Early Childhood Investment and Income Taxation*

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Abstract

We study the impact of taxation on parental investment for children and its consequence on intergenerational income correlation. We estimate a life-cycle dynastic model of households and decompose the correlations in earnings across generations. We find that the existence of taxes slightly reduce the correlation comparing to a no tax environment. However, the family size and the progressivity rate of the tax code significantly reduce the correlation. The progressivity rate of the tax code, in particular, increases income mobility across generations due to higher fertility rate (quantity) and lower educational outcome of children (quality). The progressive taxes reduces the value of females' labor which reduces households' life cycle utility. In response to this reduction, households generate more children to increase the dynastic component of the utility, though per child utility is lower due to lower educational outcome of children.

JEL classification: C13, J13, J22, J62.

Keywords: Dynastic Models, Discrete Choice, Human Capital, Income Taxation.

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1 Introduction

Intergenerational correlation of earnings is an important measure of mobility. A large positive literature has studied the sources of the correlation. This literature has analyzed parents' time and monetary investment decisions and their impact on the human capital of children which is transformed into future earnings. However, while the literature documenting the importance of parents' resource allocations on the correlation of earnings is extensive, there is almost no formal economic analysis exploring the policy implications of intergenerational correlation of earnings is not. Our paper fills this gap. We explore the effects of income tax policy considering the impact of parental investment on the correlation of earnings between parents and children. We find that the existence of a flat tax rate slightly reduces the correlation. However, the child benefits and the progressivity rate of a tax code significantly decrease the correlation. In particular, we find that the households increase fertility rate (quantity) but reduce investment in the children's educational outcome under the progressive tax regimes. Consequently, the economy has more income mobility across generations.

We make theoretical and quantitative contributions. On the theoretical side, we embed a dynastic framework of Barro-Becker into life cycle model (see Gayle et al. (2017)). The former has been used by macro and labor economist to analyze the implication of family dynamics across generations. Embedding a life cycle into this framework allows us to study the impacts of parental investment on children's per-period attainments. On the quantitative side, we estimate our model using a longitudinal household survey. The estimated model incorporates the statutory taxes using a tax simulator (TAXSIM) to study the implications of tax policy on the intergenerational mobility.The policy experiments via counterfactuals allow us analyze the quantitative implications of two major property of the US tax code; the dependency of the family tax rate on the family size and the progresivity.

One of the objectives of the progressive taxes is to reduce income inequality in the society. The progressive taxes negatively impact labor decisions and reduce the variation in the income distribution. The changes in the labor market time can indirectly impact time investment for children. This indirect changes influence inequality in children's attainment and intergenerational correlation of earnings. Therefore, the progressivity rate of a tax system can be used not only for redistribution across recent generations and but also for shaping before-tax income distribution of future generations. Empirical evidence suggests that the correlation of earnings are higher in countries where taxes are more progressive as Scandinavian countries. Moreover, the Gini coefficient of both market and disposable income in these countries are much lower comparing to the US where the progressivity rate is lower. This raises an important question: Is there a linkage between progressivity rate and the intergenerational correlation of earnings?

To answer this question, we assume that the government collects taxes according to the following tax formula: $T_n(y) = y - \lambda_n y^{1-\tau_n}$, where $T_n(y)$ is the tax liabilities of $n-$ child families who generate y income and τ_n is the progressivity rate of tax liabilities of $n-$ child families.

to be completed...

Related Literature: There exists a large public finance literature studies the impact of taxation on parental choices, especially their labor choices. On the other hand, there is a voluminous empirical studies focus on the sources of the intergenerational correlation of earnings. The former literature mainly abstracts from the correlation of earnings across generations, while the latter is silent on the impact tax policies on parental decisions and endogenous sources of the correlation. Our paper connects these two strands of the literature and shows the impact of tax policies on the parental decisions and shows how these decisions shape future generation's economic outcome.

The literature on taxation is very sparse on human capital formation in an intergenerational model. Gelber and Weinzierl (2016) and Stantcheva (2015b) are few exceptions. The former study an intergenerational model, in which parents can influence children's opportunities, and find that the optimal policy would be more redistributive than the US tax policy. The latter focuses on the optimal taxation in a dynastic model where parents monetarily invest for their children's educational outcome. Although these papers are substantial contribution to the literature, they do not investigate the parental time investment for children and the life-cycle. The time investment is, in particular, very important since it is perfectly substitutable with the market labor time.[1] Therefore, it is indirectly affected by labor income taxation. In addition, the labor literature study time allocation of households and focus on the impact of the allocation on policies (see Gayle and Shephard (2016)). In particular, parents' time investment on children is found to be a very important component (see Del Boca et al. (2013), Schoellman (2016), and Gayle et al. (2018a)).

Hendricks (2003) studies the impact of taxation on human capital accumulation and show the differences between models used in the literature. He particularly focuses on the tax elasticity on human capital accumulation and shows that an infinite horizon model generates higher tax elasticity than a overlapping generation model. We differ from Hendricks (2003) in a couple of ways. First, we model human capital accumulation in a micro production function. Moreover, the human capital is accumulated through parental investment and is not direct transfer of parental human capital as in Hendricks (2003). Our framework is, in particular, important to capture the impact of taxation on labor choices of parents with different education levels. In addition, we capture

[1] In a life cycle model, Trostel (1993) shows that human capital accumulation is negatively affected by proportional income taxes. Stantcheva (2015a) and Stantcheva (2017) study optimal taxation considering the investment of individuals on their own human capital policies. The former assumes the investment is through time and goods are the investment cost for the latter. On the other hand, our paper models parental investment through both time and income (goods) and assumes a structural tax function.

the impact of early childhood transfers which are the key components of children's educational outcomes (see Cunha et al. (2006)).

Our paper is closely related to Gayle et al. (2017) who study the sources of intergenerational correlation of earnings. Their structural model can capture a large portion of the correlation and the model is able to disentangle the impact of endogenous mechanisms such as human capital accumulation and assortative mating. Although this work is substantial to explain the correlation, the paper abstracts from, maybe one of the most important mechanisms, the impact of taxation. We embed a parametric tax function into their model and show that the tax policy can quite change socio-economic conditions. We find that when an important component of the US tax code, either the number of children or the level of income, is eliminated, parents start to have more children, but the average education level (quality) of children are reduced because per child time investment is reduced by parents during children's early childhood.

2 Model

We first introduce a simplified version of our original model to provide some insights about the impacts of taxation on parental time investment. We also show the impact of progressivity of the tax system on the intergenerational correlation of earnings.

2.1 A Toy Model

Consider a two-period model. First, altruistic parents allocate their time endowment between labor, leisure, and investment on children's productivity which is also impacted by the parental income. In the second, children observe their marginal product and maximize their utility. Households pay taxes according to HSV specification, $T(y) = y - \lambda y^{1-\tau}$, where τ is the progressivity rate.[2] Therefore, the after-tax income (consumption) is equal to $\lambda y^{1-\tau}$.

We use backward induction to solve households' problem. First, the children solve:

$$\max_{y_c} \; u(\lambda y_c^{1-\tau}) - v\left(\frac{y_c}{w_c(y_p, d)}\right)$$

where y_c, y_p are the incomes of children and parents, respectively, d is the parental time investment, and w_c is the marginal productivity of children's labor. Let U_c be the indirect utility via the optimal

[2]We provide more explanation about the tax function at next subsection.

solution. Parents with w_p marginal productivity solve:

$$\max_{y_p,d} u(\lambda y_p^{1-\tau}) - v\left(\frac{y_p}{w_p} + d\right) + \Upsilon U_c(y_p, d, \lambda, \tau)$$

where Υ is the altruistic coefficient and is set $\Upsilon = 1$ for simplicity. Assuming $u(c) = \log c$ and $v(x) = \frac{x^2}{2}$, the optimal labor income and time investment of parent i and the optimal labor income of their child are

$$y_p^i = \frac{\sqrt{1-\tau}\, w_p^i\, (1+\varepsilon^i_{w_c,y_p})}{\sqrt{1+\varepsilon^i_{w_c,y_p}+\varepsilon^i_{w_c,d}}} \quad , \quad d^i = \frac{\sqrt{1-\tau}\, \varepsilon^i_{w_c,d}}{\sqrt{1+\varepsilon^i_{w_c,y_p}+\varepsilon^i_{w_c,d}}} \quad , \quad y_c^i = \sqrt{1-\tau}\, w_c^i(d^i, y_p^i)$$

where $w_c^i(d^i, y_p^i)$ is the marginal productivity of children of parent i and $\varepsilon^i_{w_c,y_p} \equiv \frac{y_p^i}{w_c^i}\frac{\partial w_c^i}{\partial y_p^i}$ and $\varepsilon^i_{w_c,d} \equiv \frac{d^i}{w_c^i}\frac{\partial w_c^i}{\partial d^i}$ are the elasticity of the marginal productivity with respect to parental income and time investment, respectively. The optimal allocation equations are not necessarily in closed form solutions since the elasticities can be endogenous. Most studies in the macro literature assumes that these elasticities are exogenous and constant across households. If this assumption was true, then the progressivity rate (including the existence of the tax system) would not change the intergenerational correlation of earnings. We show that when these elasticities are endogenous, the impact of the progressivity rate of the tax code is drastic on the intergenerational correlation.

2.2 Model

We extend the toy model to analyze the impact of taxation in detail. The main model is an extension of the dynastic framework of Barro and Becker (1989) that each altruistic generation lives for a T period. Agents are either children, who do not make any economic decisions, or adults, who can be either females (f) or males (m), decide the fertility and time allocation between labor, leisure, and time investment on children if they any in each period of their life-cycle. These assumptions are also made by Gayle et al. (2017). However, they abstract an important policy, the income taxation, which is in the center of our model.

To make our model more tractable and to provide more insightful results, we assume that two adults get married according to a marriage matching function in the first period of adulthood and form a unitary household and do not divorce through their life-cycle. There are a couple of reasons for this assumption. First, single households face tighter time constraints and their children potentially receive less parental investment due to non-existing parent in the household. Even if they receive non-existing parental investment, we cannot observe it from the data.[3] Second, the

[3]How marital status impact parental time investment and how tax policy can affect this decision is an important

impact of tax policy on intergenerational correlations of earnings may not be precise since tax policy is affected by marital status in the US. Children raised in a single parent household may get married in their adulthood which can impact their labor decision and hence their earnings. Third, marriage is not a choice in our model but individuals are matched according to a matching function which depends on their characteristics. The matching function helps us to capture the nonrandom formation of families, which might affect the degree of investment in children as well as the family labor supply response to different tax policies. Finally, divorce is not a choice due to same reasoning above.[4]

The time line of an agent is the following: Agents are children when they are 0-17 years old. Children consume a share of the household income during the childhood, where the share depends on household characteristics. The childhood period is divided into the early childhood period (ages 0 to 5), and the later childhood period (ages 6 to 17).[5] The separation of childhood is important for our analysis as we concentrate on the early childhood. A growing literature in economics analyzes the impacts of the early investments on children life outcomes emphasize the importance of this particular period (See Cunha et al. (2006) and Cunha and Heckman (2007)). Our objective is to shed light on the impact of income tax policy on parental investment, and consequently on the human capital formation of children.

Children become adults at the age of 25 and get married according to a marriage matching function.[6,7] Married adults form unitary households. Households make fertility decisions until the age of 45 after which adults are not fertile. The time allocation decision is *discretely* made until the age of 55. Labor market time can be either no work, part time, or full time. Similarly, the time investment on children can either be low, medium, or high. The intensity of mother and father times can be different and model allows the discrete time investments of parents to affect human capital formations differently, i.e. a particular number of hours for maternal care could be a "low" choice for females and the same number for paternal care could be a "high" choice for males.

Formally, the economy is populated with females and males, and each gender is indexed by $g = \{f,m\}$. Agents' life-time invariant characteristics, their education and labor market skill, are denoted by x_g and we assume that the supports of x_f and x_m are finite. At the age of t, a household (f,m) choose a discrete choice vector $a_t = (h_{ft}, h_{mt}, d_{ft}, d_{mt}, b_t)$ which consists of household market work time $h_t = (h_{ft}, h_{mt})$, time investment on children $d_t = (d_{ft}, d_{mt})$, and whether to have a

and interesting policy question which we will leave as a future study.

[4]Potential divorce decision can play important role on intra-household allocation (see Chiappori et al. (2002)). In particular, time allocation between labor and time investment on children are affected through the decision. We leave this framework also for a future work.

[5]Therefore there can be two children in the household who are in different childhood periods.

[6]The lower bound of the age is similar to the age restriction in most of labor and public finance studies.

[7]Marriage is not a choice, but the marriage matching function is designed to recover empirical moments related to marriage decisions.

child b_t.[8] Let A represent the feasible set of action vectors. For each age, t, a vector of state variables, which consists of the history of past choices, time invariant characteristics, and the gender of each child, is denoted by $z_t = (a_{25}, \ldots, a_{t-1}, \zeta_{25}, \ldots, \zeta_{t-1}, x_f, x_m)$ where ζ is a dummy variable and denotes whether a newborn child is a female.[9]

Per-period utility derived by choosing a_t is history dependent and is represented by

$$u_{a_t}(z_t) = \tilde{u}(c_t(z_t)) + \theta_{a_t}(z_t) + \varepsilon_{a_t}$$

where c_t is the consumption of adults and θ_{a_t} is the dis/utility of time allocation and ε_{a_t} is per-period additive choice specific error. Per- period budget constraint is

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

where $\alpha(z_t)$ is the per-child consumption share of disposable income, $w_t(z_t, h_t) = w_{ft}(z_{ft}, h_{ft}) + w_{mt}(z_{mt}, h_{mt})$ is the household income where $w_{gt}(z_{gt}, h_{gt})$ is the labor income of gender g, and T is the tax function. Note that $\alpha(\cdot)$ is state dependent which allows us to capture differences in expenditures on children made by households with different incomes and characteristics. Moreover, the tax function is very general in the current form and the function includes government related transfers.[10]

The budget constraint shows that there is no borrowing or savings decision, which could be important on allocation of good resources across time. However, in an excellent survey on educational outcomes of children, Heckman and Mosso (2014) empirically show that there is *little* evidence on the importance of credit constraints on educational outcomes. Moreover, Cameron and Heckman (2001) finds that parental background and family environment is more important than the credit constraints.

The expected utility from the life-cycle of household i at the beginning of life cycle is:

$$V^i(x_f, x_m) = \mathbb{E}_{25}\left[\sum_{t=25}^{55} \beta^{t-25} \sum_{a_t \in A_t} I^o_{a_t} u_{a_t}(z_t)\right]$$

where β is the discount factor, and $I^o_{a_t}$ be the indicator variable of the optimal discrete choice of a

[8] After the age of 45, $b_t = 0$.

[9] The gender of a newborn is modeled to be equal likely. However, the exact gender composition of children in a household is somewhat endogenous in our environment, since the decisions are affected by the history and the well-known empirical finding that parents have a preference for gender balanced in the sex composition of their children (see Angrist and Evans (1998)).

[10] The literature on the impact of the government transfers is extensive. For example, Dahl and Lochner (2012) shows that targeted earned income credits can play an important role in children's cognitive skills. However, they do not particularly model the parental time investment and fertility choice, which is very important in our analysis.

household with (x_f, x_m) characteristics at time t.

Household i's expected utility from their children is

$$U^{i'}(x_{f'}, x_{m'}) = \tilde{\nu} E_{25}\left[N^{1-\nu}\overline{U}^{i'} \mid x_f, x_m\right],$$

where $\tilde{\nu}, \nu$ are altruistic coefficients and $0 < \nu < 1$ which captures the diminishing marginal returns from children, N is the number of children in the household at the end of the fertile period, and $\overline{U}^{i'}$ is the expected utility of the household i's children described by

$$\overline{U}^{i'}(x_f, x_m) = \frac{1}{N}\sum_{n=1}^{N}\sum_{f'=1}^{F}\sum_{m'=1}^{M} G(f', m')U_n^{i'}(x_{f'}, x_{m'}),$$

where F and M are the number of female and male children, $G(\cdot,\cdot)$ is the matching function, and $U_n(x_{f'}, x_{m'})$ is the expected utility of the household of child n.[11]

The aggregate utility of the household (dynasty) i is the sum of the utility from life-cycle and the utility from children:[12]

$$U^i(x_f, x_m) = V^i(x_f, x_m) + \beta^{31}U^{i'}(x_{f'}, x_{m'}).$$

We introduce functional forms and estimation strategies in the following subsections. We start with the parametric tax function.

2.2.1 Tax Specification

We assume a parametric form for the income tax function stated in Equation (1):

$$T(y) = y - \lambda y^{1-\tau} \tag{2}$$

where y is the household income. This function is first introduced by Feldstein (1969) and used widely in public finance literature (see Benabou (2000) and Benabou (2002)). More recently, Heathcote et al. (2017) use this form to examine optimal progressivity rate of the US income taxation and we name the tax function as *HSV specification*.[13] This specification has two restrictions.

[11]The matching function provides a probability of the marriage of a male and a female with x_m and x_f invariant characteristics, respectively. The quantitative analysis uses the empirical moments of the marriages.

[12]Note that the discount factor has a power of 31 because adults live for 30 years and children utility added after their adulthood.

[13]Guner et al. (2014) provide estimates of four different specification of parametric tax functions. All but HSV specifications cannot provide fine estimates when the average taxes are negative (see Kurnaz and Yip (2019)). We specifically compared the data fit of the HSV and *Log* specification, which is stated Equation (6), in the appendix. We find that the HSV specification fits the data better.

First, it does not allow a lump-sum transfer ($T(0) = 0$). However, a little income can be rewarded through this system which is similar to the outcome of the earned income tax credit program in the US. Second, the tax function is either globally convex or globally concave depending on the value of τ, which makes marginal taxes monotonic and data evidence supports this outcome for a large range of income.

On the other hand, this specification provides a very useful device to analyze the impact of the progressivity rate of the tax code. Note that $\tau = 1 - \frac{1-T'(y)}{1-\frac{T(y)}{y}}$. When $\tau > (<)0$, the tax system is progressive (regressive). When $\tau = 0$, then we have a flat tax rate. Note that progressivity rate plays important role on the redistribution. In addition, the empirical literature shows that the correlation between parents' and children's income is lower in countries whose tax code is more progressive.[14] One of the objectives of our paper is to analyze the impact of the progressivity rate on the correlation of incomes of parents and children.

We consider the labor income, y, as the pre-government income, and $y - T(y)$ as post-government income, which is pre-government income minus total taxes (federal, state, and social security taxes calculated via TAXSIM 9.2, a tax simulator of NBER) and plus benefits such as cash transfers (AFDC/TANF, SSI, and welfare receipts).[15] We differ from Heathcote et al. (2017) by allowing λ and τ depend on the number of children. Family size component is very important in the US tax code, not only in tax liability differences but also in the benefits.[16] We estimate

$$\log(y - T(y)) = \log \lambda_n + (1 - \tau_n) \log y \tag{3}$$

for each $n \in \{0, 1, 2, 3, 4\}$ and report parameters in Table 1.[17,18]

The family size is an important component in the US tax system. When the family size is ignored, the progressivity rate is $\tau_{all} = 0.1822$ which is close to the estimate ($\tau_{HSV} = 0.181$) of Heathcote et al. (2017) using the PSID waves between years 2000-2006. However, we observe that τ_n changes by family size and τ_n is generally lower for families with less children. The reasons are (i) tax benefits are relatively lower toward higher incomes, and (ii) the welfare transfers to the poor households is very large and these facts reduce the average taxes of families with children drastically. Consequently, the progressivity rate is increasing in the size of households.

Using the estimates in Table 1, we plot average and marginal taxes faced by differently sized households in Figure 1. The parametric tax function fits the data well for each family size.

[14] Jantti et al. (2006) shows that the correlation in Nordic countries is almost half of the correlation in the US. Kleven (2014) shows that the progressivity rates in Scandinavia is higher than the rate of the US.

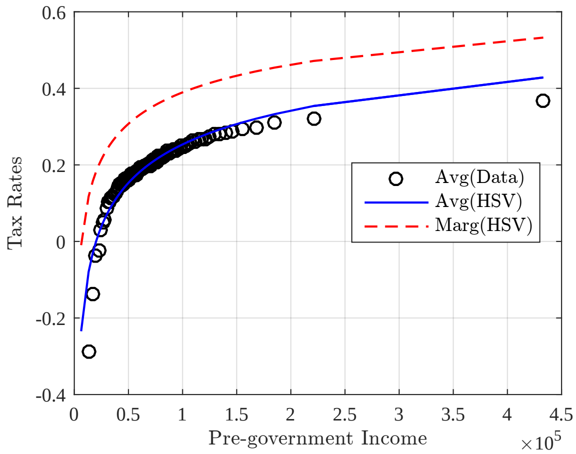
[15] Please check Heathcote et al. (2010) and Heathcote et al. (2017) for further details.

[16] Number of children changes tax credits such as the earned income credit and the child tax credit received by households. In addition, the welfare benefits depends on the federal poverty level is affected by the number of children.

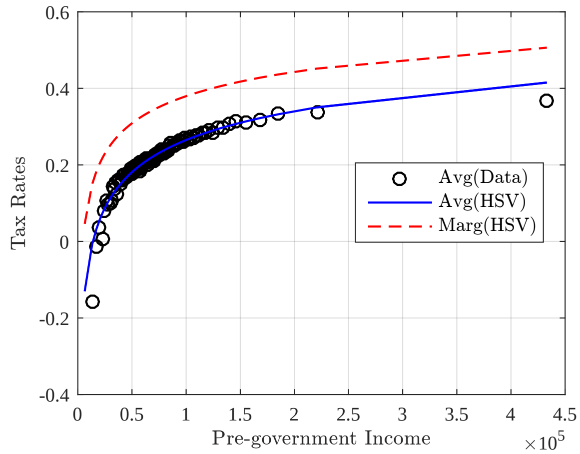
[17] Households with more than four children are considered as if they have four children.

[18] We also provide the tax parameters with different post-government income levels in the appendix at Table 13.

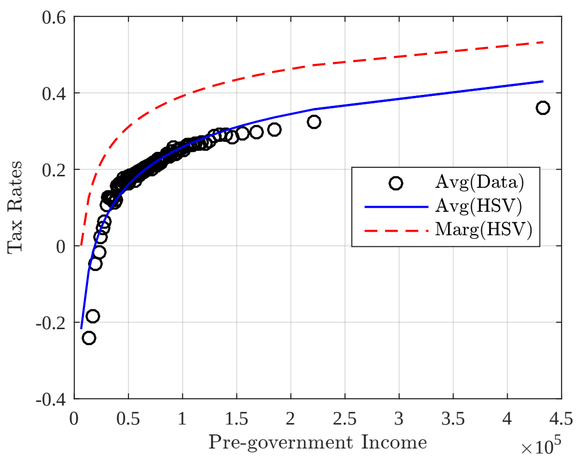
Figure 1: Average and Marginal Tax Rates with HSV Specification



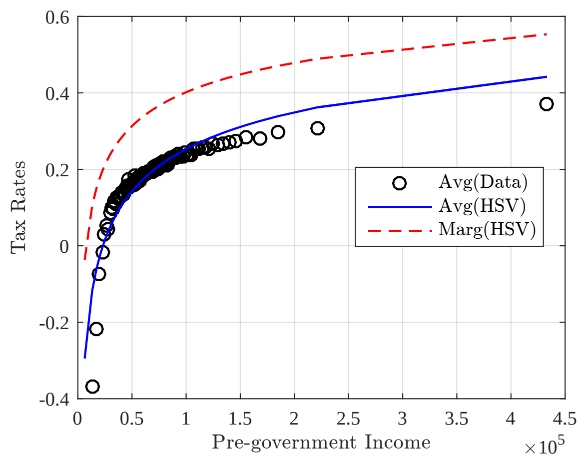
(a) All Households



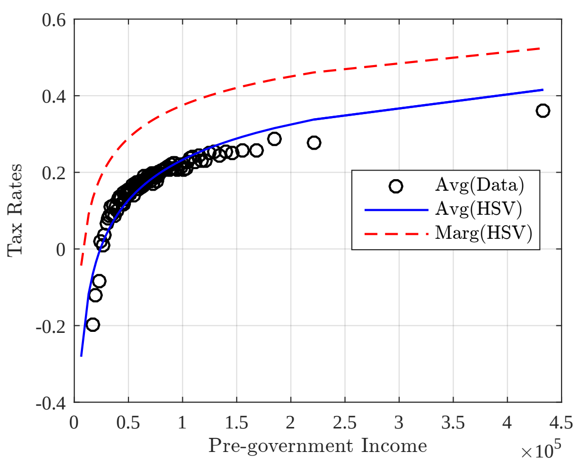
(b) Households with 0 Children



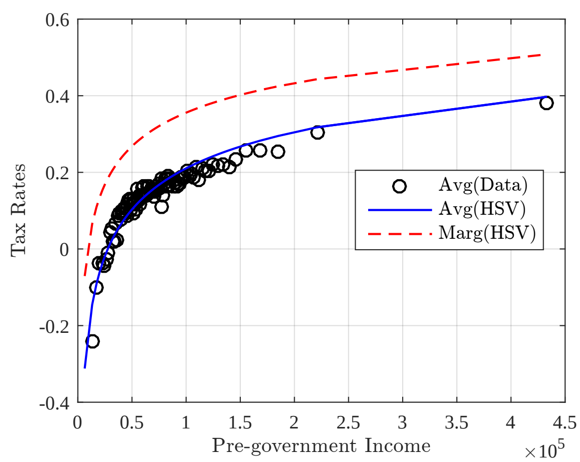
(c) Households with 1 Child



(d) Households with 2 Children



(e) Households with 3 Children



(f) Households with 4 Children

Note: Avg and Marg refer average and marginal tax rates, respectively. Parenthesis provides information that where the rate comes from.

Table 1: Estimates of Tax Parameters of HSV Specification

	Households with Different Number of Children					
	all	0 children	1 child	2 children	3 children	4 children
λ	6.0828	4.4235	5.8734	7.402	6.5081	6.5641
	(0.0104)	(0.0164)	(0.0214)	(0.0198)	(0.0322)	(0.0459)
τ	0.1822	0.1559	0.1797	0.1992	0.1857	0.184
	(0.0009)	(0.0015)	(0.0019)	(0.0018)	(0.0029)	(0.0042)
Average Taxes	0.1759	0.2105	0.1856	0.1672	0.1375	0.0838

Note1: The sample contains 25-60 years old married households (2 adults) of PSID 1967-1996 waves. Households' labor income is restricted to be above %80 and below %120 of aggregate income. This restriction, is used by many public finance studies (such as Ales et al. (2015)), ensures labor is the main source of income of households. All taxes, benefits, and incomes are converted to 2005$s. We estimate λ and τ by ordinary least square (OLS) using Equation (3).
Note2: According to NIPA Table 2.1, the mean of average taxes between 1967-1996 is 0.172.

2.2.2 Household Income Specification

We disaggregate household income to individual income and specify individual earnings. The *realized* earnings, w_{gt}, of gender g at period t is assumed to consists of four measures: the interaction of the labor productivity with labor hours, work experience, innate ability (fixed effect), and idiosyncratic error term:

$$\ln w_{gt} = W_{gt}(e, h_{gt}) + H_{gt}(h_{gT^e+1}, ..., h_{gt-1}) + \eta_g + \delta_{gt} \quad \text{for} \quad g \in \{f, m\}. \tag{4}$$

The first component, $W_g(x, h_{gt})$, captures the interaction between the market labor hours, h_{gt}, and agent's labor productivity which is related with agent's education level e. This term is in the center of the mainstream of public finance literature which assumes that labor productivities are exogenous. In this paper, we allow *endogenous* labor productivity via *endogenous* education outcome impacted by parental investment decision. Since we have a discrete choice model, $W_g(x, h_{gt})$ depends on h_{gt} in a nonlinear manner, for example, full-time work pays more than twice as such as part-time work.[19]

The second component, $H_g(h_{gT^e+1}, ..., h_{gt-1})$, represents the return of the experience on earnings and depends on the type of experience, part-time or full-time. This specification specifically captures both depreciation of human capital and differential returns to part-time versus full-time, both of which are gender-specific. In particular, this component captures an empirical evidence that the depreciation of experience is essential for females. Hence, the decision on maternal investment

[19]See Altug and Miller (1998), Gayle et al. (2012), and Gayle and Miller (2012), who document these features of the recent labor market.

can decrease the return to experience.

The third component, η_g, captures the gender specific unobserved ability to earn income. This component provides rationale for those who have same education levels and work histories to have different earnings.

The fourth component, δ_{gt}, is an i.i.d. idiosyncratic error term.

The earnings dynamics specified above distinguish between endogenous state dependence through the return to experience and persistent productivity heterogeneity via education and unobserved ability, which form the invariant characteristics of an agent: $x \equiv (e, \eta)$. The process of experience accumulation is central to our analysis because it captures the potential gender differences in the career interruptions, due to birth, and the effect of fewer labor market hours on the earnings of females and males. This may help rationalize some of the specialization patterns observed in the data. We show the estimation results in the Table 17.

2.2.3 Education Production Function Specification

We specify an education production function to account for *exogenous* parental education and market skills, $x = (e, \eta)$ as well as *endogenous* parental time investment and household income. In addition to these, we also consider that the education of children can be affected by their gender as well as the the number of young siblings in the households, S_{-5}, which can reduce potential parental time investment. Let the characteristics of children in the next generation represented by $x' \equiv (e', \eta')$, where e' denotes the education of children, and η' denotes children' market ability. The characteristics of children is determined by the following equations:

$$e' = \Gamma\left(x, \zeta, d^0, \ldots, d^5, w^0, \ldots, w^5, S_{-5}\right) + \omega' \tag{5a}$$

$$\eta' = \Gamma_\eta(e', \zeta) + \tilde{\eta}' \tag{5b}$$

$$\Pr(\tilde{\eta}' = \tilde{\eta}_i) = F(x_f, x_m) \tag{5c}$$

where ω' is the luck component and independent of $\tilde{\eta}'$ which is assumed to have finite support probability distribution function, $F(\cdot, \cdot)$. The superscripts over w and d show the age of the child. In the empirical implementation, Γ and Γ_η are both linear functions. We refer to Gayle et al. (2018a) for more details on the education production function.[20] The estimation results are shown in the Table 18.

Gayle et al. (2018a) show that both *exogenous* and *endogenous* factors are important on the children's educational outcome. For example, the probability of a college grade for a child of a college graduate parents is around thirty percent if mother spends average time and father provides

[20] Gayle et al. (2018a) find that time investment in children is a significant component using an instrumental variable identification strategy with a linear probability model.

low time with the child. However, the ratio increases more than forty percent if father provides average time investment. This result implies that educational outcome of children is impacted by the "nurture". Gayle et al. (2018a) also show that parental education levels positively impact the children's education, which is the role of the "nature".

The results stated in Gayle et al. (2018a) are causal effects. The significant impact of time investment highlights the importance of time allocation of parents. We focus on the impact of income taxation on the allocation. The impact of taxes can impact time investment both negatively, and positively. For example, an increase in the tax rate would reduce labor market time and the freed time can be devoted to child time investment. On the other hand, parents can observe that the marginal product of their time investment is reduced by the increment in the tax rate and reduce the time investment. In addition, the household disposable income would be reduced due to the increment, which negatively impacts the educational outcome. The complex impact of taxation raises the importance of our analysis.

Time Spent with Children Our data source is PSID which does not include how much parents spend time with children until 1997.[21] We follow Gayle et al. (2015) and compute the time investment as the deviation of housework hours in a particular year from the average housework hours of non-parents by gender, education, and year.[22] Negative values are set to zero and childcare hours are zero for childless families.

The number of hours are not, in particular, very important since the hours are discretized into three categories: low, medium, and high. Therefore, potential problems of measurement errors are reduced. Second, although the type of activities are not particularly measured, the discritized measure has significant explanatory power on educational outcomes of children.[23]

2.2.4 Marriage Matching Function

Marriage matching function is used to assign the spouse for the individual at age 25 in each generation. The matching depends on observed characteristics in terms of education, age and past labor supply. As in Gayle et al. (2018b), household matching with respect to education is highly assortative as expected. Due to staionary nature of our estimation, the same mathching function

[21] Child Development Supplement (CDS) is collected as a component of PSID starting 1997 waves. The focus of this supplement is the dynamic process of early human capital formation. Our study focuses on two generations of PSID and hence we are cannot use CDS.

[22] Many studies used this approach (see Hill and Stafford (1974), Leibowitz (1977), and Datcher-Loury (1988)).

[23] American Time Use Survey (ATUS) contains information on detailed childcare activities, such as playing, teaching, and basic childcare. Figure 1 of Gayle et al. (2015) shows that ATUS and PSID hours have similar patterns across different demographic groups. For example, parents with more children spend more time on childcare and white mothers spend more with their children than black mothers according to ATUS and PSID.

is applied to individuals from all generations, although empirically assortative matching in the marriage market has increased over time.

2.2.5 Shocks and Choices

We also want to summarize shocks and choices and their timing before going to utility empirical specification. There are four main shocks in our model. The timing of the realization of these shocks are crucial to understand the model predictions. The first shock is embedded in the matching probability, $G(x_m, x_f)$, is realized at the beginning of adulthood, at the age 25. The second shock, ε_{a_t} is on the per-period utility and is realized at the beginning of each period during the adulthood and is i.i.d. across households and time. Household make choices after realization of the shock for every age. The third shock, $\tilde{\eta}$, is on the unobserved ability in the labor market, which is realized at the beginning of adulthood, at the beginning of age 25, and is persistent over the household life-cycle but independent across parents and children. The final shock, ω', is on the children's educational outcome, which is realized before the adulthood starts, at the end of age 24, and is independent across generation.

2.2.6 Utility Empirical Specification

We can write the utility function, $u_{a_t}(z_t)$, as a function of only the discrete actions by substituting the binding budget constraint. This is described by the following equation:

$$u_{a_t}(z_t) = \theta_{a_t}(z_t) + \tilde{u}\left((w_t(z_t, h_t) - T(w_t(z_t, h_t)))(1 - \alpha(z_t)(N_t + b_t))\right) + \varepsilon_t$$

where $\theta_{a_t}(z)$ is dis/utility from the time allocation in choice a and the utility from consumption is $\tilde{u}(.)$ which is assumed to be linear.

We follow Gayle et al. (2018b) and assume that $\alpha(z_t)$ is based on the fertility decision and the invariant characteristics, such as both maternal and paternal education, as well as the race. Moreover, we use a parsimonious set to capture the leisure implications in the utility function of household choice combinations. More specifically, there are L disutility levels corresponding the combinations of labor supply choices of females and males (9 parameters), the combinations of time investment choices of females and males (9 parameters), and a choice for the birth decision (1 parameter) in the household.[24] Let the disposable income be represented by $\tilde{w}_t = w_t - T(w_t)$.

[24] We want to note that the choice set is restricted to the possible actions depending on the state as in Gayle et al. (2015). Basically, the household can only invest in their children only if they have a child less than five years old.

The empirical specification of the period utility can be written as:

$$u_{ta} = \sum_{1}^{L} \theta_a \mathbb{1}_a + \alpha_0 \tilde{w}_{ta} + (N_t + b_t) \times \left(\alpha_1 \tilde{w}_{ta} + \sum_e \sum_g \alpha_{eg} \tilde{w}_{ta} \mathbb{1}_{eg} + \alpha_8 \tilde{w}_{ta} \mathbb{1}_{race} \right) + \varepsilon_t$$

where $\mathbb{1}$ is the indicator function, e represents the education level which can be High School (HS), Some College (SC), and College (COL), g represents gender which can be female (f) or male (m), and race can be either white or black.[25]

According to the specification, α_0 represents the marginal utility of disposable income (consumption). The marginal utility of parents who have less than high school degrees is $\alpha_0 + \alpha_1$. The left panel of Table 15 presents the related estimates. We find that the utility of parents increase with the education level. Also, the utility is decreasing in the number of children.

The right panel of Table 15 shows the dis/utility from time allocation choices. The estimates are relative to an outside option, which is both spouses choose not to work, not to spend time with children, and not to give a birth. We observe that time devoted to labor market decreases utility except for the household working full time. In addition, the estimates for the time spent with children quite vary, which can be attributed the fact that not all childcare activities provide leisure nor they are labor (see Godbey and Robinson (1999)). Finally, we see that the birth decision reduces the instantaneous utility, which can be considered as the cost of the psychological and biological costs of the postpartum.

3 Data and Estimation

Data The estimation is conducted using data from the Family-Individual File of the PSID. Initially, individuals from 1968 to 1996 are selected into the sample. This sample consists of 12,051 males and 17,744 females; these individuals were observed for at least one year during our sample period. We restrict our main analysis to white individuals only. Various equations estimated the corresponding relevant sub samples from the initial sample. Estimation of the earnings equation required the knowledge of the last four labor market history. This, for instance eliminated observations of individuals without at least 5 years of sequential observations. Parental time investment into a child during her/his early life requires us to observe children before age of 16, therefore we excluded parents observed after that age. We also exclude parents with missing observations during their children's lives. Since we model the family, if there were missing observations for the spouse of a married individual, then that individual is excluded from our sample. With all these main restrictions, the sample contains 89,538 individual-year observations. Table 16 shows the

[25]The households where both spouses have less than high school degrees are considered as the base.

summary statistics.

Our model is a unitary model without divorce.[26] Consistent with the model, we use data on married couples. The no divorce restriction ideally requires the estimation to be done using lifelong married couples. However, this practically will leave us with very limited amount of data to conduct a meaningful inference, yet making our sample non-representative of the overall population. As in Gayle et al. (2017), we mitigate this issue by using two subsamples in the model estimation. The details of the sample can be found in Table 16. Briefly the first sample consist of all individuals that meets the above restrictions and who are married for at least one year in our sample. This is a sample of 41,448 individual-year observations and is used in to estimate all the first stage equations required int he structural model (i.e.education production function, earnings equation, the marriage market matching function, and the household choice probabilities). The sample of married couples who remain married over the years observed in the PSID construct our second sample of 32,144 individual-year observations and this is used to estimate the utility parameters.

A brief summary of our sample shows that the life-time married sample is on average about the same age as the ever-married sample. All individuals in both samples are married by construction . The female-to-male ratio is 60% in the ever-married sample.[27] In terms of education, the life-long married sample have on slightly higher education, though not statistically significant. Individuals have more children in the ever-married sample. In the life-long married sample, annual labor income and labor market hours for individuals are higher.[28] In the ever-married sample, adults have higher housework hours and time spent with children on average.[29] However, we note that none of these differences are statistically significant. A similar pattern holds for the children's generation as well.[30]

Estimation Estimation of intergenerational models with explicit life-cycle components are not trivial in general. There are both identification/econometric issues and computational issues to be solved. On the identification side, choice specific utility parameters can only be identified relative to a benchmark choice (Newey and McFadden (1994)).[31] We use the multistage framework developed in Gayle et al. (2018b) using data from the PSID. In this framework, we use forward

[26]See Fernandez and Rogerson (2001) and Fernandez et al. (2005) for theoretical and empirical models that use the unitary household formulation to introduce marital sorting in a dynastic model. For a dynastic model with a non-unitary household, see Gayle et al. (2015).

[27]It is equal to 50% by construction in the life-long married sample, since we observe the same family over years.

[28]This is consistent with the fact that child-bearing potentially reduces labor market participation, especially that of women Gayle et al. (2017).

[29] Again this is consistent with the higher number of children in the ever-married sample.

[30]Note that the children's generation is needed only to estimate the education production function since the model is stationary.

[31]This identification problem in utility based discrete choice models is well-known in the literature.

simulation (see Hotz et al. (1994)) to solve the computational cost of calculating future states and the alternative value function representation derived in Gayle et al. (2018b) to construct the moment conditions for the GMM estimator.[32] The estimation assumes a stationary environment in terms of dynasties which grants the value function representations that help us construct the moment conditions.

The estimation can be summarized in four steps. In step 1, the equations for (i) earnings, (ii) intergenerational education production, and (iii) the marriage market matching (at age 25) are estimated. In step 2, conditional choice probabilities (CCPs) of household decisions are estimated. In step 3, using the the stationary assumption, alternative value functions representation is derived. In step 4, the Hotz-Miller inversion is used to form moment conditions for a generalized method of moments (GMM) estimation of the remaining structural (utility function) parameters of the model. Discount factors are set of those in Gayle et al. (2017), however, the framework can accommodate estimation of the discount factors as a part of the structural parameters of the model.[33]

4 Model Fit

In this section, we provide how our estimation fits the data. We present the parameter estimates first and then describe the model fit measures based on statistical tests and summary table outcomes from solving the model numerically and simulating 1,000 synthetic generations.

4.1 A Note on Discount Factors

The discount factors are set $\beta = 0.813$, $\tilde{v} = 0.795$, and $v = 0.111$.[34] The discount factor is smaller than typical calibrated values in macro environments ($0.95 - 0.99$); however, recent micro studies find much lower values for the discount factors (see Arcidiacono et al. (2007) and Gayle et al. (2015)). The value of the intergenerational discount factor, $\tilde{v}$, implies that the parents value their children's utility by a factor of 79.5% of their own utility. This value is within the same range of values obtained in the literature calibrating dynastic model (see Rios-Rull and Sanchez-Marcos (2002) and Greenwood et al. (2003)). The last discount factor associated with the number of children, v, implies that the marginal increase in value from the second child is 0.68 and of the third child is 0.60.

[32] As the life-cycle is modeled from age 25 to 55, the estimation is computationally a challenging task.

[33] Discount factors can be estimated with the other structural parameters of the model in a GMM or PML estimator. This, in general, is not a trivial task since the model has three discount factors to identify instead of one as it has in the standard discrete choice models. See Gayle et al. (2018b) for details of identification and estimation of the discount factors in dynastic life-cycle models.

[34] We create a three dimensional grid to search for the best discount factors. Since the differences are negligible, we set discount parameters to the estimated parameters of Gayle et al. (2017).

4.2 Graphical Fit and Tests

We assess the fit of the model both statistically and graphically. The statistical overidentifying J-test cannot reject the overidentifying test at the 5% level. The other two criteria require us to solve the model numerically. We numerically solve the model and simulate 10,000 synthetic generations. Using the simulated outcomes, we first compute the unconditional choice probabilities of household labor supply, fertility, and parental time with children and compare them to the unconditional choice probabilities computed from the data. Visually, our estimated model can replicate the observed choices in the data well. One can interpret the fit of the model form this exercise as a visual representation and aggregated summary of the restrictions in the J-test as these are the aggregates of the moments targeted in estimation. We present the results of this comparison in the Table 3 below Data and Simulation columns.

5 Counterfactuals

In this section, we conduct four counterfactual exercises to quantify the role of income taxation in the life-cycle decisions and in the intergenerational correlation in earnings.[35] In particular, we study the effects of the progressive and family size dependent taxation which are the key features of the US tax code. First, we create a baseline counterfactual (NT) in which households pay no (zero) taxes, i.e. they consume all of the labor income. In counterfactual II (FT), we examine the impact of existence of taxes. Households face a flat tax rate (18%) regardless or their sizes or income. The rate (18%) is chosen to set a quite similar government spending requirement across counterfactuals.[36] In the counterfactual III (TWP), households face a progressive tax system. Finally, in the counterfactual IV (TWC), the average tax rates depend only on the household size. Although, the taxes are not progressive within same size households, taxes are regressive in a way that when the average rate is lower for households with more children. We summarize the taxation in each counterfactual in Table 2.

In each counterfactual analysis, we simulate outcomes for a synthetic cohort of 2,500 individuals. We calculate several life-cycle statistics to compare the effects of different tax regimes, in particular, the effects of the progressivity and children dependency aspects of the tax code. Later, given the synthetic dataset, we calculate the intergenerational correlation of earnings and compare the results to the estimates obtained from the data.

[35] Abbreviations of counterfactual exercises are NT, TWP, TWC, and FT, which refer to average taxes are zero, are progressive, depend on the number of children, and are fixed, respectively. We also refer Simulation as Sim in the figures.

[36] There are two different approaches in the literature to compare government revenue-equivalent environments. Either the per-capita tax level or the ratio of the tax collection to the GDP is closely set to each other. In our case, 18% satisfies almost both approaches.

Table 2: Tax Parameters in Counterfactuals

Counterfactual	Parameters	0 children	1 child	2 children	3 children	4 children
Simulation	λ	4.4235	5.8734	7.402	6.5081	6.5641
	τ	0.1559	0.1797	0.1992	0.1857	0.184
NT	λ	1	1	1	1	1
	τ	0	0	0	0	0
FT	λ	0.82	0.82	0.82	0.82	0.82
	τ	0	0	0	0	0
TWP	λ	6.0828	6.0828	6.0828	6.0828	6.0828
	τ	0.1822	0.1822	0.1822	0.1822	0.1822
TWC	λ	0.7895	0.8144	0.8328	0.8625	0.9162
	τ	0	0	0	0	0

Note: The table provides tax parameters of the tax function, $T(y) = y - \lambda y^{1-\tau}$, for differently sized households that are used in the relating counterfactual.

We present the averages of the probabilities of discrete choices in the Table 3. We briefly provide a discussion of these probabilities. First, the simulation column shows that our model fits the data well. Second, we observe that males' choices are almost not affected by taxes. In fact, taxes influence females' choices. For example, female labor force participation remarkably increases from Simulation to NT. When there is a flat tax rate (FT), we see that the participation significantly decmidrules. The decmidrule is more severe when the tax system is progressive (TWP). Finally, it is important to note that the households' birth decision is also affected by the tax regime. We see that income taxes increases the probability of birth decision. The impact of taxation on fertility is a controversial in the literature. Our finding is in line with Whittington (1992) who also uses PSID and finds that the impact of tax exemptions on the fertility is positive.

5.1 Life Cycle Analysis

In this subsection, we analyze the life cycle differences across counterfactuals. Before providing a detailed analysis, we discuss the model. Our model takes returns to participating in the labor market as exogenous while the earnings of families are endogenous through labor supply decisions. The time resource, which can be spent for market work, for children, and for leisure, is fixed for each spouse. Therefore, the allocation patterns of time investment should reflect the opportunity cost of foregone earnings which are exogenous, given the nature of the job (part time or full time), past participation (experience), education (human capital), ability, and gender. In this respect, our model is a partial equilibrium model and the labor supply behavior of our households can not change the offered wages for different tenure and human capital combinations in the mar-

Table 3: Probability of Choices under Counterfactuals

		Data	Simulation	NT	FT	TWP	TWC
Female							
	No work	0.26	0.23	0.19	0.25	0.35	0.25
Labor	Part time	0.14	0.20	0.16	0.18	0.18	0.18
	Full time	0.60	0.57	0.65	0.57	0.47	0.57
	Low	0.65	0.87	0.92	0.81	0.70	0.80
Time Investment	Medium	0.21	0.07	0.05	0.11	0.17	0.12
	High	0.14	0.05	0.04	0.08	0.13	0.09
Male							
	No work	0.03	0.03	0.03	0.03	0.02	0.03
Labor	Part time	0.03	0.04	0.04	0.03	0.03	0.03
	Full time	0.94	0.93	0.93	0.94	0.95	0.94
	Low	0.80	0.95	0.97	0.94	0.89	0.94
Time Investment	Medium	0.10	0.03	0.02	0.04	0.07	0.04
	High	0.09	0.02	0.01	0.02	0.04	0.02
Household							
Birth		0.10	0.04	0.03	0.06	0.09	0.06

Note: The numbers in each cell refer to the average probability of choosing action in a year over life-cycle.

ket. However, given wages, households can optimally choose the life-cycle earnings by targeting the specific experience and participation decisions precisely. Moreover, these choices affect the choices of the future generations through the labor market earning channel. In particular, parental choices create a dynamic problem which impacts children's adulthood states and therefore children's future choices, as well as their own future states in their life-cycle. In return those children adulthood outcomes which are the proxy of the children's value to parents affect parental decisions in the first place. This aspect of our model makes it different from the standard life-cycle models in terms of effect of labor market earnings.

We transform the probabilities stated in Table 3 into the average allocations (as well as labor earnings) and show results at the Table 4.

The Table 4 presents that the labor choices (earnings) of males are almost insensitive to different tax regimes. We observe slight increase in the male labor supply under TWP in response to high female labor market dropouts. We also observe that female labor supply decmidrules with more progressive tax regimes. The percentage reduction in the female labor supply from NT to TWP (22%) is more than twice the reduction (9%) from NT to FT (or TWC). We do not observe much differences between FT and TWC, on average, which requires more detailed analysis. These results imply that elasticity of labor supply is very low for males and high for females, which are in line with empirical literature (see Saez et al. (2009).)

Table 4: Average Life Cycle Allocation across Counterfactuals

	Simulation	**NT**	**FT**	**TWP**	**TWC**
Female					
Labor Supply	1.34	1.46	1.33	1.13	1.32
Income	18,203	20,683	18,066	14,730	17,899
Time Investment	0.18	0.12	0.28	0.43	0.29
Male					
Labor Supply	1.90	1.91	1.91	1.93	1.92
Income	47,980	47,956	48,251	48,774	48,448
Time Investment	0.07	0.04	0.09	0.14	0.09
Household					
Before Tax Income	66,184	68,639	66,317	63,505	66,347
Taxes	14,065	0	11,937	12,587	11,730
Average Tax Rates	0.19	0.00	0.18	0.18	0.18
Disposable Income	52,119	68,639	54,380	50,918	54,617
Children	1.21	0.78	1.78	2.93	1.86

Note: All income values are in 2005 $s and are per-capita values. Time allocation outcomes are the averages of decisions from the set of $\{0,1,2\}$, where 0,1, and 2 represent no, part, and full time, respectively. Children row represents the average number of children across households at the end of fertility age (45).

Time investment in children significantly changes across counterfactuals. Yet, the reasoning is different across gender. While the changes in male time investment are due to the variation in the number of children, the changes in the female investment also includes the differences in their labor supply.

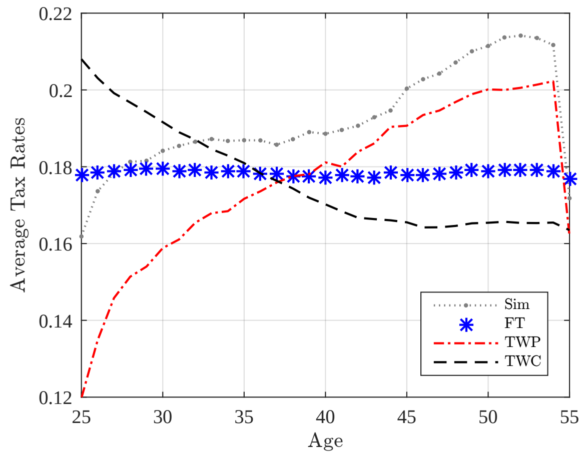
The average number of fertility (children) is quite responsive to income taxation too. We find that the fertility rate is decmidruled when there is no taxes. The introduction of flat taxes increases the fertility rate by one comparing to the rate in NT. The increment in the rate (from NT to TWP) is more than two.[37] The progressive tax system reduces the value of female labor supply.[38] In addition, the progressive taxes also reduces the life-cycle utility of children. Knowing these facts, households increase the fertility rate.[39] Finally, we also see that the fertility rate in TWC is slightly

[37]There are two channels of the fertility rate responses. First, households get a disutility just after the birth (see Table 15). Second, households get utility from the life-cycle utility of children. We find that the second channel is more strong.

[38]Since the male labor supply is almost inelastic to taxes, females can be considered as secondary earners and their labor is taxed at a higher marginal rate.

[39]Note that since the household disposable income is lower due to the lower female labor supply in response to progressive taxes, the educational outcome of children are expected to be lower. In addition, per-child time investment

Figure 2: Average Tax Rates in Life Cycle Across Counterfactuals



Note: Numbers refer to the means of average taxes. Also, tax rates of NT are zero and are not plotted.

higher than the rate in FT. This is mainly due to the fact that households receive more tax benefits when they have more children.

We first present the average taxes in each year in Figure 2. The average taxes have different patterns in the life cycle across counterfactuals. While, the rate is decreasing for TWC, it is increasing in TWP and constant in FT. This result is not very surprising. First, households get tax benefits in TWC and they have more children during the life cycle. In fact, when they reach the age of 45 (last fertile age), the rate starts to be constant. Second, households pay a fixed tax rate in FT, so the average tax rate should be flat. Third, the rate is increasing because households are tend to earn more income during the life cycle due to the history dependent earning function, and consequently, the rate is increasing in TWP.

Next, we analyze the impact of taxes on the labor income in the life-cycle. Figure 3 shows that males' earnings are not very responsive to taxes on average. Moreover, we observe similar the result for different education groups.

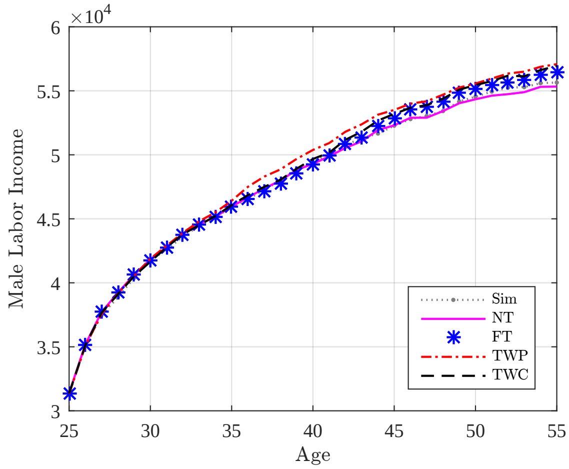
Next, we focus on the earnings of females. Figure 4 shows that taxes impact female earnings quite distinctly. Note that, Table 17 shows us that there is a gender wage gap, which is a well-known fact in the empirical literature. A unit of labor is much more productive for men, therefore, we do not observe a high variation in the males' earnings. This can be inferred as females are secondary earners.[40] Therefore, females' labor is more sensitive to changes in taxes.

We decompose the variation and find that the variation is stronger for college graduates (see

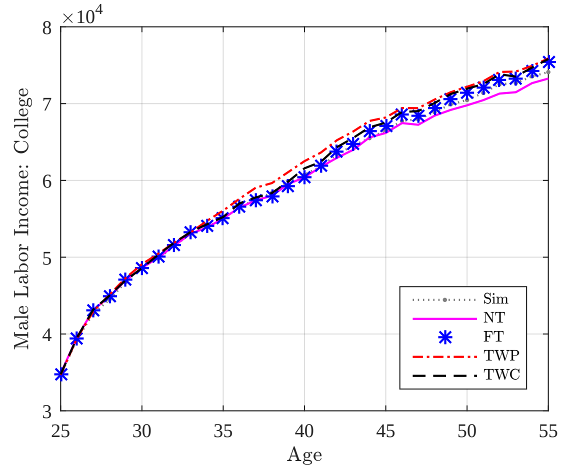
in children is also lower. As a result, the increase in the number of children (quantity), on average, can be considered because of the lower utility from the dynastic component (quality).

[40]Most of public finance papers make this assumption based on gender wage gap (see Kleven et al. (2009)).

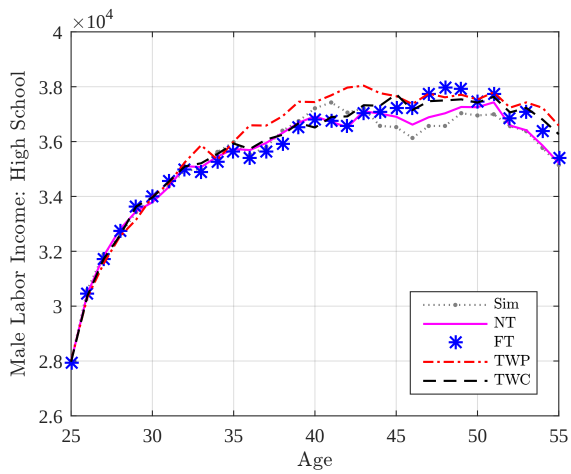
Figure 3: Male Labor Income in Life Cycle Across Counterfactuals



(a) All Households



(b) College Graduates



(c) High School Graduates

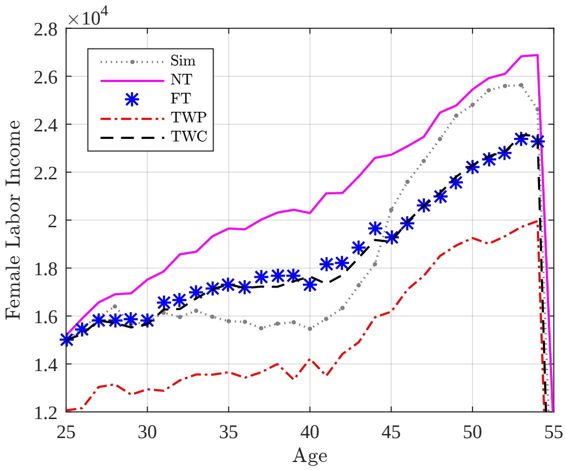
Note: Education labels refer to males' education.

Figure 4). The variation in the earnings of high school graduates is around \$400, while, the variation can reach more than \$10,000. This result is based on the price of labor. According to Table 17, we see that education increases the marginal product of labor. Therefore, taxes reduce the value of college graduate females' labor most. We see that the flat tax rate reduces the college graduate females' income comparing to income levels in NT. The reduction is much dramatic from NT to TWP. This is mainly because households know that next dollar is taxed at a higher rate in TWP. In addition, the positive correlation in the marriage function enlarges the impact.[41]

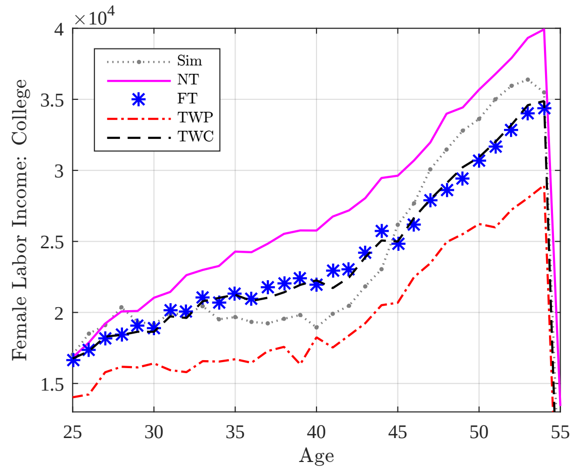
We also represent the changes in the disposable income across life cycle. We find that there is

[41] Since a college graduate female is likely to get married with a college graduate male, her first dollar earning is taxed at a much higher rate comparing to the first dollar earning of a high school graduate female, who is likely to be married with a high school graduated male whose income is lower than a college graduated male.

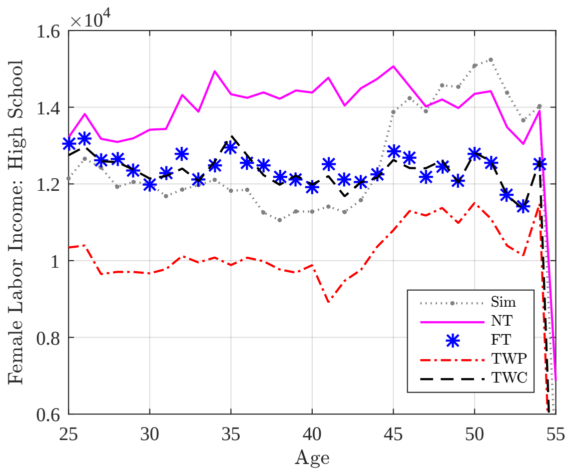
Figure 4: Female Labor Income in Life Cycle Across Counterfactuals



(a) All Households



(b) College Graduates

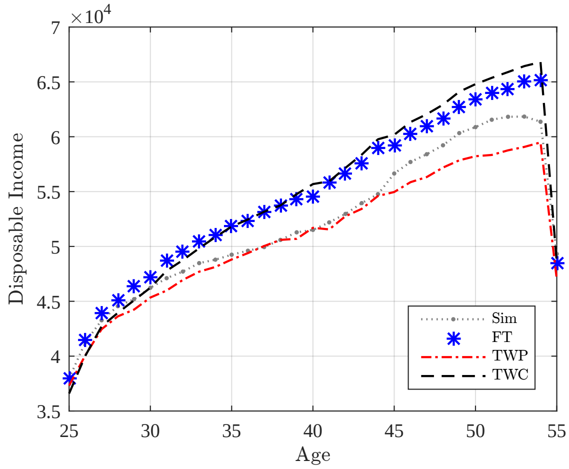


(c) High School Graduates

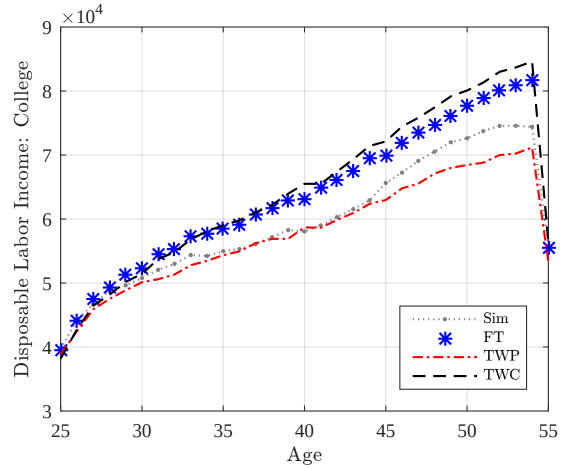
Note: Education labels refer to females' education.

a variation in the income for all households. However, when the female is a high school graduate, we do not observe a large variation. The variation for all households relies on the variation in the disposable income of households with a college graduate female. This result is combination of the results above. Yet, it is important to mention that the marriage function, which is assortative mating, is the key determinant behind the variation.

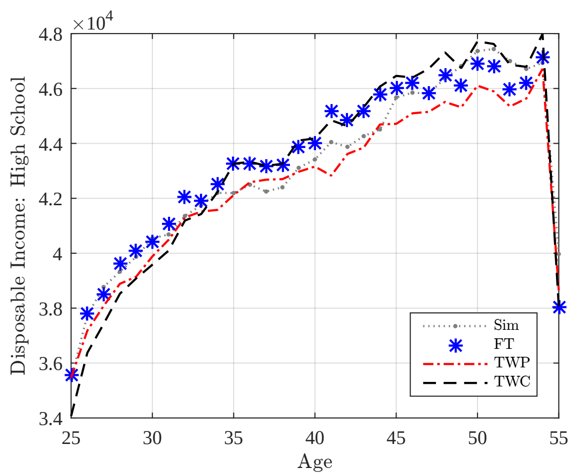
Figure 5: Disposable Income in Life Cycle Across Counterfactuals



(a) All Households



(b) College Graduates

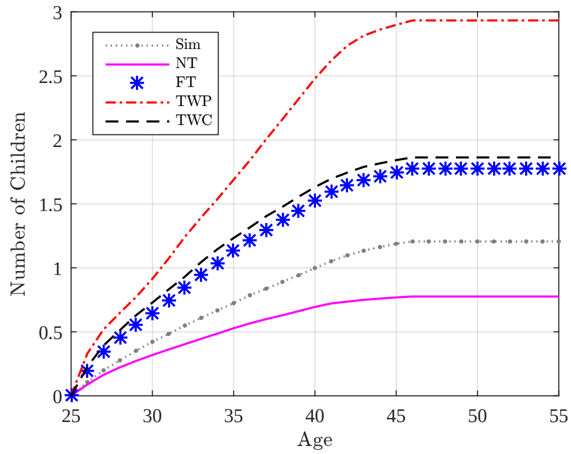


(c) High School Graduates

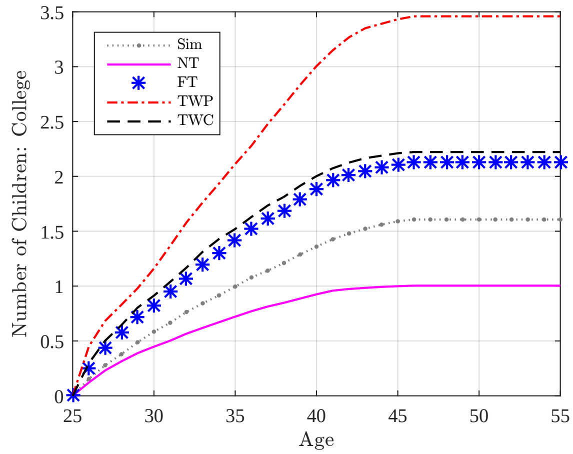
Note: Education labels refer to females' education. Disposable income in FT is not plotted on purpose, since it will not provide significant information.

Finally, we also study the impact of taxes on the fertility behavior (see Figure 6). We observe that the number of children in the household in FT is higher than the number in NT. This shows that existence of taxes positively affects the fertility. Moreover, the number is much higher in TWP, which shows that progressivity increases the fertility. These results are consistent across different

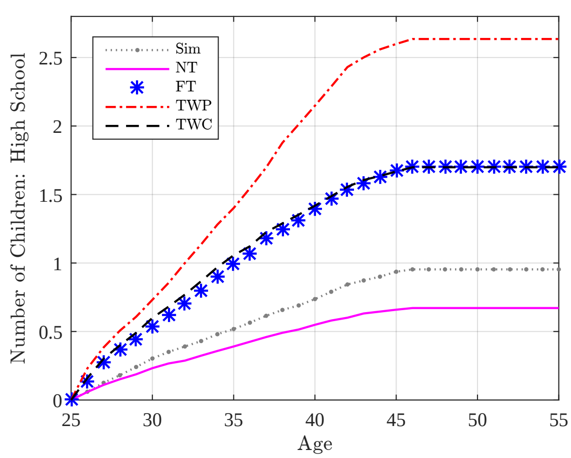
Figure 6: Number of Children in Life Cycle Across Counterfactuals



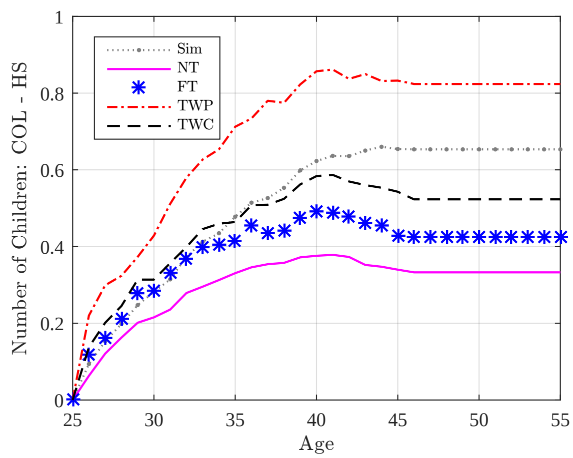
(a) All Households



(b) College Graduates



(c) High School Graduates



(d) Differences

Note: Education labels refer to females' education. Differences refer to the differences in the number of children of college graduate females from the high school graduate females.

educations. We also show the differences in the fertility rates between college graduate and high school graduate females within counterfactuals. Figure 6 shows that college graduate females tend to have more children than high school graduates. The differences vary across counterfactuals. The lowest difference is in NT since college graduate females labor is much valuable. The difference increases from NT to FT by the existence of taxes. We also observe that the differences of FT and TWC are quite similar. Yet, the difference in TWC is slightly higher since households get more tax benefit by having more children. Finally, the highest difference is in TWP. The progressive taxes reduces the value of college graduates so high, therefore, households tend to have more children.

Table 5: Average Life Cycle Allocation of Second Generation across Counterfactuals

	Simulation	**NT**	**FT**	**TWP**	**TWC**
Female					
Labor Supply	1.32	1.46	1.30	1.11	1.30
Income	16,634	19,063	15,924	12,894	15,984
Time Investment	0.18	0.10	0.29	0.44	0.30
Male					
Labor Supply	1.91	1.87	1.91	1.92	1.91
Income	45,541	43,932	44,263	43,777	44,555
Time Investment	0.07	0.03	0.09	0.14	0.09
Household					
Before Tax Income	62,175	62,995	60,187	56,670	60,540
Taxes	12,676	0	10,834	10,274	10,693
Average Tax Rates	0.19	0.00	0.18	0.16	0.18
Disposable Income	49,499	62,995	49,353	46,396	49,847
Children	1.18	0.62	1.84	2.92	1.88

Note: All income values are in 2005 $s and are per-capita values. Time allocation outcomes are the averages of decisions from the set of $\{0,1,2\}$, where 0,1, and 2 represent no, part, and full time, respectively. Children row represents the average number of children across households at the end of fertility age (45).

Discussion Above, we specifically provide the outcomes of the initial (parent) generation. The figures, of course, would be different for the second (child) generation. The reason we focus on the initial generation is to provide different policy analysis for the "current" generation which is very important for policymakers.[42] The life-cycle outcomes of the second generation is represented at the Table 5. We observe slight decreases in the female labor supply and almost no changes in males' labor supply. We see a decrease in the incomes of each spouses due to lower educational outcome (see Table 6).

We also show the educational outcomes of children in Table 6.[43] The intensity of human capital investments is altered by the income taxation. Taxation changes the returns to parents' human capital in their own generation and does this in a heterogeneous way as such, with a high progressive taxation more educated parents are disproportionately affected by the tax. Also due to the stationary taxation, returns to increased human capital for children are subjected to a higher

[42]Most of the time, a potential policy which favors future generations but hurts current generation is not implemented due to the political reasons.

[43]The required sample restrictions cause higher educational levels for both females and males in the estimated sample comparing to the raw data.

Table 6: Educational Outcome

	First Generation	*Second Generation*				
	All CFs	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Males' Education	3.12	2.96	2.93	2.83	2.75	2.83
Females' Education	3.15	2.98	2.95	2.82	2.76	2.84

Note: The cells refer to the averages of 1, 2, 3, and 4, which refer to Less than high school, high school, some college, and college graduation, respectively. CFs refers to counterfactuals including Simulation.

taxation given the positive relationship between education and earnings in the estimated earnings equation. Since human capital is the only channel in our model that allows transfers in endowments (in this case education/ability in the empirical application) from one generation to the other, the counterfactuals should reflect the changes in investments in human capital by the parents given the change in the respective aspect of the tax code.

5.2 Government Revenue

We also want to mention briefly about the government revenue (tax collection). Using the per capita taxes collected from each generation from the Table 4 and Table 5, the ratio of total taxes to the total income (GDP) is presented at the Table 7:

Table 7: Government Revenues as a share of Total Income

	Simulation	**NT**	**FT**	**TWP**	**TWC**
First Generation	0.20	0.00	0.18	0.18	0.18
Second Generation	0.21	0.00	0.18	0.20	0.18
Both Generations	0.21	0.00	0.18	0.19	0.18

Note: The numbers are rounded to second decimal.

Table 7 shows that the ratios are very close to each other in the counterfactuals (FT, TWP, and TWC), and, therefore the governments in each counterfactual can be considered as if revenue equivalent.[44] The Table 7 shows us two important results.

[44] Unfortunately, we cannot capture exact ratios due to computational difficulties since some of the computational calculations are not mechanical. We could provide little better results at a cost of huge time using hand based calculations. However, the economic intuition would not change and the current differences are negligible based on the similar tax studies in the literature.

First, moving from the current tax system (Simulation) to either a progressive tax system with no child benefits (TWP) or a tax system with only child benefits (TWC) reduces the government revenue.

Second, and more importantly, the child benefits are beneficial to the government only when the taxes are progressive. Simulation and TWP environments include progressive taxes where Simulation environment has the child tax benefits. Similarly, FT and TWC environments do not include progressive taxes where TWC environment has the child tax benefits. We see that the ratio of taxes to the GDP, the per-capita disposable income and taxes of both generations are much higher in the Simulation comparing the levels in TWP (see also Table 4 and Table 5). While the same values are quite similar in the comparison of FT and TWC.

This subsection sheds light on the two important components of the US tax code. We find that the government benefits from a tax system which is both progressive and child-dependent.

5.3 Intergenerational Analysis

In this subsection, we analyze the impact of time investment on the educational outcome for the counterfactuals. Table 8 present the time investment of each spouses and educational outcome of all couples. Later, we focus on the couples where both spouses have high school diplomas and college degrees.

Time investment across spouses have interesting patterns. First, mothers always spend more time with children than fathers and also increase time investment with the number of children, which is unsurprising. Moreover, paternal time investment does not show a clear pattern. Interestingly, college graduate fathers invest more time than high school graduate fathers. The pattern is reversed for mothers. High school graduate mothers spend more time with children than the college graduates. This result relies on two facts. First, the labor of college graduate female is much more valuable than high school graduates. Therefore, college graduate females spend more time on the labor market (see Figure 4). Fathers' labor market time do not differ by their educational outcome. However, the more fathers are educated, the higher impact of the fathers' time investment is observed on the educational outcome (see Table 18). This impact is considered as the "nature" impact in the empirical literature.

We observe an important general trend that is the elder children accomplish higher educational outcome, which is because of the fact that elder children does not likely to have too many young siblings who reduce the impact of the parental time investment and the individual educational outcome (see Table 18). The trend is much apparent from the first to second child, since the number of young siblings is much lower for the first child. The trend is also similar when both spouses have same education. This implies the importance of the "nurture" impact on the educational outcome.[45]

Interestingly, we find that the variation in the educational outcome of children is much less for the NT counterfactual. This observation is much clear for the college graduate spouses. Moreover, college graduate fathers invest more time in the NT counterfactual comparing to other counterfactuals. Since there is no taxes, we see that college graduate mothers spend more time in the labor market and the increase in the female labor force participation slightly reduces the fathers' labor market time. Consequently, college graduate fathers spend more time with children.

Next, we study the economic outcome of the educational outcome. In particular, we focus on the average household incomes when the household is between 30-40 years old because we calculate the intergenerational correlation of income based on this value.[46] Table 9 provides the before- and the after tax income as well as the educations.[47]

For all parents, we observe that the highest before tax incomes, on average, are earned in the NT counterfactual. The incomes in TWC, FT, and TWP follows the NT income in order. The patterns are also similar for the after tax incomes. The explanation of these patterns are provided in the life-cycle analysis.

We, in particular, focus on the households with different educations. When the households have college degrees, the highest educational outcome of children is obtained in the NT counterfactual. Next, we see that the educational outcome in FT and in TWC are quite close to each other. However, we find that households earn around $1,000 more in TWC comparing to FT, which is probably because the average tax rates fall below the rate in FT.

The variation in the incomes and children's educations are much apparent in the high school graduates' households. We see that the highest educational outcome in TWC after NT. The difference between FT and TWC is very significant and shows its impact on the incomes of children, as children in TWC earn around $1,500 more than children in FT.

[45]Table 8 also show the impact of "nature" via the educational outcome of children of differently educated parents.

[46]We elaborate the intergenerational correlations of income in Section 5.4.

[47]Table 9 shows the outcome of *parents*, while Table 4 shows the outcome of *first* generation (including non-parents).

Table 8: Time Investment Impact

	All Couples								
	First Child			*Second Child*			*Third Child*		
	MTI	FTI	Educ	MTI	FTI	Educ	MTI	FTI	Educ
NT	5.00	1.68	3.26	5.09	1.84	2.47	5.05	1.64	2.31
FT	5.01	1.71	3.38	5.01	1.71	2.34	5.17	1.34	2.29
TWP	4.86	1.62	3.38	5.04	1.72	2.30	5.22	1.77	2.37
TWC	5.04	1.68	3.40	5.15	1.65	2.34	5.25	1.17	2.26
	Both spouses have College Degrees								
	First Child			*Second Child*			*Third Child*		
	MTI	FTI	Educ	MTI	FTI	Educ	MTI	FTI	Educ
NT	4.91	1.98	3.37	5.00	2.54	2.68	4.56	2.55	2.63
FT	4.87	1.84	3.56	5.09	1.99	2.42	4.97	1.75	2.48
TWP	4.82	1.73	3.59	4.98	1.97	2.36	4.98	1.99	2.58
TWC	4.92	1.80	3.56	5.04	1.84	2.44	5.02	1.60	2.49
	Both spouses have High School Degrees								
	First Child			*Second Child*			*Third Child*		
	MTI	FTI	Educ	MTI	FTI	Educ	MTI	FTI	Educ
NT	4.99	1.36	3.09	5.25	1.46	2.37	5.46	1.20	2.15
FT	4.96	1.55	3.10	5.22	1.55	2.25	5.42	1.06	2.11
TWP	4.84	1.52	3.18	5.25	1.48	2.25	5.46	1.44	2.18
TWC	5.08	1.46	3.18	5.14	1.41	2.24	5.44	0.97	2.10

MTI and FTI refer to mother and father time investment, respectively. Educ refers to the educational outcome of the child. MTI and FTI is the sum of total discrete time investment in the first five years of childhood and has a range [0,10]. Education is the average of educational outcomes which are discretized from 1 to 4.

Table 9: Income and Education of Parents and Children

	Simulation	**NT**	**FT**	**TWP**	**TWC**
All Parents					
Parents' Before Tax Income	60,671	62,509	60,934	59,608	61,646
Children's Before Tax Income	58,529	60,579	57,692	54,479	58,197
Parents' After Tax Income	48,939	62,509	49,966	48,478	50,823
Children's After Tax Income	47,093	60,579	47,308	45,033	47,599
Daughters' Education	2.96	2.93	2.83	2.75	2.83
Sons' Education	2.98	2.95	2.82	2.76	2.84
College Graduates Parents					
Parents' Before Tax Income	72,482	75,490	73,991	72,278	74,920
Children's Before Tax Income	60,023	62,868	60,178	56,487	60,106
Parents' After Tax Income	56,979	75,490	60,673	56,967	62,022
Children's After Tax Income	48,122	62,868	49,346	46,387	49,207
Daughters' Education	3.03	3.10	2.97	2.91	2.97
Sons' Education	3.03	3.08	2.97	2.88	2.95
High School Graduates Parents					
Parents' Before Tax Income	45,332	47,734	46,309	45,351	46,944
Children's Before Tax Income	57,352	57,251	53,829	51,865	55,491
Parents' After Tax Income	38,335	47,734	37,974	38,826	38,482
Children's After Tax Income	46,277	57,251	44,140	43,267	45,283
Daughters' Education	2.96	2.76	2.57	2.57	2.64
Sons' Education	2.91	2.69	2.59	2.54	2.65

All income values are the averages of the household incomes from the age 30 to the age 40. Education outcomes are the averages of discritized education outcomes (LHS, HS, SC, and COL refers to 1 to 4, respectively).

5.4 Intergenerational Correlation of Income

Table 10 provides the intergenerational correlation of earnings for the model simulations as well as for the counterfactual simulations, using three different measures for constructing proxies for the permanent income. Before discussing the specific effects of the counterfactuals on the intergenerational income correlation, we note that the intergenerational correlation of the earnings in data and in our simulation are close to each other. If only the age 35 income is used as a proxy for the permanent income of parents and children family income, our model captures 88% of the correlation in the data. If the intergenerational income correlation is calculated using the average income from age 30 to 40 as a proxy of the permanent income, the model simulation produces 71% of the correlation in the data. This fact is notable since this is an independent source of model validation as these correlations are not targeted moments in the estimation stage. Of the three measure reported in Table 10, we will refer to the second measure which uses the average labor income from age 30 to 40 as a proxy for the income in the rest of the discussion.[48]

Table 10: Intergenerational Correlation and Elasticity

Correlation	**Data**	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Before Tax Income (35)	0.13	0.15	0.16	0.13	0.10	0.13
Before Tax Income (30-40)	0.26	0.23	0.27	0.26	0.20	0.22
Before Tax Income (LC)	–	0.23	0.20	0.26	0.22	0.24
Elasticity	**Data**	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Before Tax Income (35)	0.24	0.13	0.13	0.13	0.10	0.12
Before Tax Income (30-40)	0.37	0.20	0.22	0.24	0.19	0.20
Before Tax Income (LC)	–	0.21	0.16	0.24	0.20	0.23

Note: The parenthesis refer to age range, where LC refers to life cycle.

NT regime produces the highest intergenerational income correlation (0.27) and the second highest income elasticity (0.22).[49] As shown in the Section 5.1, removing taxes from the economy

[48]In the intergenerational income correlation calculations, incomes used for parents and children are assumed to proxy the permanent incomes of the respective families. There are well known econometric issues in the calculation of intergenerational correlation with permanent income proxies. The survey of Solon (1999) on the intergenerational mobility literature discuses issues related to using incomes from different parts of the life-cycle to proxy the permanent income. See also Solon (1989) for more measurement discussions on the proxies and Solon (1992) for a particular focus on the US correlation.

[49]Intergenerational income correlation and income elasticity diverges to the extent that income correlation given

creates incentives to work more for women which comes as a consequence with a lower fertility rate. Moreover, the time spent per child is slightly higher in NT. This combined with the fact that average disposable income is much higher in NT compared to the simulation produces the higher intergenerational income correlation. We see in the counterfactual output that family disposable income is disproportionately higher in higher educated parent families compared to the simulation output. Children from well educated households benefit more from the no tax regime in terms of human capital investments, which can be decomposed in a same or slightly better time investment and much better monetary investments parts. Therefore our conclusion with this counterfactual is twofold with respect to intergenerational human capital transition. First, removing taxes creates incentives to work more in the labor market for all women. However since the returns to human capital is increasing in education through the life-cycle, families with higher educated mothers benefit most in terms of returns from the labor market. Secondly, with mothers optimally decreasing fertility in NT, their children are not adversely affected from the less total time investment as such the per child time investment remains intact if not slightly higher in NT. The second effect works for all mothers regardless of their education, however, in the production function for children's education outcome, mother's education increases the child's education. Therefore, removing taxes creates a less mobile economy compared to the base model simulation through creating a more favorable environment for the higher educated in terms of transferring human capital across generations.

When the government creates a flat tax rate for all households, we do not see so much changes in the correlation (0.26). The correlation slightly decreases because income taxes creates a substitution effect and reduces labor income. However, this does not create so much variation across households. One of the biggest change is in the educational outcome of children. We observe that the educational outcome of children in FT are lower than the the outcomes of NT. This is another explanation of more mobile society.

In counterfactual TWP, the intergenerational income correlation (0.20) and the intergenerational income elasticity (0.19) are the lowest. The result is a more mobile economy as such taxation takes some of the advantage from the well educated (higher income) and redistributes it to the less educated families. Table 6, we see the average education of the female and males in children generation are 2.76 and 2.75 respectively. This important implication of the progressive taxation in the intergenerational context could not be easily inferred without a dynastic model and consequently without running a counterfactual analysis. Compared to NT (2.95 and 2.93), there is a huge drop in the children's educational attainment. In terms of evaluating the economy with this counterfactual,

by; $\rho = \frac{cov(y_p,y_c)}{\sqrt{var(y_p)var(y_c)}}$ and income elasticity given by; $\beta = \frac{cov(y_p,y_c)}{var(y_p)}$ differs. For instance if the variance of parents' (y_p) and children's income (y_c) are same, the two measures produce the same numerical value. Having a lower β is then associated with a higher income variance in the children's generation.

it would not be inappropriate to say more mobility comes with a less average human capital "quality" in the children's generation. This adverse effect of progressive taxation is naturally missing in most of the analyses that just focus on current generation of individuals for policies. Therefore we believe that it is important to add this intergenerational "quality" effect of progressive taxation to the discussion in policy making.

With TWC, we have the income correlation as 0.22 and the intergenerational income elasticity as 0.20. We observe that the average education of the female and male children (or spouses) are 2.84 and 2.83 respectively. Since the educational outcome is higher comparing to the TWP and lower than NT, our expectation that the correlation in TWC should be between the correlations of TWP and NT, is fulfilled. The interesting outcome is the comparison of FT and TWC counterfactuals. On average, the overall outcome of these two counterfactuals are quite similar (see Table 9). One would expect that the correlation in TWC would, therefore, be quite close to the correlation in FT. However, this is not true. We see that the correlation is much closer to the one in TWP. The reason lies in the impact of the taxation across different households. Table 9 shows that the educational outcome of children of the high school households are closer to their parents' in the FT counterfactual comparing to TWC. Moreover, we also observe that the variation of the children's before tax income in TWC is larger than the variation in FT. Consequently, the mobility in TWC is bigger than the mobility in FT.

Next, we study the income distribution of children when their parents are either at the bottom or at the top quintile of income distribution.

5.5 Intergenerational Transition in Income Distribution

Table 11 shows the probability of children being at the bottom 20%, at the top 50%, and at the top 20% of income distribution conditional on their parents' position at the income distribution. The analysis below is specifically provided for the average household incomes of the ages between 30-40.

For the lowest income parents, we do not observe drastic mobility difference across counterfactuals for the children at the bottom quintile or at the upper tail of income distribution.[50] Yet, the mobility pattern is very clear for the children at the top quintile. For example, the probability of a child being at the top quintile, where her parents are in the lowest quintile, is 6.2% in the NT. The probability increases to 7.9% when there is a flat tax rate. Next, the same probability equals to 9.3% and 10.2% in TWC and TWP, respectively. This result is in line with the intergenerational correlation of income stated above (see Table 10).

For the highest income parents, the pattern is much clearer. For example, the rank of the highest

[50] Although the probabilities are close to each other, the pattern supports the results stated in Table 10.

probability of being in the top 50% of income distribution is NT, FT, TWC, and TWP. In particular, the probability is reduced by 2.4% by the introducing of flat income tax rate. The decmidrule is 6.3% when the taxes are progressive. These reductions are much higher for the probabilities being at the top quintiles. From NT to FT, we see 6.2% and from NT to TWP, we see 10.3% reduction.

Table 11 shows the importance of the tax regimes in the mobility of income distribution. Not only the existence of taxes but also the type of taxation matters. The flax tax rate system slightly reduces the mobility. When the tax rates depend only on the size of households (TWC), the mobility increases again. Rather, if the taxes depend only on income and are progressive, we observe the highest mobility.

The interesting pattern emerges on the comparison of the child tax benefits. If the government introduces child tax benefits when the tax rates was flat, i.e. from FT to TWC, we see that the mobility increases. However, if the government embeds child tax benefits into a progressive tax system, i.e. from TWP to Simulation, we observe that the mobility decreases. This result is interesting as most of the child benefits, including the tax benefits, are provided to improve potential future economic outcome of children.[51]

5.6 Robustness

The main model was based on the white married households. We relax our assumption and we also calculate the correlation including the black households. Table 12 shows all correlation and elasticities. We see that the correlations are larger than the correlations of white households. This phenomenon is well established in the empirical literature that the income mobility is less for black households comparing to the white households (see Gayle et al. (2015) and references there). We find that the general trend in Section 5.4 still exists. The highest correlation appears in NT. The correlation in FT is less than the correlation in NT. Also, the correlation in TWC is closer to the correlation in TWP, which is the lowest correlation.

[51] We want to note that the tax parameters are calculated including welfare benefits, such as food stamps, which depends on the income. Therefore, the results for TWP and Simulation also includes the impact of the welfare benefits, though, we do not model them explicitly. The separation of income taxation and welfare benefits is beyond the scope of our current project, though, could be an important analysis, which we leave as a future work.

Table 11: Income Mobility

Low Income Parents (Bottom Quintile)					
	Simulation	**NT**	**FT**	**TWP**	**TWC**
Children at the bottom quintile					
Before Tax Income (35)	26.5%	22.9%	25.4%	24.3%	25.3%
Before Tax Income (30-40)	32.5%	31.9%	31.6%	30.4%	32.5%
Before Tax Income (LC)	31.8%	33.3%	31.2%	32.2%	33.2%
Children at the upper tail					
Before Tax Income (35)	40.3%	40.1%	43.8%	42.5%	42.9%
Before Tax Income (30-40)	33.9%	36.2%	34.2%	37.2%	38.0%
Before Tax Income (LC)	40.3%	39.3%	34.3%	36.1%	36.2%
Children at the top quintile					
Before Tax Income (35)	16.3%	11.9%	15.9%	14.2%	15.2%
Before Tax Income (30-40)	9.4%	6.2%	7.9%	10.2%	9.3%
Before Tax Income (LC)	12.0%	12.4%	10.0%	10.7%	10.2%
High Income Parents (Top Quintile)					
	Simulation	**NT**	**FT**	**TWP**	**TWC**
Children at the bottom quintile					
Before Tax Income (35)	16.8%	14.6%	16.7%	17.5%	17.7%
Before Tax Income (30-40)	11.2%	11.5%	12.7%	13.8%	13.9%
Before Tax Income (LC)	9.8%	11.0%	12.2%	12.2%	11.2%
Children at the upper tail					
Before Tax Income (35)	55.8%	60.8%	58.9%	55.8%	57.2%
Before Tax Income (30-40)	61.1%	64.2%	61.8%	57.9%	60.0%
Before Tax Income (LC)	60.7%	55.8%	63.2%	60.3%	63.1%
Children at the top quintile					
Before Tax Income (35)	24.6%	32.1%	26.1%	23.7%	25.9%
Before Tax Income (30-40)	30.8%	37.7%	31.5%	27.3%	30.4%
Before Tax Income (LC)	29.3%	27.6%	30.8%	27.9%	31.3%

Note: Each cell provides the probability of corresponding children when their parents are at the bottom or at the top quintile.

Table 12: Intergenerational Correlation and Elasticity

Correlation	**Data**	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Before Tax Income (35)	0.16	0.24	0.31	0.25	0.21	0.25
Before Tax Income (30-40)	0.28	0.35	0.49	0.43	0.37	0.39
Before Tax Income (LC)	–	0.36	0.42	0.45	0.39	0.43

Correlation	**Data**	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Before Tax Income (35)	0.24	0.19	0.25	0.22	0.18	0.22
Before Tax Income (30-40)	0.37	0.25	0.41	0.36	0.31	0.34
Before Tax Income (LC)	–	0.27	0.33	0.39	0.34	0.39

Note: This table provides the correlation and elasticities for both black and white married households.

6 Conclusion

This paper studies the impact of taxation in a dynastic life cycle model in which households decide fertility and time allocation between labor, leisure, and childcare (time investment) where both labor and childcare choices are either zero, part, or full time. After a careful estimation of a discrete choice model by following Gayle et al. (2017), we encounter four different counterfactuals to observe the impact of each component of the US tax code, progressivity and child benefits. We analyze both on the life cycle outcomes and on the intergenerational linkages.

Our results show that the existence and the type of the income taxation particularly impact households' optimal decisions. We observe that the existence of taxes and taxes with child benefits increases fertility. More importantly, we also see that if the taxes are progressive, the fertility increases even more. This results stem from the reduction in the life cycle utility and households try to increase the utility through dynastic component. Consistently, we observe more time investment when the fertility rate rises. Next, we find that taxes impact mostly females' labor decision and males' labor is less sensitive to tax changes. This result is consistent with the empirical literature that finds the elasticity of males' decision (in particular labor) with respect to taxes are very low, while the elasticities are much higher for females. This result originates from the gender wage gap which makes males primary earners and increases the tax rates of the first dollar earned by females.

The intergenerational linkage shows us that the existence of taxes slightly increases the income mobility across generations. When the taxes are progressive, we see a large increase in the mobility due to higher fertility rate (quantity) and lower educational outcome (quality). When the income taxes are not progressive but child dependent, we still observe an increase in the mobility but much less comparing to the increase due to progressive taxes. Although, the impact of the child dependent taxes have similar quality-quantity trade off with the impact of the existence of taxation, the variation in the impacts are much higher which causes higher mobility.

This paper sheds light on the intergenerational correlation of income considering one of the most important policy tool of governments. We conclude by describing a couple of extensions that we leave for future research. First, we abstract from the marriage decision. One of important component of the US tax code is the marital status and the impacts of the single households' taxation on the intergenerational linkage can be quite significant as the time constraints of singles are much tighter, consequently, can create a large impact. Second, introducing parental leave can impact the intergenerational linkages. Third, the differences in the correlation across races can be studied in a framework where welfare benefits and income taxation can separately be modeled.

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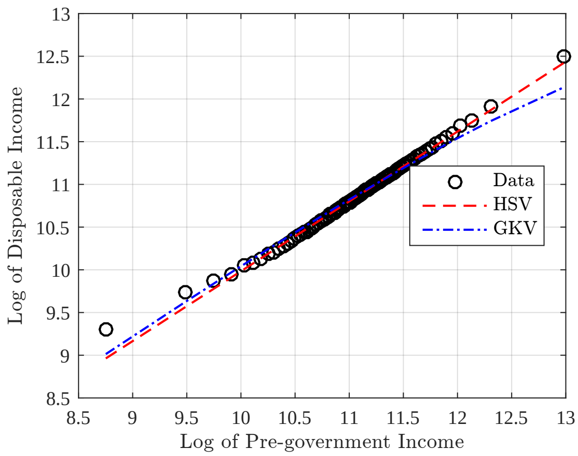
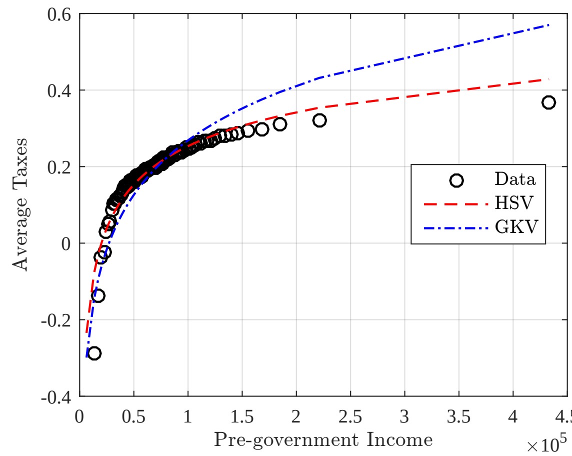


(a) Tax Fits: Log of Income



(b) Tax Fits: Average Taxes

Figure 7: Comparison HSV and GKV Tax Specifications

A Tax Function Estimates

Table 13 shows the tax parameters for different post-government income levels. First, households pay federal taxes. Second, they pay state taxes on top of federal taxes excluding the tax credits such as the earned income credits and the child tax credits. Third, they additionally pay social security taxes (Fica). Fourth, they receive federal benefits which is subtracted from total taxes. These results show that the progressivity increases dramatically when the households receive welfare benefits. Therefore, it is important to use the PSID dataset to estimate the tax function. For example, if we used a Current Population Survey (CPS) dataset, the estimates would be $\tau_{CPS} = 0.103$ and $\lambda_{CPS} = 2.421$ when family size is ignored in Equation (3).[52]

Log Specification The parametric tax function of Guner et al. (2014) is:

$$t(\tilde{y}) = \chi + \iota \log \tilde{y} \tag{6}$$

where $t(\tilde{y})$ shows average tax rate of $\tilde{y}$, the normalized income (the ratio of household income to the mean household income).

Using the parameters in Table 14, we show how each specification fits data in Figure 7. Both specification are good fit especially for low income families, however, Figure 7b implies that *HSV* specification captures top incomes' rates better.

[52]Estimates are close to the ones under the Specification 3 all column.

Table 13: Estimates of HSV Specification with Different Post-Government Income

	Specification 1: Only Federal Taxes					
	all	0 children	1 child	2 children	3 children	4 children
λ	2.6935	2.2268	2.8547	2.97	2.7135	2.6046
	(0.0038)	(0.0064)	(0.0071)	(0.0064)	(0.0089)	(0.0121)
τ	0.1019	0.0867	0.1075	0.1098	0.1008	0.0958
	(0.0003)	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0011)
Average Taxes	0.1246	0.15	0.1281	0.1154	0.1018	0.073
	Specification 2: Federal and State Taxes					
	all	0 children	1 child	2 children	3 children	4 children
λ	3.1426	2.6498	3.3524	3.4405	3.0065	2.7796
	(0.0044)	(0.0073)	(0.0086)	(0.0075)	(0.0104)	(0.0139)
τ	0.1180	0.1049	0.1242	0.1253	0.1118	0.1028
	(0.0004)	(0.0007)	(0.0008)	(0.0007)	(0.0009)	(0.0013)
Average Taxes	0.1445	0.1728	0.1487	0.1357	0.1181	0.0817
	Specification 3: Federal, State, and Fica Taxes					
	all	0 children	1 child	2 children	3 children	4 children
λ	2.9075	2.4622	3.126	3.1314	2.6812	2.4769
	(0.0051)	(0.0082)	(0.0102)	(0.0087)	(0.0123)	(0.0162)
τ	0.1175	0.1051	0.1245	0.1233	0.1075	0.0974
	(0.0005)	(0.0007)	(0.0009)	(0.0008)	(0.0011)	(0.0015)
Average Taxes	0.2037	0.2329	0.2087	0.1956	0.1754	0.1323
	Specification 4: Federal, State, and Fica Taxes excluding Benefits					
	all	0 children	1 child	2 children	3 children	4 children
λ	6.0828	4.4235	5.8734	7.402	6.5081	6.5641
	(0.0104)	(0.0164)	(0.0214)	(0.0198)	(0.0322)	(0.0459)
τ	0.1822	0.1559	0.1797	0.1992	0.1857	0.184
	(0.0009)	(0.0015)	(0.0019)	(0.0018)	(0.0029)	(0.0042)
Average Taxes	0.1759	0.2105	0.1856	0.1672	0.1375	0.0838

Note: The restriction and estimation stated in Table 1 is applied.

Table 14: Estimates of *Log* Specification

	all	0 children	1 child	2 children	3 children	4children
	Specification 4 Federal, State, and Fica Taxes excluding Benefits					
χ	0.2113	0.2259	0.2179	0.2099	0.1937	0.1789
	(0.0011)	(0.0016)	(0.0018)	(0.0023)	(0.004)	(0.0063)
ι	0.2056	0.1594	0.1868	0.2389	0.2419	0.233
	(0.0017)	(0.0024)	(0.0031)	(0.0038)	(0.006)	(0.008)

Note: The restriction and estimation stated in Table 1 is applied.

B Empirical Results

Table 15: Structural Estimates of Utility Parameter

Variable	Estimates	Variable		Estimates
Marginal Utility of Income		Disutility/Utility of Choices		
Disposable Income	0.391	Female	Male	
	(0.004)	Labor supply		
Children x Disposable Income	-0.477 (0.066)	No work	Part -time	-0.116 (0.005)
Children x HS x Disposable Income	0.159 (0.065)	No work	Full-time	0.266 (0.009)
Children x SC x Disposable Income	0.177 (0.066)	Part-time	No work	-2.020 (0.003)
Children x COL x Disposable Income	0.228 (0.065)	Part-time	Part-time	-0.681 (0.009)
Children x HS spouse x Disposable Income	0.070 (0.016)	Part-time	Full-time	-0.686 (0.008)
Children x SC spouse x Disposable Income	0.093 (0.036)	Full-time	No work	-0.140 (0.007)
Children x COL Spouse x Disposable Income	0.102 (0.026)	Full-time	Part-time	-0.626 (0.011)
Children x Black x Disposable Income	0.016 (0.003)	Full-time	Full-time	0.133 (0.010)
		Time spent with children		
		Low	Medium	0.950 (0.014)
		Low	High	0.329 (0.013)
		Medium	Low	-0.090 (0.008)
		Medium	Medium	0.348 (0.010)
		Medium	High	0.351 (0.013)
		High	Low	-0.435 (0.007)
		High	Medium	0.483 (0.011)
		High	High	-0.547 (0.012)
		Birth		-0.621 (0.025)

Note:

Table 16: Data Summary Statistics

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

Note:

Table 17: Earning Equation and Fixed Effect

Variable	Estimate	Variable	Estimate	Variable	Estimate
Demographic Variables				Fixed Effect	
Age squared	-4.0e-4	Female x Full-time work	-0.125		
	(1.0e-5)		(0.010)		
Age x LHS	0.037	Female x Full-time work ($t-1$)	0.110	Female	-0.48
	(0.002)		(0.010)		(0.01)
Age x HS	0.041	Female x Full-time work ($t-2$)	0.025	HS	0.14
	(0.001)		(0.010)		(0.01)
Age x SC	0.050	Female x Full-time work ($t-3$)	0.010	SC	0.12
	(0.001)		(0.010)		(0.01)
Age x COL	0.096	Female x Full-time work ($t-4$)	0.013	COL	0.04
	(0.001)		(0.010)		(0.01)
Current and Lags of Participation		Female x Part-time work ($t-1$)	0.150	Female x HS	-0.05
Full-time work	0.938		(0.010)		(0.01)
	(0.010)	Female x Part-time work ($t-2$)	0.060	Female x SC	0.05
Full-time work ($t-1$)	0.160		(0.010)		(0.01)
	(0.009)	Female x Part-time work ($t-3$)	0.040	Female x COL	0.04
Full-time work ($t-2$)	0.044		(0.010)		(0.01)
	(0.010)	Female x Part-time work ($t-4$)	-0.002	Constant	0.167
Full-time work ($t-3$)	0.025		(0.010)		(0.01)
	(0.010)	Individual specific effects	Yes		
Full-time work ($t-4$)	0.040				
	(0.010)				
Part-time work ($t-1$)	-0.087				
	(0.010)				
Part-time work ($t-2$)	-0.077				
	(0.010)				
Part-time work ($t-3$)	-0.070				
	(0.010)				
Part-time work ($t-4$)	-0.010	Hausman Statistics	2296		
	(0.010)	Hausman p-value	0.000		
No. of Observations			134,007		
No. of Individuals			14,018		
R^2			0.44		0.278

Note: Standard errors are listed in parentheses. LHS indicates completed education of less than high school; HS indicates completed education of high school; SC indicates completed education of some college but not a graduate; COL indicates completed education of at least a college degree.

Table 18: Education Production Function

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

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