

# The Effects of Assortative Mating on Intergenerational Mobility

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## Abstract

I study the effects of assortative mating on intergenerational mobility. More educated parents invest more time in their children and transfer more resources to them. Children whose parents both hold a college degree outperform children with at least one non-college-educated parent from early ages, and the gap does not close as they acquire education. Because marriages are increasingly between spouses with the same education level, the inequality in children's initial human capital and resources worsens, suggesting increased assortative mating increases income inequality and reduces intergenerational mobility. I extend the standard heterogeneous-agent life-cycle model with earnings risk and credit constraints to allow different degrees of assortative mating to quantitatively evaluate the importance of this mechanism. The model, estimated to the US in the 2000s, implies that if sorting in the marriage market were as low as the least sorted marriage market within the US (at a commuting-zone level), intergenerational mobility would increase by 11%, and inequality, as measured by the Gini coefficient, would decrease by 2%.

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# 1 Introduction

Intergenerational transmission of income is a key dimension of social inequality. During the last century, intergenerational income mobility in the US has significantly decreased. Rates of absolute mobility have fallen from approximately 90% for children born in 1940 to 50% for children born in the 1980s (Chetty et al. (2017)). For children born in the early 80s, there is also substantial variation in mobility across regions within the US (Chetty et al. (2014)). What factors explain these variations? In this paper, I study the effects of sorting in the marriage market on intergenerational mobility. To evaluate its quantitative importance, I develop an overlapping generations model with marriage market in which both parents' education affects children's initial conditions.

Positive assortative mating on spouses' education has grown in recent decades. Despite increases in men's and, most notably, women's educational attainment, the likelihood of men and women with the same level of education marrying each other increased more than what random matching would have predicted. Sorting in the marriage market of parents of children born in 1980 varies significantly across Commuting Zones (CZs) in the United States, as does mobility.

As shown by Fernández and Rogerson (2001), increased sorting significantly increases income inequality. Two key factors to their finding are a decreasing marginal effect of parental education on children's years of education and borrowing constraints that affect educational attainment for some low-income households. In this paper, I show that increased sorting also leads to lower intergenerational mobility, and those factors are also important for this finding.

There is extensive literature on early childhood development and the importance of early investments in children's skill formation as determinants of later socioeconomic success (e.g., Carneiro and Heckman (2003); Cunha et al. (2010)). Estimates of the skill formation technology within an explicit model of household choices find that both mother's and father's time investments are a crucial input in the child's skill formation and outcomes (Del Boca et al. (2014); Verriest (2018)). I show that marriages in which both spouses hold a college degree invest more time with their kids than other marriages, and in particular, both mother and father do so. Thus, higher sorting in the marriage market can amplify differences in early childhood development, increasing differences in initial human capital accumulation.

Del Boca et al. (2014) also find that as children age, parental time becomes less productive, and monetary expenditures productivity increases. I show that

skilled marriages (those with two college-graduated parents) invest more in their kids. Then, an increase in assortative mating increases income inequality across families (Fernández and Rogerson (2001)), increasing the inequality in resources available for monetary investments in children’s development.

I first explore the empirical evidence regarding the relationship between sorting and mobility. To do so, I exploit substantial variation across regions in the US. I focus on the cohort born in 1980-82, for which I have measures of mobility by CZ (<http://www.equality-of-opportunity.org/data/>), and I estimate how sorted were the marriages from which those kids were born using 1980 Census data. I find that CZs with higher sorting present lower rates of mobility.

To quantitatively evaluate the role of the assortative mechanism on intergenerational mobility, I build a heterogeneous-agent life-cycle model with marriage market. The type of marriage (i.e., the education profiles of both parents) influences intergenerational persistence as it affects children’s initial human capital, educational attainment through a school taste parameter, and their initial economic resources.

I estimate the model using simulated method of moments to match moments of the data of the US in the 2000s. The estimated model replicates moments of sorting in the marriage market, intergenerational mobility, and education persistence by type of marriage. I also validate the model by demonstrating its ability to replicate non-targeted moments. I then use the estimated model to evaluate how changes in sorting affect mobility. I find that if sorting were as low as the least sorted marriage market within the US (at a CZ level), mobility would increase by 11%, which is half the standard deviation in intergenerational mobility across CZs (Chetty et al. (2014)).

## ***Related literature***

This paper relates to a growing literature that incorporates early human capital development and intergenerational linkages into Aiyagari-style overlapping-generation life-cycle model to study the determinants of inequality and intergenerational persistence. Abbott et al. (2019) study the importance of liquidity constraints on education attainment in a model with endogenous initial human capital. Daruich (2019) incorporates early childhood investments in a life-cycle model to be able to study the effects of long-run large-scale early childhood policies. Daruich and Kozlowski (2020) study the impact of fertility choices on inequality and social mobility. Daruich and Fernández (2020) incorporate intergenerational linkages to study the dynamic consequences of a universal basic income policy. Finally, Lee and Seshadri (2019) allow

parental time and money investments to evaluate the role of early investments on the persistence of economic status across generations.

In all of these, except for [Abbott et al. \(2019\)](#), the agent is a household. In my model, an agent is an individual and I explicitly model how they match to form a household. This allows me to study how sorting in the marriage market affects mobility. In this sense, my paper is closely related to [Fernández and Rogerson \(2001\)](#), in which they study the effects of sorting on inequality.

The rest of the paper is organized as follows. Section 2 presents the empirical evidence. Section 3 develops the model. Section 4 details the estimation process, and Section 5 validates the model. Section 6 studies the effects of sorting on mobility and Section 7 concludes.

## 2 Empirical Findings

### 2.1 Change in sorting patterns

First, I study how the degree of educational assortative mating changes over time. Although the proportion of couples with the same level of education has increased in recent decades (see, e.g., [Schwartz and Mare \(2005\)](#), [Greenwood et al. \(2014\)](#)), determining whether this is due to secular changes in men’s and women’s educational attainment or changes in educational assortative mating is difficult.

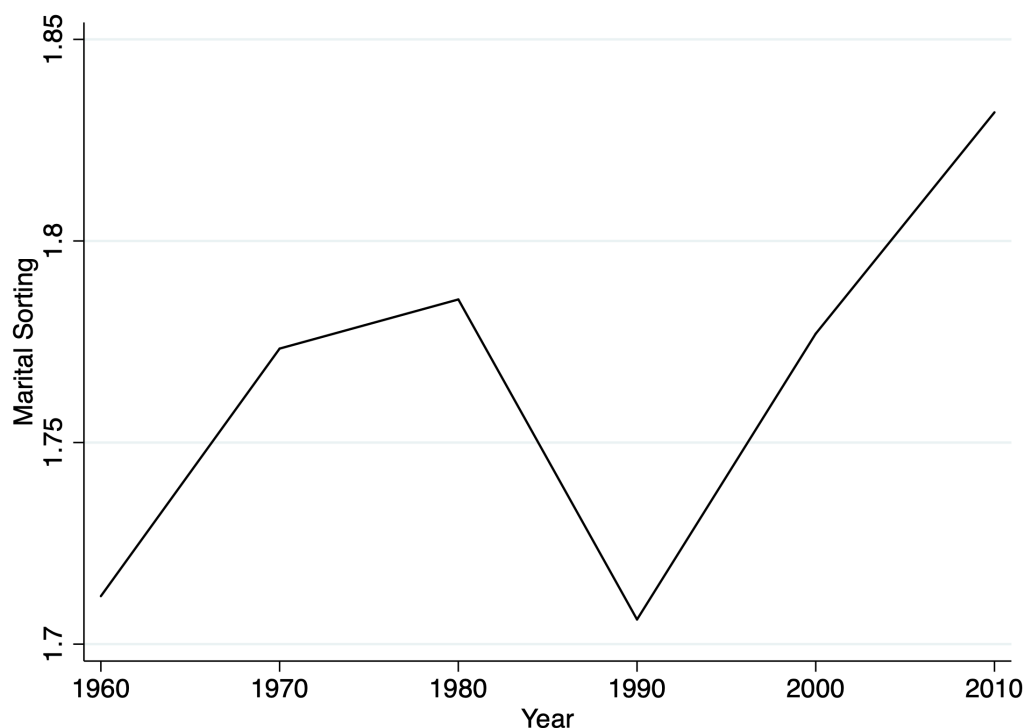
I use IPUMS US Census ([Ruggles et al. \(2020\)](#)) for the years 1960, 1970, 1980, 1990, 2000, and 2010, limiting the analysis to married couples with both spouses aged 24 to 54 and with no missing information on educational attainment, for a total of 4,897,420 households. I assign each individual to one of three mutually exclusive groups: high school dropouts (< 12 years of schooling), high school graduates (12-15 years of schooling), and college graduates (>15 years of schooling), and construct the contingency table for the educational levels of the wife and husband and a contingency table produced by random matching for husbands and wives. Following [Eika et al. \(2019\)](#), to construct an aggregate measure of sorting, I first calculate marital sorting between education levels  $e_f$  and  $e_m$  as the observed probability of a husband with education level  $e_m$  marrying a wife with education level  $e_f$ , compared to the probability under random matching with respect to education:

$$s(e_f, e_m) = \frac{P(E_f = e_f, E_m = e_m)}{P(E_f = e_f)P(E_m = e_m)}$$

where  $E_f(E_m)$  denotes the education level of the wife (husband).

Suppose the parameter  $s(e_f, e_m)$  is greater than one when  $e_f = e_m$ . In that case, it indicates positive assortative mating, meaning that men and women with the same educational level marry more frequently than would be predicted by agents marrying at random in education. Table A2 presents the full set of estimates of  $s(e_f, e_m)$  for all the years under study. For each year, I compute the weighted average of the marital sorting parameters along the diagonal to measure the overall educational assortative mating and study its evolution over the decades. Figure 1 presents the results. In the last 50 years, assortative mating has increased. In Appendix B I discuss an alternative way of studying the evolution of sorting and find a continuous increase in sorting throughout this period.

Figure 1: Marital sorting evolution



*Notes: The figure presents the weighted average of the marital sorting parameters  $s(e_f, e_m)$  along the diagonal for the years 1960, 1970, 1980, 1990, 2000, and 2010. The full set of  $s(e_f, e_m)$  estimates per decade are available in Table A2. Source: IPUMS US Census.*

## 2.2 Marital sorting and intergenerational mobility

To study the correlation between intergenerational mobility and sorting in the (parents') marriage market, I exploit geographical variation in the US at the Commuting Zone (CZ) level in both intergenerational mobility and sorting.

For measures of intergenerational mobility, I use estimates of relative mobility by CZ for the birth-cohort 1980-1982 from [Chetty et al. \(2014\)](#)<sup>1</sup>. The relative mobility measures the correlation between child and parent ranks in their respective income distribution. Children are ranked on their incomes relative to other children in the same birth cohort in their early 30s. Their parents' family income is averaged between 1996 and 2000 and ranked relative to the other parents. They find that the average rise in a child's income rank is 3.41 percentiles for every ten percentile points increase in the parent rank.

In terms of sorting, I evaluate how sorted the marriages from which the cohort 1980-82 was born were. In order to indirectly capture parents of the 1980-82 birth cohort studied by [Chetty et al. \(2014\)](#), I use data from IPUMS 1980 Census ([Ruggles et al. \(2020\)](#)) and select all marriages with a spouse present whose youngest child is at most one year old<sup>2</sup>. Additionally, following [Chetty et al. \(2014\)](#) sample selection criteria, I restrict the analysis to spouses who are between 15 and 40 years old and to those who have information on the level of education attained. The final database consists of 242,656 households. To measure sorting for each CZ, I calculate the marital sorting parameter as described in the previous section.

On average, individuals with the same level of education are nearly 1.8 times more likely to marry each other as compared to the probability of random mating. The degree of assortative mating varies significantly across CZs, as shown in Table 1. In Moses Lake, Washington, for instance, people with the same level of education are 1.4 times more likely to be married to each other than they would be from random mating, whereas in New York, New York, the likelihood rises to 2.1.

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<sup>1</sup>Available to download on <https://opportunityinsights.org/data>

<sup>2</sup>A limitation I face is that I'm assigning marriages to a certain CZs when their kid is at most one year old, while [Chetty et al. \(2014\)](#) assign families to a CZ when children were 16 years old, given that their data starts in 1996. Using more recent cohorts, they calculate that 17% of children don't live in the same CZ at age 16 as they did at age 5. I expect that proportion to increase between ages 16 and 1, but I can't correct this discrepancy

Table 1: Assortative Mating by Commuting Zone

Mean	Standard Deviation	Min	Max
1.78	0.14	1.37	2.46

*Notes: See text for details. Source: IPUMS US 1980 Census (Ruggles et al. (2020)).*

Finally, I examine the correlation between each CZ’s mobility and sorting statistics. To do so, I run the following regression:

$$Relative\_Mobility_{cz} = \alpha + \delta_{cz} Assortative\_Mating_{cz} + \epsilon, \quad (1)$$

Table 2 shows the results. Commuting zones with higher sorting in the marriage market have lower rates of intergenerational mobility; this is, they present a higher correlation between parents and children’s rank in their income distribution. Figures A1 and A2 present heat maps of both intergenerational mobility and sorting across the US.

Table 2: Mobility and Assortative Matching across CZs

	Relative Mobility: Income ranks correlation
<i>Assortative_Mating<sub>cz</sub></i>	0.0725** (0.0279)
<i>Constant</i>	0.196*** (0.0306)
Observations	708

*Notes: Standard errors clustered at the state level in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Sources: Sorting measures from IPUMS US 1980 Census (Ruggles et al. (2020)), mobility measures from <https://opportunityinsights.org/data>.*

### 2.3 Investment and outcomes by marriage type

There is extensive literature on early childhood development and the technology of skill formation. Carneiro and Heckman (2003) and Cunha et al. (2010) highlight the importance of early investment in children skill formation. Carneiro and Heckman (2003) show that cognitive and non-cognitive skills are important factors accounting

for gaps in schooling and later socioeconomic success. [Cunha et al. \(2010\)](#) find that children’s cognitive and non-cognitive skills are to a great extent determined early in life and highlight the presence of dynamic complementarity in the production of skills; this is, skills produced at one stage increase the productivity of subsequent investments.

Building on these studies, [Del Boca et al. \(2014\)](#) and [Verriest \(2018\)](#) estimate the skill formation technology within an explicit model of household choices. [Del Boca et al. \(2014\)](#) find that the mother’s time is a crucial input in the production process of child outcomes and that the father’s time is almost equally productive. They also find that parental time productivity decreases with age, whereas the impact of money expenditures increases with age. However, they estimate that the latter’s impact is modest at any age.

For computational reasons, I will abstract from explicitly modeling household time investment decisions. I will condense the skill formation technology in an intergenerational skill transmission process as an initial draw of human capital. As I show next, both parents from skilled marriages spend more time with their kids than other parents. Thus, I model the initial draw of human capital as a positive function of parents’ educational level. Lastly, [Verriest \(2018\)](#) find that childcare time spent by college-educated parents is the most productive. I abstract now from this result, but it is a future natural extension as it will strengthen the mechanism of intergenerational transmission of skills and the effects of parental sorting by education.

Using the Child Development Supplement of the Panel Study of Income Dynamics (CDS and PSID, respectively hereafter), I explore how parents of different types of marriages invest both time and money differently and how kids perform in test scores.

The PSID is a longitudinal study that began in 1968 with a sample of over 18,000 individuals living in 5,000 households, consisting of a nationally representative sample and an oversample of low-income families. In 1997, 2002, and 2007, the PSID collected detailed data on investment in children and children’s outcomes in the CDS. The original CDS included up to two children per household who were 0 to 12 years old in 1997 and followed those children over three waves, ending in 2007-08. Approximately 3,500 children in 2,400 households were included in the first wave. I restrict the analysis to children of married couples with valid information on educational attainment. I divide the sample into three types of marriages according to whether none, one, or both spouses have a college degree: unskilled, mixed, or skilled. I keep households where the type of marriage does not change across waves. Appendix A.3



describes the sample selection in detail.

The CDS provides rich data on children and their families to study the dynamic process of early human capital formation. In particular, I use the time diaries, information on expenditures on children, and children’s Letter-Word test scores.

Each child in the CDS submits a detailed 24 hours time diary for two days per week, one weekday and one weekend day. In these, they record all activities and who else participated in them. They additionally record the intensity of said participation for parents, this is, whether the parent is actively involved with them (“active time”) or just around (“passive time”). I follow [Del Boca et al. \(2014\)](#) in how to aggregate the data into weekly hours, and I restrict the analysis to active time, as they find this to be the most productive time during the first years.

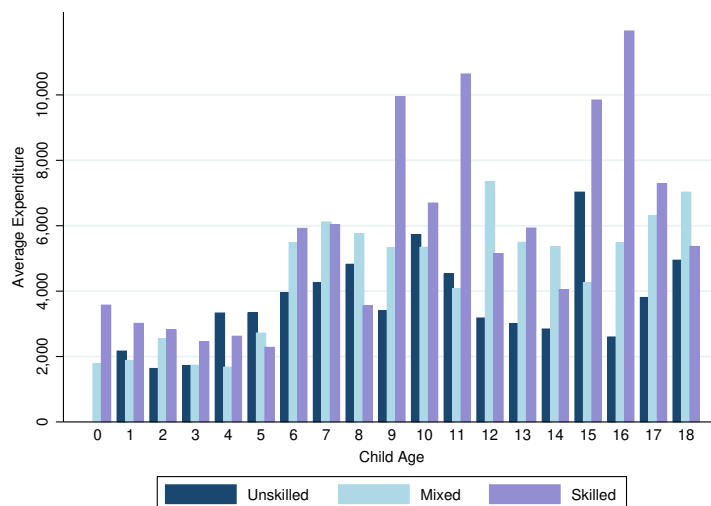
Figure 2 shows the parents’ total active time by child age for each type of marriage. For all parental education combinations, total active time reduces with age. Parents of skilled marriages devote more active time than others for all ages except the first year. Children of skilled marriages spend 6 hours per week more active time with their parents than other children. For children of unskilled and mixed marriages, the comparison is less clear. Averaging across all ages, kids from mixed marriages spend about 1.5 fewer active hours a week with their parents than kids from unskilled marriages, but who spend more or less time with their parents vary greatly with age. Figures A3a and A3b present active times separately for mothers and fathers. Mothers spend more active time with their children in all marriages than do fathers. Consistently with the literature (e.g., [Guryan et al. \(2008\)](#) and [Verriest \(2018\)](#)), I find that more educated parents spend more time with their kids. The difference in total active hours that kids from skilled marriages spend with their parents results from spending more time with their mother and father.

For money investments, I follow [Lee and Seshadri \(2019\)](#) and focus only on expenditures related to children’s skills, such as costs of child care, money spent on schooling (school tuition and school-related supplies), and extracurricular activities (such as private tutoring and lessons). Unlike time diaries and test scores, data on money expenditure is scarce: only about 10 percent of the sample reports childcare expenditure, and only half the parents report extracurricular activities. I follow [Lee and Seshadri \(2019\)](#) in how to aggregate these data.

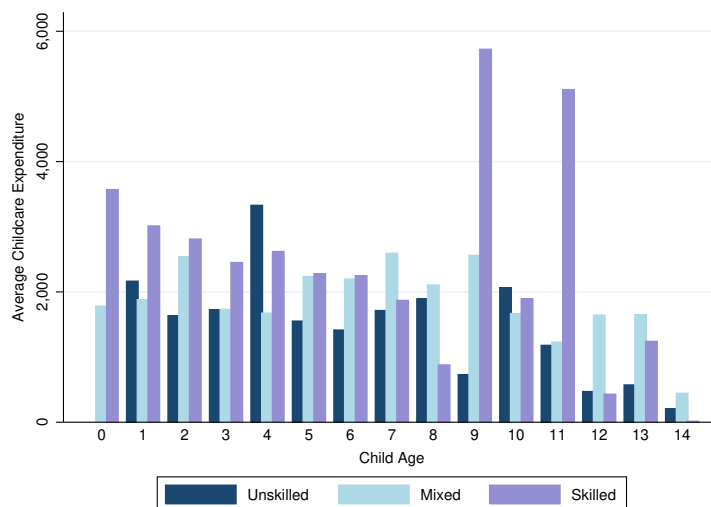
Figure 3 presents the results for total expenditure (the sum of the above three categories) and childcare expenditure in US 2000 dollars, by type of marriage. For the first five years, expenditures are almost solely childcare expenses. After that,

private schooling is the primary source of expenditures. The data is noisy, but skilled marriages invest the most money, particularly during the first years. Afterward, mixed marriages track them pretty closely.

Figure 3: Expenditure by type of marriage



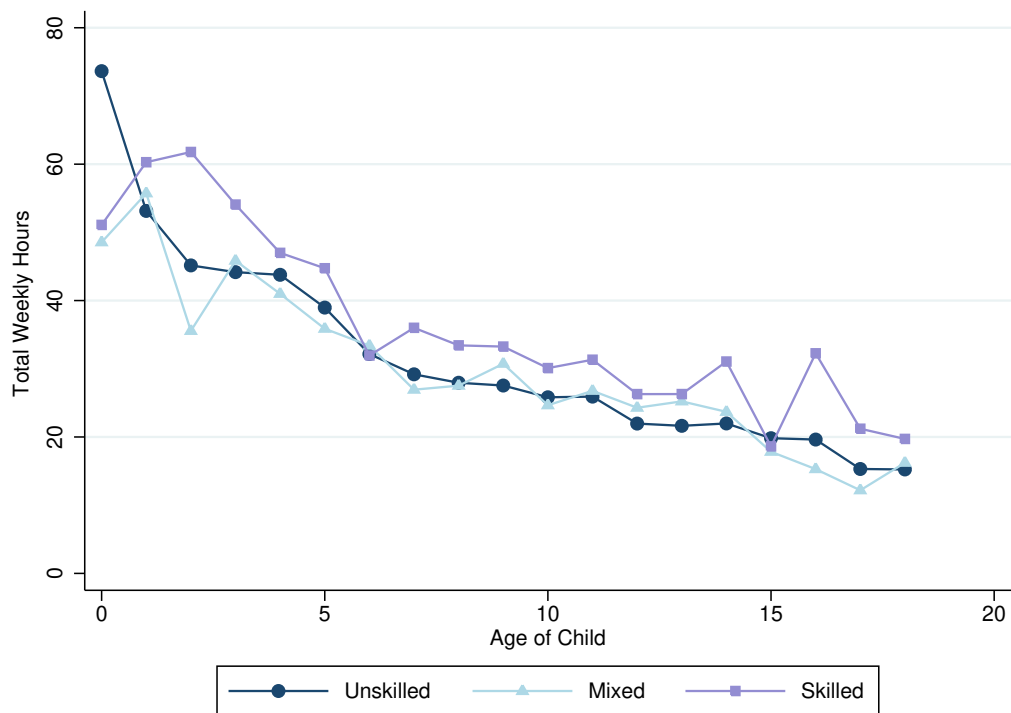
(a) Total expenditure



(b) Childcare expenditure

*Notes: Money investments in children by type of marriage. Panel (a): sum of expenditures on childcare, schooling and extracurricular activities. Panel (b): childcare expenditures. Marriages are categorized according to the presence of none, one or two parents with a college degree: unskilled, mixed, and skilled, respectively. Source: PSID, CDS.*

Figure 2: Total parental weekly time by type of marriage

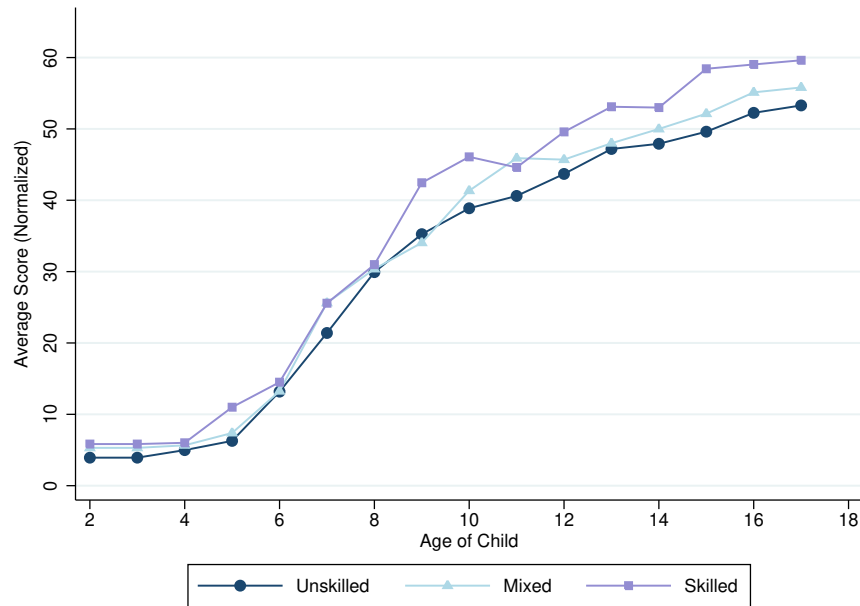


*Notes: The figure presents total active time mothers and fathers spend weekly with their kids by type of marriages. Marriages are categorized according to the presence of none, one or two parents with a college degree: unskilled, mixed, and skilled, respectively. Source: PSID, CDS time diaries.*

Lastly, I look at children outcomes. As is common in the literature, I use the Letter-Word test score that is administered to all kids in the CDS. The test contains 57 questions, and the record indicates whether it was answered correctly (1) or not (0). In order to capture children’s development, instead of raw total score (0-57), I follow [Lee and Seshadri \(2019\)](#) and calculate an adjusted score as follows: instead of 1, each question  $q$  is worth  $d_q = 1/s_q$ , where  $s_q$  is the share of children, regardless of age, that answered it correctly. The total adjusted score is the sum of  $d_q$  across all questions. Figure 4 shows the adjusted scores for children of all types of marriages, normalized to lie between 0 and 100. For all kids, scores increase with age. For all kids, scores increase with age. Consistent with the literature on early childhood development, kids who spend more active time with their parents and later receive higher money investments perform better at early ages. Furthermore, their initial advantage does not disappear but widens as they grow.

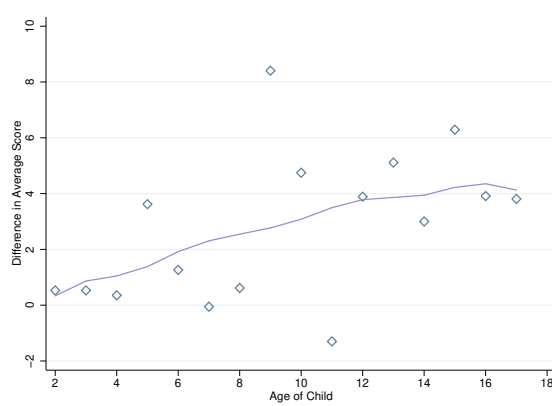
Figure 5 shows how each pair’s difference in average scores evolves. During the first years, there is practically no difference in outcomes between children with only one college-educated parent and children with two. As children age, children of skilled marriages outperform children of mixed marriages. They also perform better than unskilled marriages’ children since their early years, and the gap widens as they age, at a higher rate than it does with children from mixed marriages. Finally, children of mixed marriages perform better than children of unskilled marriages from an early age, but the difference remains fairly constant as they age.

Figure 4: Test scores

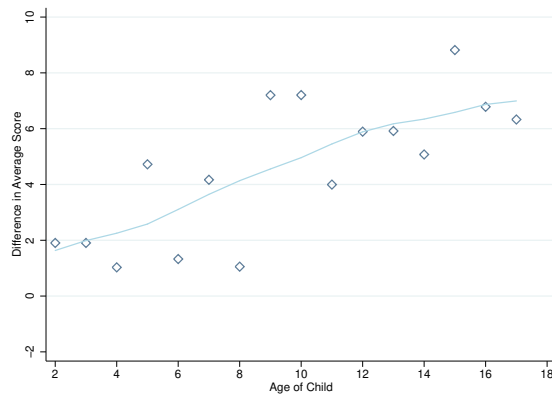


*Notes: Letter-Word adjusted test scores, normalized to lie between 0 and 100, by type of marriage. Scores are computed by weighting each question by the inverse of the share of children, regardless of age, that answered it correctly. Marriages are categorized according to the presence of none, one or two parents with a college degree: unskilled, mixed, and skilled, respectively. Source: PSID, CDS.*

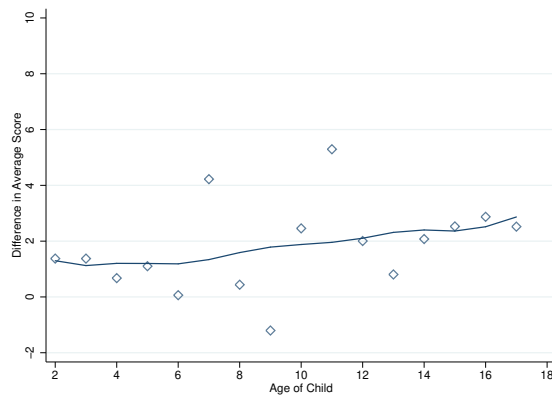
Figure 5: Differences in average scores by types of marriages pairs



(a) Skilled vs Mixed



(b) Skilled vs Unskilled



(c) Mixed vs Unskilled

*Notes: Differences in Letter-Word adjusted test scores, normalized to lie between 0 and 100, by pair of children of different types of marriages. Panel (a): skilled vs mixed marriages. Panel (b): skilled vs unskilled. Panel (c): mixed vs unskilled. Source: PSID, CDS.*

### 3 Model

#### 3.1 Overview

I follow [Daruich and Kozlowski \(2020\)](#) to study how changes in assortative marriage affect intergenerational mobility. I develop a life-cycle model in a dynastic framework with three main stages. The first stage is the education stage, in which agents choose whether to go to college and become skilled or to start working as high-school graduates. Once they exit the education stage, they enter the working stage. Income depends on their level of education, but idiosyncratic and uninsurable income risk makes individual earnings stochastic. They can borrow up to a limit and save through a non-contingent asset. During this stage, they marry an agent from the opposite sex. Once married, agents have kids. When their children become independent, they decide how much to transfer them. Last, at the retirement stage, agents have savings and retirement benefits as a source of income.

Intergenerational transmission of status arises from different sources: transmission of initial skills, school taste which depends on parents' education, and parent-to-child transfers. In section 6, I study how these sources mediate the effect of an increase in sorting on intergenerational mobility.

#### 3.2 Preliminaries

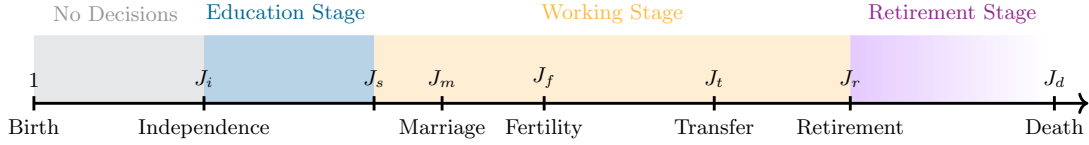
Time is discrete, and each period in the model corresponds to two years. The economy is populated by a continuum of agents, equally as many males as females. Gender is indexed by  $g$  and age by  $j$ .

Figure 6 shows the life cycle of an agent. Agents are born at age  $j = 1$  and live with parents until they reach independence at age  $j = J_i$ . Agents become independent as high school graduates and decide whether to study up until age  $j = J_s$  and enter the working stage as a college graduate or to start working at age  $j = J_i$ . At age  $j = J_m$ , agents marry and form a household. There is no divorce in the model. At age  $j = J_f$ , couples have two kids of the same sex, who live with them for  $J_i$  periods. At  $j = J_t$ , one period before their kids become independent, parents decide how much resources to transfer them. Agents retire at age  $j = J_r$  and live up to age  $j = J_d$ .

Throughout their life, agents decide how much to consume and save. They can borrow up to a limit,  $\underline{a}_{e,j}$ , that varies with age and education through a risk-free bond. The return on savings is  $1 + r$ , and agents pay  $r + \iota$  in interests if borrowing. College students can access subsidized loans.

The income process is determined by three components: human capital, an age profile, and an idiosyncratic shock. The initial human capital is a fixed component that is deterministically transformed by  $f^{s,g}(h_0)$  if agents acquire education. The age profile  $\gamma_{j,g,e}$  depends both on gender and education. The idiosyncratic shock  $z$  is an AR(1) process with persistence  $\rho_{z,g,e}$  and innovation variance  $\sigma_{\xi,g,e}$ .

Figure 6: Life cycle



### 3.3 The individual problem

#### Education stage

At age  $j = J_i$  agents become independent as high school graduates ( $e = 1$ ) and decide whether to go to college and become a college graduate ( $e = 2$ ), which takes two periods, or to start working. Agents' states at this stage are: gender  $g$ , assets  $a$ , initial human capital  $h_0$  and school taste  $\phi$ . When the agent starts to work (either at age  $j = J_i$  or  $j = J_i + 2$ ), the initial value of the persistent income component  $z_0$  is realized.

The cost of attending college is given by  $p_e$ . The total cost of education is also affected by an idiosyncratic school taste or psychological cost,  $\phi$ . This idiosyncratic cost is commonly used in the literature (e.g., [Abbott et al. \(2019\)](#); [Daruich and Kozłowski \(2020\)](#); [Daruich and Fernández \(2020\)](#)) to match the observed education patterns. The school taste affects the value of going to college as a separable element. After college, it does not affect other outcomes.

Agents can access subsidized loans to finance their education up to a limit  $\underline{a}^s$  at rate  $r^s = r + \iota^s$ . As [Daruich and Kozłowski \(2020\)](#) I follow [Abbott et al. \(2019\)](#) and assume that student debt is refinanced into a bond with interest rate  $r^-$ , where  $\tilde{a}^s(a')$  performs the transformation assuming fixed payments during 20 years<sup>3</sup>. During

<sup>3</sup>The formula is given by

$$\tilde{a}^s(a') = a' \times \frac{r^s}{1 - (1 + r^s)^{-10}} \times \frac{1 - (1 + r^-)^{-10}}{r^-}$$



college, agents also work part-time for a wage  $w_{coll}$ .

Let  $V_j^s$  and  $V_j^w$  be the value of an agent at age  $j$  at college or working, respectively. The value function at the beginning of the education stage is given by:

$$V_j(g, a, h_0, \phi) = \max \left\{ V_j^s(g, a, h_0, ) - \psi_g \phi, z \left[ V_j^w(g, a, h_0, e = 1, z) \right] \right\}. \quad (2)$$

The value of becoming skilled,  $V_j^s$ , is defined by:

$$\begin{aligned} V_j^s(g, a, h_0) &= \max_{c, a'} u(c) + \beta \tilde{V}_{j+1}^S \\ \text{s.t. } & c + a' + p_e = a(1 + r) + hw_{coll}(1 - \tau) \\ & a' \geq \underline{a}^s \\ & \log h = \log f^{g,e}(h_0) + \gamma_{j,g,e} \\ & \tilde{V}_{j+1}^S = \begin{cases} V_{j+1}^s(g, a, h_0), & \text{if } j = J_i \\ V_{j+1}^w(g, \tilde{a}^s(a'), h_0, e = 2, z), & \text{otherwise.} \end{cases} \end{aligned} \quad (3)$$

Note that the education decision is irreversible and lasts two periods (4 years). At the last period of the education stage,  $j = J_i + 1$ , the continuation value is given by  $V^w$  as the agent enters the working stage. At that stage, the initial income shock  $z$  will be realized; thus, the expectation with respect to  $V^w$ .

The value of work is given by

$$\begin{aligned} V_j^w(g, a, h_0, e, z) &= \max_{c, a'} u(c) + \beta \left[ V_{j+1}^w(a', h_0, e, z') \right] \\ \text{s.t. } & c + a' = a(1 + r) + wh(1 - \tau) \\ & \log h = \log f^{g,e}(h_0) + \gamma_{j,g,e} + z \\ & z' = \rho_{z,g,e}z + \xi, \quad \xi \sim N(0, \sigma_{\xi,g,e}), \quad a' \geq \underline{a}_{e,j} \end{aligned} \quad (4)$$

### Working stage

From  $j = J_i + 2$  to  $j = J_m - 1$ , agents remain single and their problem is equivalent to 4. At  $j = J_m$ , agents marry, drawing an opposite-sex spouse from a distribution that is estimated to reflect the educational sorting in the data. Following [Fernández and Rogerson \(2001\)](#), agents match as follows. A fraction of marriages  $\pi$  are perfectly matched, with probability  $\pi$  a college (high school) educated agent matches with another college (high school) educated agent, and the remaining fraction matches in

a purely random fashion from the pool of available spouses.

After marriage, the wealth levels of the spouses are combined. I assume that the value is shared equally between spouses and that there is no possibility of divorce. Household preferences are given by  $u(c_m, c_w) = u(c_m) + u(c_w)$ . Following Voena (2015), there are economies of scale in consumption. Total expenditure in order to consume  $c_m + c_w$  is given by

$$c = [(c_m)^\eta + (c_w)^\eta]^{\frac{1}{\eta}}.$$

The optimal allocation of consumption within the marriage requires  $c_m = c_w$ . Hence,  $c = 2^{\frac{1}{\eta}} c_g$ .

Once formed in  $j = J_m$ , the household problem during the working stage is given by

$$\begin{aligned} V_j^w(a, \mathbf{h}_0, \mathbf{e}, \mathbf{z}) &= \max_{c, a'} 2u(c) + \beta \left[ V_{j+1}^w(g, a', \mathbf{h}_0, \mathbf{e}, \mathbf{z}') \right] \\ \text{s.t. } \quad &2^{\frac{1}{\eta}} c + a' = a(1 + r) + w(h_m + h_w)(1 - \tau) \\ &\log h_g = \log f^{g, e_g}(h_{0g}) + \gamma_{j, g, e_g} + z_g, \quad \text{for } g = m, w \\ &z'_g = \rho_{z, g, e_g} z_g + \xi, \quad \xi \sim N(0, \sigma_{\xi, g, e_g}), \quad \text{for } g = m, w \\ &a' \geq \underline{a}_{\mathbf{e}, j} \end{aligned} \tag{5}$$

where bold letters represent vectors comprising both men's and women's states.

## Transfers

At age  $j = J_f$ , agents have two kids of the same sex,  $g_k$ . One period before kids become independent, parents decide how much to transfer  $\hat{a}$  to their children. Transfers are the same for the two children and weakly positive. The problem at the age when

the transfer is made,  $j = J_t$ , is defined as follows:

$$\begin{aligned}
V_j^w(a, \mathbf{h}_0, \mathbf{e}, \mathbf{z}, g_k) &= \max_{c, a', \hat{a}} 2u(c) + \beta[V_{j+1}^w(a', \mathbf{h}_0, \mathbf{e}, \mathbf{z}')] \\
&\quad + 2\lambda\beta V_{j_i}(g_k, \hat{a}, h_k, \phi_k) \\
\text{s.t.} \quad 2^{\frac{1}{\eta}}c + a' - 2\hat{a} &= a(1+r) + w(h_m + h_w)(1-\tau) \\
\log h_g &= \log f^{g, e_g}(h_{0g}) + \gamma_{j, g, e_g} + z_g, \quad \text{for } g = m, w \\
z'_g &= \rho_{z, g, e_g} z_g + \xi, \quad \xi \sim N(0, \sigma_{\xi, g, e_g}), \quad \text{for } g = m, w \\
a' &\geq \underline{a}_{\mathbf{e}, j} \\
h_k &\sim f^k(\mathbf{h}), \quad \phi_k \sim g^k(\mathbf{e}).
\end{aligned} \tag{6}$$

Parents are altruistic. They derive utility from their child's expected lifetime utility through the altruistic weight  $\lambda$ . Children's initial human capital and school taste are stochastic but depend on their parents' human capital and education level, respectively. After children become independent, parents continue to work and their problem is equivalent to 5 until retirement at age  $j = J_r$ .

### Retirement stage

At age  $j = J_r$  agents retire with two sources of income: savings and retirement benefits, which depend on the level of education. The value at this stage is given by

$$\begin{aligned}
V_j^w(a, \mathbf{e}) &= \max_{c, a'} 2u(c) + \beta V_{j+1}^w(a', \mathbf{e}) \\
\text{s.t.} \quad 2^{\frac{1}{\eta}}c + a' &= a(1+r) + \Phi(\mathbf{e}) \\
a' &\geq 0
\end{aligned} \tag{7}$$

## 4 Estimation

The model is estimated using simulated method of moments to match moments of the data. Some parameters can be estimated “externally”, while others must be estimated “internally” from the simulation of the model. For these, I numerically solve for the stationary distribution of the economy and calculate the moments of interest. Details on the computation of the stationary equilibrium are described in Appendix C. Table 5 summarizes all externally calibrated parameters and their sources, and Table 6 reports all internally estimated parameters and the moments used to estimate them.

Finally, the model is validated using non-targeted moments.

The model is estimated to match individual-level data. I use three primary data sources: IPUMS US Census (Ruggles et al. (2020)), Panel Study of Income Dynamics (PSID), and the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). There are two main selection criteria for the data. First, I drop individuals with a total income of that of a person working 20 hours a week for the minimum wage, and I keep only married individuals as there is no divorce in the model. Additional details on sample selections are described in detail in Appendix A.

## 4.1 Parameters

### Life cycle

A period in the model is two years. Individuals become independent at the age of  $J_i = 18$  as high school graduates. If they decide to go to college, the decision is irreversible and lasts two periods until age  $J_s = 22$ . Agents marry at age  $J_m = 26$  and have kids at age  $J_f = 28$ . One period before agents' children become independent, at age  $J_k = 44$ , they choose the monetary transfer to their kids. Agents retire at age  $J_r = 66$  and they all live up until age  $J_d = 80$ .

### Preferences

The period utility function is given by

$$u(c) = \frac{c^{1-\gamma_c}}{1-\gamma_c}.$$

Following the literature, I set  $\gamma_c = 0.5$  (Roys and Seshadri (2014); Manuelli and Seshadri (2009)). The altruism parameter,  $\lambda$  in 6, is internally estimated targeting average transfers from parents to children.

### Prices

All prices are in 2000 US dollars. These are normalized such that the average annual individual income at age 42, \$50,277 in the data, equals one in the model. The yearly price of college is estimated from the Delta Cost Project to be \$6,588. I use Daruich and Kozlowski (2020) estimate of wage while in college to be  $w_{coll} = 0.56$ . The annual interest rate is set at  $r = 3\%$ . The (annualized) wedge for borrowing is set to 10%, which is the average among the values for credit card borrowing interest

rates (net of  $r$  and average inflation) reported by [Gross and Souleles \(2002\)](#). Based on self-reported limits on unsecured credit by a family from the Survey of Consumer Finances, [Daruich \(2019\)](#) estimates the borrowing limits for working-age households to be  $\{20,000, 34,000\}$  for high-school and college graduate households, respectively. I consider the highest education between spouses to assign household borrowing limits.

I use [Voena \(2015\)](#) estimate of economies of scale of spouses' consumption.

## College loans

[Daruich and Kozlowski \(2020\)](#) estimate that college students have access to subsidized loans based on the National Center for Education Statistics report "Student Financing of Undergraduate Education: 1999-2000". They observe that the average loan was similar for federal and non-federal loans, but the former was more commonly used. Among the federal loans, 96% were Stafford loans. The borrowing limit while in college is set to match the cumulative borrowing limit on Stafford loans (\$23,000), and its interest rate  $\iota^s = 0.009^4$ .

## Retirement benefits

The pension replacement rate is set as 33 percent of average earnings within each respective education group, as estimated by [Mitchell and Phillips \(2006\)](#). I estimate average lifetime earning by education groups using IPUMS 2000 US Census ([Ruggles et al. \(2020\)](#)). I keep married individuals with valid education information and drop individuals with income below the equivalent to working 20 hours a week for the minimum wage (approximately \$5,400).

## School taste

Intergenerational persistence of education is difficult to match in this type of models without introducing school taste/non-pecuniary costs of education ([Abbott et al. \(2019\)](#)). As per 2, school (dis)taste affects the value of going to college in the form of a non-pecuniary (physic) cost that affects agents' utility in a linearly separable fashion. After the schooling decision is made,  $\psi_g\phi$  no longer affects outcomes.

I assume the school taste  $\phi$  to be between 0 and 1 and scaled by  $\psi_g$ , which differs by gender. The distribution of  $\phi$  depends on parents' education through parameter

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<sup>4</sup>Stafford offers multiple types of loans, some of which are subsidized and some of which are not;  $\iota^s = 0.009$  amounts to the weighted average interest rate.

$\omega_{\mathbf{e}}$ :

$$G^k(\mathbf{e}, \phi) = \phi^{\omega_{\mathbf{e}}} \quad (8)$$

where  $\mathbf{e}$  represents the parents' marriage type: low, mixed, or high.

The share of women and men college graduates will inform parameters  $\psi_g$ , while the correlation between parents and child's education by type of marriage will be informative of  $\omega_{\mathbf{e}}$ . I target the share of kids who graduate from college for each type of marriage. I use the PSID Transition into Adulthood Supplement, which contains data on young adults in PSID families, to calculate these shares. See Appendix A.4 for details on sample selection.

### Education returns

Acquiring education increases initial human capital deterministically in the following non-linear form:

$$f^g(h) = h + \alpha_g h^{\beta_g}$$

Parameter  $\alpha$  and  $\beta$  are interanally estimated for both genders to match the levels of education returns and the variance of log-income of agents.

### Income process

In addition to a fixed effect transformed by the education choice, the income process has a gender-specific age-education profile  $\gamma_{j,e}$ , and an AR(1) idiosyncratic shock  $z$  with persistence  $\rho_{z,e}$  and innovation variance  $\sigma_{\xi,e}$ .

$$\begin{aligned} \log h &= \log f^{g,e}(h_0) + \gamma_{j,e,g} + z \\ z' &= \rho_{z,e,g} z + \xi \\ \xi &\sim (0, \sigma_{\xi,e,g}) \\ z_{0,e,g} &\sim (0, \sigma_{z_{0,e,g}}) \end{aligned} \quad (9)$$

I estimate the age profile,  $\gamma_{j,e,g}$ , and persistence process  $z$  separately for men and women following [Abbott et al. \(2019\)](#) using, as [Daruich and Kozlowski \(2020\)](#), total labor income instead of hourly wages.

I estimate quadratic age polynomials separately for men and women by education

group using PSID data. For women, I use a Heckman-selection estimator to correct for observation bias in employment. In particular, I construct the Inverse Mills ratio by estimating women’s labor force participation using the number of children and year-region fixed effects separately for each education group. See Appendix A.1 for sampling selection and estimation details. Table 3 present the deterministic age profile for all groups. For both men and women, the higher the education, the steeper the income increases with age. Within the same education groups, men’s profile is steeper than women’s.

Table 3: Income Age Profiles by Gender and Education Group

	Men		Women	
	High School	College	High School	College
<i>Age</i>	0.081*** (0.00236)	0.154*** (0.00320)	0.067*** (0.00380)	0.121*** (0.00526)
<i>Age</i> <sup>2</sup>	-0.0009*** (2.83e-05)	-0.0016*** (3.86e-05)	-0.0008*** (4.58e-05)	-0.00142*** (6.44e-05)

*Notes: Estimated age polynomials’ coefficients. Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Source: PSID.*

I use the NLSY79 labor income data to estimate the AR(1) persistent shock process  $z$ . NLSY79 data is instrumental as it provides a measure of persistent skills, the AFQT89 scores. Thus, using 9 one can filter out both age profiles and ability to recover  $z$ . First, I use the age profiles to filter out age effects and then recover  $z$  as residuals from a regression of log-income on log AFQT89 scores. Second, I use a Minimum Distance Estimator using the covariances of income residuals at various lags for different age groups. Last, I transform the estimates into 2-year periods as I estimated the process using yearly data<sup>5</sup>. Table 4 presents the estimates for all groups.

<sup>5</sup>Given yearly estimates, the corresponding 2-year variables  $\rho_z$  and  $\sigma_z$  are given by:  $\rho_z = (\hat{\rho}_z)^2$  and  $\sigma_z = (1 + (\hat{\rho}_z)^2)\hat{\sigma}_z$

Table 4: Income Process by Gender and Education Group

	Men		Women	
	High School	College	High School	College
Persistence $\rho_{z,e}$	0.95	0.95	0.92	0.95
Variance Income shocks $\sigma_{z,e}$	0.02	0.02	0.05	0.06
Initial dispersion $\sigma_{z0,e}$	0.19	0.14	0.26	0.16

*Notes: 2-year periods estimates. Details on main text. Source: PSID and NLSY79.*

### Transmission of skills

The initial level of human capital is stochastic but correlated with parents' human capital. The initial draw of human capital is governed by

$$\log(h_0) = \mu_{h_0} + \rho[\log(h_p) - \log(\bar{h}_p)] + \epsilon_{h_0} \quad (10)$$

where  $h_p$  is the sum of parents' human capital,  $\bar{h}_p$  is the average human capital of parents at age 42, and  $\epsilon_{h_0} \sim N(0, \sigma_{h_0})$ . Both  $\rho$  and  $\sigma_{h_0}$  are internally estimated. The targeted moments are the intergenerational mobility as measured by the rank-rank coefficient reported by [Chetty et al. \(2014\)](#) for children of married parents, which helps pin down  $\rho$ , and the variance of the log income at age 28-29, which informs  $\sigma_{h_0}$ .

### Marriage market

Parameter  $\pi$  dictates how agents match at age  $j = J_m$ . I estimate it to match the degree of sorting in the marriage market. I use the 1980 IPUMS US Census ([Ruggles et al. \(2020\)](#)) and restrict the sample to married households with a spouse present, with a minimum of \$8,000 household income (equivalent to one household member working for a year at a minimum wage) and with valid information of education level, for a total of 1,590,442 households. I then regress the education of the wife over the education of the husband. The coefficient is equal to 0.53.

## 4.2 Results

Table 5 summarizes the remaining externally estimated parameters. There are thirteen parameters left that are estimated using simulated method of moments with thirteen targeted moments. Parameter  $\lambda$  relates to altruism;  $\rho$  dictates intergenerational persistence of skills through the initial draw of human capital, while  $\sigma_{h_0}$  defines



the standard deviation of the initial draw. Four parameters define returns to education for men and women:  $\alpha_M, \beta^M, \alpha^W, \beta^W$ . Five parameters relate to the distribution of school taste and its relation to parents' education:  $\psi_M, \psi_W, \omega_t$ , for  $t \in \{L, M, H\}$ . Lastly,  $\pi$  determines the degree of assortative matching.

Table 6 shows the estimated parameters together with the targeted moments in the simulated economy. The model provides a good fit to the data.

Table 5: Externally estimated parameters

Parameter	Value	Description	Source
<i>Prices</i>			
$w_{coll}$	0.56	Wage while in college	<a href="#">Daruich and Kozlowski (2020)</a>
$\tau$	0.124	Payroll tax	Social Security
$p_e$	6,588	Annual Price of college	Delta Cost Project
$\Phi(1)$	10,674	Annual Pension HS graduate	US Census
$\Phi(2)$	22,191	Annual Pension Coll graduate	US Census
<i>Financial markets</i>			
$r$	3%	Interest rate	<a href="#">Smets and Wouters (2007)</a>
$\underline{a}_1$	20,000	Borrowing limit HS	<a href="#">Daruich (2019)</a>
$\underline{a}_2$	34,000	Borrowing limit College	<a href="#">Daruich (2019)</a>
$\iota$	10%	Borrowing-savings wedge	<a href="#">Gross and Souleles (2002)</a>
$\iota^s$	1%	College loan wedge	<a href="#">Daruich and Kozlowski (2020)</a>
<i>Preferences</i>			
$\beta$	0.975	Discount factor	Standard
$\gamma_c$	0.5	Risk aversion	<a href="#">Roys and Seshadri (2014)</a>
<i>Economies of scale</i>			
$\eta$	1.4	Economies of scale of consumption	<a href="#">Voena (2015)</a>

Table 6: Internally estimated parameters

Parameter	Value	Moment	Data	Model
<i>Altruism</i>				
$\lambda$	0.84	Parent-to-Child Transfer	0.77	0.78
<i>Initial Draw of HC</i>				
$\rho$	0.50	Rank-Rank income correlation	0.29	0.28
$\sigma_{h0}$	0.27	Variance of log income	0.33	0.33
<i>Education returns for Men</i>				
$\alpha^M$	0.11	log(y) ratio: College - High School	0.38	0.44
$\beta^M$	0.36	Var of log(y): College	0.28	0.22
<i>Education returns for Women</i>				
$\alpha^W$	0.14	log(y) ratio: College - High School	0.44	0.44
$\beta^W$	0.24	Var of log(y): College	0.28	0.29
<i>College taste</i>				
$\psi_m$	28	College share: men	0.34	0.38
$\psi_w$	23	College share: women	0.32	0.35
$\omega_L$	1.80	Education persistence: unskilled parents	0.21	0.22
$\omega_M$	0.94	Education persistence: mixed parents	0.43	0.43
$\omega_H$	0.53	Education persistence: skilled parents	0.66	0.62
<i>Marriage sorting</i>				
$\pi$	0.61	Sorting	0.53	0.56

*Sources: Parent-to-Child transfers per-child as a share of mean income from Daruich and Fernández (2020). Intergenerational mobility of income is the rank-rank correlation for children of married parents from Chetty et al. (2014). Variance of log(income), education returns, and education shares are calculated from 2000 IPUMS US Census data (Ruggles et al. (2020)). Education persistence refers to the share of children from a given marriage type that graduate from college, calculated from PSID-TAS. Sorting is calculated as the coefficient of a regression of wife's education on husband's education using 1980 IPUMS Census data (Ruggles et al. (2020)).*

## 5 Validation

I test the model estimation by computing moments not targeted by the estimation. Table 7 shows the results. The estimation targeted and matched the correlation between parents and children's rank in their respective income distribution. However, the model also matches another measure of mobility, absolute upward income mobility. The estimated model also generates inequality measures, such as the Gini coefficient and the top-bottom income ratio, in line with the data.

Table 7: Validation: Non-targeted moments

Moment	Data	Model
<i>Intergenerational Mobility</i>		
Absolute Mobility	0.50	0.51
<i>Inequality</i>		
Gini	0.30	0.28
Top-Bottom	3.7	3.3
<i>Sources: Absolute upward income mobility from Chetty et al. (2017). Gini and Top-Bottom from Daruich and Fernández (2020)</i>		

## 6 Counterfactual

In order to study the effects of sorting on mobility I use the estimated model to run different experiments. If sorting was as low as the least sorted marriage markets within the US <sup>6</sup>, intergenerational mobility would increase by 11% and the Gini coefficient decrease by 2%.

## 7 Conclusion

In this paper, I studied how assortative mating affects intergenerational mobility. I first explored empirical evidence on the relationship between sorting and mobility by exploiting regional variation across the US. I found that for children born in CZs in which parents were married more assortatively, their position in the income distribution is more affected by that of their parents.

I then extend a heterogenous agent life cycle model to incorporate the marriage market to study the quantitative importance of the mechanism. I found that if sorting were as low as the least sorted marriage market within the US (at a CZ level), mobility would increase by 11%.

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<sup>6</sup>A coefficient of 0.44 instead of 0.56 in a regression of wife’s education on husband’s education, equal to the bottom 5%.

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## **A Data**

### **A.1 PSID: Main interview**

To estimate age profiles by sex and education level I use PSID data using both head and spouses from the original SRC sample who are between 22 and 65 years of age. I exclude income observations if the agent is self-employed. I keep individual with at least 8 observations and without extreme changes in income (defined as changes in log-earnings larger than 4 or less than -2). The final sample consists of 11,542 individuals: 3,420 high school graduate women, 2,125 college graduate women, 3,432 high school graduate men, and 2,563 college graduate men.

### **A.2 NLSY79**

The NLSY79 sample selection is as follows. I start with 12,686 individuals (355,208 observations), and keep observations between the ages of 24 and 63, reducing the number of individuals to 11,976 (178,605). I keep only the cross-sectional sample, reducing the number of individuals to 11,122 (173,687). I drop observations with top-coded earning, reducing the number of observations to 171,608. I drop individuals with less than a high-school degree, and those who change education groups. These reduces the number of individuals to 9,717 (141,985). I further drop individuals with missing AFQT89 information, which leaves 8,426 individuals (123,865). Dropping individuals who report positive hours but less than 5,000, and hourly wages above \$400 or below half the minimum wage further reduces the sample to 8,195 individuals (90,839). Finally, keeping individuals with at least 8 observations and who do not report extreme changes changes of income (i.e., above 400% or reduction by 66%) reduces the sample to 5,201 individuals (74,349). I split the sample in 4 groups by gender and education and I get the following final samples: 2,306 high-school women (26,653), 848 college women (10,481), 2,049 high-school men (28,099) and 681 college men (9,116).

### **A.3 PSID: CDS**

The CDS contains information on children's primary and secondary caregivers, who are not necessarily their parents. Using household and individual identifiers I get information on these adults merging the CDS with the main PSID study files. I keep only children who live with a married biological parent, and for which education on

both spouses is available. Additionally, I only keep children for which their parents' type of marriage does not change across waves. I also drop children if one parent is less than 18 or more than 42 year older than her. This leaves 3,150 observations across the three waves. 59.5% of them are kids from unskilled marriages, 21% from mixed marriages, and 19.5% from skilled ones.

For expenditure data, the sample is smaller. For childcare costs, there are only 620 observations across waves. There is more attrition for unskilled marriages, with only 50% of the observations belonging to kids from unskilled marriages. For any type of expenditure (childcare, schooling, or extracurricular), there are 2,432 observations in total. 56.5% of them are kids from unskilled marriages, 22.3% from mixed marriages, and 21.2% from skilled ones.

#### A.4 PSID: TAS

The Transition into Adulthood Supplement (TAS) began in 2005 to follow children from the original CDS cohort into young adulthood, collecting six waves of data through 2015. As for the CDS sample, using household and individual identifiers I get information on these young adult's parents merging the TAS with the main PSID study files.

I keep only young adults who are at least 22 years old, and define them as college graduates or not according to the maximum level of education attained across waves. This leaves 2,600 observations across waves.

## B Alternative Measure of Sorting

Drawing from [Fernández and Rogerson \(2001\)](#), [Abbott et al. \(2019\)](#) formulate an alternative measure of sorting that I hereby use to study the evolution of sorting. Let  $g_m$  and  $g_f$  be the distribution of male and female education respectively across the three education levels, and  $Q^{data}$  be the observed joint distribution.

With  $g_m$  and  $g_f$  one can construct two possible joint distributions. The “*random*” or “*non-assortative*” joint distribution,  $Q_N = g'_f \times g_m$ . And the “*assortative*” joint distribution,  $Q_A$  in which: the measure of exact spousal education matches is maximized, and among the residual mass of agents, the attainment differential is minimized.

Given these two distributions, a third one,  $Q_\nu$ , can be created by mixing the

assortative and non-assortative distributions:

$$Q_\nu(\nu) = \nu Q_A + (1 - \nu) Q_N$$

The degree of assortativeness can be estimated by estimating  $\nu$  such as

$$\hat{\nu} = \operatorname{argmin} ||Q - Q_\nu(\nu)||$$

I estimate  $\nu$  for the period 1960-2010, Table A1 presents the results. According to this alternative measure too, sorting has been increasing for the last 50 years.

Table A1: Evolution of  $\nu$ , 1970-2010

Year	$\nu$
1970	0.434
1980	0.442
1990	0.466
2000	0.473
2010	0.471

*Notes: See text for details.*

*Source: IPUMS US Census (Ruggles et al. (2020)).*

## C Computation of Stationary Equilibrium

In order to solve for the steady state, I do the usual guess-and-verify nested fixed-point algorithm, adding a guess over the distribution of potential future spouses. Besides prices, there is the need to guess the initial value function at independence age,  $V_{*j_i}$  to solve for parents' problem 6. Additionally, in order to solve the problem at the last period as singles, agents need to guess the distribution over states of their potential spouses, besides  $\pi$ , in order to calculate  $V_{J_m}$ . This is, they need to guess the probability measure over the state space at the beginning of period  $j = J_m, \mu_m$ , and, in equilibrium, that guess should be correct.

The algorithm is then as follows:

1. Guess prices. In this case, the mean draw of human capital, as wages are normalized to 1.

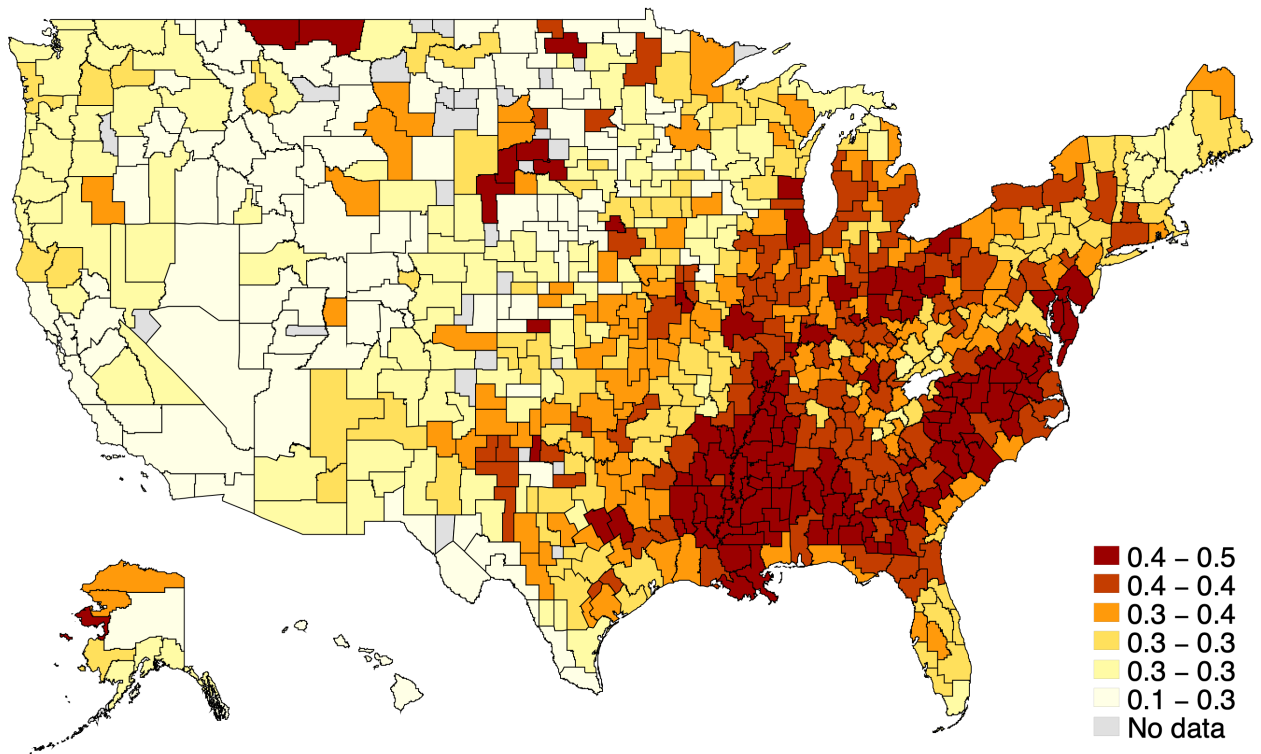


2. Guess the value of the problem at the beginning of the education stage,  $V_0^*$ . Guess the distribution of agents over the state space at the beginning of period  $J_m$  before marriage matches occur,  $\widetilde{mu}_m^0$ .
3. Given guesses, solve by backward induction the dynamic programming problems described in Section 3. Solve back until the education stage and obtain its value,  $V_1^*$ . Update guess  $V_0^*$ , and iterate over this step until  $V_0^*$  and  $V_1^*$  converge.
4. Armed with the optimal policy functions, calculate the equilibrium probability measure over the state space. For this, guess an initial density at age  $j = J_i$ ,  $\mu_{J_i}^0$ . Given guesses, the transition functions generated by the optimal policies and the exogenous processes, compute the probability measures forward until the age of parental transfers. Last, use the optimal transfer policy, draw of school taste, and draw of initial human capital to compute the initial distribution over the state space of the new generation,  $\mu_{J_i}^1$ . Iterate until  $\mu_{J_i}^0$  and  $\mu_{J_i}^1$  converge.
5. Use recently computed  $\mu_{J_{m-1}}^0$  and optimal policy functions at  $j = J_{m-1}$  to calculate distribution over state space were the agents to remain single. This is, the distribution of agents at the beginning of period  $j = J_m$ , right before being matched,  $\widetilde{mu}_m^1$ . Update  $\widetilde{mu}_m^0$  and go back to step 3 until convergence.
6. Compute the probability measures for  $j > J_t$ . Calculate mean income at age 42, if different to 1 (normalization), update guess of the mean of  $h_0$  and go back to step 2.

## D Additional Tables and Figures

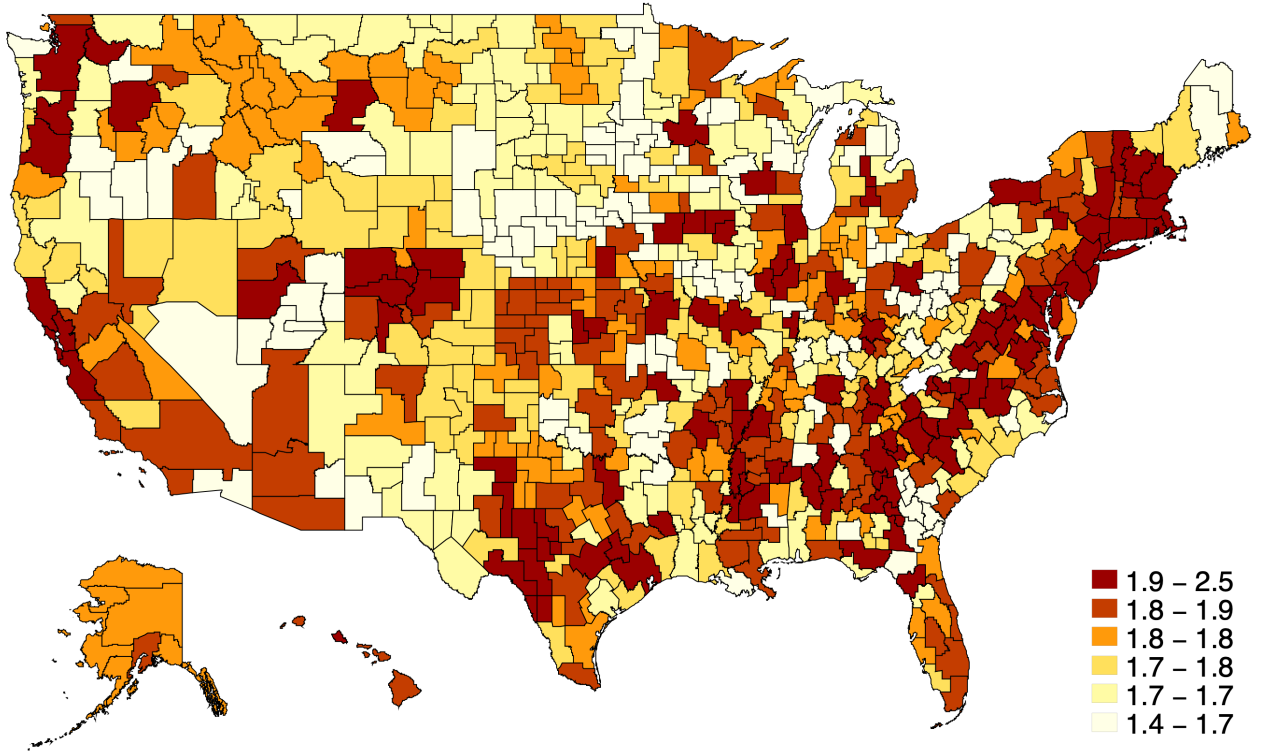
Figures A1 and A2 present heat maps of intergenerational mobility and sorting in the marriage market by CZs respectively.

Figure A1: Relative Mobility: Rank-Rank Slope by CZ



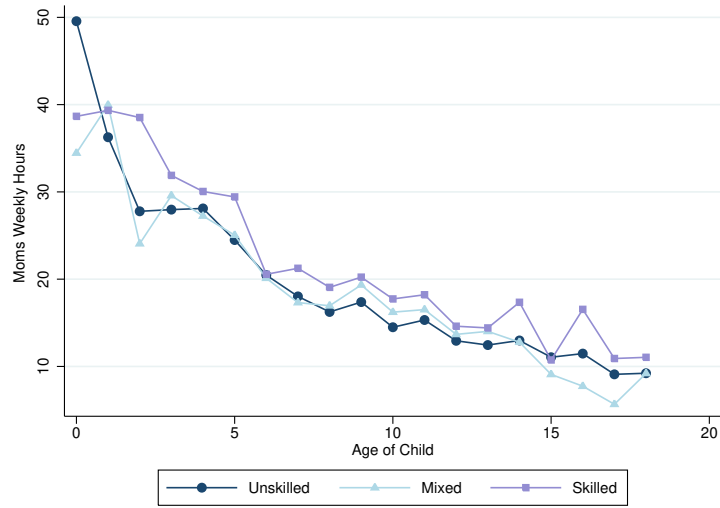
Notes: Heat map of relative mobility across the US. Source: <https://opportunityinsights.org/data>.

Figure A2: Assortative Mating by CZ

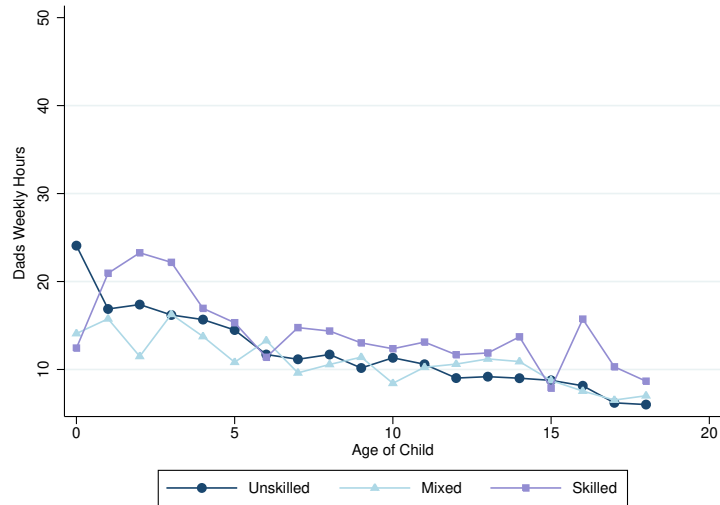


*Notes: Heat map of assortative mating across the US. Assortative mating is calculated as the weighted average of the marital sorting parameters  $s(e_f, e_m) = \frac{P(E_f=e_f, E_m=e_m)}{P(E_f=e_f)P(E_m=e_m)}$  along the diagonal of the full contingency table for each CZ. The sample contains spouses between 15 and 40 years of age with valid educational attainment information and whose youngest child is at most one year old. Source: IPUMS US Census, 1980.*

Figure A3: Average weekly active time by parents and type of marriage



(a) Mother active time



(b) Father active time

Notes: The figure presents total weekly active time spent with kids by time of marriage. Panel (a): mothers; panel (b): fathers. Marriages are categorized according to the presence of none, one or two parents with a college degree: unskilled, mixed, and skilled, respectively. Source: PSID, CDS time diaries.

Table A2: Marital Sorting Parameters

Wife education	Husband's education		
	HS Dropout	HS Graduate	College Graduate
	1960		
HS Dropout	1.5237	0.5729	0.1459
HS Graduate	0.6388	1.4146	1.2216
College Graduate	0.1562	0.7734	5.1753
	1970		
HS Dropout	1.8725	0.6496	0.1372
HS Graduate	0.6631	1.2704	0.9747
College Graduate	0.1408	0.5345	3.9998
	1980		
HS Dropout	2.7282	0.7184	0.1214
HS Graduate	0.7009	1.2181	0.7865
College Graduate	0.1088	0.4673	2.9163
	1990		
HS Dropout	4.3355	0.7914	0.1036
HS Graduate	0.8022	1.2040	0.6523
College Graduate	0.1142	0.4941	2.4124
	2000		
HS Dropout	5.7878	0.7548	0.1080
HS Graduate	0.8085	1.2649	0.5607
College Graduate	0.1397	0.5210	2.1343
	2010		
HS Dropout	6.8271	0.7042	0.0904
HS Graduate	0.8666	1.3312	0.5029
College Graduate	0.1242	0.5744	1.8870

*Notes: This table presents estimates  $s(e_f, e_m)$  for all possible types of marriages for spouses between ages 24-54. Source: IPUMS USA Census (1960, 1970, 1980, 1990, 2000, 2010).*