What is the source of the intergenerational correlation in earnings?[1]

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Abstract

This paper uses a dynastic model of household behavior to estimate and decomposed the correlations in earnings across generations. The estimate model can explain 75% to 80% of the observed correlation in lifetime earnings between fathers and sons, mothers and daughters, and families across generations. The main results are that the family and division of labor within the household are the main source of the correlation across generation and not just assorting mating. The interaction of human capital accumulation in labor market, the nonlinear return to part-time versus full-time work, and the return to parental time investment in children are the main driving force behind the intergenerational correlation in earnings and assortative mating just magnify these forces.
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1 Introduction

Understanding the determinants of intergenerational correlations is crucial for the development of public policy. Without knowing the true mechanism, it is impossible to understand how to promote the change in favor of more mobility. This is unfortunately a difficult task, as it is often the case that any particular attribute is correlated with a variety of parental characteristics, many of which cannot be observed in the data. Most of the early literature on the intergenerational mobility focused on obtaining precise estimates of correlations and elasticities across generations, but more recently literature has placed increased emphasis on the mechanisms that drive this relationship. However apart from a handful of papers, the source of intergenerational transmission of income remains to be explored. Given the importance of understanding the intergenerational mobility, coupled with the paucity of empirical research on the transmission mechanism of genetic, human capital, and other sources of life-cycle investments in terms of their contribution in accounting for the mobility, the primary purpose of this paper is to investigate the relationship between different sources and the intergenerational income correlation.

Dynastic models are used to understand intergenerational mobility and persistence in outcomes across generations. However, with endogenous fertility, Barro and Becker (1989) result shows that there is no persistence in outcomes because wealthier parents increase the number of offspring keeping transfer levels the same as less wealthier parents, so the transfer per child is the same. However, Alvarez (1999) shows under certain conditions transfer are affected by parents' wealth and persistence in outcome is achieved in dynastic models with endogenous fertility. The model we formulate satisfies some of Alvarez (1999)'s conditions, thus, predicting that wealthier and more educated parents invest more in their children. This is achieved by quantity-quality trade-off: where more educated parents have less children and they invest more in them. Moreover, in standard theory, as in Barro and Becker (1988), children are normal goods, thus, wealthier people have more children. However, in the data more educated parents (wealthier households) have less children (see Jones and Tertilt), thus in this paper we estimate a model that captures the quantity-quality trade-off by socioeconomic status of households.

Alvarez (1999)'s conditions for persistence involves first relaxing the Barro-Becker assumptions of constant costs of transfer per child. In the model estimated in this paper the transfer from one generation to another involves time investment and the opportunity cost of time is the loss earnings. In the model labor supply is modeled as a discrete choice – No work, Part-Time and Full-Time – thus, at some points increasing the number of children and the time with children can cause moving from part-time to full time work for example, but the earnings function is not linear in part-time and full time work. Furthermore, the model has returns to experience, thus reducing labor supply reduces future earnings in a non-linear fashion as the return to part-time versus full time past work are non-linear. Thus the cost of transfer of human capital per child are not constant.

In contrast to standard dynastic models and those analyzed in Alvarez (1999) the model estimated in this paper incorporates dynamic elements of the life-cycle, that involve age effect and experience. The opportunity cost of time with children therefore incorporate returns to experience, which are non-linear. The nonlinearity involved in labor supply are 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 are not always flexible and depend on occupation and jobs. Furthermore, fertility decisions are made sequentially, and due to age effects, the cost of a child vary over the life-cycle. Alvarez (1999) also shows if there exists non-separability in preferences, aggregation of the utilities from children, and the feasible set across generations that the dynastic models with endogenous fertility can generate persistence in outcomes across generation. In our model, the latter is relaxed; that is, the separability of the feasible set across generations. This is because the opportunity costs of the children depend on their education and labor market skill. However, education and labor market skills of children are linked with their parents' skills and education through the production function of education. We add an additional but important source of intergenerational mobility normally not considered in the literature: assortative mating. There is normally an issue with measure intergenerational mobility. The empirical literature normally looks at father-son income correlation but now women are 50 percent of the labor force so in order to get a complete picture of intergenerational mobility one should look at the correction of income across families. In order to do that we need a model of who marries who. In this sense assortative could increase the intergenerational correlation.

Using two generation from the PSID we use married couples to analyze the relative importance of the different sources to intergenerational correlations in the USA. We document that there are significant amount of earnings persistence in the data using three different types measurement units (i.e. father-son, mother-daughter, family-family correlations and two different measures of earnings (individual and family income), two measure of income at different point in the life-cycle (income at age 35 and average income from ages 30 to 40). We confirm what has been already been documented in the literature (see Bjorklund and Jantti (2009), Blanden (2009), Corak (2006), Grawe (2006), and Solon (1999, 2002) for comprehensive surveys of this literature) that average income for several points in the life-cycle are more robust than income measured at a single point.

Furthermore, we find that family income gives a more complete picture of intergenerational mobility than individual income. This is particularly apparent when measuring mother to daughter correlations where when using individual income we do not find significantly amount of earnings persistence but when family income is used we show that there are significant correlation of incomes across generations for mothers-daughters pair. This is because of the selection that take place in the marriage market and the effect of human capital accumulation in the labor market. When female marries a male with high earnings potential, she has a high probability of specializing in home production or to interpret this labor market participation or intensive at some point in her life-cycle. These two events are biasing downward the correlation between mothers and daughters if it is measured by individual earnings. The reason why specialization in home production biases downward the correlation because a female that specializes in home production does not have any labor income. Secondly, Human capital accumulation in the labor means that her earnings are going to be lower if she interprets her participation or intensive at the early part of her life-cycle. Using family income helps solves this bias in the intergenerational correlation between mothers and daughters. Finally, regardless how it is measured – father to son, mother to daughter, or family to family – there are significant correlations in family income across generations.

We then structural estimate our dynastic life-cycle model and show that is can replicate the intergenerational elasticity of earnings observed in the data. Next, we decompose the persistence of earnings across generations into the effect of (i) assortative mating in the marriage market, (ii) the age earnings profile in generating nonlinearity in the opportunity cost of raring children, (iii) human capital accumulation in labor market in generating nonlinearity opportunity cost of raring children and the non-separability of feasibility set across generations. (iv) the nonlinearity in the return to part-time versus full-time in generating non-linearity in opportunity cost of raring, (v) the direct cost of children depending on parent's education, and (vi) the effect of nature – the automatic transmission of economic status across generations.

We find that out model can explain more than 75% of the observed persistence of earnings across generations although the correlation of earnings was not targeted in estimation. The first, major finding is that assortative mating by itself for less than 13% of observed persistence in earnings across generation. The nonlinearity in the opportunity cost of raring children and the non-separability of feasibility set across generations cause by the accumulation of human capital in the labor market via on the job experience accounts for roughly 42% of the observed persistence in earnings across generation. Adding the nonlinearity in the return to part-time versus full-time and the model can generate more persistence that what is observed in the data. This is because female labor supply and therefore time with children are greatly affected by these factors both because of the income effects through husband's earnings and own earnings, as well as the substitution effect and the opportunity costs of time. These effects operate in different directions empirically assessing there effect is necessary. In particular, the returns to experience and returns to working full time increase opportunity cost of time of educated women reducing fertility and specialization, but also generate income effect through the earnings of the husbands which increase specialization and fertility.

Overall, we find that the increase persistence because although overall time of educated women with kids decline, fertility also declines and the investment per child increases creating persistence through the quantity-quality trade-off. While assortative mating itself did not generate much persistence, when interacted with the earnings structure, it amplifies its effect and generates more persistence. Perhaps surprisingly, the overall impact of education of parents, although it has a direct effect on children educational outcomes reduces the persistence overall due to income effect and increase demand for children. It is important to note the significance of this results: that without any effect of "nature" – the automatic transmission of economic status across generation – dynastic model in the spirit of Barro and Becker (1989) model can generation more (not less) persistence than what is observed in the data.

Additionally we find that effect of the direct cost of raring depending on parent's education acts to mute the persistence in earnings across generations. This is in line with the prediction Barro and Becker (1989) model of endogenous fertility which shows that with endogenous fertility, wealthier parents have more children and through the quantity-quality trade-off there is no persistence in wealth. Finally, overall "nurture" accounts for between 58% and 68% of the observed persistence in earnings. While there still remains a significant for nature it is of a small order of magnitude.

The rest of the paper is organized as follows. Section 2 presents the data and documents the observed persistence of earnings across generations. Highlighting the role of gender and the need to take the household seriously when computing these measures. Section 3 presents out theoretical model. Section 4 presents the empirical strategy and results. Section 5 concludes while an online appendix contains additional tables and results.

2 Data and preliminary empirical analysis

We use data from the Family-Individual File of the PSID. We select individuals from 1968 to 1996 by setting the individual level variables "Relationship to Head" to head, or wife, or son, or daughter. All sons or daughters are dropped if they are younger than 17 years of age. This initial selection produces a sample of 12,051 and 17,744 males and females, respectively; these individuals were observed for at least one year during our sample period. White individuals between the ages of 17 and 55 are kept in our sample. The earnings equation requires the knowledge of the last 4 past labor market participation decisions. This immediately eliminates individuals with fewer than five years of sequential observations. To track parental time input throughout a child's early life, we dropped parents observed only after their children are older than 16 years of age. We also dropped parents with missing observations during the first 16 years of their children's lives. Furthermore, if there are missing observations on the spouse of a married individual, then that individual is dropped from our sample. Therefore the main sample contains 89, 538 individual-year observations.

Table 1 presents the summary statistics for our sample; column (1) summarizes the full sample, column (2) focuses on the parents, and column (3) summarizes the characteristics of the children. It shows that the first generation is on average 7 years older than the second generation in our sample. As a consequence, a higher proportion is married in the first generation relative to the second generation. The male-to-female ratio is similar across generations (about 55 percent female). There are no significant differences across generations in the years of completed education. As would be expected, because on average the second generation in our sample is younger than the first generation, the first generation has a higher number of children, annual labor income, labor market hours, housework hours, and time spent with children. Our second-generation sample does span the same age range, 17 to 55, as our first sample.

2.1 Intergenerational correlation of earnings

There is large literature on the estimates of intergenerational income correlation (IGC) and/or elasticity (IGE)[1], recent estimates of IGE for the USA vary between 0.4 and 0.6. These differences in the estimates are due the differences in the datasets used and the methodology applied. These sources are now well known in the literature[2]. The first, is obtaining an appropriate measurement of '*father's permanent*' income. Early estimates of IGC and IGE mainly focused on father-son pairs and used earnings in a single year for both fathers and sons. This approach can produce sizable biases due to measurement error. This approach can be improved by averaging over multiple years of earnings data. However, averaging more data still may not be enough to produce a good proxy permanent income if the income data are not taken from proper portion of the life-cyle. This bias, known as the life-cycle bias can induce a positive or negative bias on the estimated IGE coefficient depending on the cover of the life-cycle income data for fathers and sons. As such the first panel of Table 2 presents four measures of IGC and IGE for our data, the first measures labor income at age 35 for both fathers and sons, the second averages labor income for both fathers and sons between ages 30 and 40, the third measures fathers' income at age 50 and sons' income at age 30, and the fourth measures averages between ages 40 and 45 and measures sons income at age 30[3]. We obtain IGC between 0.25 and 0.35 and IGE between 0.28 and 0.50 which are in keeping what is found in the literature (see for example Table 1 in Solon (1992). In general the IGE is greater than the IGC – given that log income is used in the both calculation – both measures would be equal if the income distribution (.i.e. variance of fathers' and sons log income) were the same. Therefore this is evidence of the income distribution shifting over time.

Given the prevalence of two-adult households, total family earnings are, in addition to individual earnings, an important subject of study. The second

[1] See Bjorklund and Jantti (2009), Blanden (2009), Corak (2006), Grawe (2006), and Solon (1999, 2002) for comprehensive surveys of this literature.

[2] See Atkinson, Maynard, Trinder (1983). Jenkins (1987), Creedy (1988), Reville (1995), Solon (1989, 1992), Zimmerman (1992), and Grawe (2004, 2006).

[3] The fourth measure is similar to the measure proposed by Solon (1992).

panel of Table 2 reports the same measures using family income for fathers and sons, it shows that the patterns are similar to individual incomes but IGC and IGE for family income is generally larger than for individual income. Until lately, most of the literature focused on the intergenerational correlation between fathers and sons, and there were few IGE estimates for daughters[4]. The third and fourth panels of Table 2 reports the IGE and IGC for mothers and daughters. It shows that these are generally smaller than the equivalent IGE and IGC for fathers and sons. The IGE and IGC for individual income are general small and insignificant however we obtain IGE and IGC of similar order of magnitude to fathers and sons for family when we average for 10 years for both parent and child. Chadwick and Solon (2002) find that, in the U.S., the elasticity of daughters' family earnings with respect to their parents' income is about 0.4, much higher than the IGE of their individual earnings[5]. Here, assortative mating can have a very strong influence. Strikingly, Chadwick and Solon (2002) also show that individual earnings of husbands and wives are as highly correlated with the incomes of their in-laws as with the incomes of their own parents.

2.2 Assortative mating and household specialization

For the estimation, we only keep married households and include the married individuals as of age 25 with all the individual years of observations whenever the family is intact up to age 40. Further to account for the time and monetary investments during the early years of the child since birth, we drop individuals who already have a kid as of age 25. This brings the sample from 89,538 (this sample includes all single and married individuals from age 17 to age 55) to 16,072 individual-year observations. Table 3 describes the key variables by race, spouse gender and education. Over all the number of children (yearly average) is increasing with education of males and females. There is a high proportion of college graduate in our sample; 45% of males and 43.2% of females have college education. Less than 3% of males and 1.5% of females have

[4] An exception is Jantti et al. (2006) that estimates IGE for fathers and daughters.
[5] An exception is Mazumder (2005).

less than high school degree. Annual labor market hours increase in education, with the exception of college educated females. However, annual income increases with education. Annual time spent with children generally increases with education, with the exception of husbands with some college. These findings might be interpreted as the complex role of human capital, income distribution, and assortative mating play in societies and will be incorporated in our model and estimation.

3 Model

This section develops a partial equilibrium model of altruistic parents that 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 Loury (1981) and Becker and Tomes (1986), fertility is exogenous while in others, such as 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 behavior model. Life-cycle is important to understanding fertility behavior, and spacing of children, as well as 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].

3.1 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. Each

[6]See Gayle, Golan and Soytas 2015.

adult has children attached to them throughout their life. A child can either female of male. Let ζ, a dummy variable, denote whether a child is a female or not. Children becomes adults after they have been raised by both parents for T^e periods.

Children, (ages 0 to T^e), do nothing. This childhood period is divided into early childhood, ages 0 to 5, and later childhood, (ages 6 to T^e) periods. Parents make active investments in 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, spent time raising young children, and consume. From age T^e+T^f+1 to T old households supply labor, spent 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 continuous choice c. The discrete choice vector is given by $a = (h_f, h_m, d_f, d_m, b)$ comprising household market work time (h_f, h_m), household home work time with children (d_f, d_m), and whether to have child or not b. We denote the feasible set of action vectors A whose elements depend on whether it is a young or old adult household. For each period, t, in their adult life couples have a vector of state variables z_t which 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 offspring.

Budget Constraint Raising children requires parental time, d, and also market expenditure. There is a per-period cost of 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 proportion of household earnings that is spent per child[7].

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

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

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

Let $I_{a_t}^o$ be the indicator variable of the optimal discrete choice of a type-(f, m) household of age. The we assumed that the utility from the life time of own action and consumption is of the form:

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

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 discounts the utility of each additional child by a factor of $1 - v$, where $0 < v < 1$ because we assume diminishing marginal returns from

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

offspring. The within generations utility, $u_{a_t}(z_t)$, can be written as function as only the discrete actions by substituting the binding budget constraint into for consumption. This is described by the following equations

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

where $\theta_a(z)$ is dis/utility from the 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 for a young adult in generation $i+1$ at age $T^e + 1$ looking forward from that point. Therefore recursively 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 household has during there fertile period and $U_n(f', m')$ is the expected utility of the household of child n.

Human Capital and Earnings Lifecycle Dynamics The earnings process depends on education, experience, and innate ability and are determined by the following sets of equations

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

$W_{f(m)}(x, h_{f(m)t})$ 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 working and its return in the labor market depends on the type of

[8]See Altug and Miller (1998), Gayle and Golan (2012) and Gayle and Miller (2014) who documented these features of the modern labor market.

experience – part-time versus full-time – and how recent the experience was obtained. Thus capturing both depreciation of human capital and differential returns to part-time versus full-time; both of which are gender specific. Innate ability, $\eta_{f(m)}$, are rewarded in the labor market.

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

Offsprings Outcomes The offspring's characteristics, $x \equiv (e, \eta)$, are affected by parents' characteristics, early childhood monetary investments, early childhood time investments, and presence and timing of siblings in early childhood. This intergenerational production function is determined by the following sets of equations

$$\begin{aligned} e'_{f(m)} &= \Gamma_{f(m)}[x, d^{(0)}, ..., d^{(5)}, w^{(0)}, ..., w^{(5)}, S_{-5})] + \omega_{f(m)} \quad (6) \\ \eta'_{f(m)} &= \Gamma_{f(m)\eta}(e') + \widetilde{\eta}'_{f(m)} \quad (7) \\ \Pr(\widetilde{\eta}' &= \widetilde{\eta}_i) = F_{f(m)}(e_f, e_m, \eta_f, \eta_m) \quad (8) \end{aligned}$$

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 education outcome of offsprings. Children 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 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 that is determined by parental inputs through the effect of the educational outcome and innate ability and a separable component that is transmitted through the parents' innate ability directly.

3.2 Discussion

In Barro and Becker (1989) formulation with endogenous fertility without restrictive assumptions on preference and childcare costs there is no persistence in income because wealthier parents increase the number of offspring keeping transfer levels the same as less wealthier parents, so the transfer per child is the same. However, several features of our model can lead to intergenerational persistence in income. These are (i) the nonlinearity in cost of transferring human across generations, (ii) non-seperability in 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 generation is described in the budget constraint in equation 1, as well as the opportunity costs of time investment input in children which is the forgone earnings. Time investment and labor supply are modeled as discrete choices. Thus introducing nonlinearity in the cost of raising children and transferring human capital. Thus the cost of transfer of human capital per child are not constant. If the cost of transferring human capital was constant then, as shown in Alvarez (1999), the standard dynastic model, ala Barro-Becker, could not generated persistence in income across generations.

By incorporating the dynamic elements of the life-cycle, that involve age effect and experience. The opportunity cost of time with children therefore incorporate returns to experience, which are non-linear. The nonlinearity involved in labor supply are 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 are not always flexible and depend on occupation

[9] See Alvarez (1999) for similar conditions which can generate persistence in income and wealth across generations in dynastic models with endogenous fertility. Also see Doepke (2004) and Jones, Schoonbroodt, Tertilt (2008) other discussion of these conditions.

and jobs. Furthermore, fertility decisions are made sequentially, and due to age effects, the cost of a child vary over the life-cycle. Mookherjee, Prina and Ray (2012) has a model with most of these characteristic and 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 opportunity costs of the children depend on the their education and labor market skill. However, education and labor market skills of children are linked with their parents' skills and education through the production function of education. This is one of the most natural way of generating persistence in the standard dynastic model.

Incorporating two household members to the model captures important issues of the degree of specialization in housework and labor market work in household with different composition of education. The importance of which spouse spends time with children (and the levels of time) depends on the production function of education of children and whether time of spouses is complement or substitute. To the best of our knowledge this 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 patterns. In our model there is potentially correlation of the cost of transfers to children (time input) with both parents' characteristics, assortative mating patterns imply 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 educational outcomes. A number of recent papers have highlighted the importance of this mechanism for explaining cross-sectional inequality. See for example Fernandez and Rogerson (2001), Fernandez, Guner, Knowles (2005) and Geenwood, Guner, Kocharkov and Santas (2014, 2015). While these papers do not directly look at mobility or persistence of earnings they use dynastic model with households behavior which are similar to the one used here.

4 Empirical strategy and results

The model is estimated using 2 generations from the PSID. A multi-stage estimation technique developed in Gayle et al. (2015) is used in the estimation. The estimation is based on a conditional choice probabilities (CCPs) estimation technique that combines forward simulation (see Hotz et al. (1994)), an alternative value function representation for stationary dynastic model (see Gayle et al. (2015)), and the Hotz-Miller inversion (see Hotz and Miller (1993)). The estimation proceeds in 4 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 CCP for household choices are estimated. In step 3 the alternative value function representation, the estimates from steps 1 and 2, and the Hotz et al. (1993)'s 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 are used to form moment conditions for a generalized method of moment (GMM) estimation of the utility function parameters and discount factors.

Of the features in our theoretical framework that could generate earnings persistence across generations only the direct monetary cost of children and intergenerational discount factors are estimated in step 4. The other important components — the earnings structure, education production and the relative importance of "nature" versus nurture, and marriage market matching function— are estimated outside of model. We are therefore using the revealed preference of household to have children and the division of labor with the household estimate the preference parameters, the monetary cost of raising children, and the discount factors. We do not target the intergenerational correlation in earnings at any time during estimation. Therefore we are able validate our model my accessing how well it is able to replicate the observed earnings correlation across generations.

The conditions under which this general class of models are semi-parametric Identified are provided in of this general class of model are established in Magnac and Thesmar (2002) and Pesendorfer and Schmidt-Dengler (2008).

The critical assumption for achieving identification in our model is the economic environment is stationary over generations. This assumption is standard in the intergenerational models and is used both in the estimation and the identification of the intergenerational discount factors. Gayle et al. (2014) have a more details discussion of identification in a more general setting.

4.0.1 Estimates of earnings dynamics and innate ability

Table 4 presents the estimates of our earnings and 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 $W_{f(m)}(x, h_{f(m)t})$ has earnings which is quadratic in age and differs by education level, however, we parsimoniously restricts this to be same for female and male. 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 to experience we adopt the learning by doing specification of Gayle and Golan (2012). Gayle and Golan (2012) show that how the estimate of this specification can rationalize by a simple labor demand model. The basic feature of this specification is that return to experience differences 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 usin a standard GMM dynamic panel data using a choices as instruments[10]

Table 4 and the top panel of figure 1 shows that the age-earnings profile gets steeper with education. This is important for the persistence of income across generations in our model of endogenous fertility and lifecycle. Parents with difference age earnings profile will choose different timing of having child and as documented in Carneiro et al. (2013) the timing of income in early childhood can affect the outcome of child. Therefore, all else being equal, low educated household would delaying have children relative to high-educated household. Given the a fixed fertile period of life high educated household

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

would have more children and we would possible observed less persistence in earnings across generation.

Table 4 shows that working full time pays 2.6 times more that working part time for males and 2.3 times for female. Coupled this with the education gender gap displaced in the bottom panel of Figure 1 shows the incentive for female to specialized less in market work. The gender gap increase with education which, all else equal, would have more specialization in assortatively matched couple with high education possibly leading to more persistence in earnings across generations.

Finally, Table 4 and panel of Figure 1 should that the return the experience is highly nonlinear in part and full work. Higher return to fulltime experience than part time experience. This specification include a depreciation of human capital and the results of the estimation shows 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 is less for female than males[11]. In general both the nonlinearity in current hours and the return to experience introduces nonlinearity into the opportunity of spending time with the children, which in our model could be a source of persistence in earnings across generations.

4.0.2 Intergenerational education production function

The direct effect of parental traits and investment on children income is through the education production function. It allows us to separate the impact of income, parental education and the time investment on children education. A well-known problem with the estimation of production functions is the simultaneity of the inputs (time spent with children and income). As is clear from the structural model, the intergenerational education production function suffers from a similar problem. However, because the output of the intergenerational education production (i.e., completed education level) is determined

[11] This feature of the labor market is not new to this paper. Gayle and Golan (2012) and Gayle and Miller (2004) pointed a similar structure for the USA and Blundell, Dias, Meghir, and Shaw (2015) document a similar feature in the British labor market.>

across generations while the inputs, such as parental time investment, are determined over the life-cycle of each generation, we can treat these inputs as predetermined and use instruments from within the system to estimate the production function.

Table 4 presents results of a Three Stage Least Squares estimation of the system of individual educational outcomes; the estimates of the two other stages are in the supplementary appendix. The system includes the linear probabilities of the education outcomes equation as well as the labor supply, income, and time spent with children equations. The estimation uses the mother's and father's labor market hours over the first 5 years of the child's life as well as linear and quadratic terms of the mother's and father's age on the child's fifth birthday as instruments. 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.

We measure parental time investment as 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 code as 2. The results in Table 5 show that while a mothers' 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, time investment of both parents is productive in terms of their children's education outcomes. It is important to note that mothers' and fathers' hours spent with children are at different margins, with mothers providing significantly more hours 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. These estimates highlights the role of both "nature" – education status is automatically transited from parents to children – and "nurture"– more parental time with children increases the probability of higher educational outcome of the children. The relative importance of "nature" versus "nurture" in accounting for the persistence of earnings across generations is quantification question that need to be answered with a n optimizing behavior framework and parents may take actions that either enhance or diminish the relative effect of "nature" versus "nurture".

4.0.3 Discount factors and the direct cost of raising children

Table 6 describes the utility function estimates including the discount factors. This section presents estimates of the intergenerational and intertemporal discount factors, the preference parameters, and child care cost parameters. Table 5 presents the discount factors. It shows that the intergenerational discount factor, λ, is 0.795. This implies that in the second to last period of the parent's life, a parent 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 include life-cycle. The estimated discount factor, β, is 0.81. The discount factor is smaller than typical calibrated values, however, few papers that estimate it find lower values (for example, Arcidiacono, Sieg, and Sloan, 2006, find it to be 0.8).[12] Lastly, the discount factor associated with the number children, υ, is 0.1. It implies that the marginal increase in value from the second child is 0.68 and of the third child is 0.60.

The lower panel in Table 6 also presents the marginal utility of income. Utility from income declines in the number of children; for a person with less

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

than high school degree and spouse with less than high school degree the coefficient on the interaction of children and family income is -0.309 implying rising net costs of raising children with number of children as well as family income.[13]. 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 the same income and number of children families, 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 captures 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, 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, there are several other channels correlated with education creating persistence, and weather wealthier households have more or less children and weather investment per child increases in more educated household is an empirical question.

4.0.4 Model fit and explanatory power

There are many criteria for assessing the fit of a model; in this paper we used 3 such criteria. The first is the statistical over-identifying J-test. We cannot reject the over-identifying test at the 5% level. The other 2 criteria require us solve the model numerically. As such we numerically solve the model and simulate 10,000 synthetic generations. The second criteria compute the unconditional choice probability of household labor supply fertility and parental time with children. And compare then to the unconditional choice probability of these unconditional choices computed from the data. It shows that our estimated model can replicate the observed choice in the data. This

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

is a visual representation and aggregated summary of the restrictions in the J-test as these aggregate of the moments targeted in estimation. Hence this criteria is not an independent source of model validation and as such the table with the result is relegated to the online appendix (see Table A-4). 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 them to the estimates from the data reported in Table 3. This is an independent source of model validation as these correlation are not moments that are targeted in estimation.

Table 7 presents the intergenerational correlation of log earnings. Panel A presents the correlation between fathers and sons using individual and family income at age 35 and average labor income between ages 30 and 40 for both fathers and sons. Panel B presents the same for mothers and daughters and Panel C presents family to family correlation combining both genders. Panel A shows that labor income at age 35 is not a good measure of permanent income. Instead, the average of labor income over multiple years produces a better measure of permanent income. Focusing on average labor income between ages 30 and 40, our estimated model can explain roughly 75% of the observed persistence in the observed data regardless of whether individual or family income is used. This is because male is normally the main bread-winner in our data and the estimated model is replicate that fact also (see Table A-4 in the online appendix). However, that is not true for mothers and daughters, where we get significant persistence in the data only if we used family income. This is also because of specialization and division of labor with the household and light the need to model household behavior in order to understand the source of the intergenerational persistence in earnings. Focusing on family income our estimated model can explain roughly 78% of the persistence in earnings observed in the data between mothers and daughters. Panel C shows that this pattern repeats itself for family to family. This demonstrates that although our estimated model did not target the correlations in earnings in estimation it can explain roughly $\frac{3}{4}$ of the earnings persistence observed in the data.

4.1 Source of the intergenerational correlations in earnings

We conduct 6 counterfactual exercises which use decompose the source of the intergenerational correlation in earnings. The baseline counterfactual (CF0) is computed eliminating the dispersion of parental education input, with the education being assigned to high school for all parents. Thus, in the education production function, only gender, parental time input gender 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 average experience of high school graduate). The returns to full-time work is set to be twice as large as the returns to part-time work, understating the returns to full-time work. Lastly, the direct monetary cost of raising children that is a function of education are set to the values of high school graduates and the only variation in direct monetary cost of raising children is due to gender. Therefore, the only source of correlation in this counterfactuals is due to differences in fertility decisions (which affects number of siblings in the production function of education), differences in parental time inputs and income (reflecting differences in labor supply). However, since all the variation in systematic components were removed, the different decisions and investment in children is driven by the variation in the idiosyncratic shocks to taste.

Each one of the counterfactuals 1-5 adds back one element at a time to the baseline counterfactual. Our model is highly non-linear and therefore, the different factors in the model interact in non-trivial ways and the effects are not additive. To isolate the effect of the different factors affecting the correlation, we add each factor separately to the baseline counterfactual and report the impact in Table X. Counterfactual 1 (CF1) 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 (CF2) 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 (CF3) adds to CF0 the estimated *returns to labor market experience* the earnings equation. Counterfactual 4 (CF4) adds the estimated *returns to full-time versus part- time* work to the earnings equation to CF0; thus in counterfactual 4. Counterfactual 5 (CF5) adds back the direct monetary cost of children estimates which vary by education group. Counterfactual 6 (CF6) adds back the effect of education in the education production function, that is the effect of "nature", to CF0.

We then conduct a second set of counterfactuals which present the cumulative effects of the different factors and captures the interactions between them. The results are reported in Table XX and in Figure 1. That is, CF1 is similar to the one in Table X, it adds the effect of assortative mating to the baseline (CF0). CF2 adds the impact of the age-earnings profiles to CF1 (so it includes both the effect of assortative mating and the age-earnings profiles); thus it capture the marginal effect of the age-earnings profiles when there is assortative mating. Counterfactual 3 adds the returns labor market experience to the model in counterfactual CF2; Counterfactual 4 adds the estimated returns for full-time and part time to the model in counterfactual 3; Counterfactual 5 adds the direct monetary cost of children estimates which vary by education group to the model in Counterfactual 4 (Thus, it only misses the direct impact of the parents education on children education). Counterfactual 6 adds the effect of education in the education production function is missing, to counterfactual 4 (thus it only misses the differential direct cost of children by education).

Since, the order in which we add the different factors matters, we repeat this exercise in different order. The third set of simulations includes 4 counterfactuals with the different factors added in a cumulative manner. Counterfactual 1 now adds the effect of the age-earnings profiles to the baseline model 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 and counterfactual 4 adds assortative mating at the end. The reason that 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 and in the second we first add the estimated earnings structure and then add the estimated assortative mating function. We farther discuss this below. Unless mentioned otherwise, the discussion focuses on correlation of average income from age 30 to 40 of families, however, the tables presents other measures as well as individual incomes correlations.

Isolating the effects of the different factors Table X presents the results of the correlations when each factor is added to counterfactual 0 in isolation. In counterfactual 0 the correlations are small, it can create less than 6% of the observed correlations in family average incomes between ages 30-40, and the correlation is statistically insignificant. Counterfactual 1 adds assortative mating. It creates about 10% of the observed correlation in earnings in families of sons and 15% for families of mothers- and daughters. Counterfactual 2 introduces deterministic age-earnings component to the earnings equation. It potentially affects labor supply, and time with children by changing the opportunity costs of time over the life-cycle, and it can also affect fertility decisions, timing and spacing of children. For families of fathers and sons it increases the correlation to 0.068 explaining about 20% of the observed correlations; however, it reduces the correlation (to negative though insignificant) for families of mothers and daughters. The third counterfactual adds learning by doing (returns to labor market experience). It introduced dynamics to the labor market decisions. It has the largest effect on all the correlations. It generates 54% of the father-son families correlation in the data and 74% of the correlation in the simulated data. It has impact on the specialization patterns in the household. Specifically, it increases the costs of reducing labor supply when children are young for less wealthy families, while allowing for more specializations in families where the husband is more educated and has higher potential earnings, thus, increases the gap in time investment in children. Since fertility is endogenous, the mechanism is more involved, and we therefore discuss it further in the cumulative exercise sections below. Counterfactual 6 adds the impact of parental education on children outcomes in the education production function. It creates the second largest persistence; in particular, it accounts for 45% of the correlation for fathers and sons families, and 20% for mothers-daughters families. The rest of the counterfactuals have fairly small effects when added individually to the baseline simulation. However, this is not the case when we measure cumulative effects which accounts for interactions between factors in the model. These interactions highlight the important mechanisms through which family structure, assortative mating and the earnings structure interact and we further analyze and discuss it below.

Cumulative Effects Table 8 and Figure 1 present the results. Table 8 presents labor supply, time with children, and fertility choices along with total and average time input in children for mothers and fathers. The first panel of Figure 1 presents decomposition of the intergenerational correlation in average earnings between age 30 and 40 outlined above while the second panel presents for robustness check. A complete table with the inputs into Figure 1 is included in the online appendix. The baseline counterfactual and counterfactual 1 (assortative mating) in Figure 1 are discussed above. CF 2, adds the age earnings profile, and its marginal impact on the intergenerational correlation in earnings is small and account for only 4.5%.

Turning the human capital accumulation in the labor market, Figure 1 shows that adding experience into the earnings equations (CF3) increases the persistence in earnings across generations significantly, account for almost 50% of the observed correlations for families of father and sons and mothers and daughters. intergenerational pairs.

Looking further into the reasons for the positive effect of earnings structure on the correlations we turn to Table 8 which shows the effects of the different factors on parental choices. Adding returns to experience did not have much effect on husbands' labor supply and slightly decreased fathers' time with children; however, it increased full time work and decreased time with children of mothers. Why did the father-son correlation in income increased then? The simulation shows that fertility declined, so both parental time inputs per child increased, creating higher persistence in income across generations. Looking at Table Y shows that the decline in fertility is larger in more educated households. In fact, maternal time input per child is always higher in households with males with some college and college education than in households in which the husband has high school education. Maternal time input per child is lowest in households in which husbands have less than high school education. Fathers time typically also rises with own education generating persistence through time spent with children. Fathers time increases in mothers education in households in which the female has some college or college education, but not in households with less educated females. Looking at the impact of introducing returns to experience in households with college educated wives shows the role of specializations: if the husband has less than high school education the women are the breadwinnes and the husband's time with children rises by 51% and maternal time declines by more than 13% relative to the case in which there are no returns to experience. Average time per child increases the most in households where the husband has some college education or more.

The introduction of the non-linear returns to full-time versus part-time work (CF4) raises the correlation to around 0.381 accounting for 140% of the intergenerational correlation in earnings in all intergenerational pairs. Looking at Table 8 reveals that it increases full-time work of women (substitution effect) and reduces male labor supply (income effect of increase in wife's earnings). Maternal time with children declines as well as paternal time; however, fertility declines and maternal average time per child raises, but father's time per child declines. Nevertheless, the impact of maternal and paternal time on children outcomes is not symmetric. Overall, the large decline in fertility, stronger at households with college educated fathers and increase in per child mothers' income raises the intergenerational correlation of income between fathers and sons. It is important to note the significance of this results: that without any effect of "nature" – the automatic transmission of economic status across generation – dynastic model in the spirit of Barro-Becker (1989) can generation more persistence than what is observed in the data.

Finally, Figure 1 shows the effect of by letting the direct monetary cost of raising children varies with education. Interestingly, this reduces the correlation from to around 0.166, accounting for between 59% and 69% of the intergenerational persistence in earnings depending on the intergenerational pair we look at. 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 Barro and Becker (1989) model wealthier households have more children so the "quality" of each child is independent of the parents' wealth. In our frame, this effect is captured through direct monetary cost of raising children that depends on education and income. Wealthier households have higher marginal utility from children which increases fertility. This can be seen in Table 8, fertility increases from 0.088 in CF4 to 0.171 in CF5. At the same time fathers' average time with children increases while mothers' average time with children is reduced to the lowest level in all counterfactual and to level below the level in the simulation. As before, the impact of mothers and fathers' time on children's outcome is not symmetric, and the overall result is lower father-son income correlation. This means that without the quality-quantity trade-off the observed persistence in earnings would have been significantly higher.

Table Y also demonstates that with the exception of households in which the wife has less than high school education, fertility monotonicaly increases in the education of both spouses in CF5 relative to CF 4, which is similar to the prediction in the Barro-Becker models. For example consider college educated females. Those married to college educated husbands have 0.96 in counterfactual 4 whereas those married to husbands with collge education have 0.24. In counterfactural 5 fertility is higher but the gap is much smaller: 1.65 for females married to high school educated husbands versus 1.56 for those married to college educated husbands. For a given husband education, the average time with children declines at a larger rates the more educated the females is when comparing Counterfactual 5 to counterfactual 4. In households in which both spouses have at least high school education, males increase average time with children in CF 5 relative to CF 4 (with a small decline in households with college educated females and high school males). This indicates decline in specialization. However, the decline in female time is larger than the increase in male time resulting in less persistence of earnings across generations. To illustrate it consider households in which both spouses have college education and households in which both parents have high school educaiton. In counterfactual 5 the average time of females in the educated households declines to 4.79 relative to 5.13 in counterfactual 4. The males in these housholds increase time from 1.6 to 1.69. For households in which both spouses have high school education the average time with a child decreased only slightly (4.74 in CF 4 versus 4.72 in CF 5), at the same time the increase in average time per child spent by fathers rises more (1 in CF 4 and 1.4 in CF 5). Therefore, the relatively larger dicline at more educated households in mothers' time and the larger relative increase in fathers time at the less educted households reduces persistence in earnings and increases mobility.

In summary, the structure of the labor market – human capital accumulated through experience and the non-linear 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 generation. Overall "nurture" accounts for between 58% and 68% of the observed persistence in earnings. While we found a small role for assortative mating in absence of the labor market structure the mechanism through which the labor structure operates is which the division of labor and specialization in the household. As such we investigate the marginal import of assortative in the presence of the labor market structure.

The complementarity of the earnings structure and assortative mating Figure 2 presents the results from an alternative counterfactual simulation where 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 nonlinearly in full-time versus part-time have significant and large impact. The main difference between the impacts of the labor market structure is that in the absence of assortative mating the impact on mothers to daughters' persistence in earnings is muted. Highlighting again the channel through which assortative mating affects the persistence in earnings over generations. However, when you add assortative mating to the earnings structure in the labor market the impact is very large and increases the source of intergenerational persistence in earnings back to CF5. Highlighting that while by itself assortative is not major source of the correlation in earnings coupled with the structure of the labor markets it has a very larger role.

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. Using simulations, the model explains 75% of the intergenerational correlation of earnings of fathers and sons and of families. We then 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, although those are typically ignored in the literature. Parental time with children is an important mechanism of transmission of human capital. Earnings structure has the largest impact on the persistence of earnings across generations. Since they have involved income and substitution effects that need to be evaluated empirically. Specifically, the nonlinearities of earnings in labor market in hours as well as returns to labor market experience affect specialization patterns in households and fertility. The disproportional 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. Therefore, labor markets earnings structure increases persistence of outcomes across generations. Moreover, assortative mating amplifies these effects of the earnings structure on persistence of earnings. Lastly, we find that the impact of parental education itself reduces the persistence of income instead of increasing it. The intuition is in the spirit of the Barro and Becker (1989) neutrality result. More educated households are wealthier which tend to increase demand for children and reduce investment of time per child.

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Table 1 : summary statistics

Variable	Total sample N	Total sample Mean	Parents N	Parents Mean	Children N	Children Mean
Female	89,538	0.54	68,856	0.55	20,682	0.53
Married	89,538	0.46	68,856	0.55	20,682	0.16
Age	89,538	26.83	68,856	28.59	20,682	20.98
		(7.86)		(7.93)		(3.64)
Education (yrs. completed)	89,538	13.63	68,856	13.70	20,682	13.39
		(2.12)		(2.15)		(2.01)
No. of children	89,538	0.65	68,856	0.79	20,682	0.18
		(0.97)		(1.02)		(0.52)
Labor income ($ US 2005)	89,221	18,767	68,739	22,295	20,482	6,926
		(2,637)		(2,779)		(1,603)
Labor market hours	89,266	1,024	68,790	1,182	20,476	891.8
		(1.059)		(1,053)		(891.7)
Housework hours	56,351	720.5	49,865	729.9	6,486	648.8
		(584.3)		(591.1)		(523.3)
Time spent with children	89,523	214.9	68,856	257.7	20,678	72.69
		(454.9)		(487.8)		(277.8)
No. of individuals	8,890		5,112		3,778	

Note: Panel Study of Income Dynamics (PSID),1968 to 1997. Standard Deviation are in parentheses.

TABLE 2: SUMMARY STATISTICS BY EDUCATION

	Wife				Husband			
Variables	LHS	HS	SC	COL	LHS	HS	SC	COL
Age	31.05	31.08	31.26	32.09	31.13	31.18	31.41	31.94
	(3.99)	(3.91)	(3.90)	(3.99)	(4.04)	(4.05)	(4.00)	(3.94)
No. of children	0.74	0.86	0.82	1.00	0.82	0.84	0.92	0.95
	(0.74)	(0.90)	(0.91)	(0.98)	(0.97)	(0.88)	(0.94)	(0.96)
Labor income ($ US 2006)	8265	16,634	20,443	26,550	32,457	42,688	47,701	64,807
	(9478)	(1514)	(1772)	(2602)	(1952)	(2228)	(2802)	(3795)
Labor market hours	828	1200	1268	1189	1995	2161	2149	2262
	(898)	(886)	(879)	(861)	(796)	(668)	(634)	(610)
Housework hours	1267	1068	946	954	339	375	374	382
	(13.5)	(11.2)	(11.0)	(10.9)	(6.88)	(6.80)	(6.67)	(5.72)
Time with children	270	280	295	360	78.20	86.40	77.20	92.50
	(421)	(423)	(459)	(499)	(196)	(217)	(224)	(206)
No. observations	204	3758	4524	7586	406	3942	3780	7944
Proportion(%)	1.4	24.8	30.7	43.2	2.9	27.1	25.0	44.9

Note: Panel Study of Income Dynamics (PSID),1968 to 1997. Standard Deviation are in parentheses. LHS is a dummy variable indicating that the individual has completed education of less than high school; HS is a dummy variable indicating that the individual has completed education of high school but college; SC is a dummy variable indicating that the individual has completed education of greater than high school but is not a college graduate; COL is a dummy variable indicating that the individual has completed education of at least a college graduate.

Table 3: intergenerational elasticity/correlation of log labor earnings

	Elasticity	Correlation	Elasticity	Correlation
	Individual earnings		Family earnings	
Fathers-sons				
Earnings at age 35	0.277	0.251	0.456	0.317
	(0.108)	(0.099)	(0.132)	(0.094)
Average earnings age 30 to 40	0.500	0.356	0.350	0.337
	(0.096)	(0.091)	(0.084)	(0.086)
Earnings parents age 50; kid age 35	0.320	0.318	0.4328	0.4323
	(0.037)	(0.072)	(0.039)	(0.097)
Earnings Solon specification	0.419	0.350	0.517	0.446
	(0.046)	(0.079)	(0.048)	(0.101)
Mothers-daughters				
Earnings at age 35	0.001	0.001	0.083	0.067
	(0.161)	(0.122)	(0.108)	(0.087)
Average earnings age 30 to 40	-0.026	-0.032	0.342	0.286
	(0.069)	(0.08)	(0.090)	(0.077)
Earnings parents age 50; kid age 35	0.035	0.037	0.181	0.248
	(0.045)	(0.047)	(0.042)	(0.056)
Earnings Solon specification	0.053	0.052	0.339	0.302
	(0.045)	(0.044)	(0.059)	(0.068)
All				
Earnings at age 35	-	-	0.233	0.175
	-	-	(0.085)	(0.064)
Average earnings age 30 to 40	-	-	0.346	0.310
	-	-	(0.061)	(0.070)
Earnings parents age 50; kid age 35	-	-	0.379	0.383
	-	-	(0.030)	(0.086)
Earnings Solon specification	-	-	0.442	0.395
	-	-	(0.035)	(0.089)

Note: Earnings at age 35 uses parent-children pairs when both are at age of 35. Average earnings from age 30 to 40 uses the average labor income for parent-children pairs when both are observed continuously between the ages of 30 and 40. Earnings parents age 50; kid age 35 uses parent-children pairs of observations when parents are 50 and children are 35 years of age respectively. Earnings Solon specification uses the average earnings for parents when parents are observed continuously between the ages of 40 and 45, and children are observed at the age of 30. The sample sizes vary depending on the particular age used and the number of years used when the average earnings is used. The maximum is 835 for parent-child pairs with earnings of parents at age 50; kid age 35. The minimum is 100 for Average earnings from age 30 to 40 for father-son pairs using family-family labor income.

Table 4: earnings equation: dependent variable: log of yearly earnings

Variable	Estimate	Variable	Estimate	Variable	Estimate
Age earning profile				Fixed Effect	
Age Squared	-4.0e-4	Female x Full-time	-0.125	Female	-0.484
	(1.0e-5)		(0.010)		(0.007)
Age x LHS	0.037	Female x Full-time (t-1)	0.110	HS	0.136
	(0.002)		(0.010)		(0.005)
Age x HS	0.041	Female x Full-time (t-2)	0.025	SC	0.122
	(0.001)		(0.010)		(0.006)
Age x SC	0.050	Female x Full-time (t-3)	0.010	COL	0.044
	(0.001)		(0.010)		(0.006)
Age x COL	0.096	Female x Full-time (t-4)	0.013	Female x HS	-0.054
	(0.001)		(0.010)		(0.008)
Return to hours worked		Female x Part-time (t-1)	0.150	Female x SC	0.049
Full-time	0.938		(0.010)		(0.006)
	(0.010)	Female x Part-time (t-2)	0.060	Female x COL	0.038
Full-time (t-1)	0.160		(0.010)		(0.007)
	(0.009)	Female x Part-time (t-3)	0.040	Constant	0.167
Full-time (t-2)	0.044		(0.010)		(0.005)
	(0.010)	Female x Part-time (t-4)	-0.002		
Full-time (t-3)	0.025		(0.010)		
	(0.010)				
Full-time (t-4)	0.040				
	(0.010)				
Part-time (t-1)	-0.087				
	(0.010)				
Part-time (t-2)	-0.077				
	(0.010)				
Part-time (t-3)	-0.070				
	(0.010)				
Part-time (t-4)	-0.010	Hausman Statistics	2296		
	(0.010)	Hausman p-value	0.000		

Note: Standard Errors are in Parentheses. LHS– less than high school; HS – completed education of high school; SC– completed education of greater than high school but is not a college graduate; COL — at least a college graduate

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Table 5: 3SLS system estimation the education production function

Variable	High School	Some College	College
High School Father	0.063	0.003	-0.002
	(0.032)	(0.052)	(0.0435
Some College Father	0.055	0.132	0.055
	(0.023)	(0.038)	(0.031)
College Father	-0.044	0.008	0.120
	(0.032)	(0.051)	(0.042)
High School Mother	0.089	0.081	-0.019
	(0.040)	(0.065)	(0.052)
Some College Mother	0.007	-0.041	0.017
	(0.030)	(0.049)	(0.039)
College Mother	0.083	0.120	0.040
	(0.036)	(0.057)	(0.047)
Mother's Time	-0.014	0.080	0.069
	(0.021)	(0.034)	(0.027)
Father's Time	0.031	0.100	0.026
	(0.019)	(0.029)	(0.025)
Mother's Labor Income	-0.025	-0.013	0.005
	(0.009)	(0.014)	(0.011)
Father's Labor Income	0.001	0.001	0.002
	(0.003)	(0.004)	(0.003)
Female	-0.002	0.135	0.085
	(0.017)	(0.028)	(0.022)
Number Siblings Under age 3	-0.014	-0.107	-0.043
	(0.017)	(0.027)	(0.022)
Number Siblings between age 3 and 6	-0.029	-0.047	-0.012
	(0.019)	(0.030)	(0.025)
Constant	0.855	-0.231	-0.359
	(0.108)	(0.172)]	(0.140)]
Observations	1335	1335	1335

Note: The exclude class is Less than High School. Standard errors are in parentheses. Instruments: Mother's and father's labor market hours over the child's first 8 years of life, linear and quadratic terms of mother's and fathers age when the child was 5 years old.

Table 6: 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 x Family labor income	-0.309	λ	0.795
	(0.053)		(0.009)
Children x HS x Family labor income	0.055	υ	0.111
	(0.032)		(0.007)
Children x SC x Family labor income	0.082		
	(0.021)		
Children x COL x Family labor income	0.101		
	(0.056)		
Children x HS spouse x Family labor income	0.044		
	(0.046)		
Children x SC spouse x Family labor income	0.058		
	(0.055)		
Children x COL spouse x Family labor income	0.084		
	(0.048)		

Note: Standard errors are in parentheses. LHS is a dummy variable indicating that the individual has completed education of less than high school; HS is a dummy variable indicating that the individual has completed education of high school but college; SC is a dummy variable indicating that the individual has completed education of greater than high school but is not a college graduate; COL is a dummy variable indicating that the individual has completed education of at least a college graduate.

Table 7: 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 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 age 30 to 40	-	-	0.31	0.236
	-	-	(0.070)	(0.053)

Note: Earnings at age 35 uses parent-children pairs at age 35. Average earnings from age 30 to 40 uses the average earnings for parent-children pairs when both are observed continuously between the ages of 30 and 40.

TABLE 8: A PAIR-WISE DECOMPPSITION OF THE IGE.

		Single Effects						
	Model	CF0	AM	AEP	RTE	FTPT	UC	NA
Panel A: Fathers-sons								
Family Income								
Labor income at age 35	0.159	0.018	0.031	0.050	0.108	-0.012	0.030	0.035
	(0.035)	(0.019)	(0.021)	(0.021)	(0.024)	(0.02)	(0.017)	(0.020)
Average labor income from age 30 to 40	0.251	0.019	0.034	0.068	0.182	0.028	0.002	0.152
	(0.056)	(0.019)	(0.020)	(0.020)	(0.041)	(0.026)	(0.017)	(0.034)
Individual Income								
Labor income at age 35	0.146	0.032	0.067	0.081	0.190	0.012	0.019	0.159
	(0.033)	(0.019)	(0.021)	(0.021)	(0.042)	(0.027)	(0.018)	(0.035)
Average labor income from age 30 to 40	0.266	0.033	0.041	0.070	0.207	0.018	0.009	0.161
	(0.060)	(0.019)	(0.020)	(0.020)	(0.046)	(0.026)	(0.017)	(0.036)
Panel B: Mothers-daughters								
Family Income								
Labor income at age 35	0.129	0.004	-0.003	0.037	0.088	0.044	-0.011	0.001
	(0.029)	(0.020)	(0.02)	(0.021)	(0.022)	(0.027)	(0.01)	(0.022)
Average labor income from age 30 to 40	0.222	0.016	0.044	-0.019	0.103	-0.024	-0.031	0.058
	(0.050)	(0.019)	(0.020)	(0.02)	(0.023)	(0.02)	(0.01)	(0.020)
Individual Income								
Labor income at age 35	0.129	0.059	0.016	0.049	0.170	0.023	-0.002	0.050
	(0.036)	(0.029)	(0.033)	(0.0308)	(0.038)	(0.037)	(0.02)	(0.033)
Average labor income from age 30 to 40	0.204	0.029	0.041	-0.008	0.143	-0.020	-0.039	0.083
	(0.046)	(0.019)	(0.02)	(0.02)	(0.032)	(0.02)	(0.01)	(0.021)
Panel C: ALL								
Family Income								
Labor income at age 35	0.143	0.012	0.014	0.042	0.098	0.019	0.007	0.017
	(0.032)	(0.014)	(0.014)	(0.015)	(0.022)	(0.019)	(0.012)	(0.014)
Average labor income from age 30 to 40	0.236	0.017	0.039	0.017	0.136	-0.004	-0.019	0.097
	(0.053)	(0.013)	(0.014)	(0.014)	(0.030)	(0.01)	(0.01)	(0.021)

CF0 - baseline. AM-Assortative mating. AEP-Age-earnings profile. RTE-Labor market experience. FTPT-Part-versus full time. UC-Education effect of direct cost: NA- parental education in the production function.

Table 9: cumulative decomposition's parental choices and inputs

	Model	CF0	AM	AEP	RTE	FTPT	UC
Wife							
Labor Supply							
Part-time	0.303	0.275	0.273	0.277	0.266	0.266	0.258
Full-time	0.477	0.412	0.417	0.420	0.468	0.557	0.477
Parental time							
Medium	0.120	0.208	0.192	0.190	0.160	0.087	0.183
High	0.110	0.195	0.182	0.178	0.155	0.088	0.171
Fertility							
Birth	0.072	0.135	0.123	0.120	0.100	0.058	0.112
Husband	Model	CF0	AM	AEP	RTE	FTPT	UC
Labor Supply							
Part-time	0.032	0.031	0.030	0.031	0.030	0.097	0.029
Full-time	0.943	0.947	0.948	0.945	0.944	0.878	0.947
Parental time							
Medium	0.049	0.069	0.066	0.062	0.053	0.042	0.067
High	0.032	0.046	0.042	0.039	0.035	0.007	0.042
Parental inputs							
Total mother's time	7.503	9.387	8.701	8.892	8.288	7.138	8.221
	(4.421)	(5.266)	(4.849)	(5.243)	(4.705)	(4.472)	(4.517)
Average mother's time per child	4.794	4.641	4.692	4.746	4.815	4.874	4.732
	(1.819)	(1.687)	(1.741)	(1.715)	(1.770)	(1.886)	(1.747)
Total father's time	2.869	3.012	2.790	2.749	2.682	1.817	2.857
	(3.298)	(3.613)	(3.267)	(3.492)	(3.324)	(2.471)	(3.171)
Average father's time per child	1.794	1.414	1.415	1.388	1.489	1.157	1.576
	(1.650)	(1.387)	(1.354)	(1.381)	(1.447)	(1.181)	(1.440)

CF0 is the baseline. AM – Assortative mating: adds assortative mating to CF0. AEP - Age-earnings profile: adds the age earnings profile effect to AM. RTE - Labor market experience: adds the labor market experience effect to AEP. FTPT - Part - versus full -time: adds the significantly higher return to full-time versus part-time work to AEP. UC - Education effect of direct cost: adds the effect of education on the direct cost of raising children to AEP. NA - adds parental education education to the production function.

Table 10: cumulative decomposition's conditional fertility and time inputs

	CF0				AEP(% change)				UC (% change)				RTE(% change)			
AVERAGE TIME WITH CHILDREN																
MALE																
	HUSBAND															
WIFE	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL
LHS	1.67	1.85	0.92	1.37	-4.2	-6.5	-2.8	-1.2	19.7	11.5	16.7	-5.8	-57.3	-23.7	-66.3	-55.4
HS	1.89	1.19	1.38	1.31	-12.4	-1.1	6.2	25.5	1.6	4.3	3.9	1.0	-23.3	-15.2	-17.3	-3.7
SC	1.90	1.30	1.50	1.78	-33.4	2.0	7.9	7.1	-1.9	2.3	2.9	2.0	-46.3	-23.2	-36.3	-14.1
COL	0.78	1.16	1.15	1.49	52.0	5.2	7.3	11.8	4.0	-1.0	2.0	-0.2	-48.8	11.8	-8.3	6.5
FEMALE																
	HUSBAND															
WIFE	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL
LHS	4.16	4.45	3.93	4.18	0.1	4.3	19.1	1.1	19.7	11.46	16.7	-5.8	16.4	3.2	16.9	-15.7
HS	4.40	4.52	4.75	4.73	-0.9	3.0	5.0	0.5	1.6	4.28	3.9	1.0	-3.3	4.8	4.8	4.2
SC	3.97	4.34	4.70	4.64	-1.1	4.6	3.7	7.2	-1.9	2.29	2.9	2.0	-4.6	7.5	7.7	6.5
COL	5.13	4.69	4.62	4.80	-13.2	3.4	4.7	4.3	4.0	-1.0	1.99	-0.2	-2.3	6.6	10.9	7.1
AVERAGE HOUSEHOLD NUMBER OF CHILDREN																
	HUSBAND															
WIFE	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL	LHS	HS	SC	COL
LHS	2.78	2.38	1.97	1.48	-4.9	-13.8	-27.1	-29.8	-64.4	-63.2	-84.3	-89.5	-29.9	-32.3	-52.6	-72.0
HS	2.65	2.28	1.93	1.39	-9.7	-15.1	-19.5	-29.6	-46.6	-38.8	-40.2	-37.7	-17.5	-36.2	-51.8	-69.8
SC	2.32	2.16	1.85	1.29	-8.8	-14.6	-20.6	-34.1	-37.5	-23.7	-21.0	-2.3	-21.2	-41.2	-55.6	-77.1
COL	2.48	1.97	1.65	1.16	-4.5	-20.3	-29.2	-36.1	-27.7	-15.9	-11.7	34.7	-17.3	-51.2	-71.1	-79.4

CF0 is the baseline. AM – Assortative mating: adds assortative mating to CF0. AEP - Age-earnings profile: adds the age earnings profile effect to AM. RTE - Labor market experience: adds the labor market experience effect to AEP. FTPT - Part - versus full -time: adds the significantly higher return to full-time versus part-time work to AEP. UC - Education effect of direct cost: adds the effect of education on the direct cost of raising children to AEP. NA - adds parental education education to the production function.

Figure 1: features of the empirical earnings equation

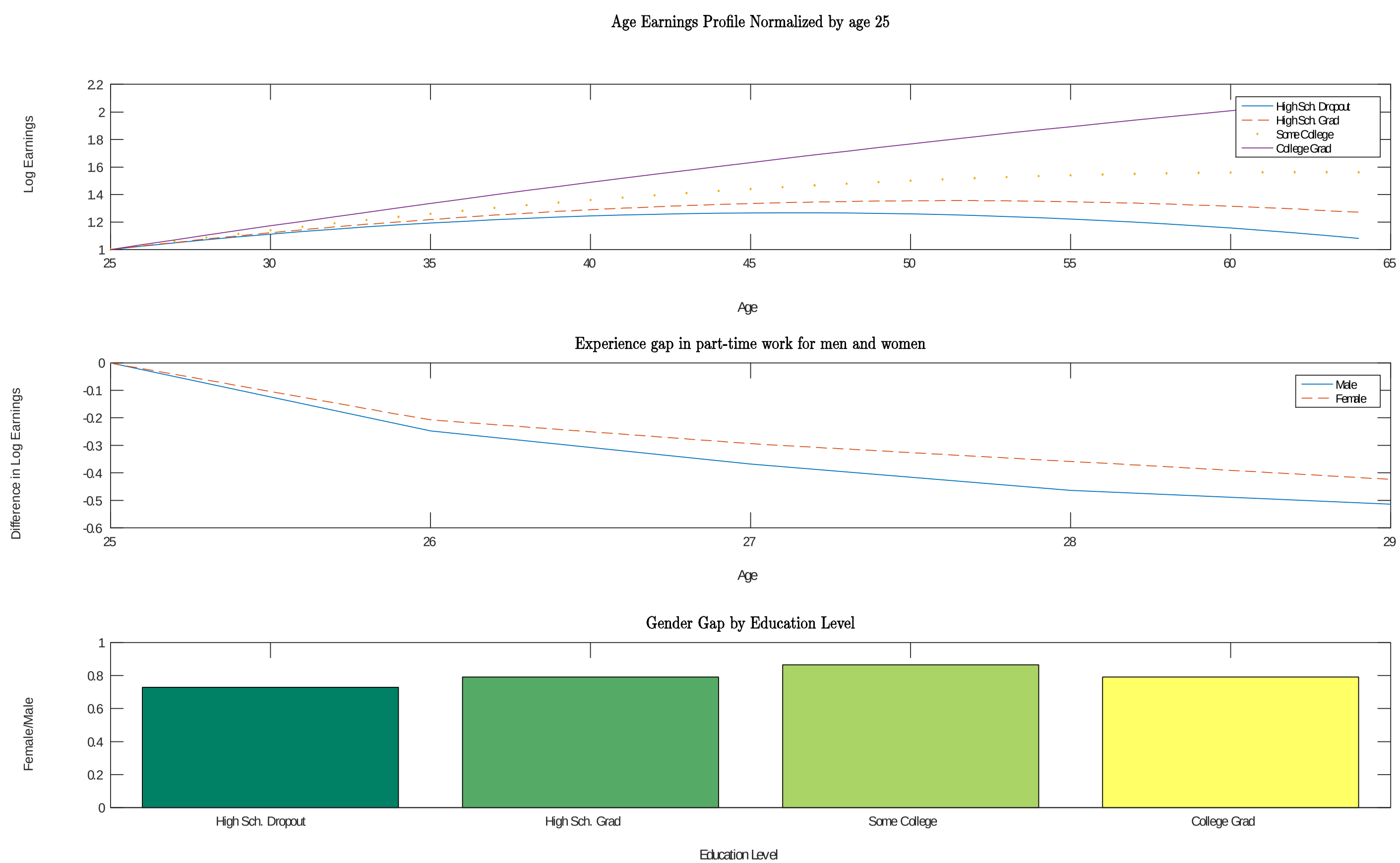


Figure 2: parental time investment versus the causal impact of parental education on the education of children

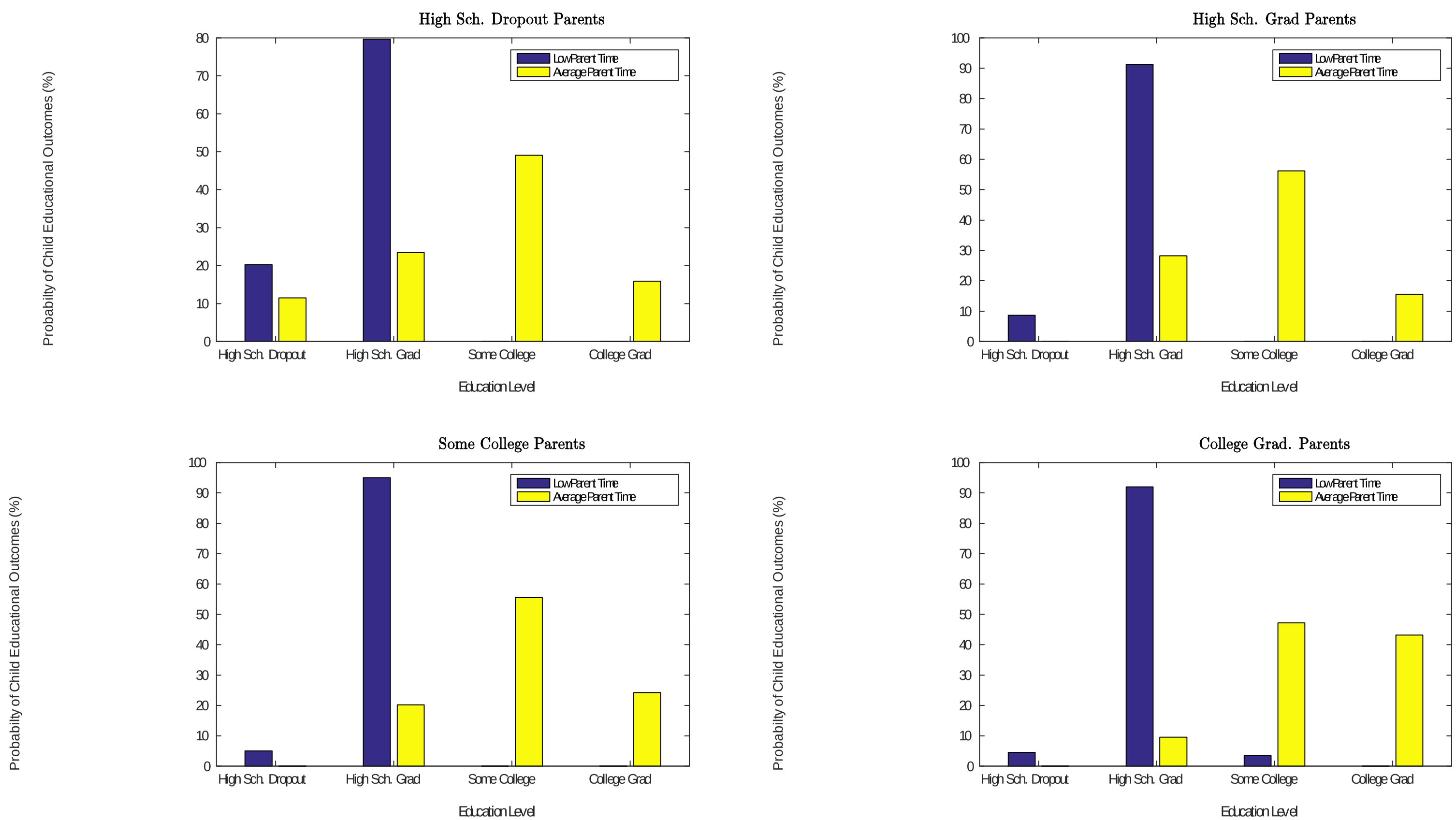
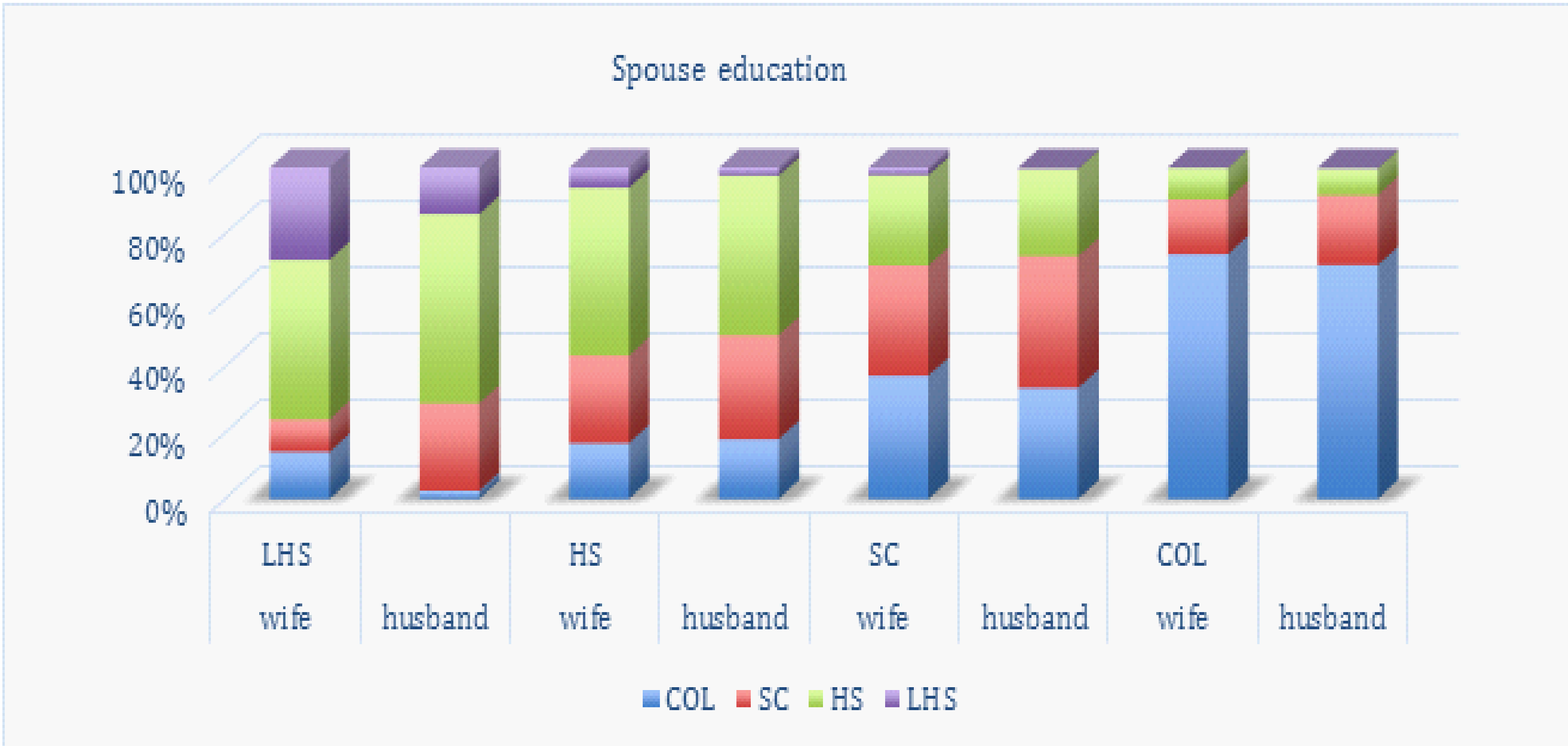
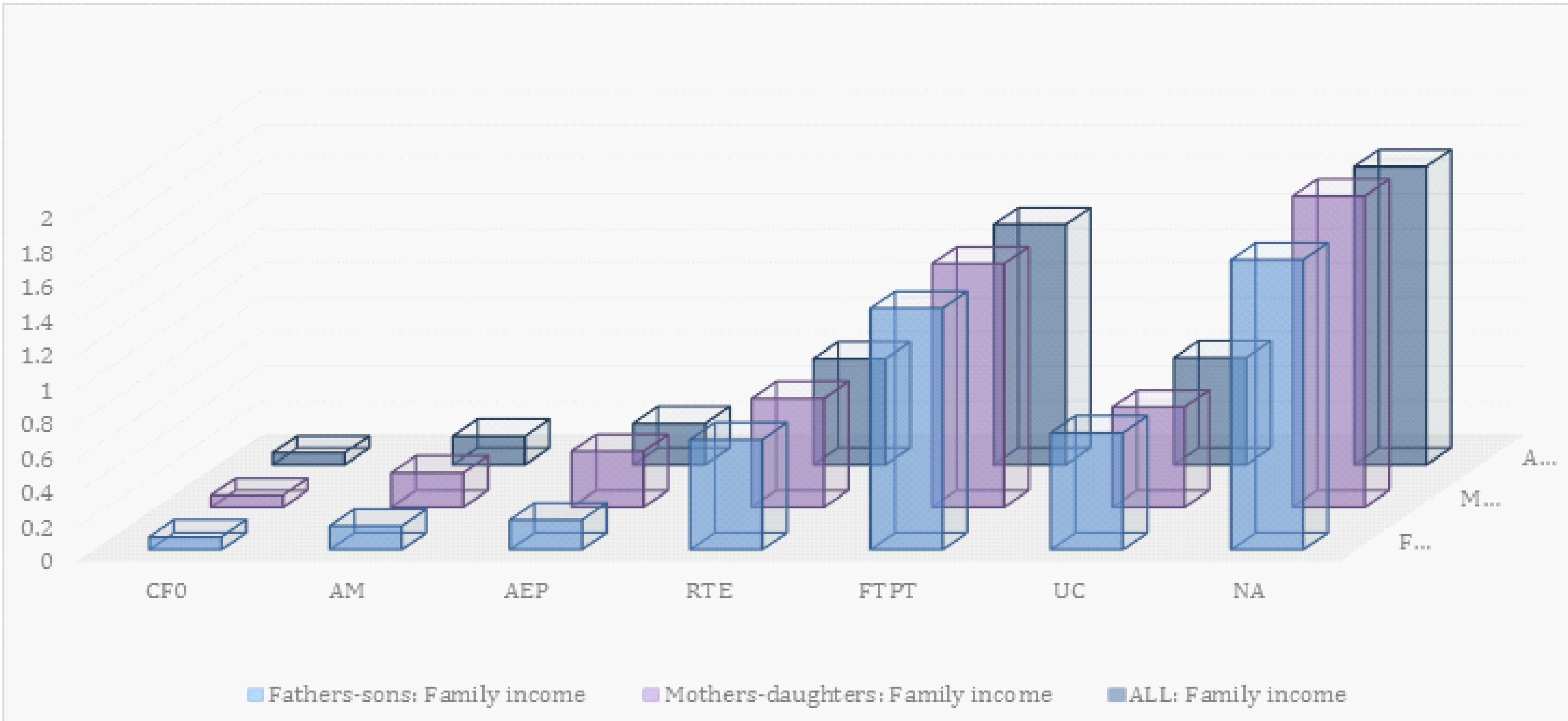


Figure 3: Empirical amorting mating patterns



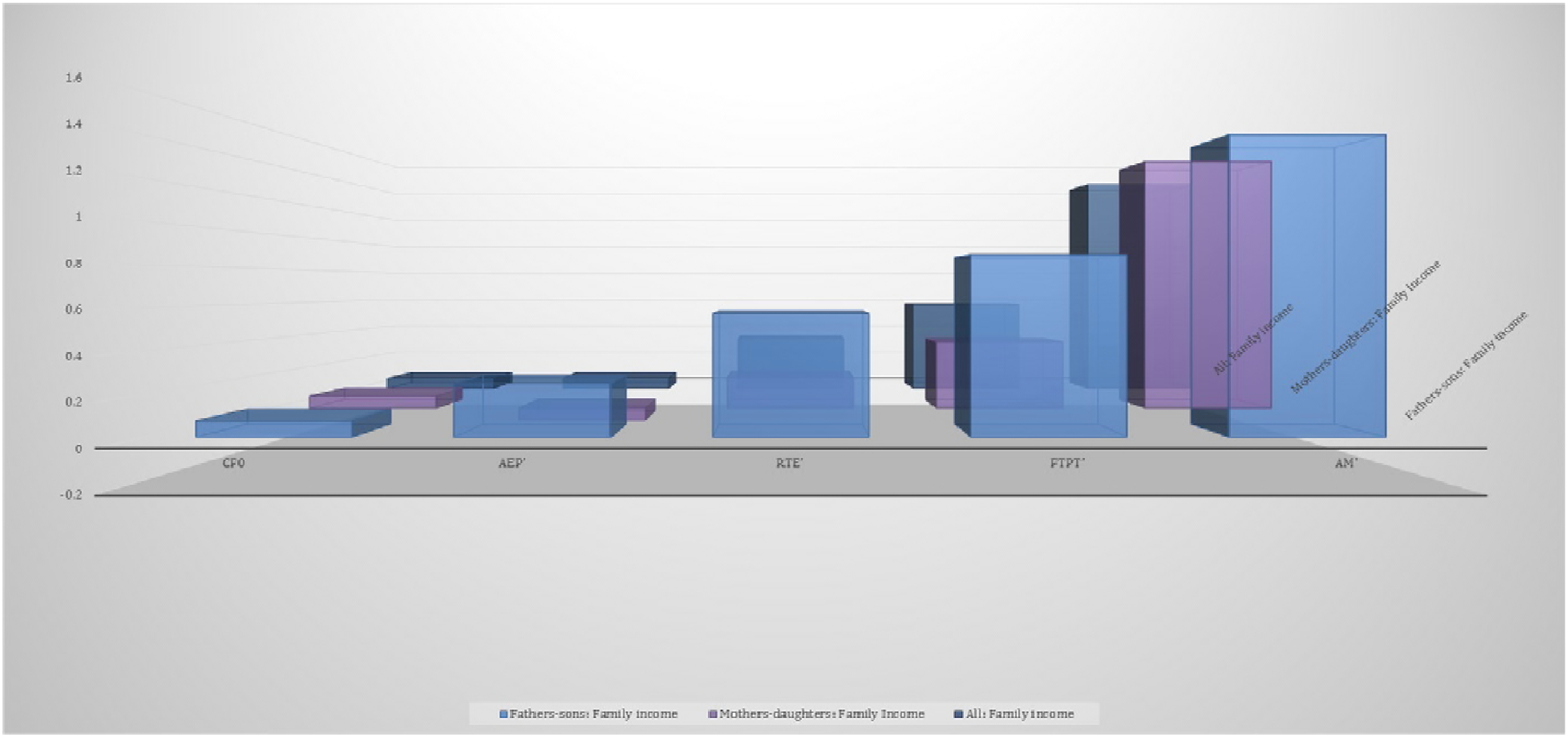
Note: LHS– less than high school; HS – completed education of high school; SC– completed education of greater than high school but is not a college graduate; COL — at least a college graduate

Figure 4: a cummulative decomposition of the source of IGC



Note: CF0-Baseline. AM-Assortative mating effect. AEP-Age-earnings profile effect. RTE-Labor market experience effect. FTPT-Part- versus full time effect. UC-Education effect of direct costof children. NA -Direct effect of Parents' Education. Effects are sequentially dded in order listed.

Figure 5: a cummulative decomposition 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 effect. AM'-Assortative mating effect. Effects are sequentially added in the order listed