Sorting in the Marriage Market: The Role of Inequality and its Impact on Intergenerational Mobility

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November 2022

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Abstract

I study the causes and consequences of increased sorting in the marriage market. First, I exploit differential effects of a trade-induced labor demand shock by gender and education level to study who marries whom and why. I find that increased skill premium for men leads to increased sorting in the marriage market, as it deters marriage formation between college-educated women and high-school-educated men. Second, 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, and children whose parents both hold a college degree outperform children with at least one non-college-educated parent from early ages. Increased sorting can then lead to higher inequality in children's initial human capital development, curtailing 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%.

*I am indebted to Raquel Fernández and Martin Rotemberg for their continuous advice on this project. I especially thank Sharon Traiberman, Elena Manresa, David Cesarini, Matias Covarrubias, and Josué Cox for valuable comments and insightful conversations. I also thank participants of the NYU Applied Micro lunch and the weekly Martin Rotemberg advisees' discussion group for helpful comments. Comments are welcome.

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1 Introduction

Assortative mating has been increasing in the US in recent decades[1]. Increased sorting in the marriage market can significantly increase the degree of income inequality (Fernández and Rogerson (2001)), and, if more educated parents invest more time in their children and transfer more resources to them, increased sorting can further curtail intergenerational mobility. In this paper I first exploit trade-induced exogenous changes in inequality and the relative economic stature of men versus women to study what drives the observed changes in marriage patterns. Second, I study the effects of sorting in the marriage market on intergenerational mobility. I show that children whose parents both hold a college degree spend more time with their parents and outperform children with at least one non-college-educated parent from early ages, and the gap does not close as they acquire education. To evaluate the quantitative importance of the sorting mechanism on intergenerational mobility, I develop and estimate an overlapping generations model with marriage market in which both parents' education affects children's initial conditions.

Why is sorting in the marriage market increasing? What determines who matchs with whom? Becker's seminal paper (Becker (1973)) on household formation proposes that marriage's economic gains arise from earnings differences in the labor market, which leads to household specialization to exploit comparative advantages: married women perform almost all household work and married men focus on market work. As household technology improved (e.g., electric washing machines and microwaves) and the labor force participation of married women increased, the traditional gender specialization norm weakened. To account for marriages with little gender-based division of labor, the literature turned to models in which gains from marriage stem from joint consumption (e.g., Fernández et al. (2005); Stevenson and Wolfers (2007)), or the joint production of public goods, such as children's human capital (e.g., Chiappori et al. (2017)). In these models, spouses' human capital are complements, and thus, an increase in the skill premium affects the incentives of whom to marry: if inequality increases, matches between different classes of individuals are less likely, as the cost of marrying down increases (Fernández et al. (2005)). I confirm these models prediction exploiting a trade-induced labor market demand shock that exogenously affects men's skill premium.

I study how a labor-demand shock caused by increased Chinese import competi-

[1] See, e.g., Schwartz and Mare (2005)

tion affected workers differently depending on their educational level and gender, as well as the implications of these differential effects on the marriage market. I find that high-school-educated workers are disproportionately affected, particularly men: (i) Unemployment increases for high-school-educated men and women, but women are able to compensate for most job losses by moving to non-manufacturing sectors; (ii) the gender gap in annual earnings decreases for high-school-educated workers but not for college-educated ones; and (iii) the skill premium increases for men and not for women. I study the consequences of these changes on marriage prevalence across different types of matches based on the education level of the spouses. Contrary to Becker's model of household specialization prediction, the decrease of relative stature of high-school-educated men versus high-school-educated women does not lead to a decrease in their marriage prevalence. Consistent with models in which spouses' human capital are complements, the increase in inequality increases assortative mating: the trade-induced decrease in marriage prevalence is driven entirely by college-educated women marrying less often with high-school-educated men, as the increase in men's skill gap increases women's cost of "marrying down".

In the second part of the paper, I study the consequences of increased sorting on intergenerational mobility. The literature on early childhood development stresses 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)). Both mother's and father's time investments have been shown to be crucial inputs in the child's skill formation and outcomes, and, as children age, monetary investments become relatively more productive (Del Boca et al. (2014); Verriest (2018)). I show that in marriages in which both spouses hold a college degree, both the mother and father invest more time with their kids than in other marriages, and that they also invest more resources in their kids. Additionally, looking at different measures of cognitive skills, I find that children from skilled marriages (i.e., both parents hold a college degree) outperform children from other type of marriages since young ages. Thus, higher sorting in the marriage market can amplify differences in early childhood development, increasing differences in initial human capital accumulation.

I exploit substantial variation both in mobility and sorting across regions in the US to analyze the empirical correlation between sorting and mobility. I focus on the cohort born in 1980-82, for which I have measures of mobility by Commuting Zone (CZ)[2], and I estimate how sorted were the marriages from which those kids were born

[2] Available at http://www.equality-of-opportunity.org/data/

using 1980 Census data. I find that CZs with higher sorting present lower rates of intergenerational mobility.

Finally, 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.

Related literature

This paper relates to several literatures. First, as previously discussed, it is related to the economics of the family and the determinants of who marries whom. Second, it belongs to the literature on the effects of increased import competition from China on local labor markets. Labor markets more exposed to import competition from China experienced larger declines in manufacturing employment, employment-population ratios, earnings for low-wage workers (Autor et al. (2013); Autor et al. (2014); Pierce and Schott (2016)); and larger increases in childhood and adult poverty, single-parenthood, and mortality related to drug and alcohol abuse, as well as greater uptake of government transfers (Autor et al. (2019))[3]. In integrating these two literatures my paper is close to Autor et al. (2019). They show how shifts in the relative economic stature of young men versus young women affected marriage prevalence. In this paper, I show that the effects on labor and marriage markets outcomes vary by education and gender, and rather than shifts in the relative economic stature of men versus women, what drives the effects on the marriage market is the increased skill premium for men.

Third, this paper relates to a growing literature that incorporates early human capital development and intergenerational linkages into Aiyagari-style overlapping-

[3]See Autor et al. (2016) and Redding (2020) for a literature review

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.

The rest of the paper is organized as follows. Section 2 describes the increase in assortative mating. Section 3 presents the effects of increased import competition from China on marriage patterns. Section 4 shows how investment in kids and kids' outcomes vary by marriage type, and the geographical correlation between sorting and integenerational mobility. Section 5 develops the model. Section 6 details the estimation process, and Section 7 validates the model. Section 8 studies the effects of sorting on mobility and Section 9 concludes.

2 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.

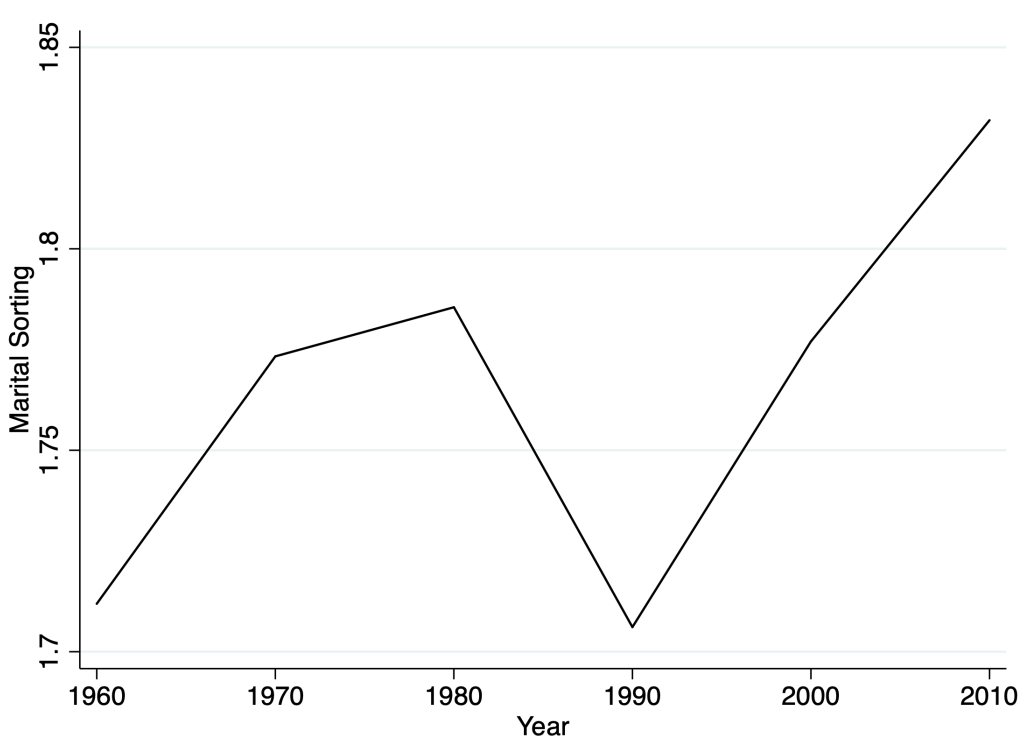
I use IPUMS US Census (Ruggles et al. (2020)) for the years 1960, 1970, 1980, 1990, 2000, and 2010, limiting the analysis to married couples with both spouses aged 24 to 54 and with no missing information on educational attainment, for a total of $4,897,420$ households. I assign each individual to one 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 A6 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 martial 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 A6. Source: IPUMS US Census.

3 Labor shock effects on marriage patterns

3.1 Empirical Strategy

My empirical strategy builds on Autor et al. (2013) and Acemoglu et al. (2016). I exploit regional variation in exposure to rising manufacturing competition from China, stemming from initial differences in industry specialization across US Commuting Zones (CZs), to understand how shocks to the labor market affect employment and marriage patterns.

The measure of the local labor market shock is the average change in Chinese import penetration in a CZ's industries, weighted by each industry's share in initial CZ employment:

$$\Delta IP_{i\tau} = \sum_j \frac{L_{ij90}}{L_{i90}} \Delta IP_{j\tau}. \tag{1}$$

Where $\Delta IP_j = \frac{\Delta M_{j\tau}}{Y_{j91}+M_{j91}-X_{j91}}$ is the growth of Chinese import penetration in the US for industry j over period τ, computed as the growth in US imports from China divided by initial absorption in 1991 (pre-shock). The change in import penetration for industry j is apportioned to each CZ according to the share of industry j in CZ i's total employment, as measured in County Business Patterns data in 1990.

I study the causal effects of trade shocks on employment and marital status of the young-adult population ages 25-34 by fitting models of the form

$$\Delta Y_{si\tau} = \alpha_\tau + \beta_1 \Delta IP_{i\tau} + \mathbf{X}'_{i\tau}\beta_2 + e_{si\tau}. \tag{2}$$

Here, $\Delta Y_{si\tau}$ is the decadal-equivalent change in outcome Y over period τ in CZ i among group s. I estimate equation (2) stacking differences across two periods, 1990 to 2000 and 2000 to 2014, including a dummy for the second period, α_τ The control vector $\mathbf{X}'_{i\tau}$ contains start-of-period CZ-level covariates to control for labor force and demographic composition.

A concern estimating equation (2) is that increased imports from China might be the result of a demand shock as the US experiences a structural change in its manufacturing employment. To identify the exogenous supply-driven component of increased Chinese import penetration in the US I instrument ΔIP_j with realized industry-level growth of Chinese imports in other eight developed countries [4]:

$$\Delta IP^O_{i\tau} = \sum_j \frac{L_{ij80}}{L_{i80}} \Delta IP^O_{j\tau}. \tag{3}$$

Additionally, the start-of-period employment shares are replaced with lagged values to mitigate simultaneity bias. The identifying assumption is that the common within-industry component of rising Chinese imports in the US and other high-income countries are a result of China's increased productivity and trade costs [5].

All outcome variables are constructed from IPUMS US Census 1990 and 2000, and pooled American Community Survey samples from 2013 through 2015 (Ruggles et al. (2020)). I allocate the Census geographic units, Public Use Microdata Areas (PUMAs), to CZs using the crosswalks in Dorn (2009)[6]. I keep all men and women aged 25 to 34. I define high school graduates as those whose educational attainment

[4]The eight comparison countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[5]See Autor et al. (2013) for a test against correlated demand shocks and an alternative estimation strategy using a gravity model of trade which yields similar results

[6]Crosswalks files are publicly available at `https://www.ddorn.net/data.htm`.

is 12th grade, I do not include those with some college. College graduates are all individuals with at least 4 years of college. For marital status, I define as married those individuals married with spouse present.

3.2 Labor market outcomes

I first study how increased trade competition affects employment by gender and education level. To do so, I estimate equation (2) where $\Delta Y_{si\tau}$ is the change in employment share of the population aged 25-34 in CZ i among group s during period τ.

Table 1 estimates the effect of increased trade exposure on employment shares for men and women. Increased import competition reduces employment for men but not among women (Panel A and B, column I). A one unit trade shock (almost equivalent to the average decade-level rise over this period) reduces the share of employed men by 1.3 percentage points, while the decrease in women's employment share is not statistically significant. Table 1 also studies how the effects on employment vary by educational level. Men's employment share decline is driven by employment loss for high school graduates. An increase in one unit trade shock decreases the share of high school graduates' employment by almost 1.6 percentage points (Panel A, column II). In contrast, men's college graduates' employment remains unaffected (Panel A, column III). The same pattern is observed for women, high school graduates employment decreases by 0.83 (p=0.105) percentage points (Panel B, columns II-III).

China's export boom disproportionately affected manufacturing workers. Table 2 shows how high school educated men and women adjusted differently to the trade shock. Rising import competition reduces manufacturing employment for both. The decrease in employment for highs school graduated men is driven by the loss of manufacturing jobs. A unit rise in trade exposure reduces manufacturing employment by 1.5 percentage points for high school graduated men, and total employment by 1.6. In contrast, women were able to re-allocate into the non-manufacturing sector. Roughly two thirds of the women's job losses in the manufacturing sector are absorbed by the non-manufacturing sector. This is consistent with Brussevich (2018), who finds that men face higher exit costs from manufacturing than women.

Next, as the trade shock disproportionately affected high-school educated workers and particularly men, I study how the trade shock impacted annual labor earnings gender gaps and skill gaps. First, I study separately the effect on annual labor earnings for high school men and women. I keep workers who worked at least 48 weeks during

Table 1: Impact of trade shock on employment by sex and education

	All	High School Educated	College Educated
Panel A: Men			
	(I)	(II)	(III)
Δ Import Penetration	-1.272***	-1.571***	-0.336
	(0.284)	(0.331)	(0.246)
Panel B: Women			
	All	High School	College
	(I)	(II)	(III)
Δ Import Penetration	-0.440	-0.831	-0.0934
	(0.357)	(0.512)	(0.296)
Observations	1,444	1,444	1,444

Notes: Dependant variable is the change in percentage population age 25-34 that is employed. Regressions include a dummy for the 2000-2014 period; star-of-period shares of CZs that is Hispanic, black, Asian, and other race; time trends for US census divisions; lagged share of CZ employment in manufacturing; start-of-period indices of employment in routine occupations and of employment in off-shorable occupations. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the last calendar year, and who usually worked at least 19 hours per week. Both men's and women's annual labor earnings are negatively affected by the trade shock. A one unit of trade shock decreases men's annual earnings by 1.7 percentage points and 1.3 points that of women's. The decrease in labor earnings is explained by losses for those working in the non-manufacturing sector.

Table 2: Impact of trade shock on manufacturing and non-manufacturing employment by sex and education

	Employment	Manufacturing Employment	Non-Manufacturing Employment
Panel A: High school educated men			
	(I)	(II)	(III)
Δ Import Penetration	-1.571***	-1.499***	0.0518
	(0.331)	(0.374)	(0.405)
Panel B: High school educated women			
	Employment	Manufacturing Employment	Non-Manufacturing Employment
	(I)	(II)	(III)
Δ Import Penetration	-0.831	-1.921***	1.316***
	(0.512)	(0.393)	(0.481)
Observations	1,444	1,444	1,444

Notes: Dependent variables: change in percentage of population age 25-34 that is employed (I), employed in manufacturing (II), employed in non-manufacturing sector (III). All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Impact of trade shock on annual labor earnings by sex and education

Panel A: High school educated men			
	All	Manufacturing Sector	Non-Manufacturing Sector
	(I)	(II)	(II)
Δ Import Penetration	-1.661**	-0.766	-2.023***
	(0.746)	(1.122)	(0.738)
Panel B: High school educated women			
	All	Manufacturing Sector	Non-Manufacturing Sector
	(I)	(II)	(II)
Δ Import Penetration	-1.327*	0.950	-1.757**
	(0.679)	(2.181)	(0.536)
Observations	1,444	1,444	1,444

Notes: Dependent variable is the change in percentage of annual and salary earnings for high school educated men and women who worked at least 48 weeks and usually at least 19 hours per week. All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

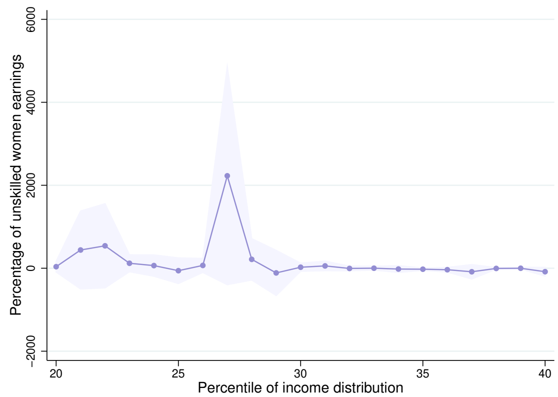
I now quantify the impact of increased import competition on gender gap and skill premium on the unconditional annual wage and salary earnings. Figure 2 reports the trade-induced earning losses on annual earnings for all high school educated men and women, irrespective of weeks or hours worked. The trade induced earning losses are greater for men than women for almost all ventiles, significantly so at the top and bottom of the distribution. This is, the trade shock differentially depressed high-school men earnings relative to women's. For college-educated men and women the pattern is similar, but the differences are significant only at the very bottom of the distribution (Figure A1).

Finally, I analyze the effects of the trade shock on inequality as measured by the earnings gaps across skill levels. Figure 3 shows the impact of a unit trade shock on the difference of the skilled-unskilled annual earnings gap as a percentage of the unskilled earnings in 1990. Figures 3a and 3b show that the trade shock does not affect the skill premium for women for any percentile of the distribution. On the contrary, Figure 3c shows how a unit trade shock increases the unskilled-skilled earnings gap for men. A one-unit trade shock increases skilled men relative to unskilled men's earnings, significantly so for those in the middle percentiles.

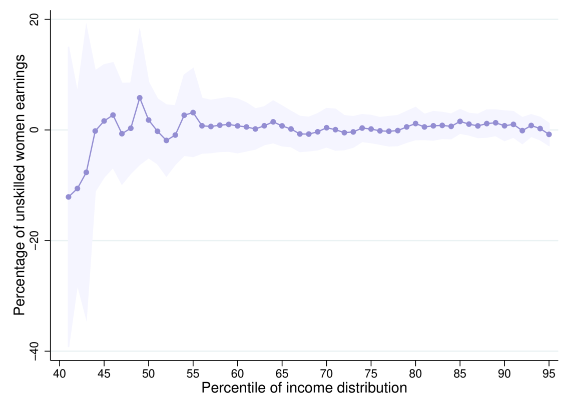
Figure 2: Impact of trade shock on high-school educated men and women annual labor earnings by venitle

Notes: The figure measures the impact of a unit trade shock on the unconditional distribution of annual wage and salary earnings for high-school educated men and women. Each dot is the coefficient from a separate IV quantile regression that includes the full set of control variables from Table 1. Shaded areas represent the 95 percent confidence interval.

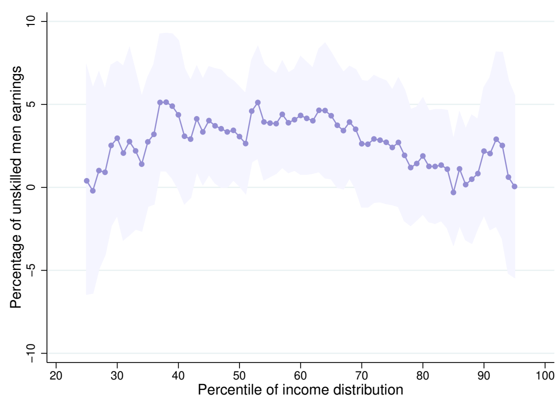
Figure 3: Change in skilled-unskilled annual earning gaps by gender



(a) Women: bottom percentiles



(b) Women: top percentiles



(c) Men

Notes: The figures present the impact of a unit trade shock on the difference in the skilled-unskilled earnings gap by gender as a percentage of the unskilled earnings in 1990 for each percentile. Each dot is a coefficient from a separate IV quantile regression that controls for the set of control variables from Table 1. Shaded areas represent a 95 percentila confidence interval.

3.3 Marriage market outcomes

In this section I evaluate how the labor market shock affects the marriage market. To summarize, high-school-educated workers are disproportionately affected by the trade-induced labor market demand shock, particularly men: (i) Unemployment increases for high-school-educated men and women, but women are able to compensate for most job losses by moving to non-manufacturing sectors; (ii) the gender gap in annual earnings decreases for high-school-educated workers and college-educated ones; and (iii) the skill premium increases for men and not for women. I exploit these exogenous changes on inequality and relative economic stature of men versus women to test the main predictions of the two main models of gains from marriage. In models in which the gains from marriage stem from household specialization, a fall in the relative economic status of men diminishes the gains from marriage, deterring household formation. In models in which the gains from marriage arise from joint consumption or production, increases in the skill premium deters matches across skilled and unskilled agents, as the cost of marrying down increase.

I first study the impact of the trade shock on women's marital status. I estimate equation 2, with the change in the share of women that are currently married, never married or the change in divorce rate as outcome variables. Panel A of Table 4 shows that a one-unit trade shock reduces the share of currently married women by 0.5 percentage points and increases the share of women who never married by 0.75 percentage points [7]. But not all women are equally affected by the trade shock; as seen in the previous section, unskilled workers are disproportionately affected by it. Panel B and C of Table 4 shows that the trade-induced decrease in women currently married is driven by college educated women. A one-unit shock predicts a 0.9 percentage points reduction in the fraction of college women currently married, while the share of high-school educated women currently married is not affected. The impact on the share of never married is positive and significant for both high-school and college educated women.

To understand what drives the changes in marriage prevalence, I further analyze how do marriage patters change. This is, I study how the labor market shock affects who marries whom, or who stops marrying whom. For each education group, I divide the share of married individuals according to their spouse's education and study how these shares evolve. I divide the share of married women into those who married up

[7] See Table A4 for impact on men's marital status.

Table 4: Impact of trade shock on women's marital status by education

	Married (I)	Never Married (II)	Divorce Rate (III)
Panel A: All women			
Δ Import Penetration	-0.536*	0.753**	-0.129
	(0.283)	(0.307)	(0.199)
Panel B: High school educated women			
Δ Import Penetration	-0.317	0.741*	-0.343
	(0.392)	(0.423)	(0.342)
Panel C: College educated women			
Δ Import Penetration	-0.829**	1.077***	-0.187
	(0.405)	(0.371)	(0.215)
Observations	1,444	1,444	1,444

Notes: Dependent variables are the change in percentage in the share of women who are currently married (I), who never married (II), and in divorce rate (III). The divorce rate is the ratio of women who are divorced over the sum of women who are currently married or divorced. All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

or down. For a given level of education E I do the following decomposition:

$$\frac{\text{Married Women(E)}}{\text{Total Women(E)}} = \frac{\text{Women(E) Married Down}}{\text{Total Women(E)}} + \frac{\text{Women(E) Married Up}}{\text{Total Women(E)}}, \qquad (4)$$

where Women(E) refers to women of education level E.

For high school educated women, I divide them into those married with a spouse with at most the same level of education as themselves ("married down") and those married with a spouse with higher education than themselves ("married up"). For college graduates, I divide them into those married with a spouse with lower education than themselves ("married down") and those married with a spouse with same level of education as themselves ("married up").

To evaluate how marriage patterns change, I estimate equation (2) for the decadal change of each term of equation (4)[8]. Table 5 shows how marriage patterns change with the trade-induced labor market shock[9],[10].

Table 5: Impact of trade shock on marriage patterns by women's education

Panel A: High school educated women			
	Married (I)	Married Down (II)	Married Up (III)
Δ Import Penetration	-0.405	-0.146	-0.232
	(0.328)	(0.350)	(0.246)
Panel B: College educated women			
	Married (I)	Married Down (II)	Married Up (III)
Δ Import Penetration	-0.748**	-0.607**	-0.127
	(0.381)	(0.371)	(0.254)

Notes: The dependent variables are the decadal change of each term of equation (4). All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Contrary to Becker's model of household specialization, even if the relative economic stature of high-school (college) educated men worsens relative to high-school (college) educated women, their marriage prevalence is not affected by the trade shock. The share of high-school educated women married to high-school educated men remains unchanged. Similarly, even though the earnings gap between college men and women is negatively affected by the trade shock, the marriage prevalence between this two groups remains unchanged. The trade-induced decrease in marriage prevalence for college educated women is entirely driven by them marrying less frequently with high school educated men. This confirms Fernández et al. (2005) prediction, an increase in inequality leads to an increase of sorting, as the cost of marrying down

[8]It is important to note that the results are not driven by changes in educational attainment for men or women. The trade shock does not affect their educational attainment nor the ratios across gender-education pairs. See Tables A3 and A2

[9]The change in the fraction of currently married women slightly changes in value, but not significance, for both education groups in comparison to Table 4. This is due to a slight change on the sample, as for this exercise I only considered married women those with valid information on their spouse's education.

[10]See Table A5 for men's results.

increases.

4 Sorting and Intergenerational Mobility: Empirical Findings

4.1 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)[11]. 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 [12]. 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 6. In Moses Lake, Washington, for instance, people with the same level of education are

[11] Available to download on https://opportunityinsights.org/data

[12] 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

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.

Table 6: 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:

$$Relative\_Mobility_{cz} = \alpha + \delta_{cz} Assortative\_Mating_{cz} + \epsilon, \tag{5}$$

Table 7 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 A2 and A3 present heat maps of both intergenerational mobility and sorting across the US.

Table 7: Mobility and Assortative Matching across CZs

	Relative Mobility: Income ranks correlation
$Assortative\_Mating_{cz}$	0.0725**
	(0.0279)
$Constant$	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.*

4.2 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.

As I show next, both parents from skilled marriages spend more time with their kids than other parents.

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.

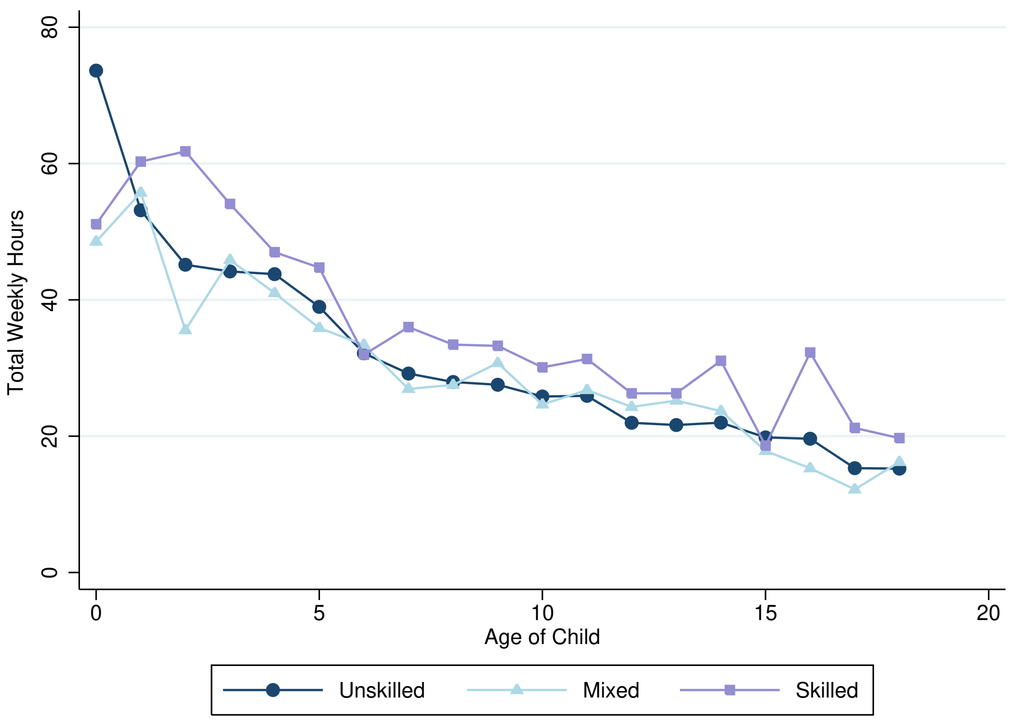
Each child in the CDS submits a detailed 24 hours time diary for two days per week, one weekday and one weekend day. In these, they record all activities and who else participated in them. They additionally record the intensity of said participation for parents, this is, whether the parent is actively 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 4 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 A4a and A4b 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.

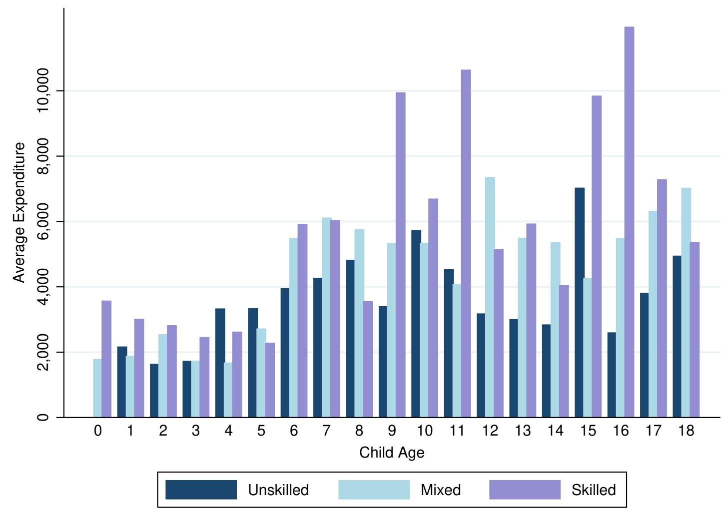
Figure 5 presents the results for total expenditure (the sum of the above three categories) and childcare expenditure in US 2000 dollars, by type of marriage. For the first five years, expenditures are almost solely childcare expenses. After that, private schooling is the primary source of expenditures. The data is noisy, but skilled marriages invest the most money, particularly during the first years. Afterward, mixed marriages track them pretty closely.

Figure 4: Total parental weekly time by type of marriage

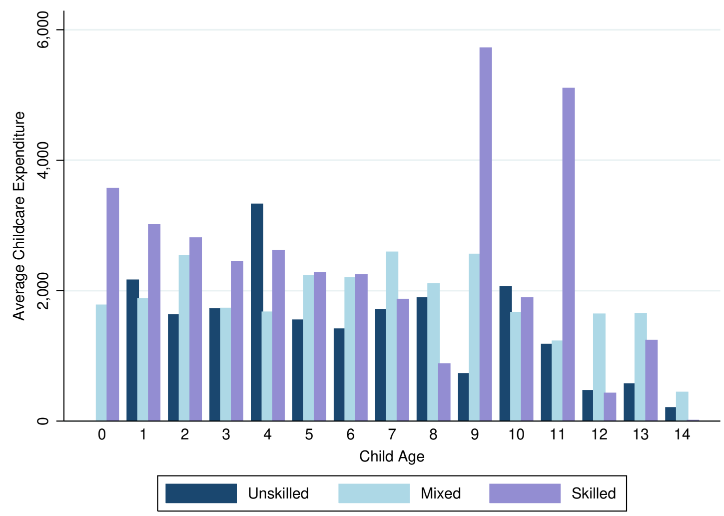


Notes: The figure presents total active time mothers and fathers spend weekly with their kids by type of marriages. Marriages are categorized according to the presence of none, one or two parents with a college degree: unskilled, mixed, and skilled, respectively. Source: PSID, CDS time diaries.

Figure 5: Expenditure by type of marriage



(a) Total expenditure



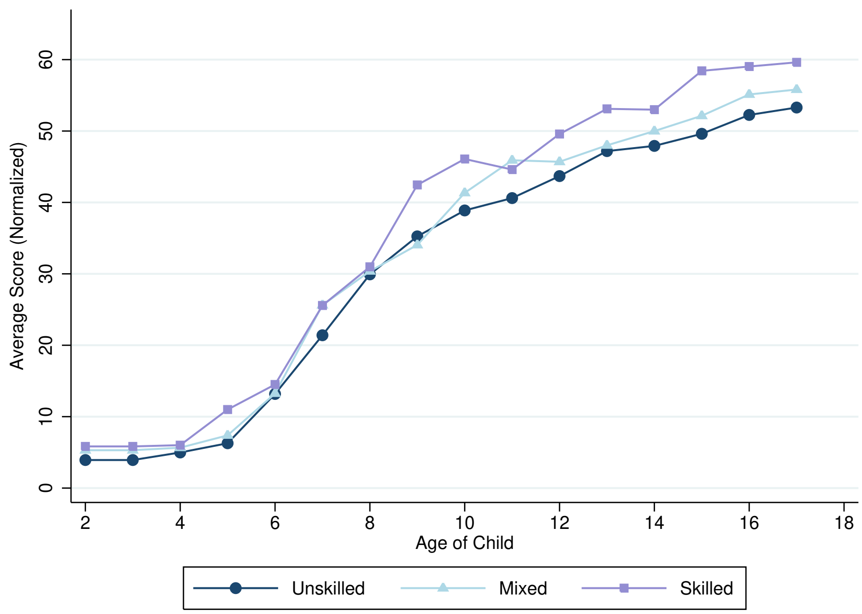
(b) Childcare expenditure

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.

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 6 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.

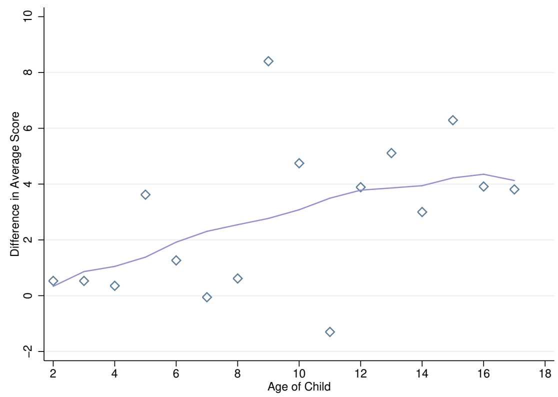
Figure 7 shows how each pair's difference in average scores evolves. During the first years, there is practically no difference in outcomes between children with only one college-educated parent and children with two. As children age, children of skilled marriages outperform children of mixed marriages. 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 6: Test scores

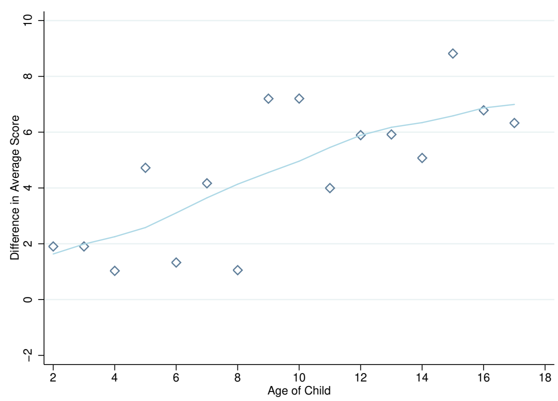


Notes: Letter-Word adjusted test scores, normalized to lie between 0 and 100, by type of marriage. Scores are computed by weighting each question by the inverse of the share of children, regardless of age, that answered it correctly. Marriages are categorized according to the presence of none, one or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

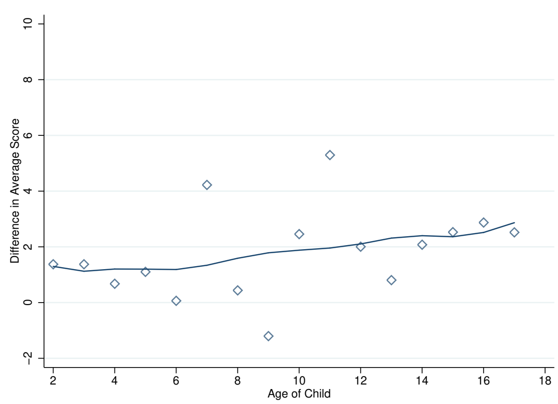
Figure 7: Differences in average scores by types of marriages pairs



(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.

5 Model

5.1 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 8, I study how these sources mediate the effect of an increase in sorting on intergenerational mobility.

5.2 Preliminaries

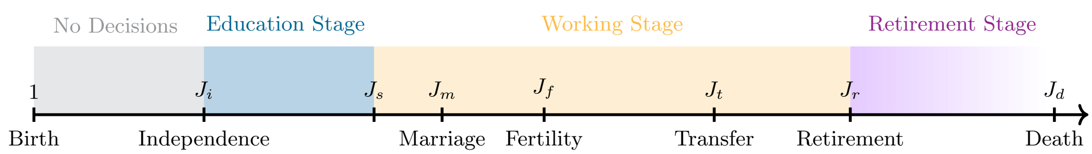
Time is discrete, and each period in the model corresponds to two years. The economy is populated by a continuum of agents, equally as many males as females. Gender is indexed by g and age by j.

Figure 8 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 8: Life cycle



5.3 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 ϕ. 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, ϕ. This idiosyncratic cost is commonly used in the literature (e.g., Abbott et al. (2019); Daruich and Kozlowski (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 Kozlowski (2020) I follow Abbott et al. (2019) and assume that student debt is refinanced into a bond with interest rate r^-, where $\widetilde{a}^s(a')$ performs the transformation assuming fixed payments during 20 years[13]. During

[13]The formula is given by

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

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:

$$V_j(g,a,h_0,\phi) = \max\Big\{V_j^s(g,a,h_0,) - \psi_g\phi,\ {}_z\Big[V_j^w(g,a,h_0,e=1,z)\Big]\Big\}. \tag{6}$$

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

$$\begin{aligned} V_j^s(g,a,h_0) &= \max_{c,\ a'} u(c) + \beta \widetilde{V}_{j+1}^S \\ \text{s.t} \quad & c + a' + p_e = a(1+r) + hw_{coll}(1-\tau) \\ & a' \geq \underline{a}^s \\ & \log h = \log f^{g,e}(h_0) + \gamma_{j,g,e} \\ & \widetilde{V}_{j+1}^S = \begin{cases} V_{j+1}^s(g,a,h_0), \ \text{if} \ \ j = J_i \\ V_{j+1}^w(g,\widetilde{a}^s(a'),\ h_0,\ e=2,\ z), \ \text{otherwise.} \end{cases} \end{aligned} \tag{7}$$

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

$$\begin{aligned} V_j^w(g,a,h_0,e,z) &= \max_{c,\ a'} u(c) + \beta\Big[V_{j+1}^w(a',h_0,e,z')\Big] \\ \text{s.t} \quad c + a' &= a(1+r) + wh(1-\tau) \\ \log h &= \log f^{g,e}(h_0) + \gamma_{j,g,e} + z \\ z' &= \rho_{z,g,e} z + \xi, \quad \xi \sim N(0,\sigma_{\xi,g,e}), \quad a' \geq \underline{a}_{e,j} \end{aligned} \tag{8}$$

Working stage

From $j = J_i + 2$ to $j = J_m - 1$, agents remain single and their problem is equivalent to 8. 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 π are perfectly matched, with probability π 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

$$\begin{aligned} V_j^w(\,a,\ \mathbf{h_0},\ \mathbf{e},\ \mathbf{z}) &= \max_{c,\ a'} 2u(c) + \beta\Big[V_{j+1}^w(g,\ a',\ \mathbf{h_0},\ \mathbf{e},\ \mathbf{z}')\Big] \\ \text{s.t} \quad 2^{\frac{1}{\eta}} c + a' &= a(1+r) + w(h_m + h_w)(1-\tau) \\ \log h_g &= \log f^{g,e_g}(h_{0g}) + \gamma_{j,g,e_g} + z_g, \quad \text{for} \quad g = m, w \\ z'_g &= \rho_{z,g,e_g} z_g + \xi, \quad \xi \sim N(0, \sigma_{\xi,g,e_g}), \quad \text{for} \quad g = m, w \\ a' &\geq \underline{a}_{\mathbf{e},j} \end{aligned} \tag{9}$$

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:

$$
\begin{aligned}
V_j^w(\,a,\ \mathbf{h_0},\ \mathbf{e},\ \mathbf{z}, g_k) &= \max_{c,\ a'\ \hat{a}} 2u(c) + \beta[V_{j+1}^w(\,a',\ \mathbf{h_0},\ \mathbf{e},\ \mathbf{z}')] \\
&\quad + 2\lambda\beta V_{j_i}(g_k,\ \hat{a},\ h_k,\ \phi_k) \qquad (10)\\
\text{s.t} \qquad 2^{\frac{1}{\eta}}c + a' - 2\hat{a} &= a(1+r) + w(h_m + h_w)(1-\tau) \\
\log h_g &= \log f^{g,e_g}(h_{0g}) + \gamma_{j,g,e_g} + z_g, \quad \text{for} \quad g = m, w \\
z'_g &= \rho_{z,g,e_g} z_g + \xi, \quad \xi \sim N(0, \sigma_{\xi,g,e_g}), \quad \text{for} \quad g = m, w \\
a' &\geq \underline{a}_{\mathbf{e},j} \\
h_k &\sim f^k(\mathbf{h}), \quad \phi_k \sim g^k(\mathbf{e}).
\end{aligned}
$$

Parents are altruistic. They derive utility from their child's expected lifetime utility through the altruistic weight λ. 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 9 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

$$
\begin{aligned}
V_j^w(a, \mathbf{e}) &= \max_{c,\ a'} 2u(c) + \beta V_{j+1}^w(a', \mathbf{e}) \qquad (11)\\
\text{s.t} \quad 2^{\frac{1}{\eta}}c + a' &= a(1+r) + \Phi(\mathbf{e}) \\
a' &\geq 0
\end{aligned}
$$

6 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 10 summarizes all externally calibrated parameters and their sources, and Table 11 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.

6.1 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 funcion 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, λ in 10, 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 $\iota^s = 0.009$[14].

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 6, 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 ϕ to be between 0 and 1 and scaled by ψ_g, which differs by gender. The distribution of ϕ depends on parents' education through parameter

[14]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.

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

$$G^k(\mathbf{e}, \phi) = \phi^{\omega_{\mathbf{e}}} \tag{12}$$

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

The share of women and men college graduates will inform parameters ψ_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 α and β are interanlly 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 $\sigma_{\xi,e}$.

$$\begin{aligned} \log h &= \log f^{g,e}(h_0) + \gamma_{j,e,g} + z \\ z' &= \rho_{z,e,g} z + \xi \\ \xi &\sim (0, \sigma_{\xi,e,g}) \\ z_{0,e,g} &\sim (0, \sigma_{z_0,e,g}) \end{aligned} \tag{13}$$

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 8 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 8: Income Age Profiles by Gender and Education Group

	Men		Women	
	High School	College	High School	College
Age	0.081***	0.154***	0.067***	0.121***
	(0.00236)	(0.00320)	(0.00380)	(0.00526)
Age^2	-0.0009***	-0.0016***	-0.0008***	-0.00142***
	(2.83e-05)	(3.86e-05)	(4.58e-05)	(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 13 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[15]. Table 9 presents the estimates for all groups.

[15]Given yearly estimates, the corresponding 2-year variables ρ_z and σ_z are given by: $\rho_z = (\hat{\rho_z})^2$ and $\sigma_z = (1 + (\hat{\rho_z})^2)\hat{\sigma_z}$

Table 9: 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

$$\log(h_0) = \mu_{h_0} + \rho[\log(h_p) - \log(\overline{h_p})] + \epsilon_{h_0} \tag{14}$$

where h_p is the sum of parents' human capital, $\overline{h_p}$ is the average human capital of parents at age 42, and $\epsilon_{h_0} \sim N(0, \sigma_{h_0})$. Both ρ and σ_{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 ρ, and the variance of the log income at age 28-29, which informs σ_{h_0}.

Marriage market

Parameter π 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.

6.2 Results

Table 10 summarizes the remaining externally estimated parameters. There are thirteen parameters left that are estimated using simulated method of moments with thirteen targeted moments. Parameter λ relates to altruism; ρ dictates intergenerational persistence of skills through the initial draw of human capital, while σ_{h0} 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: ψ_M, ψ_W, ω_t, for $t \in \{L, M, H\}$. Lastly, π determines the degree of assortative matching.

Table 11 shows the estimated parameters together with the targeted moments in the simulated economy. The model provides a good fit to the data.

Table 10: Externally estimated parameters

Parameter	Value	Description	Source
Prices			
w_{coll}	0.56	Wage while in college	Daruich and Kozlowski (2020)
τ	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
Financial markets			
r	3%	Interest rate	Smets and Wouters (2007)
$\underline{a_1}$	20,000	Borrowing limit HS	Daruich (2019)
$\underline{a_2}$	34,000	Borrowing limit College	Daruich (2019)
ι	10%	Borrowing-savings wedge	Gross and Souleles (2002)
ι^s	1%	College loan wedge	Daruich and Kozlowski (2020)
Preferences			
β	0.975	Discount factor	Standard
γ_c	0.5	Risk aversion	Roys and Seshadri (2014)
Economies of scale			
η	1.4	Economies of scale of consumption	Voena (2015)

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Table 11: Internally estimated parameters

Parameter	Value	Moment	Data	Model
Altruism				
λ	0.84	Parent-to-Child Transfer	0.77	0.78
Initial Draw of HC				
ρ	0.50	Rank-Rank income correlation	0.29	0.28
σ_{h0}	0.27	Variance of log income	0.33	0.33
Education returns for Men				
α^M	0.11	log(y) ratio: College - High School	0.38	0.44
β^M	0.36	Var of log(y): College	0.28	0.22
Education returns for Women				
α^W	0.14	log(y) ratio: College - High School	0.44	0.44
β^W	0.24	Var of log(y): College	0.28	0.29
College taste				
ψ_m	28	College share: men	0.34	0.38
ψ_w	23	College share: women	0.32	0.35
ω_L	1.80	Education persistence: unskilled parents	0.21	0.22
ω_M	0.94	Education persistence: mixed parents	0.43	0.43
ω_H	0.53	Education persistence: skilled parents	0.66	0.62
Marriage sorting				
π	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)).

7 Validation

I test the model estimation by computing moments not targeted by the estimation. Table 12 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 12: Validation: Non-targeted moments

Moment	Data	Model
Intergenerational Mobility		
Absolute Mobility	0.50	0.51
Inequality		
Gini	0.30	0.28
Top-Bottom	3.7	3.3

Sources: Absolute upward income mobility from Chetty et al. (2017). Gini and Top-Bottom from Daruich and Fernández (2020)

8 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 [16], intergenerational mobility would increase by 11% and the Gini coefficient decrease by 2%.

9 Conclusion

In this paper, I studied the causes and consequences of increased assortative mating in the US. I studied how the labor market shock induced by increased import competition affected men and women differently by education group. High school-educated men and women are disproportionately affected by it. While high school men's unemployment increases, women reallocate and compensate for the job losses in the manufacturing sector. I then showed how these differential effects by education affect the marriage market. While the relative decrease in men's earnings decreases marriage prevalence, the inequality shock induced by the increased import competition also changes the incentives of whom to marry. As the earnings skill premium increases for men, women's cost of marrying unskilled men increases. As their costs of marrying down increase, college women marry less with high school-educated men.

Second, 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

[16] 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%.

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%.

References

Abbott, Brant, Giovanni Gallipoli, Costas Meghir, and Giovanni L Violante, "Education policy and intergenerational transfers in equilibrium," *Journal of Political Economy*, 2019, *127* (6), 2569–2624.

Acemoglu, Daron, David H Autor, David Dorn, Gordon H Hanson, and Brendan Price, "Import competition and the great US employment sag of the 2000s," *Journal of Labor Economics*, 2016, *34* (S1), S141–S198.

Autor, David H, David Dorn, and Gordon H Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–68.

_ , _ , and _ , "The China shock: Learning from labor-market adjustment to large changes in trade," *Annual review of economics*, 2016, *8*, 205–240.

_ , _ , and _ , "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men," *American Economic Review: Insights*, September 2019, *1* (2), 161–78.

_ , _ , _ , and Jae Song, "Trade adjustment: Worker-level evidence," *The Quarterly Journal of Economics*, 2014, *129* (4), 1799–1860.

Becker, Gary S, "A theory of marriage: Part I," *Journal of Political economy*, 1973, *81* (4), 813–846.

Boca, Daniela Del, Christopher Flinn, and Matthew Wiswall, "Household choices and child development," *Review of Economic Studies*, 2014, *81* (1), 137–185.

Brussevich, Masha, "Does trade liberalization narrow the gender wage gap? The role of sectoral mobility," *European Economic Review*, 2018, *109*, 305–333.

Carneiro, Pedro Manuel and James J Heckman, "Human capital policy," 2003.

Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang, "The fading American dream: Trends in absolute income mobility since 1940," *Science*, 2017, *356* (6336), 398–406.

_ , Nathaniel Hendren, Patrick Kline, and Emmanuel Saez, "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *The Quarterly Journal of Economics*, 2014, *129* (4), 1553–1623.

Chiappori, Pierre-André, Bernard Salanié, and Yoram Weiss, "Partner choice, investment in children, and the marital college premium," *American Economic Review*, 2017, *107* (8), 2109–67.

Cunha, Flavio, James J Heckman, and Susanne M Schennach, "Estimating the technology of cognitive and noncognitive skill formation," *Econometrica*, 2010, *78* (3), 883–931.

Daruich, Diego, "The macroeconomic consequences of early childhood development policies," *Working Paper*, 2019.

_ **and Julian Kozlowski**, "Explaining intergenerational mobility: The role of fertility and family transfers," *Review of Economic Dynamics*, 2020, *36*, 220–245.

_ **and Raquel Fernández**, "Universal Basic Income: A Dynamic Assessment," Working Paper 27351, National Bureau of Economic Research June 2020.

Dorn, David, "Essays on Inequality, Spatial Interaction, and the Demand for Skills," 2009. Dissertation University of St. Gallen no. 3613.

Eika, Lasse, Magne Mogstad, and Basit Zafar, "Educational assortative mating and household income inequality," *Journal of Political Economy*, 2019, *127* (6), 2795–2835.

Fernández, Raquel and Richard Rogerson, "Sorting and long-run inequality," *The Quarterly Journal of Economics*, 2001, *116* (4), 1305–1341.

Fernández, Raquel, Nezih Guner, and John Knowles, "Love and money: A theoretical and empirical analysis of household sorting and inequality," *The Quarterly Journal of Economics*, 2005, *120* (1), 273–344.

Greenwood, Jeremy, Nezih Guner, Georgi Kocharkov, and Cezar Santos, "Marry your like: Assortative mating and income inequality," *American Economic Review*, 2014, *104* (5), 348–53.

Gross, David B and Nicholas S Souleles, "Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data," *The Quarterly journal of economics*, 2002, *117* (1), 149–185.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney, "Parental education and parental time with children," *Journal of Economic perspectives*, 2008, *22* (3), 23–46.

Lee, Sang Yoon and Ananth Seshadri, "On the intergenerational transmission of economic status," *Journal of Political Economy*, 2019, *127* (2), 855–921.

Manuelli, Rodolfo E and Ananth Seshadri, "Explaining international fertility differences," *The Quarterly Journal of Economics*, 2009, *124* (2), 771–807.

Mitchell, Olivia S and John WR Phillips, "Social security replacement rates for alternative earnings benchmarks," *Michigan Retirement Research Center Research Paper No. WP*, 2006, *116.*

Pierce, Justin R and Peter K Schott, "The surprisingly swift decline of US manufacturing employment," *American Economic Review*, 2016, *106* (7), 1632–62.

Redding, Stephen J, "Trade and Geography," Working Paper 27821, National Bureau of Economic Research September 2020.

Roys, Nicolas and Ananth Seshadri, "On the origin and causes of economic growth," *The Social Systems Research Institute (SSRI)*, 2014, pp. 4–5.

Ruggles, Steven, Sarah Flood, Ronald Goeken, Josiah Gover, Erin Meyer, Jose Pacas, and Matthew Sobek, "IPUMS USA: Version 10.0. Minneapolis, MN: IPUMS.," 2020.

Schwartz, Christine R and Robert D Mare, "Trends in educational assortative marriage from 1940 to 2003," *Demography*, 2005, *42* (4), 621–646.

Smets, Frank and Rafael Wouters, "Shocks and frictions in US business cycles: A Bayesian DSGE approach," *American economic review*, 2007, *97* (3), 586–606.

Stevenson, Betsey and Justin Wolfers, "Marriage and divorce: Changes and their driving forces," *Journal of Economic perspectives*, 2007, *21* (2), 27–52.

Verriest, Ewout, "Household labor supply, child development and childcare policies in the United States," *Child Development and Childcare Policies in the United States (December 31, 2018)*, 2018.

Voena, Alessandra, "Yours, mine, and ours: Do divorce laws affect the intertemporal behavior of married couples?," *American Economic Review*, 2015, *105* (8), 2295–2332.

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 ore 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-assortatative"* joint distribution, $Q_N = g_f' \times g_m$. And the *"assortatative"* 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_ν, 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 ν such as

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

I estimate ν 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 ν, 1970-2010

Year	ν
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, $V*_{Ji}$ to solve for parents' problem 10. 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 π, in order to calculate V_{Jm}. This is, they need to guess the probability measure over the state space at the beginning of period $j = J_m$, μ_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 5. 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 $j = J_i$, μ_{Ji}^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, μ_{Ji}^1. Iterate until μ_{Ji}^0 and μ_{Ji}^1 converge.

5. Use recently computed μ_{Jm-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 $h0$ and go back to step 2.

D Additional Tables and Figures

Figures A2 and A3 present heat maps of intergenerational mobility and sorting in the marriage market by CZs respectively.

Table A2: Impact of trade shock on education attainment by sex

	Men		**Women**	
	High School Educated	College Educated	High School Educated	College Educated
Δ Import Penetration	0.214	-0.0262	-0.0488	0.111
	(0.361)	(0.265)	(0.381)	(0.258)
Observations	1,444	1,444		

Notes: Dependant variable is the change in percentage men or women age 25-34 whose highest educational attainment is 12th grade (I) or at least 4 years of college (II). All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state..

Table A3: Impact of trade shock on education attainment by sex

	$\frac{\text{Women}}{\text{Men}}$	$\frac{\text{HS Women}}{\text{HS Men}}$	$\frac{\text{HS Women}}{\text{Coll Men}}$	$\frac{\text{Coll Women}}{\text{HS Men}}$	$\frac{\text{Coll Women}}{\text{Coll Men}}$
Δ Import Penetration	0.140	-0.123	-0.140	0.0849	0.0433
	(0.128)	(0.181)	(0.435)	(0.327)	(0.225)
Observations	1,444	1,444	1,444	1,444	1,444

Notes: Dependent variables are the change in gender ratio and change in gender ratio by education pairs combinations. All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state..

Table A4: Impact of trade shock on men's marital status by education

Panel A: All men			
	Married (I)	Never Married (II)	Divorce Rate (III)
Δ Import Penetration	-0.0515	0.173	-0.253
	(0.317)	(0.272)	(0.262)
Panel B: High school educated men			
	Married (I)	Never Married (II)	Divorce Rate (III)
Δ Import Penetration	-0.187	0.511	-0.340
	(0.433)	(0.362)	(0.542)
Panel C: College educated men			
	Married (I)	Never Married (II)	Divorce Rate (III)
Δ Import Penetration	-0.324	0.419	-0.141
	(0.442)	(0.427)	(0.220)
Observations	1,444	1,444	1,444

Notes: Dependent variables are the change in percentage in the share of men who are currently married (I), who never married (II), and in divorce rate (III). The divorce rate is the ratio of women who are divorced over the sum of women who are currently married or divorced. All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.

Table A5: Impact of trade shock on marriage patterns by men's education

Panel A: High school educated men			
	Married (I)	Married Down (II)	Married Up (III)
Δ Import Penetration	-0.501	-0.00393	-0.499***
	(0.323)	(0.314)	(0.217)
Panel B: College educated men			
	Married (I)	Married Down (II)	Married Up (III)
Δ Import Penetration	-0.318	0.358*	-0.250
	(0.381)	(0.185)	(0.430)

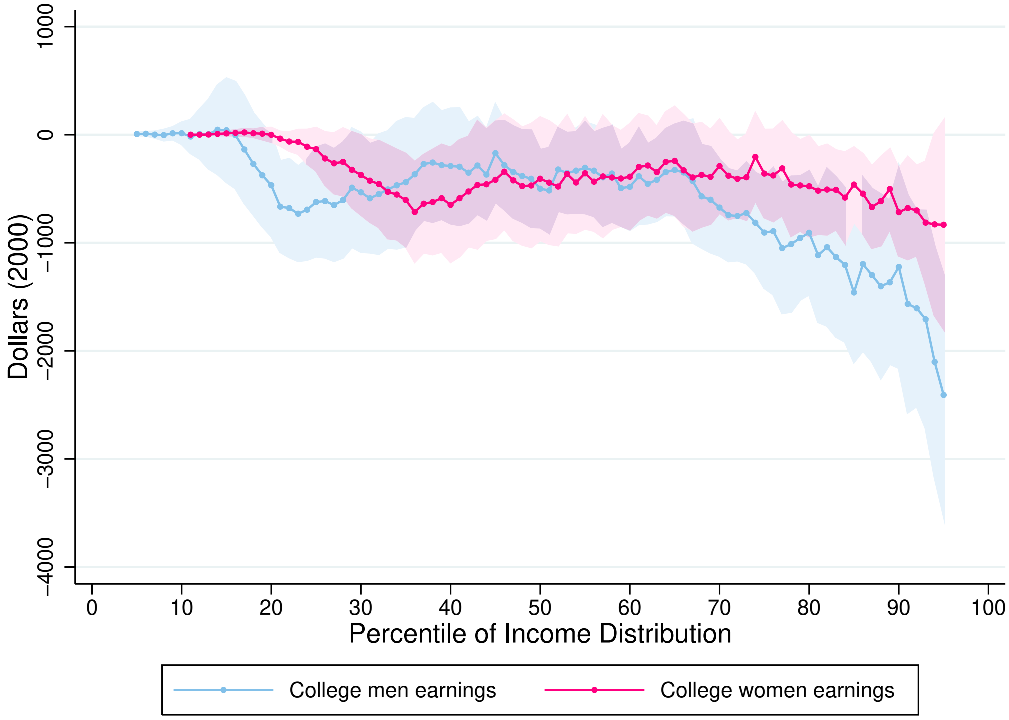
Notes: The dependent variables are the decadal change of each term of equation (4). All regressions include the full set of control variables from Table 1. Regressions are weighted by the product of period length and commuting zone share of start-of-period US mainland population. Robust standard errors in parentheses are clustered on state.

Table A6: 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

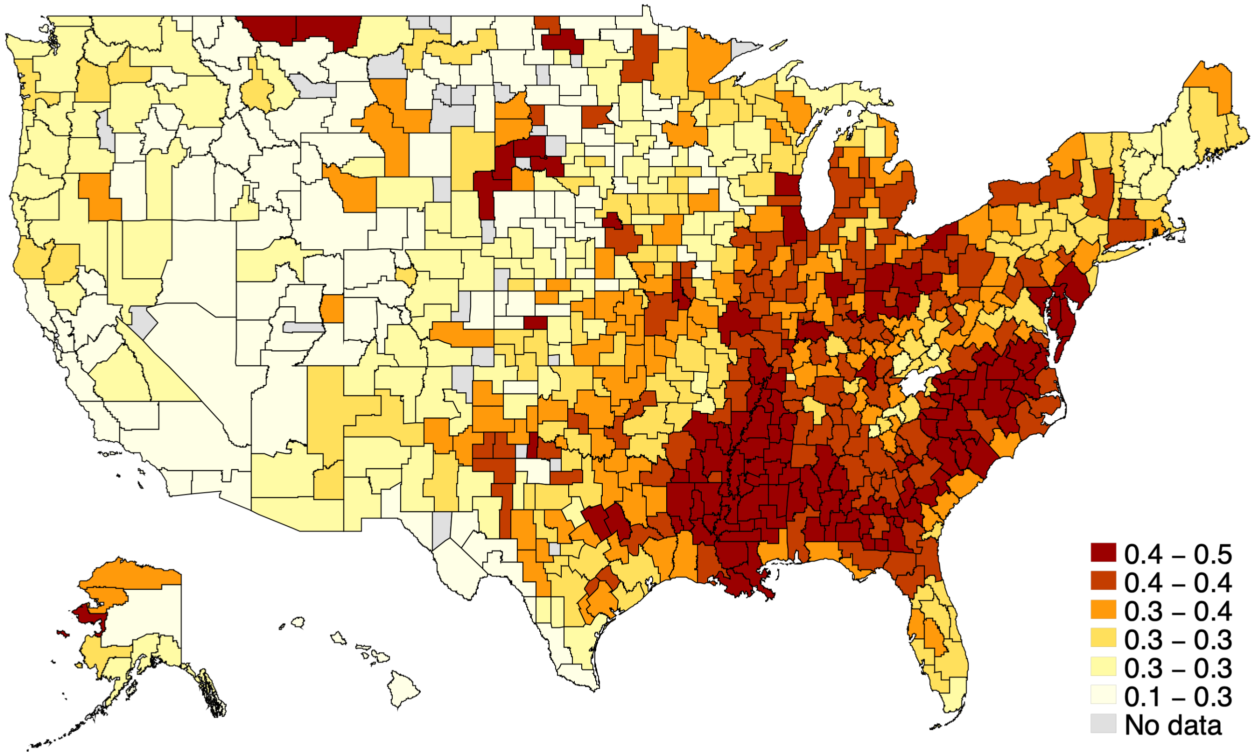
Notes: This table presents estimates $s(e_f, e_m)$ for all possible types of marriages for spouses between ages 24-54. Source: IPUMS USA Census (1960, 1970, 1980, 1990, 2000, 2010).

Figure A1: Impact of trade shock on college educated men and women annual labor earnings by percentile



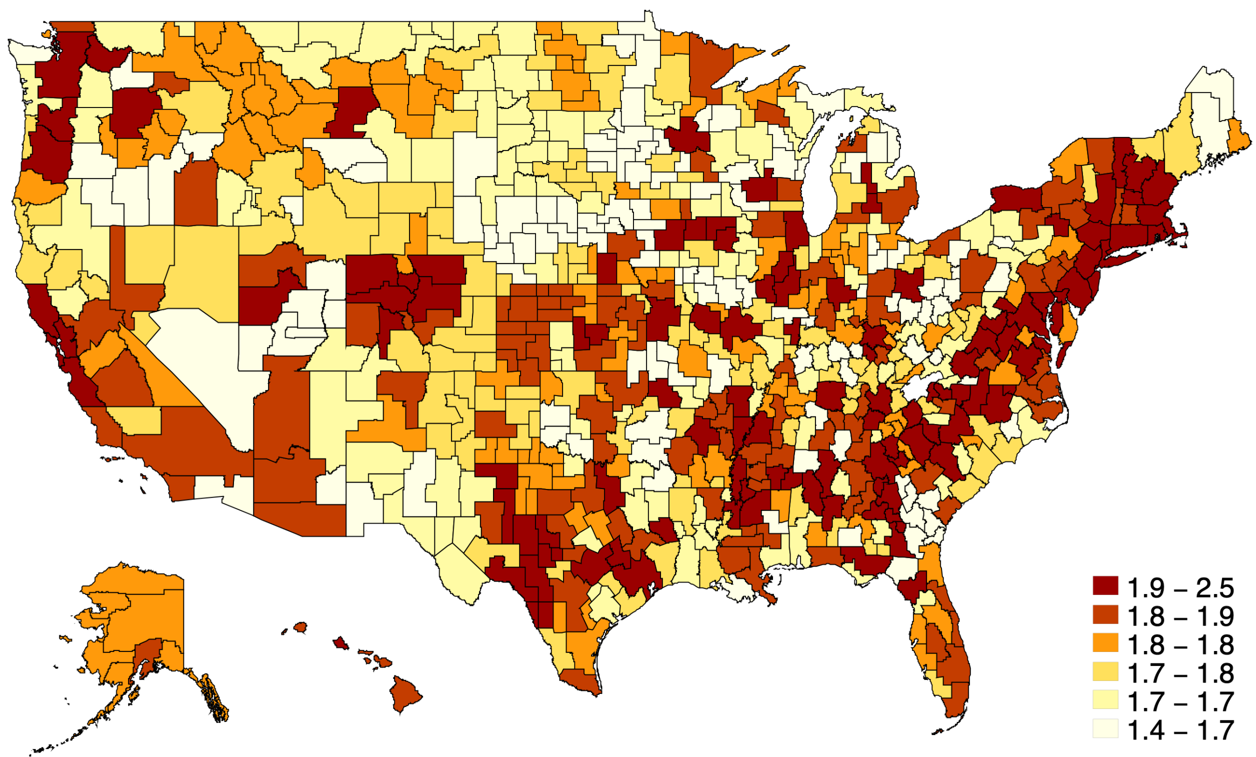
Notes: The figure measures the impact of a unit trade shock on the unconditional distribution of annual wage and salary earnings for college educated men and women. Each dot is the coefficient from a separate IV quantile regression that includes the full set of control variables from Table 1. Shaded areas represent the 95 percent confidence interval.

Figure A2: Relative Mobility: Rank-Rank Slope by CZ



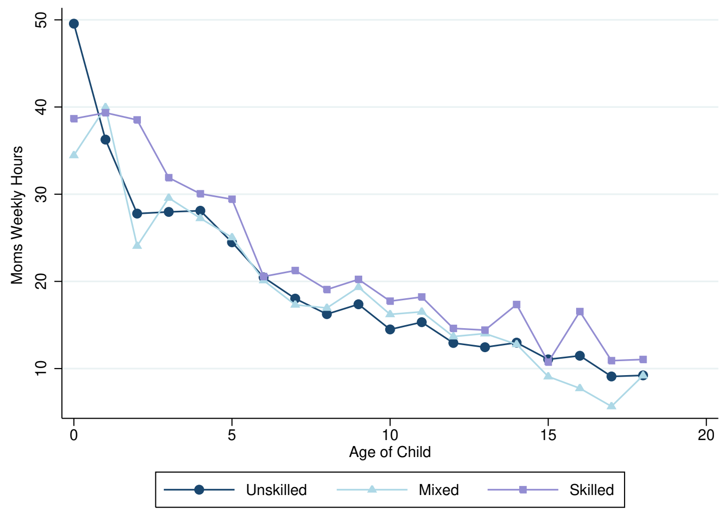
Notes: *Heat map of relative mobility across the US. Source:* *https://opportunityinsights.org/data.*

Figure A3: Assortative Mating by CZ

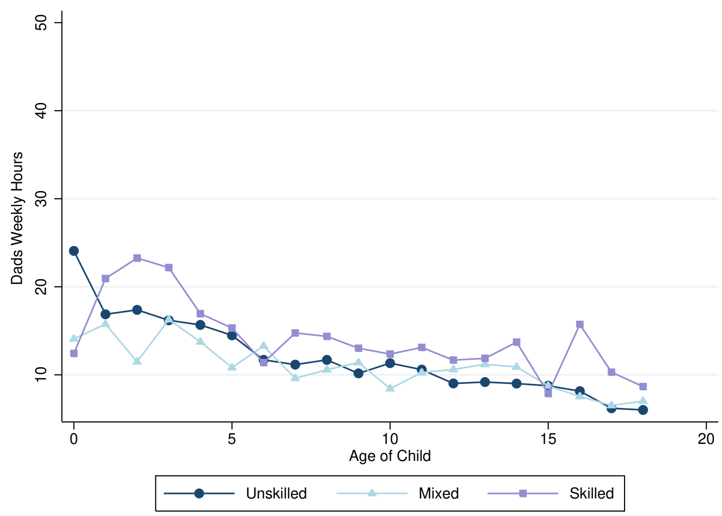


Notes: Heat map of assortative mating across the US. Assortative mating is calculated as the weighted average of the martial sorting parameters $s(e_f, e_m) = \frac{P(E_f=e_f,\, E_m=e_m)}{P(E_f=e_f)P(E_m=e_m)}$ *along the diagonal of the full contingency table for each CZ. The sample contains spouses 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 A4: 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.