	0.85	1.34	1.54	1.39	0.71	1.06	1.60	1.73	0.89	1.35
		2	1.89	1.19	1.38	1.31	1.90	1.16	1.33	1.31	1.67	1.10	1.54	1.47	1.66	1.18	1.46	1.65
		3	1.90	1.30	1.50	1.78	1.11	1.25	1.52	1.81	1.54	1.29	1.46	1.78	1.27	1.33	1.62	1.91
		4	0.78	1.16	1.15	1.49	0.94	1.37	1.23	1.50	1.11	1.11	1.12	1.48	1.19	1.22	1.23	1.66
FEMALE: Home time	F. ED	1	4.16	4.45	3.93	4.18	4.45	4.44	4.23	4.02	4.16	4.64	4.68	4.22	4.84	4.59	4.59	3.52
		2	4.40	4.52	4.75	4.73	4.37	4.63	4.76	4.63	4.37	4.66	4.99	4.76	4.26	4.74	4.98	4.93
		3	3.97	4.33	4.70	4.64	4.13	4.46	4.82	4.72	3.92	4.54	4.87	4.98	3.79	4.66	5.06	4.95
		4	5.13	4.69	4.62	4.79	4.89	4.68	4.63	4.81	4.45	4.85	4.84	5.00	5.01	5.00	5.13	5.14
Birth	F. ED	1	0.12	0.10	0.09	0.06	0.10	0.09	0.08	0.05	0.13	0.10	0.08	0.06	0.11	0.09	0.06	0.04
		2	0.11	0.10	0.09	0.06	0.10	0.09	0.07	0.05	0.11	0.09	0.08	0.04	0.10	0.08	0.07	0.04
		3	0.10	0.09	0.08	0.06	0.09	0.08	0.07	0.05	0.11	0.09	0.07	0.04	0.09	0.08	0.06	0.03
		4	0.11	0.09	0.07	0.05	0.11	0.08	0.07	0.05	0.12	0.08	0.06	0.04	0.11	0.07	0.05	0.03
No. of children	F. ED	1	2.78	2.38	1.97	1.48	2.42	2.16	1.90	1.21	2.85	2.17	1.77	1.34	2.65	2.05	1.44	1.04
		2	2.65	2.28	1.93	1.39	2.46	2.04	1.74	1.26	2.62	2.17	1.78	1.08	2.39	1.93	1.56	0.98
		3	2.32	2.16	1.85	1.29	2.09	1.97	1.64	1.17	2.46	2.10	1.72	1.05	2.12	1.85	1.47	0.85
		4	2.48	1.96	1.65	1.16	2.53	1.88	1.50	1.07	2.51	1.84	1.49	0.95	2.37	1.57	1.17	0.74
MALE: LS Part-time	F. ED	1	0.06	0.07	0.02	0.06	0.03	0.04	0.00	0.04	0.04	0.03	0.01	0.04	0.04	0.04	0.01	0.06
		2	0.03	0.04	0.03	0.03	0.03	0.03	0.02	0.03	0.04	0.04	0.02	0.04	0.04	0.03	0.02	0.05
		3	0.05	0.03	0.02	0.03	0.04	0.03	0.02	0.03	0.05	0.03	0.02	0.04	0.05	0.03	0.02	0.04
		4	0.01	0.03	0.02	0.04	0.01	0.02	0.02	0.04	0.00	0.03	0.02	0.04	0.02	0.03	0.02	0.04
MALE: LS Full-Time	F. ED	1	0.85	0.91	0.95	0.89	0.91	0.93	0.97	0.90	0.93	0.92	0.94	0.87	0.89	0.94	0.98	0.92
		2	0.91	0.94	0.95	0.95	0.90	0.95	0.96	0.95	0.90	0.94	0.95	0.94	0.90	0.94	0.96	0.94
		3	0.87	0.95	0.95	0.95	0.87	0.95	0.96	0.95	0.80	0.95	0.96	0.95	0.85	0.94	0.96	0.94
		4	0.98	0.96	0.96	0.95	0.98	0.96	0.95	0.95	0.95	0.95	0.96	0.94	0.93	0.95	0.95	0.94
MALE: Part. rate	F. ED	1	0.91	0.98	0.97	0.95	0.94	0.97	0.97	0.95	0.97	0.95	0.95	0.91	0.93	0.98	0.99	0.98
		2	0.95	0.98	0.98	0.99	0.93	0.98	0.98	0.98	0.94	0.98	0.98	0.98	0.94	0.98	0.98	0.98
		3	0.92	0.98	0.98	0.99	0.91	0.98	0.98	0.99	0.85	0.98	0.98	0.98	0.90	0.97	0.98	0.98
		4	0.98	0.99	0.98	0.98	0.98	0.98	0.97	0.98	0.95	0.98	0.98	0.98	0.95	0.97	0.98	0.98
FEMALE: LS Part-time	F. ED	1	0.11	0.16	0.13	0.15	0.09	0.15	0.15	0.14	0.12	0.15	0.10	0.13	0.10	0.14	0.12	0.13
		2	0.13	0.14	0.15	0.17	0.13	0.14	0.15	0.18	0.12	0.14	0.15	0.20	0.13	0.14	0.16	0.20
		3	0.16	0.14	0.15	0.18	0.14	0.14	0.15	0.18	0.15	0.14	0.15	0.20	0.16	0.14	0.16	0.20
		4	0.10	0.15	0.16	0.18	0.09	0.14	0.15	0.18	0.11	0.15	0.16	0.20	0.10	0.14	0.17	0.20
FEMALE: LS Full-time	F. ED	1	0.19	0.20	0.27	0.26	0.16	0.19	0.19	0.32	0.17	0.21	0.25	0.28	0.16	0.22	0.25	0.35
		2	0.18	0.19	0.22	0.25	0.17	0.19	0.22	0.25	0.19	0.19	0.23	0.29	0.18	0.21	0.25	0.32
		3	0.19	0.20	0.22	0.26	0.17	0.20	0.23	0.26	0.17	0.20	0.23	0.30	0.19	0.22	0.27	0.37
		4	0.27	0.21	0.24	0.29	0.26	0.22	0.25	0.30	0.20	0.21	0.27	0.34	0.20	0.28	0.35	0.44
FEMALE: Part. rate	F. ED	1	0.30	0.35	0.40	0.40	0.25	0.34	0.34	0.46	0.29	0.36	0.35	0.41	0.25	0.36	0.36	0.48
		2	0.31	0.33	0.37	0.42	0.31	0.33	0.37	0.42	0.31	0.34	0.39	0.49	0.31	0.35	0.40	0.52
		3	0.34	0.34	0.37	0.43	0.32	0.34	0.38	0.44	0.32	0.34	0.38	0.50	0.35	0.36	0.42	0.57
		4	0.37	0.36	0.40	0.47	0.35	0.36	0.40	0.48	0.31	0.36	0.43	0.54	0.31	0.43	0.52	0.64

CF0, baseline. AM: adds assortative mating to CF0. AEP: adds the age-earnings profile to AM. RTE: adds the labor market experience to AEP. LS: labor supply; Part. rate: labor market participation rate; M.ED(F.ED): male(female) education, 1(LHS), 2 (HS), 3(SC), 4(COL).

TABLE 5B: CUMULATIVE DECOMPOSITION CHOICES

VARIABLE			CF0				FTPT				UC				NA			
			M. ED				M. ED				M. ED				M. ED			
			1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
MALE Home time	F. ED	1	1.67	1.85	0.92	1.37	0.71	1.41	0.31	0.61	1.10	1.69	1.38	0.00	0.61	1.41	0.31	0.61
		2	1.89	1.19	1.38	1.31	1.45	1.01	1.14	1.26	1.16	1.32	1.63	1.83	1.45	1.01	1.14	1.26
		3	1.90	1.30	1.50	1.78	1.02	1.00	0.96	1.53	1.29	1.41	1.73	1.91	1.00	1.00	0.96	1.53
		4	0.78	1.16	1.15	1.49	0.40	1.30	1.05	1.58	0.45	1.28	1.28	1.69	0.40	1.30	1.05	1.58
FEMALE: Home time	F. ED	1	4.16	4.45	3.93	4.18	4.84	4.59	4.59	3.52	4.98	4.96	4.58	3.93	4.91	4.59	4.59	3.52
		2	4.40	4.52	4.75	4.73	4.26	4.74	4.98	4.93	4.48	4.72	4.93	4.78	4.26	4.74	4.97	4.93
		3	3.97	4.33	4.70	4.64	3.79	4.66	5.06	4.95	3.89	4.43	4.83	4.73	3.80	4.66	5.06	4.95
		4	5.13	4.69	4.62	4.79	5.01	5.00	5.13	5.14	5.33	4.65	4.71	4.79	5.01	5.00	5.13	5.14
Birth	F. ED	1	0.12	0.10	0.09	0.06	0.08	0.07	0.04	0.02	0.04	0.04	0.01	0.01	0.08	0.07	0.04	0.02
		2	0.11	0.10	0.09	0.06	0.09	0.06	0.04	0.02	0.06	0.06	0.05	0.03	0.09	0.06	0.04	0.02
		3	0.10	0.09	0.08	0.06	0.08	0.05	0.03	0.01	0.06	0.07	0.06	0.05	0.08	0.05	0.03	0.01
		4	0.11	0.09	0.07	0.05	0.10	0.04	0.02	0.01	0.08	0.07	0.06	0.06	0.10	0.04	0.02	0.01
No. of children	F. ED	1	2.78	2.38	1.97	1.48	1.95	1.61	0.94	0.41	0.99	0.88	0.31	0.16	1.94	1.61	0.94	0.41
		2	2.65	2.28	1.93	1.39	2.19	1.45	0.93	0.42	1.42	1.40	1.16	0.87	2.19	1.45	0.94	0.42
		3	2.32	2.16	1.85	1.29	1.83	1.27	0.82	0.30	1.45	1.65	1.46	1.26	1.83	1.27	0.82	0.30
		4	2.48	1.96	1.65	1.16	2.05	0.96	0.48	0.24	1.79	1.65	1.46	1.56	2.05	0.96	0.48	0.24
MALE: LS Part-time	F. ED	1	0.06	0.07	0.02	0.06	0.20	0.23	0.06	0.05	0.01	0.05	0.01	0.05	0.22	0.23	0.06	0.05
		2	0.03	0.04	0.03	0.03	0.27	0.17	0.08	0.08	0.03	0.04	0.03	0.05	0.27	0.17	0.08	0.08
		3	0.05	0.03	0.02	0.03	0.23	0.13	0.06	0.05	0.04	0.03	0.02	0.03	0.24	0.13	0.06	0.05
		4	0.01	0.03	0.02	0.04	0.21	0.08	0.03	0.05	0.01	0.03	0.02	0.03	0.21	0.08	0.03	0.05
MALE: LS Full-Time	F. ED	1	0.85	0.91	0.95	0.89	0.70	0.72	0.90	0.90	0.90	0.87	0.97	0.89	0.68	0.72	0.90	0.90
		2	0.91	0.94	0.95	0.95	0.66	0.79	0.90	0.90	0.89	0.93	0.95	0.93	0.66	0.79	0.90	0.90
		3	0.87	0.95	0.95	0.95	0.63	0.84	0.92	0.92	0.86	0.95	0.96	0.95	0.63	0.84	0.92	0.92
		4	0.98	0.96	0.96	0.95	0.73	0.90	0.94	0.93	0.98	0.95	0.96	0.96	0.73	0.90	0.94	0.93
MALE: Part. rate	F. ED	1	0.91	0.98	0.97	0.95	0.90	0.95	0.97	0.95	0.90	0.92	0.97	0.94	0.90	0.95	0.97	0.95
		2	0.95	0.98	0.98	0.99	0.93	0.97	0.98	0.98	0.92	0.97	0.98	0.98	0.93	0.97	0.98	0.98
		3	0.92	0.98	0.98	0.99	0.86	0.97	0.98	0.98	0.90	0.98	0.98	0.98	0.87	0.97	0.98	0.98
		4	0.98	0.99	0.98	0.98	0.94	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.94	0.98	0.98	0.98
FEMALE: LS Part-time	F. ED	1	0.11	0.16	0.13	0.15	0.14	0.16	0.20	0.22	0.18	0.21	0.27	0.29	0.14	0.16	0.20	0.22
		2	0.13	0.14	0.15	0.17	0.14	0.16	0.19	0.26	0.14	0.16	0.17	0.20	0.14	0.16	0.19	0.26
		3	0.16	0.14	0.15	0.18	0.15	0.16	0.20	0.24	0.16	0.14	0.16	0.16	0.15	0.16	0.20	0.24
		4	0.10	0.15	0.16	0.18	0.13	0.18	0.19	0.22	0.15	0.15	0.14	0.15	0.13	0.18	0.19	0.22
FEMALE: Full-time	F. ED	1	0.19	0.20	0.27	0.26	0.20	0.23	0.31	0.51	0.25	0.30	0.44	0.55	0.19	0.24	0.31	0.51
		2	0.18	0.19	0.22	0.25	0.18	0.27	0.35	0.46	0.28	0.26	0.31	0.36	0.18	0.27	0.35	0.46
		3	0.19	0.20	0.22	0.26	0.22	0.30	0.39	0.54	0.24	0.26	0.28	0.31	0.22	0.30	0.39	0.54
		4	0.27	0.21	0.24	0.29	0.24	0.41	0.54	0.63	0.24	0.29	0.32	0.31	0.24	0.41	0.54	0.63
FEMALE: Part. rate	F. ED	1	0.30	0.35	0.40	0.40	0.33	0.40	0.51	0.73	0.43	0.50	0.71	0.84	0.33	0.40	0.51	0.73
		2	0.31	0.33	0.37	0.42	0.33	0.42	0.54	0.72	0.42	0.42	0.48	0.56	0.33	0.42	0.54	0.72
		3	0.34	0.34	0.37	0.43	0.37	0.47	0.59	0.79	0.41	0.40	0.44	0.47	0.37	0.47	0.58	0.79
		4	0.37	0.36	0.40	0.47	0.37	0.58	0.73	0.84	0.40	0.43	0.46	0.46	0.37	0.58	0.73	0.84

CF0, baseline. FTPT, adds returns to full- vs. part -time work to RTE. UC, adds the effect of education on the direct child raising cost to FTPT. NA, adds parental education to the production function. to FTPT. LS: Labor supply; Part. rate: Labor market participation rate; M.ED(F.ED): male(female) education, 1(LHS), 2(HS), 3(SC), 4(COL).

Figure 1: Features of the Empirical Earnings Equation

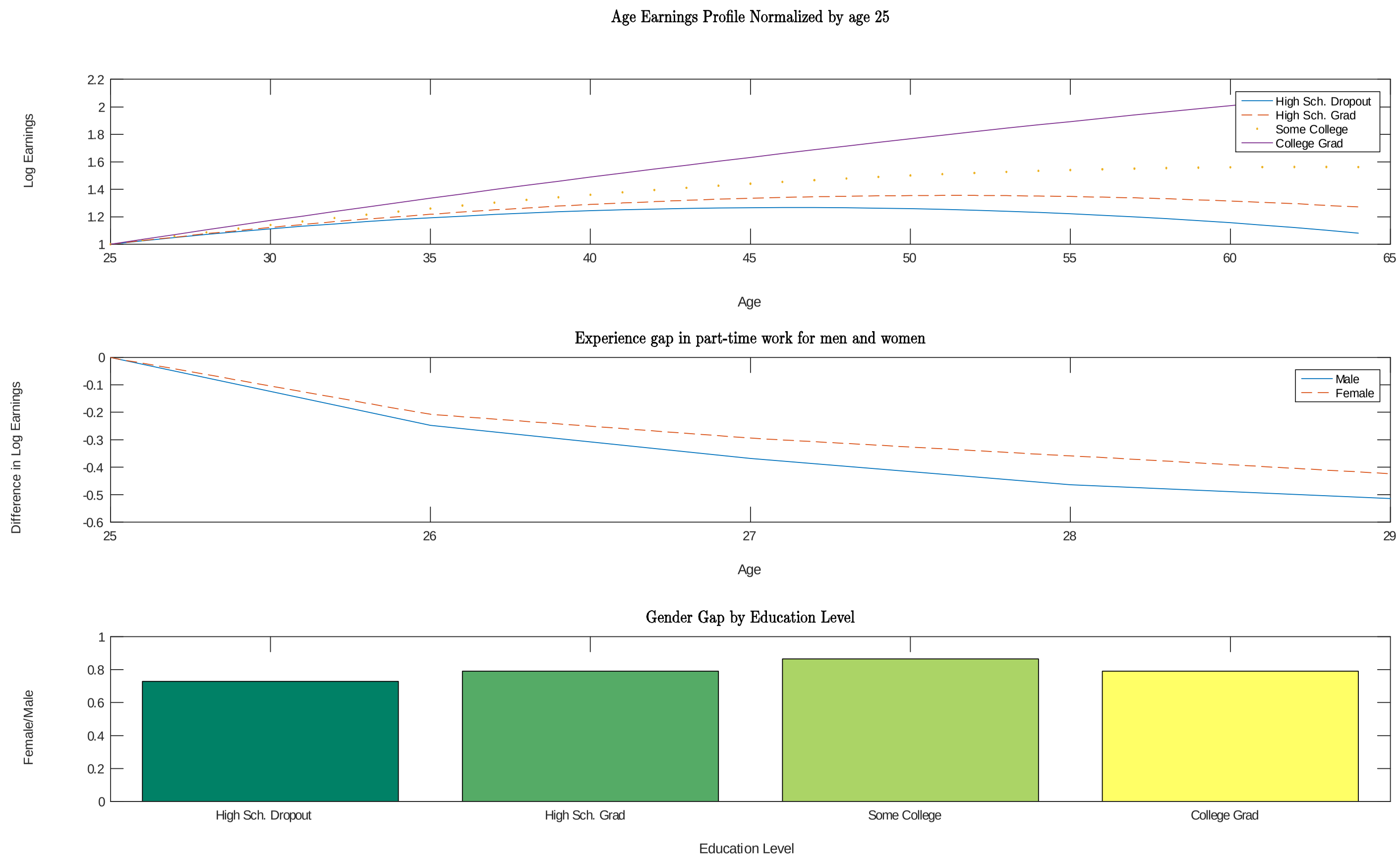
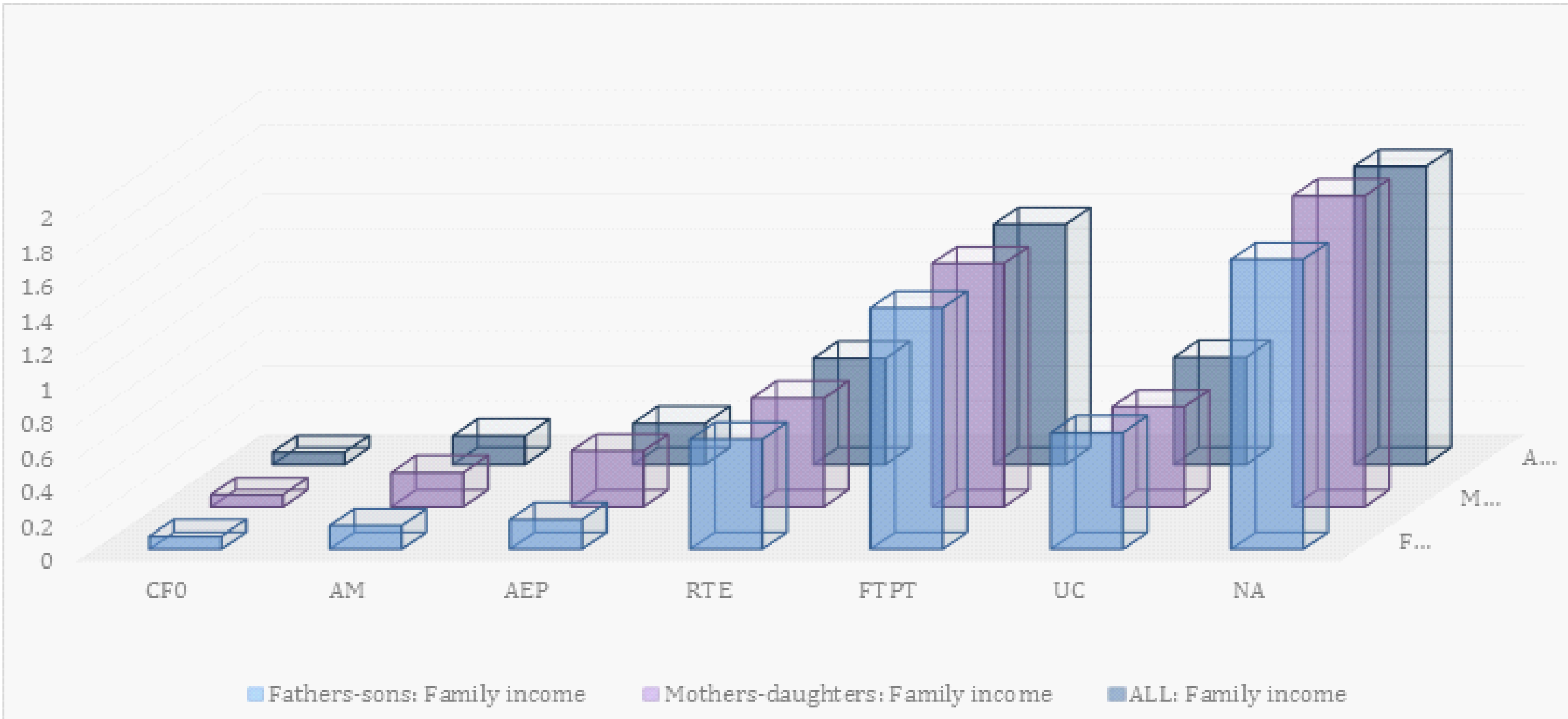
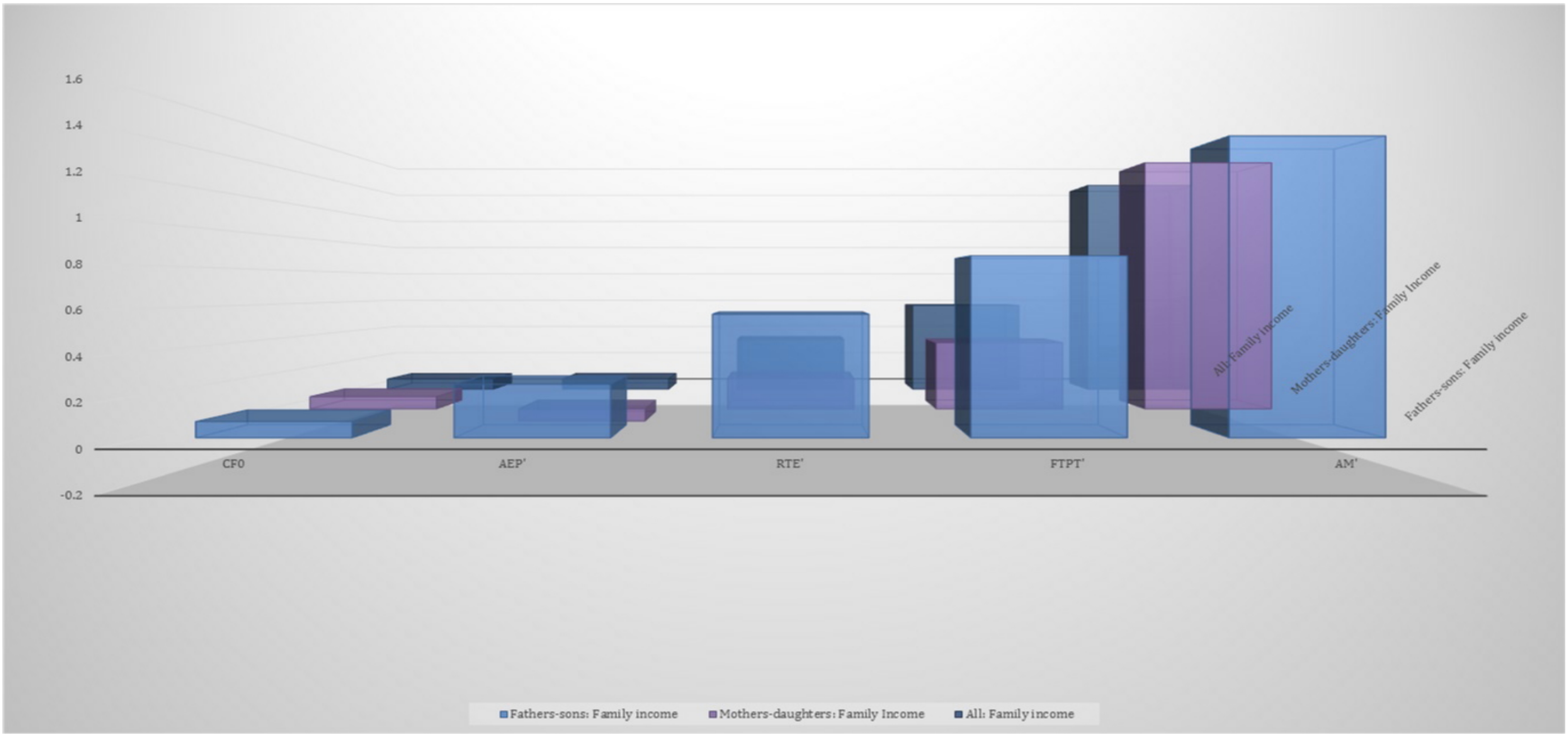


Figure 2: Cummulative Decomposition of the Source of Intergenerational correlation



Note: CF0, baseline. AM, assortative mating effect. AEP, age-earnings profile effect. RTE, labor market experience effect. FTPT, part- versus full-time work effect. UC, education effect of direct costs of children. NA, direct effect of parents' education. Effects are sequentially added in the order listed.

Figure 3: Cummulative Decomposition of the Source of IGE: Impact of Assortative Mating



Note: CF0, baseline. AEP',age-earnings profile effect. RTE', labor market experience effect. FTPT', part- versus full-time work effect. AM'-assortative mating effect. Effects are sequentially added in the order listed.