Intergenerational Income Mobility and Income Taxation*

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Abstract

We study the impact of income taxation on intergenerational income correlation. We estimate a life cycle dynastic model and conduct counterfactual analysis to observe the effects of various tax regimes. Compared to a no tax environment, a flat tax regime reduces the correlation only by one percentage points. If the flat tax regime provides child benefits, the correlation additionally declines by four percentage points. Finally, if the taxes are progressive, the reduction, which is due to the increase in the fertility rate (quantity) and the decrease in the educational outcome of children (quality), is highly significant (seven percentage points).

JEL classification: H24, J13, J22, J62.

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1 Introduction

“It is hard to look at these figures (the Great Gatsby curve) and not be concerned.”

Alan Krueger

The negative relationship between income inequality and intergenerational social mobility− the Great Gatsby curve− implies that climbing social ladders has become harder in the US over last four decades. This inference conflicts with the American dream and has recently attracted the attention of the US policymakers. On the other hand, the literature studying the effects of a government policy on the intergenerational income inequality is sparse. In this paper, we fill this gap by studying the effects of income tax policy on the intergenerational correlation of income (ICI). We estimate a dynastic life cycle model using two generations of Panel Study of Income Dynamics (PSID) and conduct four counterfactual analysis to measure the impact of different tax regimes. Compared to a no tax environment, we find that a flat tax system reduces the ICI only by one percentage point. If the flat tax system provides child benefits, the ICI additionally declines by four percentage points. On the other hand, we observe the highest reduction (seven percentage points) via progressive taxes. The sources of this reduction rely on the increase in the fertility rate (quantity) and the decrease in the children’s educational outcome (quality).

We make theoretical and quantitative contributions. On the theoretical side, we embed a life cycle model into a Barro-Becker (dynastic) framework. The latter has been used by macro and labor economists to analyze the implication of family dynamics across generations. Embedding a life cycle allows us to study the impacts of income 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 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: progressiveness and child benefits.

One of the policy objectives of progressive taxes is to reduce income inequality since an increase in the progressivity rate, in general, decreases labor market time. This decrease can increase time spent with children, which positively influence children’s educational outcomes and consequently can impact their future earnings and ICI. On the other hand, an increase in the progressiveness reduces the net return to investment in children’s human capital, which can negatively impact parental investment behavior. Therefore, the impact of the progressivity rate cannot be observed at a first glance. Empirical evidence suggests that the ICI are lower in countries where taxes are more progressive, such as in Scandinavian countries. Moreover, the Gini coefficients in these countries are much lower compared to the one in the US, where taxes are less progressive. Linking these facts with the Great Gatsby curve raises an important question: Is there a relationship between progressivity rate and the ICI?

To answer this question, an explicit modeling of children's behavior in a dynastic model is required. We adapt the structural approach in Gayle et al. (2017), and study a dynastic model of altruistic unitary households, who make a fertility choice and decide time allocation between labor market, leisure, and childcare during their life cycles. The most recent empirical literature finds that parental care, which we name *time investment* in children, is a very important component of children's human capital. The literature additionally states that the time investment is especially crucial during early childhood. Therefore, we particularly focus on the early childhood investment, which impacts the educational attainments of children. The education of an individual not only affects her labor income but also impacts her household formation as spouses are likely to have similar educations (assortative mating). The household income, total labor income of spouses, is taxed by a parametric tax function: $T_n(w) = w - \lambda_n w^{1-\tau_n}$, where $T_n(w)$ is the tax liabilities of $n-$ child families who generate w income and τ_n is the progressivity rate of tax liabilities of $n-$ child families. This parametric tax function, in particular, simplifies to answer the question above as we can directly observe the impact of progressivity rate in the households' behavior and its consequences on ICI.

One of the major benefits of the structural econometric approach is the ability to conduct a full counterfactual analysis concerning the intergenerational effects of taxation. The literature on the empirical structural models mostly incorporates intergenerational concerns by modifying the standard dynamic structural estimation methods. This modification, in general, creates a proxy for the parental valuation for children as a function of state variables. In particular, the children's educational outcomes or test scores are the widely used proxies.[1] The proxy approach simplifies the estimation stages, but comes at a cost. Their counterfactual exercise does not model the choices of the future generations, which can be unrealistic for many important economic problems. Especially, the income taxation not only affects the current generation's incomes directly, it also impacts the return of parental investment, since children's future (choices) incomes are arguments in the valuation of children from parents' perspective.[2] 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 them. The structure that does not explicitly model the second generation does not allow the functional form of the mapping to change. This is, in fact, crucial to answer questions in tax literature since the changes in taxes alter households' behavior not only for the current generation but also for future generations.

[1] Bernal (2008), Brown and Flinn (2011), and Del Boca et al. (2013) are some examples.

[2] 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.

We estimate our model using two generations from the PSID dataset and show that the model successfully fits the data. We then conduct four counterfactuals to analyze the impact of income taxation. In the first, households do not pay income taxes and we set this counterfactual to be our base counterfactual. In the second, households pay a flat tax rate. In the third counterfactual, the taxes are progressive but do not provide child benefits. In the fourth, the average tax rate is the same for households of the same size but decline when a child is born. We compare the households' decisions and their consequences on the ICI across counterfactuals.

Our first important finding is that while males' labor supply decisions are almost unresponsive to tax changes, females' labor is very sensitive. 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 the reduction from no tax to flat taxes environment. One of the main reasons of this sensitivity is the gender wage gap, which is well documented in the literature. Due to the gap, females' labor is less productive, which makes them secondary earners of married households. Therefore, their first dollar earnings are started to be taxed at a high rate and the rate gradually increases if the taxes are progressive. Consequently, the return on females' labor decreases and females work less. This result is in line with empirical labor literature, as the elasticity of females' labor supply with respect to taxes is much higher than the elasticity of males' labor supply.

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. There are many reasons behind this result but two are the most significant. First, as stated above, the female labor supply is reduced more when taxes are progressive, which potentially increases time investment, i.e. females have more time to raise more children. Second, households know that the dynastic component of the utility declines due to progressive taxes (for similar reasons as above). Considering 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, but the type of taxation matters. To measure the ICI, we use the average of the household incomes that are earned when households are between 30 and 40 years old. This approach simply reduces potential measurement errors as well as provides a fine estimate of the permanent income as households are mostly productive during this period of their life cycles.[3] 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 percentage 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)

[3]The literature measuring ICI focuses on the *permanent* income, whose definition is somewhat controversial as researchers have different methodologies to calculate it.

and the decline in the children's educational outcome (quality). Consequently, income mobility increases in the economy. The reason for the reduction for the child dependent (and flat) tax regime is that households invest more time in children and this impact is more significant for households with less 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 rest of the paper proceeds as follows. After a brief literature review, Section 2 provides a motivational example for a structural model. Section 3 introduces a micro-founded model and specifies its key mechanisms. Section 4 briefly states the summary statistics in the data and the estimation strategy. We refer to 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 are many public finance studies on the impact of taxation on parental choices, especially their labor choices. On the other hand, there is also high volume of empirical studies that focus on the ICI. The former literature mainly abstracts from the correlation in income across generations, while the latter is silent on the impact of tax policies on the correlation. Our paper connects these two strands of literature and shows the impact of tax policies on the parental decisions and how these decisions shape the future generation's economic outcome.

The literature on taxation is very sparse in regards to human capital formation in an intergenerational model. Stantcheva (2015b) and Gelber and Weinzierl (2016) are a few exceptions. The latter study an intergenerational model, in which parents can influence children's opportunities. The former focuses on the optimal taxation in a dynastic model where parents monetarily invest in their children's educational outcome. Although these papers are a substantial contribution to the literature, they do not incorporate life cycle decisions and do not investigate the parental time investment for children. The time investment is, in particular, very important since it is a perfect substitute for the market labor time.[4] In particular, parents' time investment, which is indirectly affected by labor income taxation, is found to be a very important component (see Del Boca et al. (2013) and Schoellman (2016)).[5]

A change in the income tax policy can have effects across generations, both due to the re-

[4]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 by considering the individuals investment in own human capital policies. The former focuses on the time investment while the latter focuses on monetary investment. In fact, time and monetary investment (costs) can play important role on the optimal tax design even in a static model (see Kurnaz (2018)). Another important component of the optimal tax design is the preferences for redistribution which is affected by beliefs about intergenerational mobility (see Alesina et al. (2018)).

[5]Recently, the labor literature studies time allocation of households on optimal income taxation (see Blundell and Shephard (2011) and Gayle and Shephard (2019)).

optimization of parents (who will reallocate resources through time and monetary investment) and the re-optimization of children (who will face a different initial endowment to start their life cycle). For instance, a progressive income tax schedule reduces both the returns on labor hours and the returns to acquiring human capital.[6] Hendricks (2003) studies the impact of taxation on 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. In a more close to study to ours, Holter (2015) studies the impact of progressivity of income tax schedule on the intergenerational income persistence. Similar to our model, Holter (2015) studies a dynastic life cycle model of (single) males who intensively decide labor choices and exogenously have one child. We differ from previous studies in a couple of ways. First, we model human capital accumulation in a micro-production function. Human capital is accumulated not only through monetary investment, but also through time investment.[7] Time investment channel creates another impact of progressive taxes as more progressive taxes might lead agents to reduce labor market time and devote more time into childcare (time investment), which is supported by our counterfactual exercises. Moreover, we model unitary married households, which allows to study the labor supply decisions of mothers more realistically, especially when fertility is a choice. Note that fertility choice can be very important, yet, is neglected in the structural models (including Holter (2015)) studying taxation and intergenerational mobility. In particular, when taxes are more progressive, the life cycle utility of households falls because of the reduction in labor supply. Similarly, the dynastic component of the utility also falls as the return on parental investment decreases. Consequently, parents might seek to increase their utility through the dynastic component by increasing the number of children, which would reduce per-child investment and children's human capital. As a result, income mobility in children's generation might increase.[8] Moreover, the number of children is a very important component of US income tax schedule and progressivity changes by the number (see Table 1 and Guner et al. (2014)). Therefore, our simulation exercise can capture the impact of changes in the progressivity through family size component of the tax schedule.

The literature on intergenerational mobility is extensive.[9] In terms of its structure, our paper is closely related to Gayle et al. (2017) who study the sources of ICI.[10] Their structural model can capture a large portion of the correlation and the model is able to disentangle the impact of

[6]See Heckman et al. (1998), Krueger and Ludwig (2013), and Guvenen et al. (2014)).

[7]Recent applied micro studies show that time investment can be more important than monetary investment (see Del Boca et al. (2013)).

[8]We elaborate this argument in Section 5.

[9]We refer to the excellent study of Black and Devereux (2011) on recent developments in intergenerational mobility.

[10]Lee and Seshadri (2019) also study the mechanisms underlying the ICI by focusing parental investment on children's human capital where fertility is exogenous.

endogenous mechanisms such as human capital accumulation and assortative mating.[11] However, the paper abstracts from one of the most important policy analyses, income taxation, which directly impacts labor (and hence labor income) and indirectly impacts time investment (and hence children's education which is an important source of their income). We incorporate their structural model with a parametric tax function and show that income taxes can significantly change socio-economic conditions.

2 Motivational Example

We present a motivational example to provide some insights into the effects of progressive income taxes on the ICI. We 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 parental income. In the second, children observe their marginal product and maximize their utility. Households pay taxes according to $T(y) = y - \lambda y^{1-\tau}$. 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 though they model the bequest choice.[12]

We use backward induction to solve the 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:[13]

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

Assuming $u(c) = \log c$ and $v(x) = \frac{x^2}{2}$, the optimal choices imply

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

[11] Most of macro studies using a dynastic framework are unable to generate enough intergenerational persistence. Alvarez (1999) and Cordoba et al. (2016) show the key assumptions needed to generate such persistence in a macro model.

[12] Cordoba et al. (2016) show the conditions to generate the ICI with bequest motive by focusing on the elasticity of consumption across periods and across generations. See also Cordoba and Ripoll (2019).

[13] Altruistic coefficient is set to one.

where $w_c^i(d^i, y_p^i)$ is the marginal productivity of children of parent i and $\varepsilon^i_{w_c,y_p} \equiv \frac{y_p^i}{w_c^i}\frac{\partial w_c^i}{\partial y_p^i}$ and $\varepsilon^i_{w_c,d} \equiv \frac{d^i}{w_c^i}\frac{\partial w_c^i}{\partial d^i}$ are the elasticity of the marginal productivity with respect to parental income and time investment, respectively.[14] Most studies in the macro literature assume that these elasticities are exogenous and constant across households. If this was true, then the progressivity rate (including the existence of the tax system) would not change the ICI. However, there are a lot of heterogeneity in the data in terms of family types. For example, the elasticity of children's income (which is a proxy for wages) with respect to parents' income is only 0.25 if parents have at most high school degrees.[15] The same elasticity is 0.48 if parents have at least some college degree. Similarly, the elasticity of children's income with respect to parents' time investment is 0.18 and 0.61 when parents are at most high school graduates and at least some college graduates, respectively.[16] All these simple elasticity calculations from the raw data suggest that there are various complex dynamics including the household formation and differences in investment productivity in forming households. Despite its crudeness, this example shows us the need for a structural model for a fair analysis of the relationship between income taxation and the ICI.[17]

3 Model

The model is an extension of the dynastic framework of Barro and Becker (1989) where 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), and decide the fertility and time allocation between labor, leisure, and time investment on children if they have any in each period of their life cycle. The model assumptions are similar to those in Gayle et al. (2017), who do not focus on policy implications on the ICI. Yet, we particularly focus on the impacts of income taxation not only on the life cycle outcomes but also their implications on the ICI.

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 a non-existing parent in the household.[18] Even

[14]The optimal allocation equations are not necessarily in closed form solutions since the elasticities can be endogenous.

[15]The correlation is calculated using the average household income earned between ages 30 and 40. Though, we obtain similar results using different incomes.

[16]The elasticities also differ across genders. Our estimates are also in line with Ramey and Ramey (2009).

[17]Holter (2015) introduce heterogeneity through parental education in his model, yet, the model lacks an important channel, fertility choice, which is crucially important in the parental investment and the persistence of income correlation.

[18]See Bernal (2008) and Gayle et al. (2015).

if they can receive non-existing parental investment, we cannot observe it from the data.[19] Second, children raised in a single-parent household may get married in their adulthood which can impact their labor decision and hence their labor income. Therefore, the impact of tax policy on ICI may not be precise since income taxation is affected by marital status in the US.[20] 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.[21]

The timeline of an agent is as follows: Agents are children when they are 0-17 years old. Children consume a share of the household income during childhood, and 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).[22] The division of childhood into two periods is important for our analysis as we concentrate on early childhood. A growing literature in economics that analyzes the impacts of early investments on children life outcomes emphasize the importance of this particular period (See Cunha et al. (2006) and Cunha and Heckman (2007b)). Our objective sheds 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.[23,24] Married adults form unitary households. Households make fertility decisions until the age of 45 after which adults are infertile. 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.

Agents' lifetime invariant characteristics, which are their gender ($g \in \mathscr{G} = \{f, m\}$, female and male), their education ($e \in \mathscr{E} = \{LHS, HS, SC, COL\}$, less than high school, high school, some college, and college), and labor market skill ($\eta \in [\underline{\eta}, \overline{\eta}]$), are denoted by $x_g = (e_g, \eta_g)$. At the age of t, a household (f, m) chooses a discrete choice vector $a_t = (h_{ft}, h_{mt}, d_{ft}, d_{mt}, b_t)$ which consists

[19]How marital status impacts 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.

[20]Chetty et al. (2014) shows that family stability is an important component of higher income mobility. Our assumption on marriage without divorce creates a base for us to show the causal effects of income taxation.

[21]Potential divorce decisions can play an important role on intra-household allocation (see Chiappori et al. (2002)). We leave this framework for future research as well.

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

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

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

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.[25] 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 $z_t = (a_{25}, \ldots, a_{t-1}, \zeta_{25}, \ldots, \zeta_{t-1}, x_f, x_m)$ where ζ is a dummy variable and denotes whether a newborn child is a female.[26]

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

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

where c_t is the consumption of adults and θ_{a_t} is the dis/utility of time allocation and ε_{a_t} is per-period additive choice specific shock, which is distributed according to an Extreme Value Type I distribution, which is a standard assumption in empirical literature. Households' per-period budget constraint is

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

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.[27]

The budget constraint shows that there is no borrowing or savings decision, which could be important for allocation of good resources across time. However, in an excellent survey on educational outcomes of children, Heckman and Mosso (2014) show empirically that there is *little* evidence of the importance of credit constraints on educational outcomes. Moreover, Cameron and Heckman (2001) find that parental background and family environment is more important than the credit constraints. In macro studies, Han and Mulligan (2001) and Holter (2015) find that the impact of borrowing constraints on the ICI is very small compared to the impact of parental investment.

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

[26] 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 balance in the sex composition of their children (see Angrist and Evans (1998)).

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

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

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

where β is the discount factor, and $I^o_{a_t}$ be the indicator variable of the optimal discrete choice of a household with a state variable of z_t. Household i's expected utility from their children is

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

where $\tilde{v}, v$ are altruistic coefficients and $0 < v < 1$ 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.[28] The aggregate utility of the household (dynasty) i is the sum of the utility from life cycle and the utility from children:

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

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

Tax Specification We assume that the income tax function has a parametric form:

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

where w is the household income and n is the number of children.[29] Without the family size component, this functional form is used by Heathcote et al. (2017), and known as the *HSV* specification in the literature.[30] This specification has two restrictions. First, it does not allow a lump-sum transfer ($T(0) = 0$). However, a little income can be largely rewarded through this system, which is similar to the outcome of the earned income tax credit program in the US. Second, the tax function is either globally convex or globally concave depending on the value of τ, which makes marginal

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

[29] Feldstein (1969) introduced this form without family size component (see also Benabou (2000), Benabou (2002), and Heathcote et al. (2010)).

[30] There are four main specifications for tax function in the literature (see Guner et al. (2014)). Among those, the *HSV* specification is the best to provide fine estimates when the average taxes are negative (see Kurnaz and Yip (2019)). We also find that the model fits the data better when the taxes are in the *HSV* specification in the Online Appendix.

taxes monotonic. Data evidence supports this restriction for a large range of income. Despite its minor restrictions, this specification provides a very useful as the impact of the progressivity rate can easily be analyzed. Note that the progressivity rate is $\tau = 1 - \frac{1-T'(w)}{1-\frac{T(w)}{w}}$. When $\tau > (<)0$, the tax system is progressive (regressive). When $\tau = 0$, then taxes are flat. Note that progressivity rate plays an important role in shaping income inequality. In addition, the empirical literature shows that the ICI is lower in countries whose tax code is more progressive.[31] Our counterfactual analysis will show whether this observation is causal.

We consider the labor income, w, as the pre-government income, and $w - T(w)$ as post-government income, which is pre-government income minus total taxes (federal, state, and social security taxes calculated via TAXSIM 9.2, a tax simulator of NBER) and plus benefits such as cash transfers (AFDC/TANF, SSI, and welfare receipts).[32] We differ from Heathcote et al. (2017) by allowing λ and τ depend on the number of children. The family size component is very important in the US tax code, not only for tax liability differences but also for benefits.[33] We estimate

$$\log(w - T(w)) = \log \lambda_n + (1 - \tau_n) \log w \tag{2}$$

for each $n \in \{0, 1, 2, 3, 4\}$ and report parameters in Table 1.[34]

If 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). However, we observe that τ_n changes by family size and 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 are very large and these facts drastically reduce the average taxes of families with children. Consequently, the progressivity rate is mainly increasing in the size of households.

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

Household Income Specification Household income consists of the sum of individual incomes. The *realized* individual income, w_{gt}, of gender g at age $t > 25$ is assumed to consists of three components: the interaction of the labor productivity with labor hours, work experience, and innate

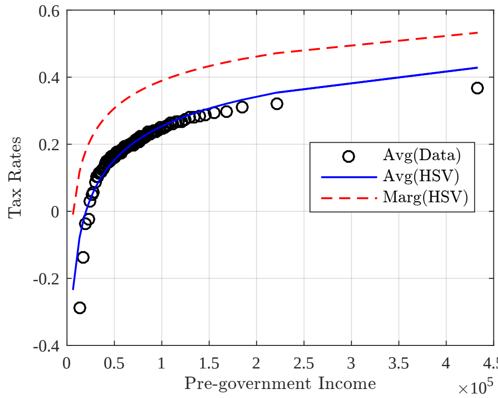
[31] Jantti et al. (2006) show that the correlation in Nordic countries is almost half of the correlation in the US. Kleven (2014) shows that the progressivity rates in Scandinavia are higher than the rate in the US.

[32] Please see Heathcote et al. (2010) and Heathcote et al. (2017) for further details.

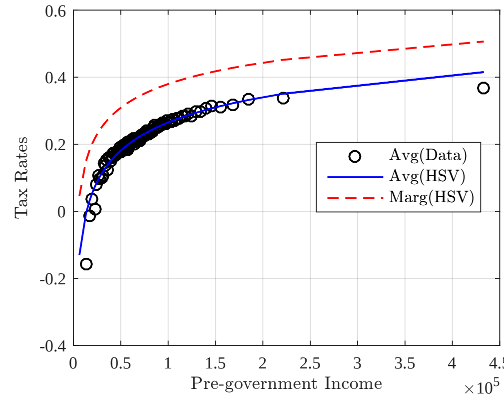
[33] The number of children changes tax credits such as the earned income credit and the child tax credit. In addition, the welfare benefits depends on the federal poverty level, which is affected by the number of children.

[34] We also provide the tax parameters for different post-government income levels in the Online Appendix in Table 15.

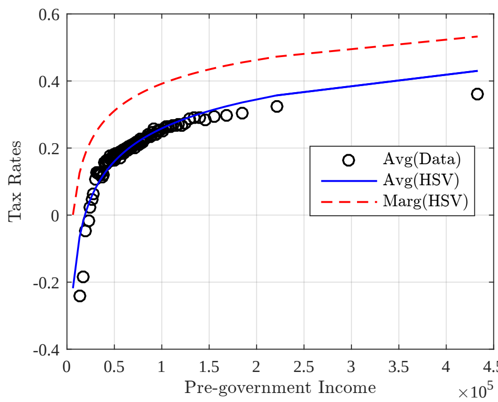
Figure 1: Average and Marginal Tax Rates with HSV Specification



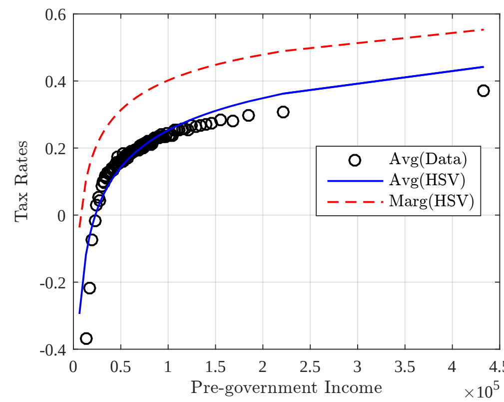
(a) All Households



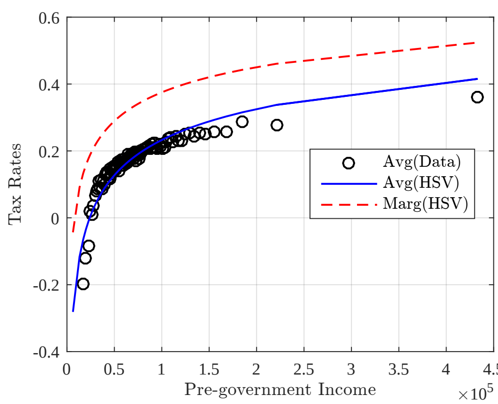
(b) Households with 0 Children



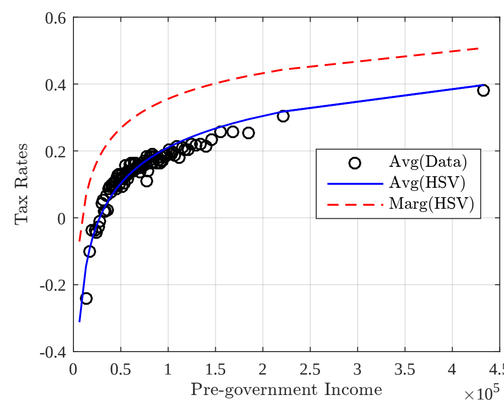
(c) Households with 1 Child



(d) Households with 2 Children



(e) Households with 3 Children



(f) Households with 4 Children

Note: Avg and Marg refer to average and marginal tax rates, respectively. Parentheses provide information as to where the rate comes from.

Table 1: Estimates of Tax Parameters of HSV Specification

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

Note1: The sample contains 25-60 year old married households (two adults) of PSID 1968-1997 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)) and ensures labor is the main source of income of households. All taxes, benefits, and incomes are converted to 2005$s. We estimate λ and τ by ordinary least square (OLS) using Equation (2).
Note2: According to NIPA Table 2.1, the mean of average taxes between 1968-1997 is 0.172.

ability (fixed effect):[35]

$$\ln w_{gt} = W_{gt}(e, h_{gt}) + H_{gt}(h_{g25}, ..., h_{gt-1}) + \eta_g \quad \text{for} \quad g \in \{f, m\}.$$

The first component, $W_{gt}(e, h_{gt})$, captures the interaction between agent's education and her market labor hours. Since we have a discrete choice model, $W_g(e, h_{gt})$ depends on h_{gt} in a non-linear manner− full-time work pays more than twice as much as part-time work.[36] The second component, $H_g(h_{g25}, ..., h_{gt-1})$, represents the return of the experience in income and depends on the type of experience, part-time or full-time. This component specifically captures the gender-specific depreciation of human capital, as empirical evidence suggests that the depreciation is critical for females. The third component, η_g, captures the gender-specific unobserved ability to earn income.[37] We show the estimation results in Table 13.

Education Production Function Specification Most of labor studies show that parental investment is much more important than pre-birth conditions (see Black et al. (2019)). In addition, timing of parental investment is important on the children outcomes (see Cunha and Heckman (2007a)). Moreover, Restuccia and Urrutia (2004) also shows that early childhood investment in education is

[35] In particular, we estimate $\ln w_{gt} = \delta_0 + \delta_1 age \times education + \delta_2 age^2 + \left(\sum_{j=0}^{4} \delta^{ft}_{t-j} \mathbb{1}^{ft}_{t-j} + \sum_{j=0}^{4} \delta^{pt}_{t-j} \mathbb{1}^{pt}_{t-j}\right) + \eta_g + \varepsilon_t$ where *ft* and *pt* refer to full- and part time.

[36] See Altug and Miller (1998), Gayle et al. (2012), Gayle and Miller (2012), and Gayle et al. (2017), who document these features of the recent labor market.

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

more important in the persistence in intergenerational income. Therefore, we particularly focus on the early childhood investment of parents. We specify an education production function to account for *exogenous* parental invariant characteristics, $x = (x_f, x_m)$, as well as *endogenous* parental time investment (d_f, d_m) and parental income (w_f, w_m). Also, we consider that the education of children can be affected by their gender as well as the number of young siblings in the household, S_{-5}, which can potentially reduce the impact of parental time investment. Let the characteristics of a child of gender g' be represented by $x'_{g'} = (e'_{g'}, \eta'_{g'})$ where $e'_{g'}$ denotes the education of the child, and η' denotes the child's market ability. The characteristics of the child are 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 $\tilde{t}$ is the age of the child; ω' is the luck component and independent of $\tilde{\eta}'$. In the empirical implementation, Γ and $\tilde{\Gamma}$ are both linear functions. We refer to Gayle et al. (2018a) for more details on the education production function. The estimation results are shown in Table 14. We find that the parents' educations positively impact the children's education ("nature"). Also, we observe that parental time investment impacts the potential educational outcome more than parental income. The significant impact of time investment highlights the importance of the parental time allocation, which is affected by income taxation. The impact of taxes, though, is complicated. First, an increase in the tax rate would reduce labor market time which could increase time investment. On the other hand, the increase in the rate reduces the return to parental investment, which can make parents reluctant to invest more time. The complex impact of taxation highlights the importance of our analysis. Next, we briefly state how we use and measure time investment from the data.

Our data source is PSID, which does not include how much parents spend time with children until 1997.[38] 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.[39] Negative values are set to zero and childcare hours are zero for childless households. The intensity of time investment can be quite different for mothers and fathers. For instance, white mothers in our sample spend, on average, 724 hours annually for their children, while the corresponding average for fathers is only 129 hours in 1975.[40] This large difference

[38]The Child Development Supplement (CDS) is collected as a component of PSID starting with the 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.

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

[40]The average childcare hours in the American Time Use Survey 1975 wave dataset are 721 and 231 for white mothers and white fathers, respectively.

urges us to define the intensity levels for fathers and mothers separately, as fathers' and mothers' time are different inputs to the children's education production function and marginal increases in either can have different effects. This implies, for instance, that a mother showing a medium time investment might, in fact, be spending more hours in practice than a father spending the full time investment.

Marriage Matching Function A 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 is to be expected. Due to stationary nature of our estimation, the same matching function is applied to individuals from all generations, although, the assortativeness of matching in the marriage market has increased over time.

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 and assuming $\tilde{u}(.)$ to be linear. We use a parsimonious set to capture the leisure implications in the utility function of household choice combinations. More specifically, there are 17 dis/utility levels corresponding to the combinations of labor supply choices of females and males (eight parameters), the combinations of time investment choices of females and males (eight parameters), and a choice for the birth decision (one parameter) in the household.[41] Note that the action of no birth, no work, and no time investment by each spouse is chosen to be the base action, and all related estimates capture the utility conditional conditional on the base action.[42]

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:

$$u_{ta} = \sum_{i=1}^{17} \theta_{a_i} \mathbb{1}_{a_i} + \alpha_0 \tilde{w}_{ta} + (N_t + b_t) \times \left(\alpha_1 \tilde{w}_{ta} + \sum_{e \in \mathscr{E}} \sum_{g \in \mathscr{G}} \alpha_{eg} \tilde{w}_{ta} \mathbb{1}_{eg} + \alpha_8 \tilde{w}_{ta} \mathbb{1}_{race} \right) + \varepsilon_t$$

where $\mathbb{1}$ is the indicator function, and race can be either white or black.[43]

Table 11 presents the related estimates. We find that the utility of parents is increasing in education and is decreasing in the number of children. Moreover, we observe that time devoted

[41] The choice set is restricted to the possible actions depending on the state as the household can only invest in their children if they have a child that is less than five years old.

[42] In fact, there are nine choices of time allocation for each gender and there are $9 \times 9 \times 2$ choices to be estimated, which is technically hard. For simplicity, we link labor market decisions of spouses and time investment decisions of parents and reduce the required number of estimation parameters to 17.

[43] The households, in which both spouses have less than high school degrees, are considered as the base. Therefore, if less than high school graduates are nonparents, their marginal utility of disposable income (consumption) is α_0 and if they are parents the marginal utility is $\alpha_0 + \alpha_1$.

to labor market decreases utility except for the household working full time. In addition, the estimates for the time spent with children vary a good deal, which can be attributed the fact that not all childcare activities provide leisure nor are they 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 period.

Shocks and Choices We summarize shocks and choices and their timing. There are four main shocks in our model. The timing of the realization of these shocks is crucial to understand the model predictions. The first shock is embedded in the matching probability, $G(x_m, x_f)$, and is realized at the beginning of adulthood, at the beginning of age 25. The second shock, ε_{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, ω', is on the children's educational outcome, which is realized before adulthood starts, at the end of age 24, and is independent across generations.

Model Discussion Before providing a detailed analysis, we discuss the model. Our model takes the returns from participating in the labor market as exogenous while the incomes of households are endogenous through labor supply decisions. The time endowment, which can be spent for work, children, and 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 cannot 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 that impacts children's adulthood states and therefore their future choices. Consequently, the changes in the expected future outcomes of children, which are the proxy of the children's value to parents, can alter parental individual decisions. This aspect of our model sets it apart from the standard life cycle models in terms of effect of labor market earnings.

4 Data and Estimation

The estimation is conducted using data from the Family-Individual File of the PSID 1968 - 1997 waves. 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 subsamples from the initial sample. Estimation of the earnings equation requires the knowledge of the last four years of labor market history. This requirement, for instance, eliminates observations of individuals without at least five years of sequential observations. Parental time investment in a child during her/his early life requires us to observe children before the 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 12 shows the summary statistics.

Our model is a unitary model without divorce.[44] 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 will practically leave us with a very limited amount of data to conduct a meaningful inference, but 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 meet the above restrictions and who are married for at least one year in our sample. This is a sample of 41,448 individual-year observations and is used 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 observation and this is used to estimate the utility parameters.

A brief summary of our sample shows that the lifetime 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.[45] In terms of education, the lifelong married sample have slightly higher education, though this not statistically significant. Individuals have more children in the ever-married sample. In the lifelong married sample, annual labor income and labor market hours for individuals are higher.[46] In the ever-married sample, adults have

[44] 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).

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

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

more housework hours and spend time with children on average.[47] 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 children's generation is needed only to estimate the education production function.

Estimation of intergenerational models with explicit life cycle components is 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)).[48] 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 generalized method of moments (GMM) estimator.[49] 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 stationary assumption, we derive alternative value function representations. In step 4, the Hotz-Miller inversion is used to form moment conditions for a GMM estimation of the remaining structural (utility function) parameters of the model.[50]

4.1 Model Fit

In this subsection, we describe 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 10,000 synthetic generations.

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

[47] This is consistent with the higher number of children in the ever-married sample.

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

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

[50] The discount factors are set as $\beta = 0.813$, $\tilde{\nu} = 0.795$, and $\nu = 0.111$ (see Gayle et al. (2017)). 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 by studies 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, ν, implies that the marginal increase in value from the second child is 0.68 and 0.60 from the third.

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 successfully replicate the observed choices in the data well. One can interpret the fit of the model form this exercise as a visual representation and aggregated summary of the restrictions in the J-test as these are the aggregates of the moments targeted in estimation. We present the results of this comparison in the Table 3 below the 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.[51] 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 labor income. In counterfactual II (FT), households face a flat tax rate (18%) regardless or their size or income. The rate (18%) is chosen to fulfill a similar government spending requirement across counterfactuals.[52] 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 flat for same-size households, taxes are regressive in a way that the average rate is lower for households with more children. We summarize the taxation in each counterfactual in Table 2.

We calculate several life cycle statistics to compare the effects of different tax regimes. 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 Table 3, which we briefly discuss. The simulation column shows that our model fits the data well. Moreover, while taxes do not influence males' choices, they greatly affect 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' fertility behaviors are also affected by the tax regime. We see that income taxes increase the probability of birth decision.

[51] 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.

[52] There are two different approaches in the literature to compare environments whose governments are revenue equivalent. 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 18% tax rate satisfies almost both approaches.

Table 2: Tax Parameters in Counterfactuals

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

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

Table 3: Probability of Choices under Counterfactuals

		Data	Simulation	NT	FT	TWP	TWC
Female							
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
Male							
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
Household							
Birth		0.10	0.04	0.03	0.06	0.09	0.06

Note: The numbers in each cell are rounded to second decimal and refer to the average probability of choosing action in a year over life cycle.

Table 4: Average Annual Life Cycle Allocation across Counterfactuals

	Simulation	NT	FT	TWP	TWC
Female					
Labor Supply	1.34	1.46	1.33	1.13	1.32
Income	18,203	20,683	18,066	14,730	17,899
Time Investment	0.18	0.12	0.28	0.43	0.29
Male					
Labor Supply	1.90	1.91	1.91	1.93	1.92
Income	47,980	47,956	48,251	48,774	48,448
Time Investment	0.07	0.04	0.09	0.14	0.09
Household					
Before Tax Income	66,184	68,639	66,317	63,505	66,347
Taxes	14,065	0	11,937	12,587	11,730
Average Tax Rates	0.19	0.00	0.18	0.18	0.18
Disposable Income	52,119	68,639	54,380	50,918	54,617
Children	1.21	0.78	1.78	2.93	1.86
Children (HS)	0.95	0.67	1.71	2.64	1.70
Children (COL)	1.61	1.00	2.13	3.46	2.22

Note: All income values are in 2005 \$s. 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). Children (HS) and Children (COL) rows represent the number of children in the households in which females are high school and college graduates, respectively.

5.1 Life Cycle Analysis

In this subsection, we analyze the life cycle differences across counterfactuals. First, we transform the probabilities stated in Table 3 into the average life cycle outcomes and show them in Table 4.

Labor supply (income) responses to taxes vary across genders. While there is not much differences in labor supply and income for males, there are large variations in the female's. The percentage reduction in the female labor supply from NT to TWP (22%) is more than twice the reduction (9%) from NT to FT (and TWC). These results imply that elasticity of labor supply is very low for males and high for females, which is in line with empirical literature (see Saez et al. (2009)). In addition, we also observe variation in the time investment in children which is mainly due to the variation in the number of children.

Fertility behavior is quite responsive to income taxation. Across counterfactuals, we observe a negative relationship between household income and fertility, which is in line with Jones and Tertilt (2008), who document the negative relationship using Census data.[53] From NT to FT, the average number of children in the households increase by one.[54] Also, the increase is more than

[53]In a recent macro study, Cordoba and Ripoll (2015) show the conditions for the negative relationship in a dynastic model.

[54]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.

two from NT to TWP. To understand the reasons of fertility responses to taxes, we link the impact of taxes on the utility and potential responses to the impact through fertility behavior. Taxes reduce not only per period utility (consumption) of parents but also the utility from the life cycle utility of children as children's per period utility is reduced too. Therefore, the households increase their utility by increasing the number of children, although households get a disutility just after the birth (see Table 11). These facts are valid both for flat and progressive taxes. However, the impacts are much stronger via progressive taxes. Consequently, we observe much larger increase in the fertility rate in TWP.

We also study the differences in fertility rates between college graduate and high school graduate females within counterfactuals. We find 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 elasticity of fertility with respect to male income is positive when females are more educated. The differences vary across counterfactuals. The lowest difference is in NT, since college graduate females labor is not taxed and females work in the labor market heavily. The difference increases from NT to FT due to 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 benefits by having more children. In fact, the child benefits are much more valuable for college graduate females as their average tax rates fall by having an extra child. Therefore, we observe a slight higher fertility rate in TWC compared to the rate in FT for college graduate females. Finally, the highest difference is in TWP. The progressive taxes reduces the net return to labor of college graduates so high, therefore, households tend to have more children (see aforementioned explanations).

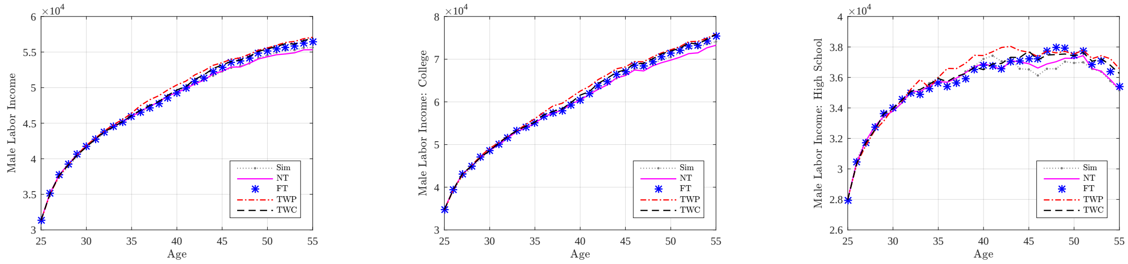
Next, we analyze the impact of taxes on the labor income during the life cycle. First, we observe that regardless of educational differences, males' labor incomes across counterfactuals are quite similar to each other during their life cycles (Figure 2). However, females' labor income responses to taxes quite vary (Figure 3). This result mainly stems from the gender wage gap (see Table 13), which is a well-known fact in the empirical literature. Due to the gap, females can be inferred as secondary earners.[55] Therefore, females' labor is more sensitive to tax changes as their first dollar earnings is taxed at a higher rate due to the jointness of the US tax code.[56] Moreover, the impact of gender wage gap is strengthen by the education wage premium (see Table 13). Due to the premium, taxes relatively reduce the return to labor of college graduate females more than others. In particular, we observe that the highest difference in the income of high school graduates across counterfactuals is around \$400, while the difference can reach more than \$10,000 for college graduates.[57] We also note that the assortative mating enhances female labor supply responses.

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

[56] The tax unit is the household income in the US.

[57] The largest differences occur between NT and TWP because households respond to the progressive taxes more

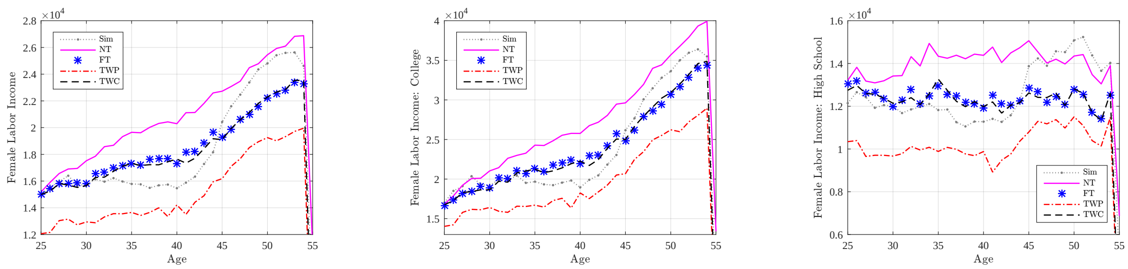
Figure 2: Male Labor Income in Life Cycle Across Counterfactuals



(a) All Households (b) College Graduates (c) High School Graduates

Note: Education labels refer to males' education.

Figure 3: Female Labor Income in Life Cycle Across Counterfactuals



(a) All Households (b) College Graduates (c) High School Graduates

Note: Education labels refer to females' education.

Since a college graduate female is likely to get married to a college graduate male, her first dollar earning is taxed at a much higher rate compared to the first dollar earning of a high school graduate female, who is likely to be married to a high school graduated male, whose income is, on average, lower than a college graduate male's income.

Discussion Above, we specifically provide the outcomes of the initial (parent) generation, because we want to present the impact of policy analysis for the "current" generation, which is very important for policymakers.[58] The results, of course, would be different for the second (child) generation, which is represented in 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 spouse due to lower educational outcomes (see Table 6).

than flat taxes.

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

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

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

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

Government Revenue We also briefly mention government revenues (tax collection) across counterfactuals. Using the per-capita taxes collected from each generation from Table 4 and 5, the ratio of total taxes to the total income (GDP) is very close to 0.18 in each counterfactuals (FT, TWP, and TWC), and therefore the governments in counterfactuals can be considered revenue equivalent governments.

5.2 Intergenerational Analysis

In this subsection, we focus on the parental investment and educational and economic outcomes of children. Table 6 presents the parental income (both before and after tax income), parental total time investment, and the number of children not only for all parents as well as parents with high school and college degrees.[59] As shown in Table 4, the intensity of human capital investments is altered by income taxation. In particular, we see that parental total time investments are the lowest (highest) in NT (TWP) than in all other counterfactuals. If the education production function did not depend on other factors, we would expect the lowest (highest) educational outcome for children in NT (TWP). Yet, Table 4 shows completely opposite outcomes. This is mainly because there are other components in the education function. The most significant one is the number of existing siblings less than five years old. In fact, we observe the lowest (highest) fertility in NT

[59]Table 6 shows the outcome of *parents*, while Table 4 shows the outcome of *first* generation (including non-parents).

(TWP). Therefore, we can infer that per-child time investment is the highest (lowest) in NT (TWP), and highest (lowest) educational outcome for children is observed in NT (TWP). With similar intuition, we observe similarity in the educational outcome of children between FT and TWC as both parental time investments and the number of children are very close to each other. However, high school graduate parents have less number of children in TWC than in FT. Therefore, per-child time investment is higher which yields a higher educational outcome. This result is, in particular, important since it can impact income mobility because when children are more educated, they have chances to move on social ladders. In the next subsection, we measure the ICI.

5.3 Intergenerational Correlation in Income

Table 7 provides the ICI for the model simulations as well as for the counterfactuals, using different measures of the permanent income.[60] Before discussing the specific effects of the counterfactuals on the ICI, we note that the ICI in the 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− these correlations are not targeted moments in the estimation stage. We focus particularly on the average income from age 30 to 40 to measure the ICI by following Haider and Solon (2006) who find that years income earned around the age 40 are the best proxies for permanent income.[61] However, our qualitative results hold for different measurements.

The NT regime produces the highest ICI (0.27). Moving from a no-tax environment to an environment with flat taxes, we do not see much change in the ICI (0.26). The correlation slightly decreases because income taxes create a substitution effect and reduces labor income. However, this does not create that much variation across households. One of the biggest changes is in the educational outcomes of children. We observe that these outcomes are lower in FT then in NT. However, this reduction is very similar for households with different levels of educations. There-

[60]ICI differs from the income elasticity as the correlation is calculated as $\frac{cov(y_p,y_c)}{\sqrt{var(y_p)var(y_c)}}$ and income elasticity is measured by $\frac{cov(y_p,y_c)}{var(y_p)}$. For instance, if the variance of parents' (y_p) and children's income (y_c) are the same, the two measures produce the same numerical value. Having a lower β is then associated with a higher income variance in the children's generation.

[61]The literature measuring the ICI targets to use permanent incomes of parents and children and creates some proxies. 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 for approximation correspond to a particular period in the individuals' life cycles. The survey of Solon (1999) on the intergenerational mobility literature discuses issues related to using incomes from different parts of the life cycle to proxy the permanent income. See also Solon (1989) for more measurement discussions on the proxies and Solon (1992) for a particular focus on the US correlation.

Table 6: Income and Education of Parents and Children

	Simulation	NT	FT	TWP	TWC
All Parents					
Parents' Before Tax Income	60,671	62,509	60,934	59,608	61,646
Parents' After Tax Income	48,939	62,509	49,966	48,478	50,823
Maternal Time Investment	0.25	0.23	0.32	0.45	0.31
Paternal Time Investment	0.10	0.08	0.10	0.15	0.10
Children	1.66	1.44	2.04	3.04	2.00
Daughters' Education	2.96	2.93	2.83	2.75	2.83
Sons' Education	2.98	2.95	2.82	2.76	2.84
Children's Before Tax Income	58,529	60,579	57,692	54,479	58,197
Children's After Tax Income	47,093	60,579	47,308	45,033	47,599
College Graduates Parents					
Parents' Before Tax Income	72,482	75,490	73,991	72,278	74,920
Parents' After Tax Income	56,979	75,490	60,673	56,967	62,022
Maternal Time Investment	0.27	0.22	0.31	0.47	0.32
Paternal Time Investment	0.13	0.09	0.11	0.18	0.11
Children	1.85	1.44	2.08	3.34	2.10
Daughters' Education	3.03	3.10	2.97	2.91	2.97
Sons' Education	3.03	3.08	2.97	2.88	2.95
Children's Before Tax Income	60,023	62,868	60,178	56,487	60,106
Children's After Tax Income	48,122	62,868	49,346	46,387	49,207
High School Graduates Parents					
Parents' Before Tax Income	45,332	47,734	46,309	45,351	46,944
Parents' After Tax Income	38,335	47,734	37,974	38,826	38,482
Maternal Time Investment	0.23	0.22	0.34	0.45	0.32
Paternal Time Investment	0.08	0.06	0.09	0.12	0.08
Children	1.47	1.38	2.10	2.91	1.96
Daughters' Education	2.96	2.76	2.57	2.57	2.64
Sons' Education	2.91	2.69	2.59	2.54	2.65
Children's Before Tax Income	57,352	57,251	53,829	51,865	55,491
Children's After Tax Income	46,277	57,251	44,140	43,267	45,283

All income values are the averages of the household incomes from the age 30 to the age 40. Education outcomes are the averages of {1,2,3,4} (LHS, HS, SC, and COL). Time investment is the average of annual choices of {0,1,2} (no, part, and full time). Children row represents the average number of children in the household at the end of fertile period.

Table 7: Intergenerational Correlation

Variable	Data	Simulation	NT	FT	TWP	TWC
Correlation						
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
Income at age 35	0.13	0.15	0.16	0.13	0.10	0.13
Elasticity						
Average Income between age 30-40	0.37	0.20	0.22	0.24	0.19	0.20
Average Income between age 35-45	0.36	0.18	0.25	0.23	0.18	0.20
Income at age 35	0.24	0.13	0.13	0.13	0.10	0.12

Note: Income is the before-tax household income. Sample consists of white married households.

fore, we do not observe as much variation in the ICI.

The ICI in the counterfactual TWP is 0.20, which is much lower compared the correlation in NT.[62] The reason for this decrease is the increase in the fertility rate (quantity) and the decrease in the educational outcome of children (quality). First, as explained in Section 5.1, progressive taxes impact female labor decisions dramatically. For the parental generation, the reduction in the labor supply basically increases 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 in not only the life cycle component but also in the dynastic component of the utility, households increase the number of children. In the meantime, 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 7).[63] Moreover, Table 6 shows that 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 educations of children are quite similar across TWC and FT. A natural question arises: why is the income mobility higher in TWC compared to FT? Table 6 shows that the educational outcome of children

[62] Similar to our findings, Erosa and Koreshkova (2007) also show that the ICI under flat tax regime is bigger than the ICI under progressive tax regime.

[63] In particular, we observe that the educational outcome is higher for the elder 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.

of college graduate parents are quite similar to each other. However, the children's education of high school graduate parents differ as the education levels are higher in TWC. This states that high school graduate parents have relatively more educated children in TWC and consequently their children's income is relatively far away from the parental income.[64] As a result, the income mobility is higher in TWC.

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

5.4 Analysis on Gender Decomposition in Children

Table 8 presents the ICI across genders.[65] 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 changes at the individual income level. As stated in Section 5.1, while males' labor supply is barely affected by taxes, the impact on females' labor supply is drastic. The direct impact can be seen via the income levels. Table 4 and 5 show that the average income variation of males across counterfactuals is very small compared 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 for females.

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

5.5 Intergenerational Transition in Income Distribution

Table 9 shows the probability of children being in the bottom 20%, the top 50%, and the top 20% of income distribution conditional on their parents' position. 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.[66] 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, while 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

[64] 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.

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

[66] Although the probabilities are close to each other, the pattern supports the results in Table 7.

Table 8: Intergenerational Correlation in Income across Genders

	Data	Simulation	NT	FT	TWP	TWC
Correlation						
Fathers-Sons						
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
Mothers-Daughters						
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
Elasticity						
Fathers-Sons						
Family Income	0.37	0.22	0.24	0.25	0.19	0.22
Individual Income	0.52	0.24	0.21	0.23	0.21	0.22
Mothers-Daughters						
Family Income	0.37	0.17	0.21	0.23	0.18	0.18
Individual Income	-0.06	0.18	0.20	0.22	0.16	0.17

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 children's household income.

to 9.3% and 10.2% in TWC and TWP, respectively. This result is in line with the ICI stated above (see Table 7).

For the highest income parents, the pattern is much clearer. For example, the rank of counterfactuals in terms of the probability of being in the top 50% of income distribution is NT, FT, TWC, and TWP. In particular, the probability is reduced by 2.4% by flat taxes. 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 a 10.3% reduction.

Table 9 shows the importance of the tax regimes in the mobility of income distribution. Not only the existence of taxes but also the type of taxation matters. The flax tax rate system slightly increases 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.

Table 9: Income Mobility

Low Income Parents (Bottom Quintile)					
	Simulation	**NT**	**FT**	**TWP**	**TWC**
Children at the bottom quintile					
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%
Children at the upper tail					
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%
Children at the top quintile					
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%
High Income Parents (Top Quintile)					
	Simulation	**NT**	**FT**	**TWP**	**TWC**
Children at the bottom quintile					
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%
Children at the upper tail					
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%
Children at the top quintile					
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.

5.6 Robustness

The main results were based on white married households. We also calculate the correlation including the black households. Table 10 shows that the ICI's are larger than the ICI's in Table 7, which is a well established fact in the empirical literature that income mobility is less for black households (see Chetty and Hendren (2018), and Chetty et al. (2018)). Yet, our qualitative results hold.

Table 10: Intergenerational Correlation: Robustness Analysis

Variable	**Data**	**Simulation**	**NT**	**FT**	**TWP**	**TWC**
Correlation						
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
Income at the age 35	0.16	0.24	0.31	0.25	0.21	0.25
Elasticity						
Average Income between age 30-40	0.37	0.27	0.41	0.36	0.32	0.35
Average Income between age 35-45	0.27	0.24	0.41	0.36	0.29	0.32
Income at the age 35	0.24	0.20	0.25	0.22	0.18	0.23

Note: Income is the before-tax household income.

6 Conclusion

This paper studies the impact of taxation on the intergenerational income mobility in a dynastic life cycle model in which households decide fertility and time allocation between labor, leisure, and childcare (time investment). 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 link.

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, fertility increases even more. These results stem from the reduction in the life cycle utility and in response to this reduction, households try to increase the utility through dynastic component. We also show that taxes mostly impact 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' decisions (labor in particular) with respect to taxes is 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 analysis presents that the existence of taxes slightly increases the income mobility across generations. Compared to a no tax environment, we see a large increase in the mobility due to higher fertility rates (quantity) and lower educational outcomes (quality), when income taxes are progressive. When the taxes are not progressive but are 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 a similar quality-quantity trade-off with the impact of flat taxes, 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 by considering one of the most important policy tools of governments. We conclude by describing a couple of extensions that we leave for future research. First, we abstract from the marriage decision. One important component of the US tax code is marital status and the impact of taxation on single households' on the intergenerational correlation can be quite significant as the time constraints of singles are much tighter, and consequently, can create a large impact. Second, a potential increase in child-care hours without hurting income stream, which is known as parental leave and widely used in European countries, can impact the intergenerational correlation. Third, the differences in the correlation across races can be studied in a framework where welfare benefits and income taxation are separately modeled.

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Appendices

Tables

Table 11: Structural Estimates of Utility Function's Parameters

Variable	Estimates	Variable		Estimates
Marginal Utility of Income		Disutility/Utility of Choices		
Disposable Income	0.391	Female	Male	
	(0.004)	Labor supply		
Children x Disposable Income	-0.477	No work	Part -time	-0.116
	(0.066)			(0.005)
Children x HS x Disposable Income	0.159	No work	Full-time	0.266
	(0.065)			(0.009)
Children x SC x Disposable Income	0.177	Part-time	No work	-2.020
	(0.066)			(0.003)
Children x COL x Disposable Income	0.228	Part-time	Part-time	-0.681
	(0.065)			(0.009)
Children x HS spouse x Disposable Income	0.070	Part-time	Full-time	-0.686
	(0.016)			(0.008)
Children x SC spouse x Disposable Income	0.093	Full-time	No work	-0.140
	(0.036)			(0.007)
Children x COL Spouse x Disposable Income	0.102	Full-time	Part-time	-0.626
	(0.026)			(0.011)
Children x Black x Disposable Income	0.016	Full-time	Full-time	0.133
	(0.003)			(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: Standard Errors are listed in parenthesis. LHS is a dummy variable indicating that the individual has less than a high school education; HS is a dummy variable indicating that the individual has high school; SC is a dummy variable indicating that the individual has some college education but has not completed college; COL is a dummy variable indicating that the individual has completed college. Disposable Income is family income after taxes.

Table 12: Data Summary Statistics

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

Note: PSID 1968 - 1997 waves are used. The number of observations of families is 16,072. For samples of married individuals, the total number of observations is two times the number of households since table uses both individual and spouse information Standard deviations are listed in the parentheses.

Table 13: Earning Equation and Fixed Effect

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

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

Table 14: Education Production Function

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

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

Tax Function Estimates

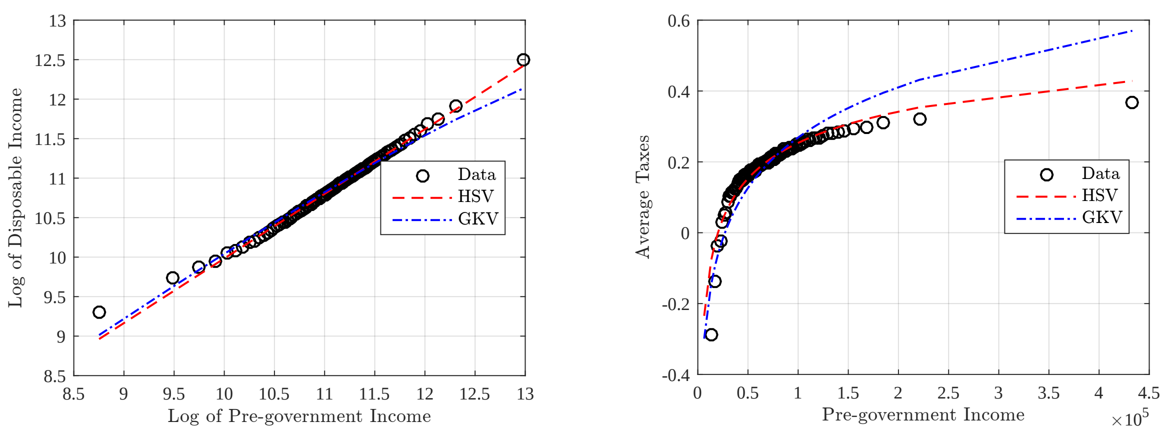
Table 15 shows the tax parameters of *HSV* specification for different post-government income levels, household income minus (i) federal taxes;(ii) minus state taxes; (iii) minus social security taxes (FICA); (iv) plus welfare benefits. We observe that the progressivity increases dramatically when the 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 $\tau_{all,CPS} = 0.103$ and $\lambda_{all,CPS} = 2.421$ when family size is ignored.

Table 16 shows estimates of *Log* specification (see Guner et al. (2014)), which is:

$$t(\tilde{y}) = \chi + \iota \log \tilde{y} \tag{3}$$

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

Figure 4 shows that although both specifications are good fits, *HSV* specification captures top incomes' rates better.



(a) Tax Fits: Log of Income

(b) Tax Fits: Average Taxes

Figure 4: Comparison HSV and GKV Tax Specifications

Table 15: Estimates of HSV Specification with Different Post-Government Incomes

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

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

Table 16: Estimates of *Log* Specification

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

Note: Same restriction stated in Table 1 is applied.