

# Early Childhood Investment and Income Taxation\*

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## Abstract

We study the impact of the income taxation on parental investment for children and its consequence on intergenerational income correlation. We estimate a life-cycle dynastic model of households and conduct counterfactual analysis to observe the effects of various tax regimes. Comparing to a no tax environment, we find that the flat taxes reduce the correlation only by one percentage points. The reduction is, however, much significant (seven percentage points) if the taxes are progressive, the average tax rate is increasing in income. The increase in income mobility is due to the increase in the fertility rate (quantity) and the decrease in the educational outcome of children (quality). We also show that when the taxes are flat within same size households but provide child benefits, which is an important component of the US income taxation, the intergenerational income correlation is four percentage points less compared to the correlation under the flat tax regime. This reduction occurs because parents with lower education invest more time in children's human capital comparing to a flat tax regime which increases their children's educational outcome and increases income mobility.

**JEL classification:** C13, J13, J22, J62.

**Keywords:** Dynastic Models, Discrete Choice, Fertility, Income Taxation.

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# 1 Introduction

The positive relationship between inequality and intergenerational social mobility, which is known as the Great Gatsby curve, has recently been on the policymakers' agenda. A large positive literature has focused on the magnitude of the intergenerational correlation in income (ICI), the correlation of parents' income and their children's income. Recently, some has studied the sources of the correlation focusing on the 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 is extensive, the policy implications exploring the ICI is not. Our paper fills this gap. We explore the effects of income tax policy considering the impact of parental investment on the intergenerational correlation in income. We find that the income taxes reduce the correlation. Comparing to a no tax environment, we find that a flat tax system reduces the correlation only by one percentage points. Yet, a flat tax system with the child benefits reduces the correlation by five percentage points. We observe the highest reduction (seven percentage points) by a progressive tax schedule without child benefits. The sources of the reduction rely on the increase in the fertility rate (quantity) and the decrease in the investment in the children's educational outcome (quality).

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 taxes on the parental investment in children's educational attainments. On the quantitative side, we estimate our model using two generations in the Panel Study of Income Dynamics (PSID) dataset. 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 to analyze the quantitative implications of two major components of the US tax code; the progressiveness and the child benefits.

One of the policy objectives of progressive taxes is to reduce income inequality in society. The progressiveness of the taxation, in general, negatively impact labor decisions and reduce the variation in income distribution. The changes in the labor market time can indirectly impact time investment for children. These indirect changes influence inequality in children's educational outcomes, which is an important component of future earnings, and ICI. On the other hand, parents can also alter their investment behavior as their return to investment in children's human capital decreases by progressive taxes. Therefore, the progressivity rate of a tax system does not only shape current generations' income distribution and but also impacts the income distribution of future generations. Empirical evidence suggests that the ICI are lower in countries where taxes are

more progressive such as in Scandinavian countries. Moreover, the Gini coefficient of both before-tax and disposable income in these countries are much lower comparing to the US where the taxes are less progressive. This raises an important question: Is there a linkage between progressivity rate and the intergenerational correlation in income?

The intergenerational implications of tax policies require a dynastic model with explicit modeling of children's behavior in the second generation. For this purpose, we adapt the structural approach in [Gayle et al. \(2017\)](#). In particular, we study a dynastic life cycle model, in which altruistic unitary households decide fertility choice and individual time allocation between labor market, leisure, and childcare. Most recent empirical literature shows that paternal care, which we name *time investment* in children, is a very important component in children's human capital. In addition, the empirical literature finds that the time investment in children is crucial especially during early childhood. Therefore, we particularly focus on the early childhood investment which creates the deterministic part of the educational outcome of children. The education of households is one of the key determinants in labor income, which is also affected by labor market history. The total labor income of spouses constitutes the household income which is the tax unit. The government collects taxes according to a parametric tax function:  $T_n(y) = y - \lambda_n y^{1-\tau_n}$ , where  $T_n(y)$  is the tax liabilities of  $n$ - child families who generate  $y$  income and  $\tau_n$  is the progressivity rate of tax liabilities of  $n$ - child families. This function is known as the *HSV* specification in the public finance literature, yet, we differ from the main specification by assuming family size dependent parameters.

One of the major benefits of this structural econometric approach is the ability to conduct a full counterfactual analysis concerning generational effects of taxation. The literature on the empirical structural models mostly incorporates intergenerational/altruistic concerns by modifying the standard dynamic structural estimation methods. This modification, in general, creates a proxy for the altruistic value as a function of state variables. The educational outcomes or test scores of the children are the widely used proxies.<sup>1</sup> The proxy approach simplifies the estimation stages, yet, it comes at the cost as such, counterfactual exercise does not affect the choices of the future generations which can be unrealistic in many important economic problems. Particularly, in our model, the income taxation does not only affect the current generation's incomes directly, but also impacts the return of parental investment since future incomes of children are arguments in the valuation of children from parents' perspective.<sup>2</sup> That is, in a counterfactual environment, the value parents place on their children's quality changes in two ways, the value of the state variables and the functional form of the mapping between the state variables and the utility derived from

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<sup>1</sup>[Bernal \(2008\)](#), [Brown and Flinn \(2011\)](#), and [Del Boca et al. \(2013\)](#) are some examples.

<sup>2</sup>See [Gayle et al. \(2018b\)](#) for the technical details of how the counterfactual analysis is conducted and also its implications in the life-cycle dynastic model.

those state variables. The structure without explicitly modeling the second generation does not allow the functional form of the mapping to change. This is, in fact, crucial in answering questions in tax literature since the changes in taxes alter the behavior of the households not only in the current generations but also in the future generations.

We estimate the model using two generations from the PSID dataset and show that the model successfully fits with the moments in the data. We, then, conduct four counterfactuals to analyze the impact of income taxation. First, we exclude income taxation from the environment. In the second, the households pay a flat tax rate. In the third counterfactual, the taxes are progressive but do not provide child benefits.<sup>3</sup> In the fourth, the average tax rate is the same for same size households but decline when a child is born. Our first important finding is that while males' labor supply decisions are almost unresponsive to tax changes, females' labor is very sensitive and decreases by taxes. In particular, we observe that from a no tax environment to a progressive taxes environment, the reduction in the female labor supply is more than twice than the reduction due to flat taxes. One of the main reasons is the gender wage gap, which is well documented in the literature. Therefore, females can be considered as if the secondary earner of the household. Hence, first dollar earning of females is taxed at a higher rate comparing to a flat tax regime if the taxes are progressive. When females continue to earn more, their labor incomes are gradually taxed at a higher rate. Consequently, the return to females' labor is decreasing in work and females' labor supply declines. This result is in line with empirical labor literature, as the elasticity of labor supply with respect to taxes are quite low for males and are higher for females.

Our second important result is that taxes significantly increase the number of children in the household. The increment is substantial when the taxes are progressive. Among many, there are two pronounced reasons behind this result. First, as stated above, female labor supply is reduced more when taxes are progressive which potentially increases time investment. Second, households know that the dynastic component of the utility is declined due to progressive taxes (with similar reasons above). Combining these two reasons, households increase the number of children to increase the utility from the dynastic component.

Our third major result is that the taxes reduce the ICI, yet, the type of taxation matters. The literature on the ICI in income focuses on the *permanent* income, whose definition is somewhat controversial as researchers have different methodologies to calculate the permanent income. In this paper, we use the average of the household incomes that are earned when households are between thirty and forty years old. This approach simply reduces potential measurement errors as well as provides a fine estimate of the permanent income as households mostly productive during this period. Though, our qualitative results are robust by changing the age range of households. We observe that from no tax regime to a flat tax system, the correlation is reduced by one per-

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<sup>3</sup>Taxes are exactly as in [Heathcote et al. \(2017\)](#), i.e.  $\lambda$  and  $\tau$  are independent of family size.

centage point. However, we see a significant reduction (five and seven percentage points) when the taxes are child dependent or progressive, respectively. The main reasons for the reduction for the progressive taxes are due to the increase in the number of children (quantity) and the decline in the children's educational outcome (quality). Consequently, income mobility increases in the economy. The reason for the reduction for child dependent (and flat) tax regime is that households invest more time in children and this impact is more significant for households with lesser education. Consequently, those households' children have relatively more education and income mobility is higher even though this effect is mitigated by the increase in fertility.

The remaining of the paper proceeds as follows. After a brief literature review, Section 2 motivates the need for a structural model and shows the impact of taxation in a macro setup. Section 3 introduces a micro-founded model and specifies key mechanisms of the model. Section 4 briefly states the summary statistics in the data and the estimation strategy. We refer Gayle et al. (2018b) for a detailed estimation strategy. Using the estimated forms, we conduct counterfactuals and show the main results in Section 5. We present both analyses on the households' life cycle choices as well as the intergenerational mobility. Section 6 concludes the paper.

**Related Literature:** There exist a large public finance literature studies the impact of taxation on parental choices, especially their labor choices. On the other hand, there are voluminous empirical studies focus on the ICI. The former literature mainly abstracts from the correlation in income across generations, while the latter is silent on the impact tax policies on 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 the 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. 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 a 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 a perfect substitute for the market labor time.<sup>4</sup> Therefore, it is indirectly affected by labor income taxation. In addition, the labor literature studies 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

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<sup>4</sup>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.

a very important component (see [Del Boca et al. \(2013\)](#), [Schoellman \(2016\)](#), and [Gayle et al. \(2018a\)](#)).

The implications of a change in the tax policy can have an across generations effect, both due to re-optimization of parents (who will reallocate resources through time and money investment) and re-optimization of children (who will face a different initial endowment to start their life cycle). For instance, a tax schedule with increasing marginal rates reduces both the returns to working more hours and the returns to acquiring human capital (e.g., [Heckman et al. \(1998\)](#); [Krueger and Ludwig \(2013\)](#); [Guvenen et al. \(2014\)](#)). Of the two aforementioned effects, the former takes more attention in the tax literature ([Gayle and Shephard \(2016\)](#)). Studying the second effect quantitatively requires a dynastic model with explicitly modeled children's behavior in the next generation. Therefore a dynastic model as the one introduced in this paper with a life-cycle component can be used as a natural framework to study the effect of taxation on altering generational behavior and the consequently to quantify the welfare implications of tax policy in terms of intergenerational income mobility. In this respect, our paper is one of the first attempts to quantify the effects of income taxation on the intergenerational income mobility.

In an interesting paper, [Hendricks \(2003\)](#) studies the impact of taxation on the human capital accumulation and show the differences between the 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 an 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 a 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 the impact of early childhood transfers which are the key components of children's educational outcomes (see [Cunha et al. \(2006\)](#)). Lastly, fertility is a choice in our setup, which is a key decision on the intergenerational correlation in income.

Our paper is closely related to [Gayle et al. \(2017\)](#) who study the sources of ICI. 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.<sup>5</sup> Although this work is substantial to explain the correlation, the paper abstracts from one of the most important policy analysis, income taxation, which directly impacts labor (and hence labor income) and indirectly time investment (and hence children's education which is an important source of their income). 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

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<sup>5</sup>Most of macro studies using dynastic framework are unable to generate intergenerational persistence. [Alvarez \(1999\)](#) and [Cordoba et al. \(2016\)](#) show the key assumptions needed to generate such persistence.

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 Motivational Example

We first introduce a motivational example, which is a simplified version of our original model, to provide some insights into the effects of progressive income taxes on the ICI.

Consider a two-period model. In the first period, altruistic parents allocate their time endowment between labor, leisure, and time investment in 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  $\tau$  is the progressivity rate.<sup>6</sup> There is no bequest choice, therefore, the after-tax income (consumption) is equal to  $\lambda y^{1-\tau}$ . Most of the macro studies in the literature are unable to generate enough intergenerational correlation even they model the bequest choice. [Cordoba and Ripoll \(2015\)](#) and [Cordoba et al. \(2016\)](#) focus on the elasticity of consumption across periods and across generations and show the conditions to generate the ICI with bequest motive.

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 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  $\Upsilon$  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

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

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<sup>6</sup>We provide more explanation about the tax function at the next section.

where  $w_c^i(d^i, y_p^i)$  is the marginal productivity of children of parent  $i$  and  $\varepsilon_{w_c, y_p}^i \equiv \frac{y_p^i}{w_c^i} \frac{\partial w_c^i}{\partial y_p^i}$  and  $\varepsilon_{w_c, d}^i \equiv \frac{d^i}{w_c^i} \frac{\partial w_c^i}{\partial d^i}$  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 assume 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 ICI. We show that when these elasticities are endogenous, the impact of the progressivity rate of the tax code is drastic on the intergenerational correlation.

Despite its crudeness, this example shows us the need for a structural model to be able to generate the ICI and also to see the impact of the taxation on the ICI.

### 3 Model

The 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. The model assumptions are similar to those in [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.<sup>7</sup> Second, the impact of tax policy on ICI 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 labor income. 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 the same reasoning above.<sup>8</sup>

<sup>7</sup> How marital status impact parental time investment and how tax policy can affect this decision is an important and interesting policy question which we will leave as a future study.

<sup>8</sup>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



The timeline 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 two periods: the early childhood period (ages 0 to 5) and the late childhood period (ages 6 to 17).<sup>9</sup> The division of childhood into two periods is important for our analysis as we concentrate on 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.<sup>10,11</sup> 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 in children  $d_t = (d_{ft}, d_{mt})$ , and whether to have a child  $b_t$ .<sup>12</sup> Let  $A$  represent the feasible set of action vectors. For each age  $t$ , a vector of state variables- the history of past choices, time invariant characteristics, and the gender of each child- is denoted by  $z_t = (a_{25}, \dots, a_{t-1}, \zeta_{25}, \dots, \zeta_{t-1}, x_f, x_m)$  where  $\zeta$  is a dummy variable and denotes whether a newborn child is a female.<sup>13</sup>

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

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

this framework also for a future work.

<sup>9</sup> Therefore there can be two children in the household who are in different childhood periods.

<sup>10</sup>The lower bound of the age is similar to the age restriction in most of labor and public finance studies.

<sup>11</sup>Marriage is not a choice, but the marriage matching function is designed to recover empirical moments related to marriage decisions.

<sup>12</sup>After the age of 45,  $b_t = 0$ .

<sup>13</sup>The gender of a newborn is modeled to be equally 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 \(1998\)](#)).

where  $c_t$  is the consumption of adults and  $\theta_{a_t}$  is the dis/utility of time allocation and  $\varepsilon_{a_t}$  is per-period additive choice specific error, which is distributed from an Extreme Value Type I distribution which is a standard assumption in empirical literature. Per- period budget constraint is

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

where  $\alpha(z_t)$  is the per-child consumption share of disposable income,  $N_t$  is the number of children in the beginning of the year,  $w_t(z_t, h_t) = w_{ft}(z_{ft}, h_{ft}) + w_{mt}(z_{mt}, h_{mt})$  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.<sup>14</sup>

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:

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

where  $\beta$  is the discount factor, and  $I_{a_t}^o$  be the indicator variable of the optimal discrete choice of a household with  $(x_f, x_m)$  characteristics at time  $t$ .

Household  $i$ 's expected utility from their children is

$$\Omega^{\tilde{i}}(x'_f, x'_m) = \tilde{v} E_{25} \left[ N^{1-\nu} \sum_{n=1}^N \sum_{f'=1}^F \sum_{m'=1}^M G(x'_f, x'_m) U_n^{\tilde{i}}(x'_f, x'_m) \mid x_f, x_m \right],$$

where  $\tilde{v}, \nu$  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,  $F$  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  $n$ .<sup>15</sup>

<sup>14</sup>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.

<sup>15</sup>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.

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

$$U^i(x_f, x_m) = V^i(x_f, x_m) + \beta^{31} \Omega^i(x'_f, x'_m).$$

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

### 3.1 Tax Specification

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

$$T(w, n) = w - \lambda_n w^{1-\tau_n} \tag{2}$$

where  $w$  is the household income and  $n$  is the number of children.<sup>16</sup> Without the family size component, this functional form is used by [Heathcote et al. \(2010\)](#) and [Heathcote et al. \(2017\)](#), and known as the *HSV* specification in the literature.<sup>17</sup> This specification has two restrictions. 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  $\tau$ , 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  $\tau = 1 - \frac{1-T'(w)}{1-\frac{T(w)}{w}}$ . 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.<sup>18</sup> 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,  $w$ , as the pre-government income, and  $w - T(w)$  as post-

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<sup>16</sup>[Feldstein \(1969\)](#) introduced this form without family size component. This tax function is widely used in public finance literature (see [Benabou \(2000\)](#) and [Benabou \(2002\)](#)).

<sup>17</sup>In an important analysis, [Guner et al. \(2014\)](#) provide estimates of four different specification of parametric tax functions used in the literature. Among those, the *HSV* specifications is the best to provide fine estimates when the average taxes are negative (see [Kurnaz and Yip \(2019\)](#)). We specifically compared the data fit using both the *HSV* and *Log* specification, which is stated Equation (5), in the appendix. We find that the model fits the data better when the taxes are in the *HSV* specification.

<sup>18</sup>[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.

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).<sup>19</sup> We differ from [Heathcote et al. \(2017\)](#) by allowing  $\lambda$  and  $\tau$  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.<sup>20</sup> We estimate

$$\log(w - T(w)) = \log \lambda_n + (1 - \tau_n) \log w \quad (3)$$

for each  $n \in \{0, 1, 2, 3, 4\}$  and report parameters in Table 1.<sup>21,22</sup>

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
$\lambda$	6.0828 (0.0104)	4.4235 (0.0164)	5.8734 (0.0214)	7.402 (0.0198)	6.5081 (0.0322)	6.5641 (0.0459)
$\tau$	0.1822 (0.0009)	0.1559 (0.0015)	0.1797 (0.0019)	0.1992 (0.0018)	0.1857 (0.0029)	0.184 (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\$. We estimate  $\lambda$  and  $\tau$  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.

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  $\tau_n$  changes by family size and  $\tau_n$  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.

<sup>19</sup>Please check [Heathcote et al. \(2010\)](#) and [Heathcote et al. \(2017\)](#) for further details.

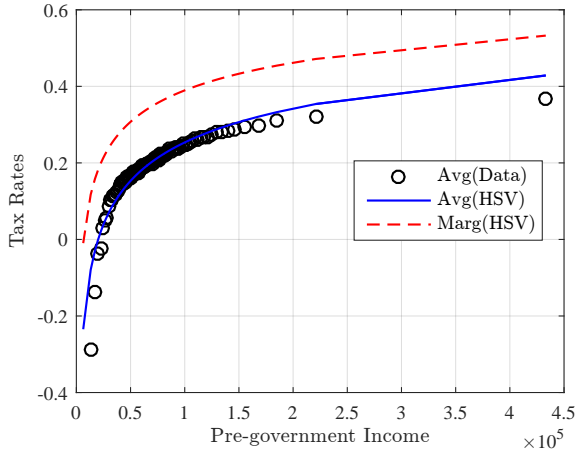
<sup>20</sup>Number of children changes tax credits such as the earned income credit and the child tax credit received by households. In addition, the welfare benefits depends on the federal poverty level is affected by the number of children.

<sup>21</sup>Households with more than four children are considered as if they have four children.

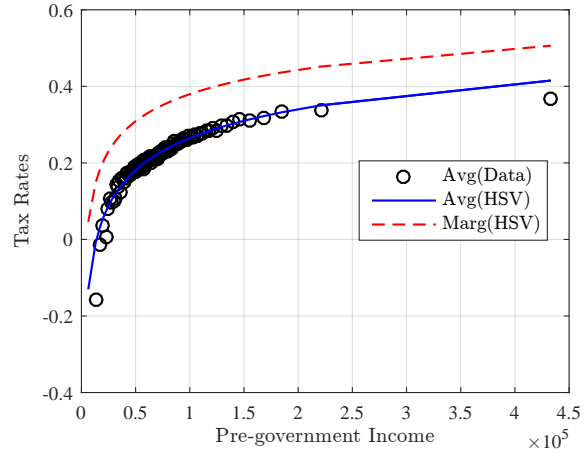
<sup>22</sup>We also provide the tax parameters with different post-government income levels in the appendix at Table 14.

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.

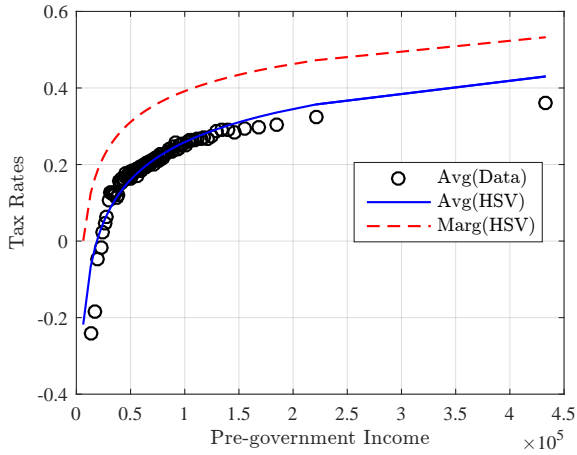
Figure 1: Average and Marginal Tax Rates with HSV Specification



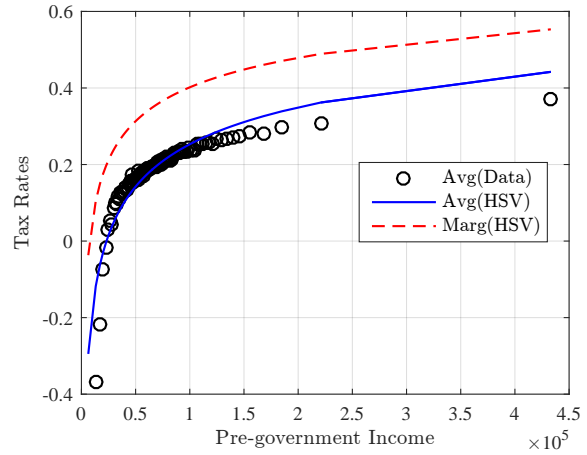
(a) All Households



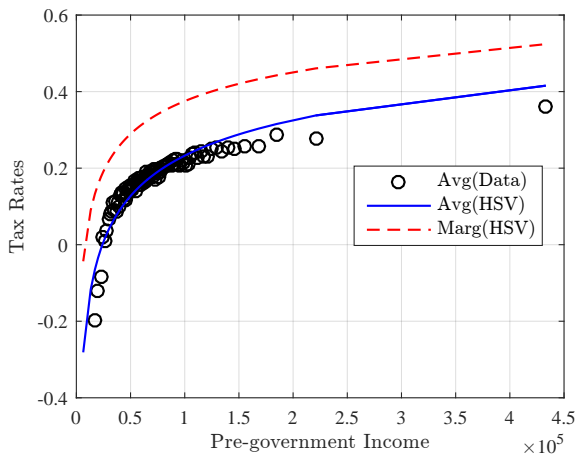
(b) Households with 0 Children



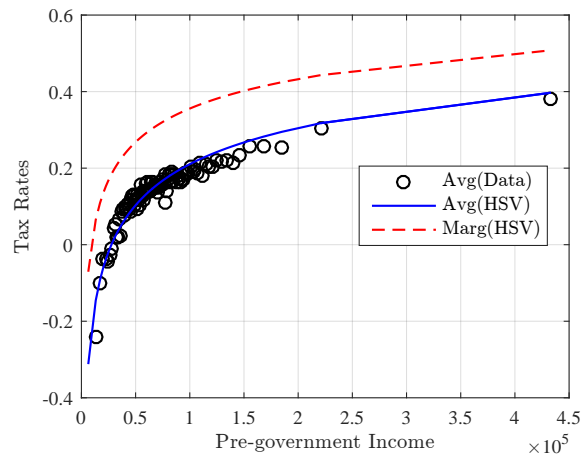
(c) Households with 1 Child



(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.

## 3.2 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 consist of four measures: the interaction of the labor productivity with labor hours, work experience, and innate ability (fixed effect):<sup>23</sup>

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

The first component,  $W_g(e, h_{gt})$ , captures the interaction between the market labor hours,  $h_{gt}$ , and agent's labor productivity which is related with agent's education level  $e$ .<sup>24</sup> 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,  $W_g(e, h_{gt})$  depends on  $h_{gt}$  in a nonlinear manner, for example, full-time work pays more than twice as much as part-time work.<sup>25</sup>

The second component,  $H_g(h_{gT^e+1}, \dots, h_{gt-1})$ , 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 can decrease the return to experience.

The third component,  $\eta_g$ , 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.<sup>26</sup>

The earning 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 18.

<sup>23</sup>In particular, we estimate  $\ln w_{gt} = \delta_0 + \delta_1 \text{age} \times \text{education} + \delta_2 \text{age}^2 + \left( \sum_{j=0}^4 \delta_{t-j}^{ft} \mathbb{1}_{t-j}^{ft} + \sum_{j=0}^4 \delta_{t-j}^{pt} \mathbb{1}_{t-j}^{pt} \right) + \eta_g$  where  $ft$  and  $pt$  refers to full- and part time.

<sup>24</sup>Education level is considered as the completion of degrees. Next subsection explains the education level in detail.

<sup>25</sup>See Altug and Miller (1998), Gayle et al. (2012), and Gayle and Miller (2012), who document these features of the recent labor market.

<sup>26</sup>The fixed effect estimation uses the following equation:  $\eta_g = \varphi_0 + \varphi_1 \text{race} + \varphi_2 \text{gender} + \sum_e \sum_r \varphi_{er} \mathbb{1}_{er}$  where  $e, r$  refer to education and race, respectively.

### 3.3 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 ( $d_f, d_m$ ) and parental income ( $w_f, w_m$ ). 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  $\eta'$  denotes children' market ability. The characteristics of children is determined by the following equations:

$$e' = \Gamma \left( x, g, \sum_{\tilde{t}=1}^5 d_{m\tilde{t}}, \sum_{\tilde{t}=1}^5 d_{f\tilde{t}}, \sum_{\tilde{t}=1}^5 w_{m\tilde{t}}, \sum_{\tilde{t}=1}^5 w_{f\tilde{t}}, S_{-5} \right) + \omega'$$

$$\eta' = \tilde{\Gamma}(e', g) + \tilde{\eta}'$$

where  $e' \in \{LHS, HS, SC, COL\}$  which refer to less than high school, high school, some college and college degree, respectively,  $g$  is the gender of child,  $\tilde{t}$  is the age of the child,  $\omega'$  is the luck component and independent of  $\tilde{\eta}'$  which is assumed to have finite support. In the empirical implementation,  $\Gamma$  and  $\tilde{\Gamma}$  are both linear functions. We refer to [Gayle et al. \(2018a\)](#) for more details on the education production function.<sup>27</sup> The estimation results are shown in the Table 19. Accordingly, we observe that parental time investment, in fact, impacts the potential educational outcome more than parental income. In addition, educations of parents positively impacts the children's education. Finally, being a female increases the chances of getting at least some college degree.

[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 mothers spend average time and fathers provide 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 the 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

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<sup>27</sup>[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.



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.<sup>28</sup> 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.<sup>29</sup> Negative values are set to zero and childcare hours are zero for childless households.

The number of hours are not, in particular, very important since the hours are discretized into three categories: low, medium, and high.<sup>30</sup> Therefore, potential problems of measurement errors are reduced. Second, although the type of activities are not particularly measured, the discretized measure has significant explanatory power on educational outcomes of children.<sup>31</sup>

### 3.4 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 stationary nature of our estimation, the same matching function is applied to individuals from all generations, although empirically assortative matching in the marriage market has increased over time.

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<sup>28</sup>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 cannot use CDS.

<sup>29</sup>Many studies used this approach (see [Hill and Stafford \(1974\)](#), [Leibowitz \(1977\)](#), and [Datcher-Loury \(1988\)](#)).

<sup>30</sup>Time investment is operationalized as three discrete levels in our estimation. However its intensity can be quite different for mothers and fathers. For instance, in 1975, white mothers in our sample spend, on average, 724 hours annually as time investment, while the corresponding average for fathers is only 129 hours. We check the time investment hours from PSID with to the American Time Use Survey 1975 wave dataset, in which the average childcare hours are 721 and 231 for white mothers and white fathers, respectively. This large difference urges us to define the intensity levels for fathers and mothers separately, as fathers and mothers time are different inputs to the child production function and marginal increases in either can have different effects. Therefore this implies, for instance, a mother spending medium time investment can in fact might be spending more hours in practice than a father spending full time investment.

<sup>31</sup>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.

### 3.5 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:

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

where  $\theta_{a_t}(z)$  is dis/utility from the time allocation in choice  $a$  and  $\tilde{u}(\cdot)$  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.<sup>32</sup> Let the disposable income be represented by  $\tilde{w}_t = w_t - T(w_t)$ . 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,  $g$  represents gender, and race can be either white or black.<sup>33</sup>

According to the specification,  $\alpha_0$  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 16](#) 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 16](#) 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.

<sup>32</sup>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.

<sup>33</sup>The households, in which both spouses have less than high school degrees, are considered as the base.

**Shocks and Choices** We summarize shocks and choices and their timing before going to the next section. 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 beginning of age 25. The second shock,  $\varepsilon_{a_t}$  is on the per-period utility and is realized at the beginning of each age during the adulthood and is i.i.d. across households and time. Households 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,  $\omega'$ , 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.

## 4 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 17 shows the summary statistics.

Our model is a unitary model without divorce.<sup>34</sup> 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. Briefly the first sample consist of all individuals that meets the above restrictions and

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<sup>34</sup>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).

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 in the 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.<sup>35</sup> 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.<sup>36</sup> In the ever-married sample, adults have higher housework hours and time spent with children on average.<sup>37</sup> However, we note that none of these differences are statistically significant. A similar pattern holds for the children's generation as well. In fact, as the model is stationary, the only need for the children's generation is needed to estimate the education production function.

**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)).<sup>38</sup> We use the multistage framework developed in Gayle et al. (2018b) using data from the PSID. In this framework, we use forward 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 generalized method of moments (GMM) estimator.<sup>39</sup> 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 GMM estimation

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<sup>35</sup>It is equal to 50% by construction in the life-long married sample, since we observe the same family over years.

<sup>36</sup>This is consistent with the fact that child-bearing potentially reduces labor market participation, especially that of women Gayle et al. (2017).

<sup>37</sup> Again this is consistent with the higher number of children in the ever-married sample.

<sup>38</sup>This identification problem in utility based discrete choice models is well-known in the literature.

<sup>39</sup> As the life-cycle is modeled from age 25 to 55, the estimation is computationally a challenging task.

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.<sup>40</sup>

## 4.1 Model Fit

In this subsection, 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.

**A Note on Discount Factors** The discount factors are set  $\beta = 0.813$ ,  $\tilde{\nu} = 0.795$ , and  $\nu = 0.111$ .<sup>41</sup> 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,  $\tilde{\nu}$ , 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,  $\nu$ , implies that the marginal increase in value from the second child is 0.68 and of the third child is 0.60.<sup>42</sup>

**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 from this exercise as a visual representation and aggregated summary of the restrictions in

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<sup>40</sup>Discount factors can be estimated with the other structural parameters of the model in a GMM or Pseudo Maximum Likelihood (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.

<sup>41</sup>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. \(2017\)](#).

<sup>42</sup>The literature on the estimation of the altruism coefficient studies is sparse. In a recent paper, [Cordoba and Ripoll \(2019\)](#) tackle this problem in a macro setup and focus on the elasticity of intertemporal and intergenerational substitution in a dynastic model with bequest motive. They find that the former one is smaller than one while the latter is greater. In our work, these elasticities are equal to each other as the parental transfers are only modeled through human capital channel.

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 ICI.<sup>43</sup> 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 of their sizes or income. The rate (18%) is chosen to set a quite similar government spending requirement across counterfactuals.<sup>44</sup> 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.

Table 2: Tax Parameters in Counterfactuals

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

<sup>43</sup>The abbreviations NT, FT, TWP, and TWC, refer to ‘no taxes’, ‘flat taxes’, ‘taxes with progressivity’, ‘taxes with child benefits’, respectively. We also refer Simulation as Sim in the figures.

<sup>44</sup>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, the tax rate 18% satisfies almost both approaches.

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 ICI and compare the results to the estimates obtained from the data.

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. The female labor force participation remarkably decreases from NT to FT. The decline is more severe from NT to 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 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.

Table 3: Probability of Choices under Counterfactuals

		<u>Data</u>	<u>Simulation</u>	<u>NT</u>	<u>FT</u>	<u>TWP</u>	<u>TWC</u>
<u>Female</u>							
Labor	No work	0.26	0.23	0.19	0.25	0.35	0.25
	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
Time Investment	Low	0.65	0.87	0.92	0.81	0.70	0.80
	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
<u>Male</u>							
Labor	No work	0.03	0.03	0.03	0.03	0.02	0.03
	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
Time Investment	Low	0.80	0.95	0.97	0.94	0.89	0.94
	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
<u>Household</u>							
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.

## 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 incomes of households 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 market. 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. In return, those children’s adulthood outcomes which are the proxy of the children’s value to parents affect parental decisions. 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.

Table 4: Average Life Cycle Allocation across Counterfactuals

	<u>Simulation</u>	<u>NT</u>	<u>FT</u>	<u>TWP</u>	<u>TWC</u>
<u>Female</u>					
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
<u>Male</u>					
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
<u>Household</u>					
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).

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 decmiduals 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. 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. \(2009\)](#).)

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 declined 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.<sup>45</sup> The progressive tax system reduces the value of female labor supply.<sup>46</sup> In addition, the progressive taxes also reduces the life-cycle utility of children. Knowing these facts, households increase the fertility rate.<sup>47</sup> Finally, we also see that the fertility rate in TWC is slightly 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 when 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 in TWP 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.

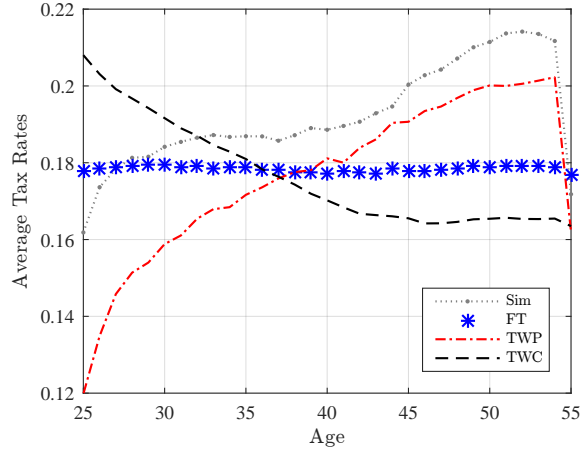
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<sup>45</sup>There are two channels of the fertility rate responses. First, households get a disutility just after the birth (see [Table 16](#)). Second, households get utility from the life-cycle utility of children. We find that the second channel is more strong.

<sup>46</sup>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.

<sup>47</sup>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 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).

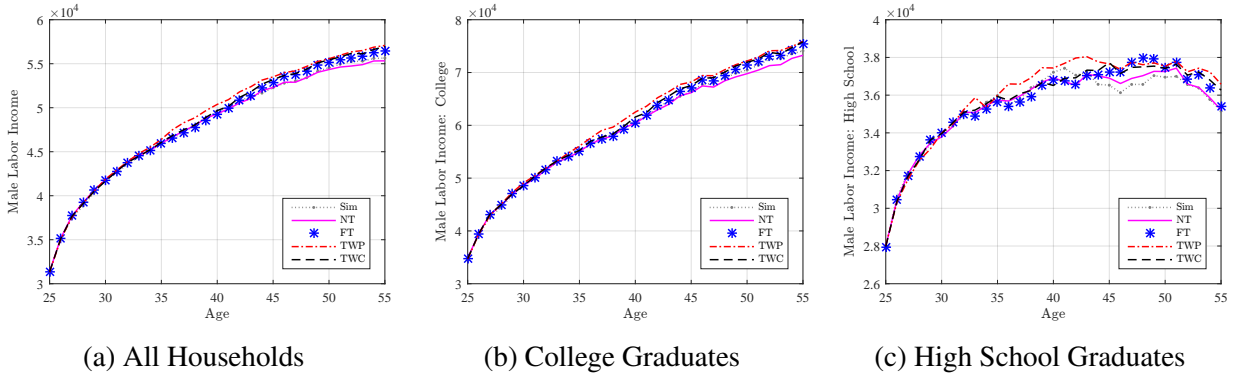
Figure 2: Average Tax Rates in Life Cycle Across Counterfactuals



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

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.

Figure 3: Male Labor Income in Life Cycle Across Counterfactuals



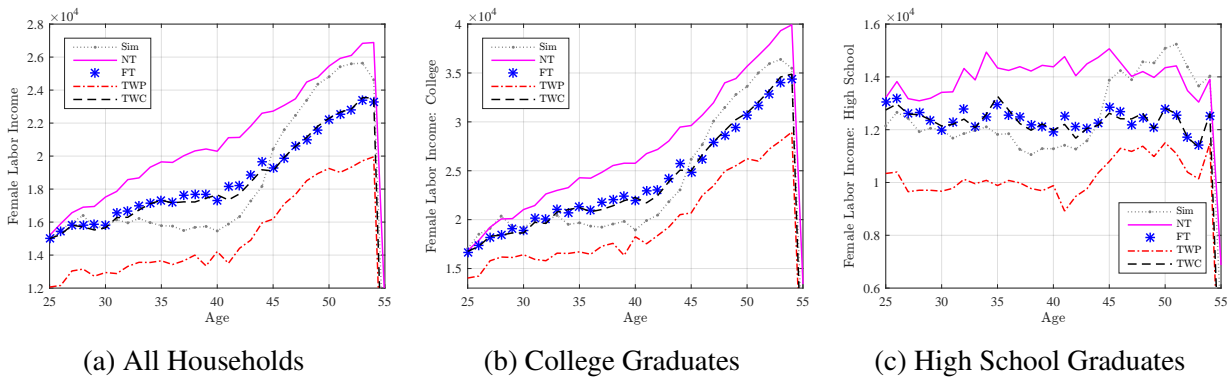
Note: Education labels refer to males' education.

Next, we focus on the earnings of females. Figure 4 shows that taxes impact female earnings quite distinctly. Note that, Table 18 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.<sup>48</sup> Therefore, females' labor is more sensitive to changes in taxes.

<sup>48</sup>Most of public finance papers make this assumption based on gender wage gap (see Kleven et al. (2009)).

We decompose the variation and find that the variation is stronger for college graduates (see Figure 4 and 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 18, 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.<sup>49</sup>

Figure 4: Female Labor Income in Life Cycle Across Counterfactuals

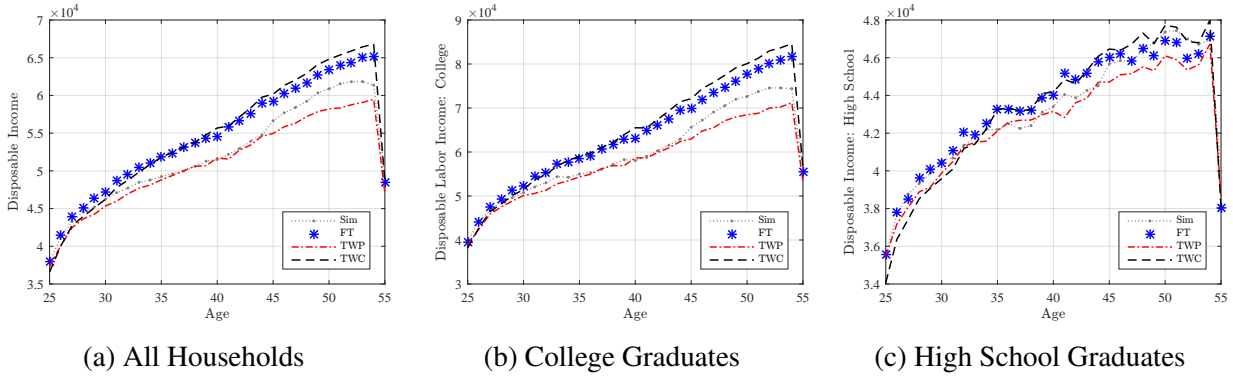


Note: Education labels refer to females' education.

We also present the changes in the disposable income across life cycle in Figure 5. We find that there is 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.

<sup>49</sup>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 5: Disposable Income in Life Cycle Across Counterfactuals

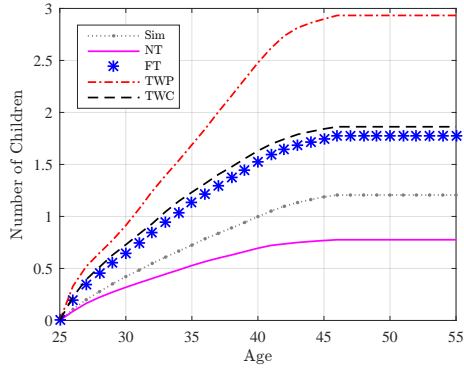


Note: Education labels refer to females' education. Disposable income in FT is not plotted on purpose, since it will not provide significant information.

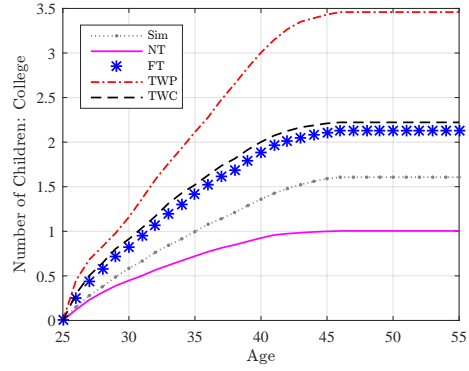
Finally, we also study the impact of taxes on the fertility behavior (see Figure 6). We observe that the number of children in the household in FT is higher than the number in NT. This shows that existence of taxes positively affects the fertility. Moreover, the number is much higher in TWP, which shows that progressivity increases the fertility.<sup>50</sup> These results are consistent across different 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 which is in line with [Black et al. \(2013\)](#) who show that male income elasticity is positive when females have more education. 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.

<sup>50</sup> Across counterfactuals, we observe negative relationship between household income and fertility, which is in line with [Jones and Tertilt \(2008\)](#), who document the negative relationship using Census data. For a more recent macro study, we refer to [Cordoba and Ripoll \(2015\)](#) who show the conditions for the negative relationship in a dynastic model.

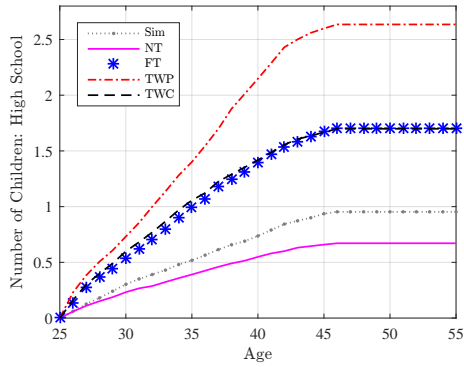
Figure 6: Number of Children in Life Cycle Across Counterfactuals



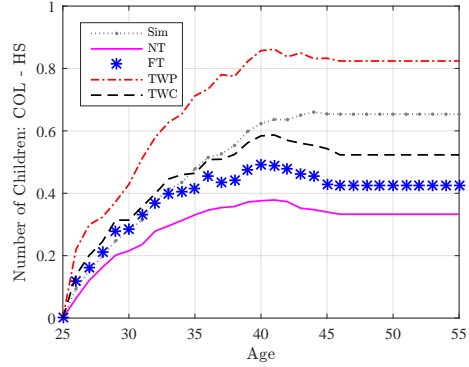
(a) All Households



(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.

**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.<sup>51</sup> 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).

<sup>51</sup>Most of the time, a potential policy which favors future generations but hurts current generation is not implemented due to the political reasons.

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

	<b><u>Simulation</u></b>	<b><u>NT</u></b>	<b><u>FT</u></b>	<b><u>TWP</u></b>	<b><u>TWC</u></b>
<b><u>Female</u></b>					
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
<b><u>Male</u></b>					
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
<b><u>Household</u></b>					
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).

We also show the educational outcomes of children in Table 6.<sup>52</sup> 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 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.

<sup>52</sup>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

	<i>First Generation</i>	<i>Second Generation</i>				
	<u>All CFs</u>	<u>Simulation</u>	<u>NT</u>	<u>FT</u>	<u>TWP</u>	<u>TWC</u>
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.

## 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

	<u>Simulation</u>	<u>NT</u>	<u>FT</u>	<u>TWP</u>	<u>TWC</u>
<b>First Generation</b>	0.21	0.00	0.18	0.20	0.18
<b>Second Generation</b>	0.20	0.00	0.18	0.18	0.18
<b>Both Generations</b>	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.<sup>53</sup> important results.

## 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

<sup>53</sup>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.



all couples. Also, 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, we observe that high school graduate mothers spend more time with children than the college graduate mothers. This pattern is reversed for fathers, college graduate fathers invest more time than high school graduate fathers. Fathers' labor market time do not differ by their educational outcome. However, the higher educated fathers are educated, the higher impact of the fathers' time investment is observed on the educational outcome (see Table 19).

We also 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 19). 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.

Table 8 shows the importance of both the "nature" and the "nurture". It is very clear that a formal analysis should have both as an ingredient to analyze the impact of parental inputs in children's human capital.

Table 8: Time Investment Impact

<b>All Couples</b>									
	<i>First Child</i>			<i>Second Child</i>			<i>Third Child</i>		
	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
<b>Both spouses have College Degrees</b>									
	<i>First Child</i>			<i>Second Child</i>			<i>Third Child</i>		
	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
<b>Both spouses have High School Degrees</b>									
	<i>First Child</i>			<i>Second Child</i>			<i>Third Child</i>		
	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.

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.<sup>54</sup> Table 9 provides the before- and the after tax income as well as the educations.<sup>55</sup>

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.

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<sup>54</sup>We elaborate the intergenerational correlations of income in Section 5.4.

<sup>55</sup>Table 9 shows the outcome of *parents*, while Table 4 shows the outcome of *first* generation (including non-parents).

Table 9: Income and Education of Parents and Children

	<u>Simulation</u>	<u>NT</u>	<u>FT</u>	<u>TWP</u>	<u>TWC</u>
<u>All Parents</u>					
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
<u>College Graduates Parents</u>					
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
<u>High School Graduates Parents</u>					
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 discretized education outcomes (LHS, HS, SC, and COL refers to 1 to 4, respectively).

## 5.4 Intergenerational Correlation in Income

Table 10: Intergenerational Correlation

Variable	Data	Simulation	NT	FT	TWP	TWC
Average Income between age 30-40	0.26	0.23	0.27	0.26	0.20	0.22
Average Income between age 35-45	0.17	0.21	0.29	0.25	0.19	0.22
Average Income between age 25-35	0.32	0.23	0.21	0.24	0.21	0.23
Average Income between age 25-55	0.36	0.18	0.24	0.24	0.19	0.21
Income at the age 35	0.13	0.15	0.16	0.13	0.10	0.13
Income at the age 46	–	0.16	0.17	0.17	0.13	0.15
Income at the age 50	–	0.11	0.17	0.17	0.14	0.16

Note: Income is the before tax household income. Sample consists of white married households. The correlation when households are at the age of 46 and 50 cannot be measure due to the lack of observation, i.e. the child generation is not aged much since the sample covers the observation up to 1996.

Table 10 provides the ICI for the model simulations as well as for the counterfactual simulations, using 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 ICI in data and in our simulation are close to each other. If the ICI is calculated using the average income from age 30 to 40 as a proxy of the permanent income, the model simulation produces 88% 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. We particularly focus on the average income from age 30 to 40 to measure the ICI.<sup>56</sup> However, our qualitative results hold for different measurements (see Table 10).

NT regime produces the highest intergenerational income correlation (0.27).<sup>57</sup> As shown in the Section 5.1, removing taxes from the economy creates incentives to work more for women and

<sup>56</sup> In the ICI 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. One major problem is the attenuation bias due to classical measurement error. To alleviate this, permanent income is generally approximated by averaging annual incomes from multiple years. One other econometric issue is the so called life-cycle bias that arises since the incomes used corresponds to particular period in the individuals' life-cycles. The survey of Solon (1999) on the intergenerational mobility literature discusses 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.

<sup>57</sup> ICI differs from the income elasticity as the correlation is calculated as  $\rho = \frac{cov(y_p, y_c)}{\sqrt{var(y_p)var(y_c)}}$  and income elasticity

reduces the fertility rate. Moreover, the time spent per child is slightly higher in NT. In particular, we observe that children of well educated households benefit more from the no tax regime in terms of human capital investments. Therefore we observe much higher correlation in NT comparing to all other counterfactuals.

Moving from a no tax environment to an environment to flat taxes for all households, we do not see much changes in the ICI (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. However, this reduction is very similar for households with different educations. Therefore, we do not observe so much variation in the ICI.

The ICI in the counterfactual TWP is 0.20, which is much lower comparing the correlation in NT. The reason for this decrease is the increase in the fertility rate (quantity) and decrease in the educational outcome of children (quality). First, as explained in the Section 5.1, progressive taxes impact female labor decision dramatically. For the parental generation, the reduction in the labor supply basically increase females' nonlabor time which could be used for time investment in children. In addition, the reduction in the labor supply reduces the labor income and hence the dynastic component of the utility. To compensate the reduction not only the life cycle component but also the dynastic component of the utility, households increase the number of children. In the meanwhile, although the total time investment increases, per child investment is reduced because of the increase in the number of children. Consequently, compared to NT, the educational outcome of children falls to 2.76 and 2.75 for daughters and sons, respectively (see Table 6).<sup>58</sup> Moreover, Table 9 shows that the the education of children for college graduate parents is the lowest in TWP. Since the variation in the educational outcome is reduced, we observe a more mobile society.

The ICI is 0.22 in TWC, which is lower than the correlation in FT. First, we observe that the fertility rate of TWC is slightly higher than the rate in FT. Moreover, the average education of children are quite similar across TWC and FT. A natural question arises that why the income mobility is higher in TWC compared to FT? Table 9 shows that the educational outcome of children of college graduate parents are quite similar to each other. However, the children's education of high school graduate differ as the education levels are higher in TWC. This states that high school graduate parents relatively have more educated children in TWC and consequently their children's

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is measured by  $\beta = \frac{cov(y_p, y_c)}{var(y_p)}$ . 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  $\beta$  is then associated with a higher income variance in the children's generation.

<sup>58</sup>In particular, we observe that the educational outcome is reduced for the younger children. As the number of children increases, the educational outcome falls. In fact, if we calculate the ICI between parents and the eldest children, we observe similar ICI's across counterfactuals. This result implies that the number of children decision is very important on the ICI.

income relatively far away from the parental income.<sup>59</sup> As a result, the income mobility is higher in TWC.

Next, we focus on the ICI across same genders. In particular, we focus on the correlation between fathers and sons as well as mothers and daughters.

## 5.5 Analysis on Gender Decomposition in Children

We present the ICI for same genders across generations.

Table 11: Intergenerational Correlation in Income across Genders

	<b>Data</b>	<b>Simulation</b>	<b>NT</b>	<b>FT</b>	<b>TWP</b>	<b>TWC</b>
<u>Fathers-Sons</u>						
Family Income	0.26	0.27	0.29	0.27	0.22	0.24
Individual Income	0.37	0.30	0.27	0.27	0.24	0.25
<u>Mothers-Daughters</u>						
Family Income	0.27	0.18	0.24	0.25	0.19	0.20
Individual Income	-0.01	0.22	0.28	0.25	0.20	0.19

Note: Income is the average income of before tax incomes between ages 30 and 40. The individual income directly refers to personal incomes. Family income is the household income of children's depending on the

Table 11 presents the ICI across genders.<sup>60</sup> We observe that the ICI is lower for the mothers-daughters relationship. While the differences in ICI across counterfactuals are similar for family income levels, we see much changes at the individual income level. As stated in Section 5.1, while males' labor supply is barely affected by taxes, the impacts on females' labor supply are drastic. The direct impact can be seen via the income levels. Table 4 and Table 5 show that the average income variation of males across counterfactuals are very small comparing to the variation of females. Therefore, while the difference in ICI between NT and TWP is only three percentage points for males, the difference is eight percentage points.

<sup>59</sup>In general, we can consider that whenever the educational outcome is close to parental education, children's incomes follow similar patterns with their parents and the ICI is higher.

<sup>60</sup>The ICIs under the simulation show that our model captures the data well. Although we do not target these moments, the model captures the ICI moments across genders well. The only moment we could not capture is the ICI across mothers and daughters at the individual income level.

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

## 5.6 Intergenerational Transition in Income Distribution

Table 12 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.<sup>61</sup> 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 counterfactuals in terms of probabilities 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 decline 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 12 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 flat 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.

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<sup>61</sup>Although the probabilities are close to each other, the pattern supports the results stated in Table 10.



Table 12: Income Mobility

<b>Low Income Parents (Bottom Quintile)</b>					
	<b><u>Simulation</u></b>	<b><u>NT</u></b>	<b><u>FT</u></b>	<b><u>TWP</u></b>	<b><u>TWC</u></b>
<u>Children at the bottom quintile</u>					
Income at the age 35	26.5%	22.9%	25.4%	24.3%	25.3%
Average Income between age 30-40	32.5%	31.9%	31.6%	30.4%	32.5%
<u>Children at the upper tail</u>					
Income at the age 35	40.3%	40.1%	43.8%	42.5%	42.9%
Average Income between age 30-40	33.9%	36.2%	34.2%	37.2%	38.0%
<u>Children at the top quintile</u>					
Income at the age 35	16.3%	11.9%	15.9%	14.2%	15.2%
Average Income between age 30-40	9.4%	6.2%	7.9%	10.2%	9.3%
<b>High Income Parents (Top Quintile)</b>					
	<b><u>Simulation</u></b>	<b><u>NT</u></b>	<b><u>FT</u></b>	<b><u>TWP</u></b>	<b><u>TWC</u></b>
<u>Children at the bottom quintile</u>					
Income at the age 35	16.8%	14.6%	16.7%	17.5%	17.7%
Average Income between age 30-40	11.2%	11.5%	12.7%	13.8%	13.9%
<u>Children at the upper tail</u>					
Income at the age 35	55.8%	60.8%	58.9%	55.8%	57.2%
Average Income between age 30-40	61.1%	64.2%	61.8%	57.9%	60.0%
<u>Children at the top quintile</u>					
Income at the age 35	24.6%	32.1%	26.1%	23.7%	25.9%
Average Income between age 30-40	30.8%	37.7%	31.5%	27.3%	30.4%

Note: Income is the before tax household income. Each cell provides the probability of corresponding children when their parents are at the bottom or at the top quintile.

## 5.7 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 13 shows the ICI using different income bases. We see that the correlations are larger than the correlations of white households. This fact 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.

Table 13: Intergenerational Correlation

Variable	Data	Simulation	NT	FT	TWP	TWC
Average Income between age 30-40	0.28	0.35	0.49	0.43	0.37	0.39
Average Income between age 35-45	0.21	0.34	0.49	0.43	0.34	0.39
Average Income between age 25-35	0.34	0.38	0.44	0.44	0.39	0.44
Average Income between age 25-55	0.39	0.30	0.48	0.42	0.34	0.40

Note: Income is the before tax household income.

## 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 time investment 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 the life cycle outcomes and 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. 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. 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 across educational groups 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 Function Estimates

Table 14 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).<sup>62</sup>

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<sup>62</sup>Estimates are close to the ones under the Specification 3 all column.

Table 14: Estimates of HSV Specification with Different Post-Government Income

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

**Log Specification** The parametric tax function of [Guner et al. \(2014\)](#) is:

$$t(\tilde{y}) = \chi + \iota \log \tilde{y} \quad (5)$$

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

Table 15: Estimates of *Log Specification*

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

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

Using the parameters in Table 15, 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.

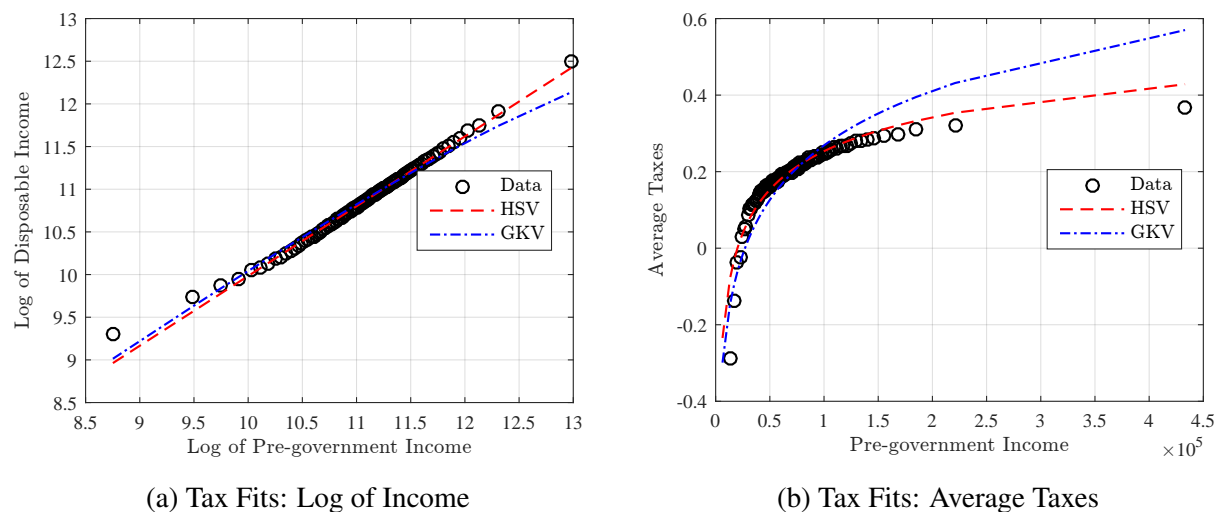


Figure 7: Comparison HSV and GKV Tax Specifications

## B Empirical Results

Table 16: Structural Estimates of Utility Parameter

Variable	Estimates	Variable	Estimates	
Marginal Utility of Income		Disutility/Utility of Choices		
Disposable Income	0.391 (0.004)	Female	Male	
		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 17: Data Summary Statistics

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

Note:

Table 18: Earning Equation and Fixed Effect

Variable	Estimate	Variable	Estimate	Variable	Estimate	
Demographic Variables			Fixed Effect			
Age squared	-4.0e-4 (1.0e-5)	Female x Full-time work	-0.125 (0.010)	Female	-0.48 (0.01)	
Age x LHS	0.037 (0.002)	Female x Full-time work ( $t - 1$ )	0.110 (0.010)	HS	0.14 (0.01)	
Age x HS	0.041 (0.001)	Female x Full-time work ( $t - 2$ )	0.025 (0.010)	SC	0.12 (0.01)	
Age x SC	0.050 (0.001)	Female x Full-time work ( $t - 3$ )	0.010 (0.010)	COL	0.04 (0.01)	
Age x COL	0.096 (0.001)	Female x Full-time work ( $t - 4$ )	0.013 (0.010)			
Current and Lags of Participation			Female x Part-time work ( $t - 1$ )	0.150	Female x HS	-0.05 (0.01)
Full-time work	0.938 (0.010)	Female x Part-time work ( $t - 2$ )	0.060 (0.010)	Female x SC	0.05 (0.01)	
Full-time work ( $t - 1$ )	0.160 (0.009)	Female x Part-time work ( $t - 3$ )	0.040 (0.010)	Female x COL	0.04 (0.01)	
Full-time work ( $t - 2$ )	0.044 (0.010)	Female x Part-time work ( $t - 4$ )	-0.002 (0.010)	Constant	0.167 (0.01)	
Full-time work ( $t - 3$ )	0.025 (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 (0.010)	Hausman Statistics	2296			
		Hausman p-value	0.000			
No. of Observations			134,007			
No. of Individuals			14,018			
R <sup>2</sup>			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 19: Education Production Function

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