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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 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 modelled 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 Solan (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 (2003, 2004).

[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, based on previous work such as Heckman, Hotz and Walker (1985) and Hotz and Miller (1988) into an infinite horizon model of dynasties. 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. For clarity of exposition we begin with a single genderless agent making decisions. We than extend it to a unitary household and capture the importance of the household type (defined as the education of the spouses) and patterns of specialization within the household on the intergenerational correlation of earnings. Parental characteristics such as education and skill affect the human capital outcomes of children as well as the endogenous decisions on transfers. Time investment in children is a transfer that affects the educational outcome of the child. We assume no borrowing and savings. Thus, each per-period labor supply choice affects determines earnings which affect the human capital of children. Fertility is also endogenous and has important implications to intergenerational transfers, and the quantity-quality trade-offs parents makes when they choose transfers as well as number of offsprings. In addition, all choices are made sequentially over the life-cycle. Life-cycle is important to understanding fertility behavior, and spacing of children, as well as timing of different types of investments.

3.1 Basic life-cycle framework

In the model adults live for T periods. We set the number of an adult's periods in each generation to $T = 30$ and measure the individual's age where $t = 0$ is age 25. This is because at this age most individuals would have completed their education and started their family in the data. Each adult from generation $g \in \{0, ...\infty\}$ makes discrete choices about labor supply, h_t, time spent with children, d_t, and birth, b_t, in every period $t = 1...T$. For labor time individuals choose no work, part time, or full time ($h_t \in (0, 1, 2)$ and for time spent with children individuals choose none, low and high ($d_t \in (0, 1, 2)$. The three levels of labor supply correspond to working 40 hours a week; an individual working fewer than three hours per week is classified as not working, individuals working between 3 and 20 hours per week are classified as working part-time, while individuals working more than 20 hours per week are classified as working full-time. There are three levels of parental time spent with children corresponding to no time, low time, and high time. To control for the fact that females spend significantly more time with children than males, we use a gender-specific categorization. We use the 50th percentile of the distribution of parental time spent with children as the threshold for low versus high parental time with children, and the third category is 0 time with children. This classification is done separately for males and females. Finally, birth is a binary variable; it equals 1 if the mother gives birth in that year and 0 otherwise. The birth decision is binary ($b_t \in (0, 1)$. The individual does not make any choices during childhood, when $t = 0$. All the discrete choices can be combined into one set of mutually exclusive discrete choice, represented as k, such that $k \in (0, 1...17)$. Let I_{kt} be an indicator for a particular choice k at age t; I_{kt} takes the value 1 if the k^{th} choice is chosen at age t and 0 otherwise.

These indicators are defined as follows:

$$\begin{aligned} I_{0t} &= I\{h_t = 0\}I\{d_t = 0\}I\{b_t = 0\},\ I_{1t} = I\{h_t = 0\}I\{d_t = 0\}I\{b_t = 1\},\ ..., \\ I_{16t} &= I\{h_t = 1\}I\{d_t = 2\}I\{b_t = 1\},\ I_{17t} = I\{h_t = 2\}I\{d_t = 2\}I\{b_t = 1\} \quad (1) \end{aligned}$$

These indicators are mutually exclusive and hence $\sum_{k=0}^{17} I_{kt} = 1$. We define a vector, x, to include the time invariant characteristics of education, skill, and race of the individual. Incorporating this vector, we further define the a vector z to include all past discrete choices and as well as time invariant characteristics, such that $z_t = (\{I_{k1}\}_{k=0}^{17}, ..., \{I_{kt-1}\}_{k=0}^{17}, x)$.

We let earnings, w_t, be given by the earnings function $w_t(z_t, h_t)$, which depends on the individual's time invariant characteristics, choices that affect human capital accumulated with work experience, and the current level of labor supply, h_t. The choices and characteristics of parents are mapped onto offspring's characteristics, x', via a stochastic production function of several variables. The offspring's characteristics are affected by parents' time invariant characteristics, parents' monetary and time investments, and presence and timing of siblings. These variables are mapped into the child's skill and educational outcome by the function $M(x'|z_{T+1})$. Since z_{T+1} includes all parents choices and characteristics and contains information on the choices of time inputs and monetary inputs. Because z_{T+1} also contains information on all birth decisions, it captures the number of siblings and their ages. We assume there are four mutually exclusive outcomes of offspring's characteristics: Less than high school (LH), High school (HS), Some college (SC) and College (Coll). Therefore $M(x'|z_{T+1})$ is a mapping of parental inputs and characteristics into a probability distribution over these four outcomes.

We normalize the price of consumption to 1. Raising children requires parental time, d_t, and also market expenditure. The per-period cost of expenditures from raising a child. Since we do not observe expenditures on children in the data, we assume that the expenditure is proportional to individual's current earnings and the number of children, but we allow this proportion, $\alpha_{Nc}(z_t)$, to depend on state variables. This assumption allows us to capture the differential expenditures on children made by individuals with different incomes and characteristics. Practically this allows us to observe differences in social norms of child rearing among different socioeconomic classes. Given the assumption of no borrowing and savings, the per period budget constraint is given by:

$$w_t(x, h_t) = c_t + \alpha_{Nc}(z_t)(N_t + b_t)w_t(x, h_t) \quad (2)$$

We assume that the utility function is the same for adults in all generations.

An individual receives utility from discrete choice and from consumption of a composite good, c_t. The utility from consumption and leisure is assumed to be additively separable because the discrete choice, I_{kt}, is a proxy for the leisure, and is additively separable from consumption. The utility from I_{kt} is further decomposed in two additive components: a systematic component, denoted by $u_{1kt}(z_t)$, and an idiosyncratic component, denoted by ε_{kt}. The systematic component associated with each discrete choice k represents an individual's net instantaneous utility associated with the dis-utility from market work, the dis-utility/utility from parental time investment, and the dis-utility/utility from birth. The idiosyncratic component represents preference shock associated with each discrete choice k which is transitory in nature. To capture this feature of ε_{kt} we assume that the vector $(\varepsilon_{0t}, .., \varepsilon_{17t})$ is independent and identically distributed across the population and time, and is drawn from a population with a common distribution function, $F_\varepsilon(\varepsilon_{0t}, .., \varepsilon_{17t})$. The distribution function is assumed to be type 1 extreme value. Altruistic preferences are introduced under the same assumption as the Barro-Becker model: Parents obtain utility from their adult offsprings' expected lifetime utility. Two separable discount factors capture the altruistic component of the model. The first, β, is the standard rate of time preference parameter, and the second, $\lambda N^{1-\nu}$, is the intergenerational discount factor, where N is the number of offspring an individual has over her lifetime. Here λ $(0 < \lambda < 1)$ should be understood as the individual's weighting of his offsprings' utility relative to her own utility[6]. The individual discounts the utility of each additional child by a factor of $1-\nu$, where $0<\nu<1$ because we assume diminishing marginal returns from offspring.[7] The sequence of optimal choice for both discrete choice and consumption is denoted as I_{kt}^{o} and c_t^o respectively.

Solving for consumption from equation (2) and substituting for consumption in the utility equation, $u_{2kt}(c_t^o, z_t)$, we can rewrite the component of the per-period utility function, specified as $u_{2kt}(z_t)$, as a function of just z_t:

$$u_{2kt}(z_t){=}u_t[w_t(x,h_t)-\alpha_{Nc}(z_t)(N_t{+}b_t)w_t(x,h_t),z_t]. \tag{3}$$

The discrete choices now map into different levels of utility from consumption, hence, we can get rid of the consumption as choice and write the systematic contemporary utility associated with each discrete choice k as $u_{kt}(z_t) = u_{1kt}(z_t) + u_{2kt}(z_t)$. We can thus denote the expected lifetime utility at time $t=0$ of a person with characteristics x in generation g, excluding the dynastic component, as

$$U_{gT}(x) = E_0\left[\sum_{t=0}^{T}\beta^t\sum_{k=0}^{17}I_{kt}^{o}[u_{kt}(z_t)+\varepsilon_{kt}]|x\right]. \tag{4}$$

The total discounted expected lifetime utility of an adult in generation g including the dynastic component is

$$U_g(x) = U_{gT}(x) + \beta^T\lambda N^{-\nu}E_0\left[\sum_{n=1}^{N}U_{g+1,n}(x_n')|x\right], \tag{5}$$

where $U_{g+1,n}(x_n')$ is the expected utility of child n $(n = 1,..,N)$ with characteristics x'. In this model individuals are altruistic and derive utility from offsprings' utility, subject to discount factors β,and $\lambda N^{1-\nu}$.

When empirically implementing the model, we assume that parents receive

[6] Technically this definition is assuming he has one period left in his lifetime and only have one child.

[7] Note that this formulation can be written as an infinite discounted sum (over generations) of per-period utilities as in the Barro-Becker formulation.

utility from adult children,whose educational outcome is revealed at the last period of their life regardless of the birth date of the child. This assumption is similar to the Barro-Becker assumptions. We avoid situations where the outcome of an older child is revealed while parents make fertility and time investment decisions to ensure that (i) these decisions are not affected by adult child outcomes, and (ii) that adult children's behavior and choices do not affect investment in children and fertility of the parents, in which case solutions to the problems are significantly more complicated and it is not clear whether a solution exists.

Alvarez (1999) analyzes and generalizes the conditions under which dynastic models with endogenous fertility lead to intergenerational persistence in income and wealth. Following his analysis, we show which assumptions are relaxed in our model and lead to persistence in income. The first is constant cost per-child. In our model the per-period cost of raising and transferring human capital is the costs described in Equation 2, as well as the opportunity costs of time input in children d_t: $w(x, 1 - d_t - leisure_t)$. Time input in children as well as labor market time are models as discrete choice with three levels. This introduces nonlinearities Even if we were able to capture the proportional increase in time with children as the number of children increases, the non-linearity in labor supply decisions implies that the opportunity cost of time with children is not linear. Thus the cost of transfer of human capital per child are not constant. Furthermore, in contrast to standard dynastic models and those analyzed in Alvarez (1999) we incorporate 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 nonlinearities 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. The second condition is non-separability in preferences, aggregation of the utilities from children and the feasible set. 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 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.

3.2 Unitary households

In order to capture the effect of assortative mating and specialization patterns within households on the intergenerational correlation of earnings, we extend the basic framework to include household decisions and gender. There are many model of household decisions; here we show how extend the model incorporate a unitary decisions maker. Let individual's gender, subscripted as σ, takes the value of m for a male and f for a female: $\sigma = \{f, m\}$. Gender is included in the vector of invariant characteristics x_σ. Let K describe the number of possible combinations of actions available to each household. Individuals get married at time 0, and for simplicity we assume that there is no divorce (see Gayle, Golan, and Soytas 2014 for application with marriage and divorce).

We assume that all individuals enter the first period of the life-cycle married. That is, they transition into a married household immediate after becoming adult. When individuals transition into a married household, their spouses' characteristics are drawn from the known matching function $G(x_{-\sigma}| x_\sigma)$. Since the matching function depends on the individual's state variables– it separately captures the effect of number of children and past actions that affect labor market experience for example, on the spouse's characteristics.

Households are assumed to live for T periods and die together. Time zero is normalized to take account of the normal age gap within married couples, which would imply that men has a longer childhood than female. All individual variables and earnings are indexed by a the gender subscript σ. We omit the gender subscript when a variable refers to the household (both spouses). The state variables are extended to include the gender of the offspring. Let the vector ζ_t indicate the gender of a child born at age t, where $\zeta_t = 1$ if the child is a female and $\zeta_t = 0$ otherwise. The vector of state variables is expanded to include the gender of the offspring:

$$z_t = (\{I_{k1}\}_{k=0}^{K}, ..., \{I_{kt-1}\}_{k=0}^{K}, \zeta_0, .., \zeta_{t-1}, x_f, x_m).$$

We assume that households invest time and money in the children in the household. The function $w_{\sigma t}(z_t, h_{\sigma t})$ denotes the earnings function; the only difference from the single agent problem is that gender is included in z_t and can thus affect earnings. The total earnings is the sum of individual earnings as $w_t(z_t, h_t) = w_{1t}(z_t, h_{ft}) + w_{2t}(z_t, h_{mt})$ where $h_t = (h_{ft}, h_{mt})$. The educational outcome of the parents offsprings is mapped from the same parental inputs as the single agent model: income and time investment, number of older and younger siblings, and parents' characteristics such as education, race, and labor market skill. In the extension gender is also included as a parental characteristic.

We assume that an individual's earnings depend on gender age, age squared, and dummy variables indicating whether the individual has high school, some college, or college (or more) education interacted with age respectively; the omitted category is less than high school. Let η_σ be the individual-specific ability, which is assumed to be correlated with the individual-specific time-invariant observed characteristics. Earnings are assumed to be the marginal productivity of workers and are assumed to be exogenous, linear additive, and separable across individuals in the economy. The earnings equations are given by

$$w_{\sigma t} = \exp(\delta_{0\sigma} z_{\sigma t} + \sum_{s=0}^{\rho} \delta_{\sigma,s}^{pt} \sum_{k_{t-s} \in \mathcal{H}_{P\sigma}} I_{k_{t-s}\sigma} + \sum_{s=1}^{\rho} \delta_{\sigma,s}^{ft} \sum_{k_{t-s} \in \mathcal{H}_{F\sigma}} I_{k_{t-s}\sigma} + \eta_\sigma) \quad (6)$$

where $\mathcal{H}_{P\sigma}$ and $\mathcal{H}_{F\sigma}$ are the set of choices for part-time and full-time work, respectively. Therefore, the earnings equation depends on experience accumulated while working part-time and full-time and the current level of labor supply. Thus, $\delta_{\sigma,s}^{pt}$ and $\delta_{\sigma,s}^{ft}$ capture the depreciation of the value of human capital accumulated while working part-time and full time, respectively. In the estimation we assume $\rho = 4$ given that the effect of experience with higher lags is insignificant (Gayle and Golan, 2012; Gayle and Miller, 2013).

Thus the production function is still denoted by $M(x'|z_{T+1})$ where z_{T+1} represents the state variables at the end of the parents' life-cycle, T. We assume that race is transmitted automatically to children and rule out interracial marriages and fertility. This is done because there is insufficient interracial births in our sample to study this problem. Therefore, parental home hours when the child is young affect the future educational outcome of the child, which is denoted by Ed'_{σ}, and innate ability, η'_{σ}, both of which affect the child's earnings. The state vector for the child in the first period of the life-cycle is determined by the intergenerational state transition function $M(x'|z_{T+1})$; specifically,

$$M(x'|z_{T+1}) = [\Pr(\eta'_{\sigma} \mid Ed'_{\sigma}), 1] \Pr(Ed'_{\sigma} \mid z_{T+1}) \tag{7}$$

Thus, we assume that the parental inputs and characteristics (parental education and fixed effects) determine educational outcomes according to the probability distribution $\Pr(Ed'_{\sigma} \mid z_{T+1})$. In our empirical specification the state vector of inputs, z_{T+1}, contains the parental characteristics, the cumulative investment variables (low time and high time) of each parent up to period T, the permanent income of each parent, and the number of siblings..In the data, we observe only total time devoted to children each period; thus, we assign each child age 5 or younger in the household the average time investment, assuming all young children in the household receive the same time input. Parental characteristics include the education of the father and mother, their individual-specific effects, and race. Once the education level is determined, it is assumed that the ability η'_{σ} is determined according to the probability distribution $\Pr(\eta'_{\sigma} \mid Ed'_{\sigma})$. The above form of the transition allows us to estimate the equations separately for the production function of children given as the first two probabilities and the marriage market matching given as the last term.

In the household, the total per period expenditures cannot exceed the combined income of the spouses. The budget constraint for the household is given by

$$w_t(z_t, h_t) - \alpha_N(z_t)(N_t + b_t)w_t(z_t, h_t) = c_t \tag{8}$$

The right hand side represents expenditures on personal consumption of the parents, c_t, and on children. Parents pay for the children living in their household, regardless of the biological relationship, and do not transfer money to any biological children living outside of the household. Assuming $u_{1kt} = \theta_k(z_t)$ and substitute for consumption in u_2, we obtain the following household utility function:

$$u_{kt}(z_t) = \theta_k(z_t) + u_t[w_t(z_t, h_t)(1 - \alpha_N(z_t)(N_t + b_t)), z_t]. \tag{9}$$

For notation simplicity let $x_f, \in \{f\}_{f=1}^{F}$, $x_m \in \{m\}_{m=1}^{M}$, and P_{fm} be the probability that type f female married type m make at age 0. We can then defined the expected lifetime utility for a type (f, m) household at age 0, excluding the dynastic component, as

$$U_T(f, m) = E_0 \left[\sum_{t=0}^{T} \beta^t \sum_{k=0}^{K} I_{kt}^0 \{u_{kt}(z_t) + \varepsilon_{kt}\} \right], \tag{10}$$

and the expected lifetime utility for a type (f, m) household at age 0 as

$$U(f, m) = U_T(f, m) + \beta^T \lambda E_0 \left[N^{-\nu} \sum_{n=1}^{N} \sum_{f'=1}^{F} \sum_{m'=1}^{M} P_{f'm'} U_n(f', m') | f, m \right]. \tag{11}$$

The addition of the 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. Furthermore, we capture patterns of assortative mating which 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.

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. Here we briefly provide an overview of the procedure and refers the reader to Gayle et al. (2015) for more details. The details on step of estimation are provided in the relevant empirical results section.

The estimation is based on a conditional choice probabilities (CCPs) estimation technique that combines forward simulation (see Hotz et al. (1993)), an alternative value function representation for stationary dynastic model (see Gayle et al. (2015)), and the Hotz-Miller inversion (see Hotz and Miller (1992)). The proceeds in 4 steps. In step 1 we estimate the (i) earnings equation, (ii) intergenerational education production function, and (iii) the marriage market matching function at age 25. In step 2 we estimate CCP for household choices. In step 3 we used the alternative value function representation, the estimates from steps 1 and 2, and the Hotz et al. (1993)'s forward simulation technique to estimate the household continuation value for each age in the life-cycle. Finally, in step 4 we used the Hotz-Miller inversion to form moment conditions for a generalized method of moment (GMM) estimation of the utility function parameters and discount factors.

Of the important elements that the theoretical literature suggests could generate earnings persistence across generations which are included in our theoretical framework 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. Therefore we are using variation in the labor market, household formation patterns, the impact of time the parents spend with their young children on the final educational outcome to the these parameters. Also we are 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), Pesendorfer and Schmidt-Dengler (2008) and Norets and Tang (2014). The model is semi-parametrically identified we assume that the researcher knows the distribution of the preference shocks and show that the other parameters of the model are identified non-parametrically. 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.

4.1 Empirical results

This section presents results of estimation and analysis of the structural model. First, we present estimates from step 1 of our estimation procedure. Second, we present estimates from step 4 of the estimation. The results from the step 3 are presented in on Online appendix. Third, we present results that assess how well our model fits the data. Finally, we present counterfactual experiments that decomposed the source of the intergenerational correlation in earnings.

4.1.1 Earnings equation and unobserved skills

Table 3 presents the estimates of the earnings equation and the function of unobserved (to the econometrician) individual skill (see also Gayle et al. (2014)). The estimation used a standard GMM dynamic panel data using a choices as instruments. See Altug and Miller (1998), Blundell and Bond (1998), among others for details. These estimates are important for understanding the sources of persistence because the opportunity costs of time of individuals in different types of households (by types we mean education of the spouses) depends on the labor market returns to time and education. Therefore, these estimates can potentially play important roles in fertility, time allocation decisions and the persistence of income across generation. The top panel of the first column shows that the age-earnings profile is significantly steeper for higher levels of completed education; the slope of the age-log-earnings profile for a college graduate is about 3 times that of an individual with less than a high school education. However, the largest gap is for college graduates; the age-log-earnings profile for a college graduate is about twice that of an individual with only some college. These results confirm that there are significant returns to parental time investment in children in terms of the labor market because parental investment significantly increases the likelihood of higher education outcomes, which significantly increases lifetime labor market earnings.

The bottom panel of the first column and the second column of Table 4 show that full-time workers earn 2.6 times more than part- time workers for males, and 2.3 times more than part time workers for females (see also Gayle et al. (2014)). It also shows that there are significant returns to past full-time employment for both genders; however, females have higher returns to full-time labor market experience than males. The same is not true for part-time labor market experience; males' earnings are lower if they worked part time in the past while there are positive returns to the most recent female part-time experience. However, part-time experiences 2 and 3 years in the past are associated with lower earnings for females; these rates of reduction in earnings are, however, lower than those of males. These results are similar to those in Gayle and Golan (2012) and perhaps reflect statistical discrimination in the labor market in which past labor market history affects beliefs of employers on workers' labor market attachment in the presence of hiring costs.[8] These results imply there are significant costs in the labor market in terms of the loss of human capital from spending time with children, if spending more time with children comes at the expense of working more in the labor market. This cost may be smaller for female than males because part-time work reduces compensation less for females than males. If a female works part-time for 3 years, for example, she loses significantly less human capital than a male working part-time for 3 years instead of full-time. This difference may give rise to females specializing in child care; this specialization comes from the labor market and production function of a child's outcome as is the current wisdom.

The unobserved skill (to the econometrician) is assumed to be a parametric function of the strictly exogenous time-invariant components of the individual variables. This assumption is used in other papers (such as those by MaCurdy, 1981; Chamberlain, 1986; Nijman and Verbeek, 1992; Zabel, 1992; Newey, 1994; Altug and Miller, 1988); and Gayle and Viauroux, 2007). It allows us to introduce unobserved heterogeneity to the model while still maintaining the assumption on the discreteness of the state space of the dynamic programming problem needed to estimate the structural parameters from the dynastic model. The Hausman statistic shows that we cannot reject this correlated fixed effect specification. Column (3) of Table 4 presents the estimate of the skill as a function of unobserved characteristics; it shows that females have lower unobserved skill than males. Education increases the level of the skill but it increases at a decreasing rate in the level of completed education. The rates of increase for females with some college and a college degree are higher than those of their male counterparts. This pattern is reversed for females with a high school diploma. Notice that the skill is another transmission mechanism through which parental time investment affects labor market earnings in addition to education.

[8] These results are also consistent with part-time jobs differing more than full-time jobs for males more than for females.

4.1.2 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 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".

4.1.3 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).[9] 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 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.[10]. 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.

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

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

4.1.4 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 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.

4.2 Source of the intergenerational correlations in earnings

We conduct 5 counterfactual exercises which use decompose the source of the intergenerational correlation in earnings. The baseline counterfactual (CF0-Baseline) is computed eliminating the dispersion of parental education input, with the education being assigned to high school for all parents. Thus, 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. Each one of the counterfactuals 1-5 adds back one element relative to the previous counterfactual. Counterfactual 1 (CF1-Assortative mating) 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-Age-earnings profile) adds back the age-earnings relationship into the earnings equations (in addition to the assortative mating added in CF1). Thus, it measures the age effect on earnings in the observed correlation. Counterfactual 3 (CF3-Labor market experience) adds to CF2 the experience effect in the earnings equation. Counterfactual 4 (CF4-Part- versus full time) adds the true returns to full time versus part time to the earnings equation; thus in counterfactual 4, the matching function and the earnings equations are similar to the one in the original simulation. Counterfactual 5 (CF5-Education effect of direct cost) adds back the direct monetary cost estimates which vary by education group. Therefore, in this counterfactual, only the effect of education in the education production function is missing, that is the effect of nurture. The order in which we add elements matters, and hence we repeat this exercise in different order in which we add assortative mating at the end. This allow us isolate the effect of assortative mating.

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. Figure 1 shows that the baseline counterfactual simulation can only generate around 7% of the intergenerational correlation in earnings. Assortative mating (CF1) increases the correlation but still can only marginally account for between 10% and 13% of the correlation. The increase in the persistence from assortative mating is more significant for mothers-daughters and family-family than for fathers-sons. This highlights the mechanism through which assortative mating can generate persistence across generation which via mothers to daughters transmission of status. The age earnings profile marginal impact on the intergenerational correlation in earnings is small and account for only around 4%.

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 around 61% of the observed persistence for all intergenerational pairs. Looking further into the reasons for the increase we turn to Table 8 which shows the effects 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 increased, creating higher persistence in income across generations.

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 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 (1999) can generation more (not less) 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 close to 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.

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.

Figure 2 presents the results from an alternative counterfactual simulation where we add assortative mating after adding the labor market structure. The baseline is the same as before while CF1' adds the age-earnings relationship into the earnings equations to CFF0. CF2' adds to CF1" the experience effect in the earnings equation. CF3'- adds the true returns to full time versus part time to the earnings equation to CF2' and CF4' adds back the assortative mating function in the data to CF3'. 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 non-linearly 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

Variables	Wife LHS	Wife HS	Wife SC	Wife COL	Husband LHS	Husband HS	Husband SC	Husband 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.

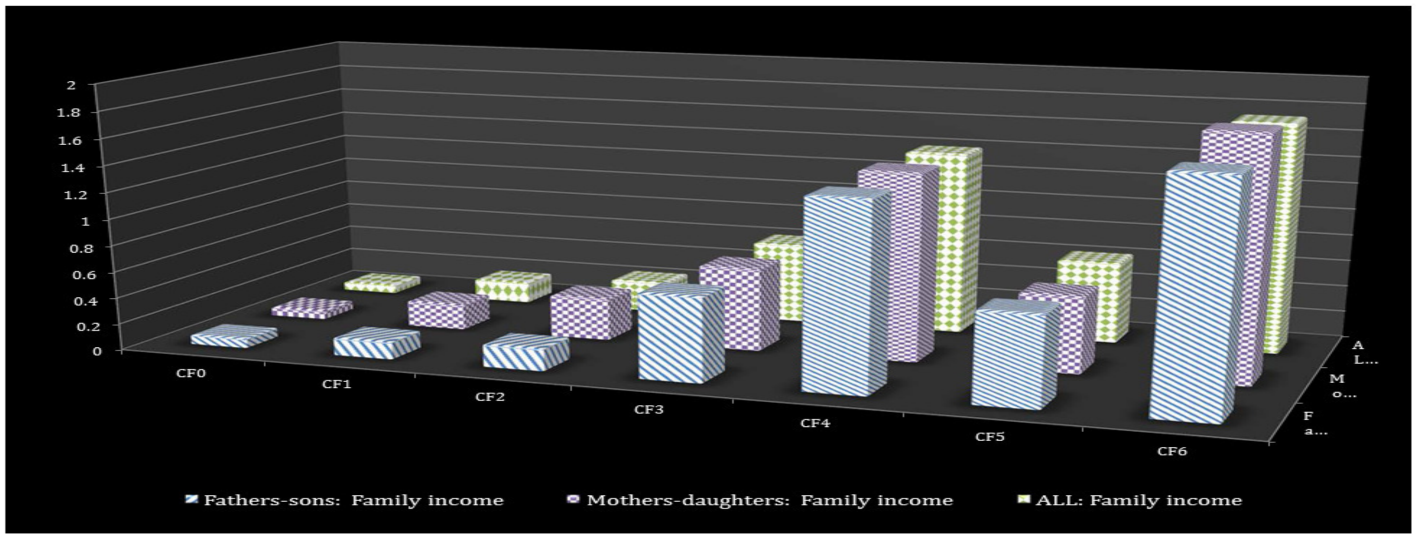
Table 8: counterfactual simulations: parental choices and inputs

	Model	CF0	CF1	CF2	CF3	CF4	CF5
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	CF1	CF2	CF3	CF4	CF5
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 counterfactual with only the effect of parental time and gender specific cost of raising children. CF1 adds assortative mating to CF0. CF2 adds the age earnings profile effect to CF1. CF3 adds the labor market experience effect to CF2. CF4 adds the significantly higher return to full-time versus part-time work to CF3. CF5 adds the effect of education on the direct cost of raising children to CF4.

Figure 1: decomposition of the source of IGC

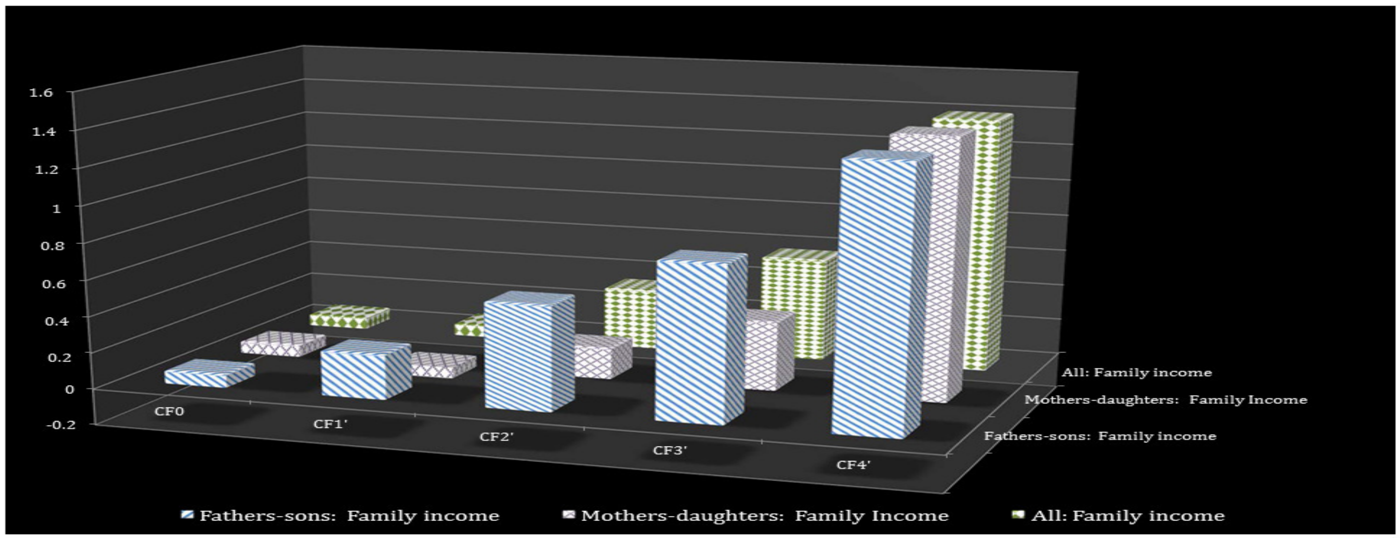
1new



1.pdf
CF0-Baseline. CF1-Assortative mating effect. CF2-Age-earnings profileeffect. CF3-Labor market experience effect. CF4-Part- versus full time effect. CF5-Education effect of direct costof children.

Figure 2: Source of IGE: impact of assortative mating

2new



Note: [2.pdf] The baseline is the same as before while CF1' adds the age-earnings relationship into the earnings equations to CFF0. CF2' adds to CF1" the experience effect in the earnings equation. CF3'- adds the true returns to full time versus part time to the earnings equation to CF2' and CF4' adds back the assortative mating function in the data to CF3'.