THE UNIVERSITY OF CHICAGO

ASSORTATIVE MATING AND INEQUALITY

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To my parents

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ABSTRACT

This paper studies the evolution of assortative mating based on the permanent income (the individual-specific component of income) in the U.S., its role in the increase in family income inequality, and the factors behind this evolution. I first document a remarkable trend in the assortative mating, as measured by the permanent-income correlation of couples, across families formed around 1970 and those formed around 1990. I show that this trend accounts for almost one-third of the increase in family income inequality across these family cohorts. I then argue that the increased marriage age across these cohorts contributed to the assortative mating and thus to the rising inequality. Individuals face a large degree of uncertainty about their permanent incomes early in their careers. If they marry early, as most individuals around 1970 did, this uncertainty leads to weak marital sorting along permanent income levels. But when marriage is delayed, as around 1990, the sorting becomes stronger as individuals are more able to predict their likely future incomes. After providing reduced-form evidence on the impact of marriage age, I build and estimate a marriage model with income uncertainty, and show that the increase in marriage age can explain almost 75% of the increase in the assortative mating.

CHAPTER 1

INTRODUCTION

Family income inequality in the U.S. has increased substantially since the 1970s (Piketty and Saez 2003). A great many studies have attempted to understand its causes, which is important for the design of public policy especially redistributive policies. These studies have predominantly focused on the factors affecting labor market: for example, skill-biased technological change (Bound and Johnson 1992; Katz and Murphy 1992; Autor et al. 2008), the falling real value of minimum income (Card and Dinardo 2002), and the compositional changes in the labor force (Lemieux 2006). However, studies addressing the role of the marriage market remain limited, albeit the remarkable transformation happened in the U.S. marriage market since the 1970s, most notably with the rising marriage age and the declining marriage rates (Stevenson and Wolfers 2007; Greenwood and Guner 2008).

In this paper, I argue that the increased marriage age has contributed to the rising income inequality by increasing the degree of assortative mating based on permanent income. This argument, which to my knowledge hasn't been made before, builds on two steps. First, I address whether, and to what extent, the assortative mating affected family income inequality. To do that, I divide dual-earner families into cohorts according to the year they form a family, and quantify the increase in within-cohort inequality that is due to the assortative mating. I document that families formed around 1990 (the 90s cohort) display a substantially higher level of the assortative mating than those formed around 1970 (the 70s cohort), and this increase accounts for almost one-third of the rise in family income inequality across these family cohorts–and more than 40 percent of the rise in the residual part of it. Hyslop (2001) and Hryshko et al. (2017) attribute a much smaller role to the assortative mating because they make comparisons over time rather than across cohorts, which together with the short horizons of their analyses masks the large changes across cohorts that I document.[1]

1. Hyshlop (2001) looks at assortative mating based on the permanent part of earnings for dual-earner couples during the 1980s, and attributes less than 10 percent to the assortative mating. Hryshko et al.

Second, I show that increased marriage age can explain most of the increase in the assortative mating–thus, a significant part of the rise in family income inequality mechanically–by providing both empirical and structural evidence. I take the increase in marriage age as exogenously given by building on the extensive literature on the factors behind the increase in marriage age: for example, diffusion of oral contraceptives (Goldin and Katz 2002), and changes in abortion laws (Choo and Siow 2006).[2] The effect that I attribute to the marriage age, thus, should be interpreted as the indirect effect of those factors on the assortative mating by shifting marriage age.

My empirical evidence builds on a strong positive relationship that I document between the degree of assortative mating and the years of work experience before marriage, which cannot be explained by the observed individual heterogeneity. I argue that this relationship is not driven by unobserved heterogeneity either by showing that individuals display stronger marital sorting in their second marriages than in their first marriages, that is, when they have more experience before marriage.[3]

I have an intuitive explanation of why an increase in marriage age leads to stronger marital sorting. Individuals face a large degree of uncertainty about their permanent incomes early in their careers, which quickly resolves with work experience (Boar 2018). If they marry early, as most individuals in the 70s cohort did, this uncertainty leads to weak marital sorting along permanent income levels. But when marriage is delayed, as in the 90s cohort, the sorting becomes stronger as individuals are more able to predict permanent incomes. This learning story is not the only possible explanation, two other explanations come to mind. First,

(2017) reach a similar conclusion by extending the horizon to the early 2000s.

2. Goldin and Katz (2002) show that diffusion of oral contraceptives in the early 1970s explains a considerable part of the increase in marriage age by exploiting cross-state variation in the availability of these drugs among young women. Moreover, they likely underestimate the impact of these drugs due to their crude measure of state laws. Choo and Siow (2006) find that legalizing abortion explains a significant amount of the decrease in rates of marriage and of the increase in marriage age from 1971 to 1981 by using cross-state variation in the timing of legalized abortion.

3. This still doesn't establish a clean causal relationship both due to the selection into marrying more than once and also due to the fact that divorces might have changed marital preferences of individuals in a different way than that would happen if they simply postpone their first marriages.

increased marriage age coupled with longer marital search could lead to stronger sorting in the existence of search frictions. However, Hitsch et al. (2010) doesn't find support for search frictions by comparing sorting in the online dating market and marriage market. Second, marital preferences for income might become stronger with age. However, South (1991) doesn't find support for drastic changes in marital preferences by age using a national survey on mate selection preferences. Moreover, unlike the learning story, these two explanations aren't directly testable due to the absence of search behavior and marital preferences in the data.

I then give substance to the learning story above with a model to quantify the effect of marriage age on the assortative mating. In the model, individuals don't observe their productivities, which manifest themselves with job tenure. They quit their jobs when they detect a mismatch with their current employers. Due to learning by trial and error, they change jobs more frequently early in their careers to find more productive jobs, thus creating considerable permanent-income uncertainty in early work life that resolves quickly with work experience. Their marital preferences partly depend on future family income realizations, which create the motive for the assortative mating. I estimate this model and do the following counterfactual exercise: All else being fixed, what would happen to the assortative mating if the 70s cohort married at the same ages as the 90s cohort? Consistent with my empirical evidence, I find that the increase in marriage age explains almost 75% of the increase in the assortative mating. Finally, I establish that this strong finding is not due to an exaggeration of income uncertainty or its resolution speed by showing that they are similar in the model and data.

CHAPTER 2

RELATION TO PREVIOUS LITERATURE

This paper is related to two strands of literature. First, it adds to the research measuring the importance of assortative mating on rising income inequality. Only few studies have looked at couple's correlation in permanent income. Hyshlop (2001) looks at couple correlation on the permanent part of earnings for dual-earner couples during the 1980s and attributes a relatively small role to assortative mating. Hryshko et al. (2017) reach a similar conclusion by extending the horizon to the early 2000s. They attribute less than 10% of the increase in family income inequality among dual-earner couples to assortative mating. These papers make comparisons over time rather than across cohorts, which together with short horizons of their analyses masks the large changes across cohorts that I document. Cancian et al. (1993), Cancian and Reed (1998), Devereux (2004), and Pencavel (2006) also investigate the link between assortative mating in economic outcomes on family income inequality. Most of the remaining work is restricted to focusing on educational assortative mating.[1] Although many authors have documented an increase in educational homogamy (Lam 1988; Mare 1991; Pencavel 1998; Schwartz and Mare 2005), it has been shown to have a negligible impact on household income inequality trends (Greenwood et al. 2014; Eika et al. 2017).[2] Additionally, this paper complements the theoretical work on assortative mating and inequality (Fernandez and Rogerson 2001; Fernandez et al. 2005; Greenwood et al. 2016) by introducing a novel mechanism that operates through increased marriage age.

Second, this paper is related to the literature that estimates mate preferences through a structural model (Wong 2003; Choo and Siow 2006; Flinn and Del Boca 2005; Hitsch et al.

1. Few papers have examined marital sorting along other dimensions: parental wealth (Charles et al. 2013), spousal occupation (Hout 1982), and spousal ethnicity and biological characteristics (Pagnini and Morgan 1991; Eppstein and Guttman 1984).

2. Greenwood et al. (2014) ask what would have happened to household income inequality if couples in 2005 were matched as in 1960. They find that household income Gini barely moves from 0.430 to 0.429. Also, see Figure 12 in Eika et al. (2017), which shows the actual evolution of household income inequality is almost indistinguishable from the counterfactual inequality where they hold educational sorting fixed at its 1962 level.

2010). Wong (2003) uses a search theoretic framework to explain marriage outcomes in the data. She uses data on marriage age to estimate the arrival rate of marriage opportunities. Choo and Siow (2006) use a frictionless transferable utility framework to estimate marital behavior from 1971 to 1981. Their estimates show that gains from marriage drop substantially for younger adults. Using cross-state variation in the timing of the legalization of abortion, they find that legalized abortion explains a significant amount of decrease in marriage gains and marriage rates. Flinn and Del Boca (2005) and Hitsch et al. (2010) use the Gale-Shapley procedure for the marriage market as in this paper. Hitsch et al. (2010) show that marriage preferences, without search frictions, can generate realistic sorting patterns in marriage.

CHAPTER 3

TRENDS IN ASSORTATIVE MATING AND ITS EFFECT ON FAMILY INCOME INEQUALITY

In this section I document the evolution of the assortative mating based on permanent income and quantify its mechanical impact on family income inequality. I remain agnostic on why assortative mating changed, which is analyzed in next sections.

I use Panel Study of Income Dynamics (PSID) survey, with all the available family and individual files (1968-2017). As is standard in the literature, I exclude the Survey of Economic Opportunity (SEO) because it oversamples from low-income households. I also exclude Hispanic and Immigrants subsamples, which were added to the PSID later, to keep demographics constant over time. I use heterosexual couples living in the same family unit, who are either legally married or cohabiting by sharing expenses and income. For ease of reference, I define marriage broadly to include both cohabiting unions and legal marriages.

I estimate permanent incomes with the following regression equation:

$$\log w_{it} = \alpha + X_{it}\beta + \epsilon_{it}, \tag{3.1}$$

where w_{it} is annual labor income of individual i in year t, X_{it} is the full set of year dummies, and ϵ_{it} is the residual term. I define a person's permanent income as the exponential of average residual from his/her observations. Family income is simply the sum of permanent incomes of spouses. I analyze the rise in residual part of family income inequality as well since it is the main focus of a large part of the literature. To do that, I construct residual permanent incomes by estimating the regression equation above with the additional controls for age, education, and sector of work.[1] Residual family income is defined as the sum of

1. More precisely, it includes a quartic polynomial in age; four education dummies that are interacted with time and sex to account for the gender-specific rise in education premium over time; and, sixteen sector dummies. Four education categories are less than high school, high school, some college, and four years of college or more. Sector categories are constructed by aggregating industry-occupation pairs into sixteen groups as in Boar (2018).

residual permanent incomes of spouses.

I use a fairly standard sample selection. I use observations from individuals when they are between 18 and 65 years old, and drop an observation if the individual works less than 1,000 hours during the year. I also drop an observation if the individual earns less than half the federal minimum hourly income or more than 1,000 (real) dollars as an hourly compensation. To measure permanent incomes more precisely and limit the downward bias in the correlation from using fewer observations, as argued by Solon (1992)[2], I use couples who have at least five income observations for each person in the couple.

There are fewer observations for recently formed couples. To make things worse, they are predominantly from earlier years of work. To circumvent these problems and make a fair comparison across the cohorts, I use only the first available five years of income observations for each individual in the regression equation to construct permanent incomes. I don't use wage observations before marriage because they aren't available for most of the individuals.[3] I use families that are formed between 1967 and 2012, and group five consecutive years to increase sample size.[4] For ease of reference, I call the families that were formed between 1967 and 1971 the 70s cohort, and those formed between 1987 and 1991 the 90s cohort.

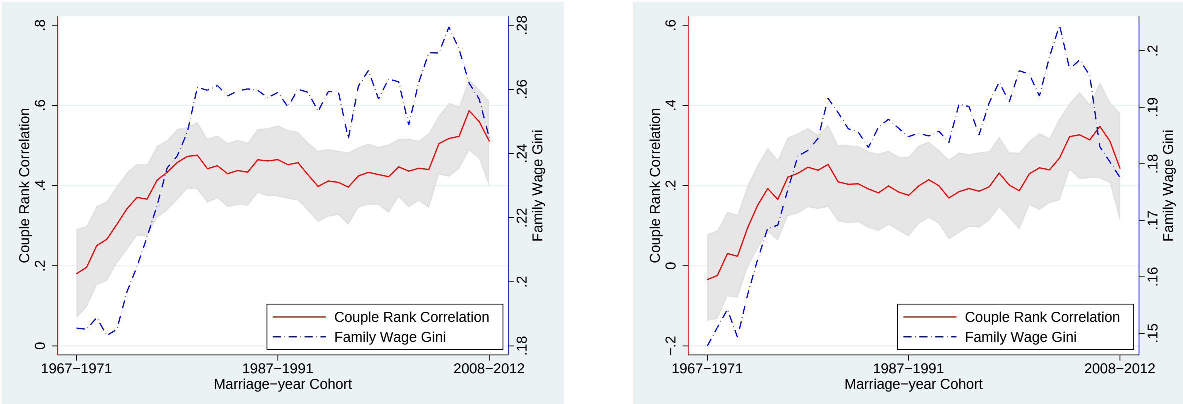
Changes in the labor market attachment of women across the cohorts, whether on the intensive or extensive margin, don't have any mechanical effect on my findings. This is because I use dual-earner families, and use observations when individuals work full time. Moreover, women's labor force participation increased only slightly across the cohorts in my sample because women in my initial cohort–that is, women who married around 1970–had

2. Solon (1992) finds that using more observations increases the father-son income correlations when less than five observations are used. I also don't find significant changes in the correlations by using more than five observations.

3. PSID doesn't ask retrospective wage questions to people, who are added into PSID sample after their marriage to a PSID member. Moreover, PSID doesn't collect detailed income information for individuals, who aren't a "head" or spouse of a family. Finally, almost half of the women in the early part of my sample started working after marriage.

4. I exclude families formed before 1967 because income observations are available after 1967. Also, families formed after 2012 don't have five years of wage observations.

Figure 3.1: Trends in the Assortative Mating and Family Income Inequality



(a) Full (b) Residual

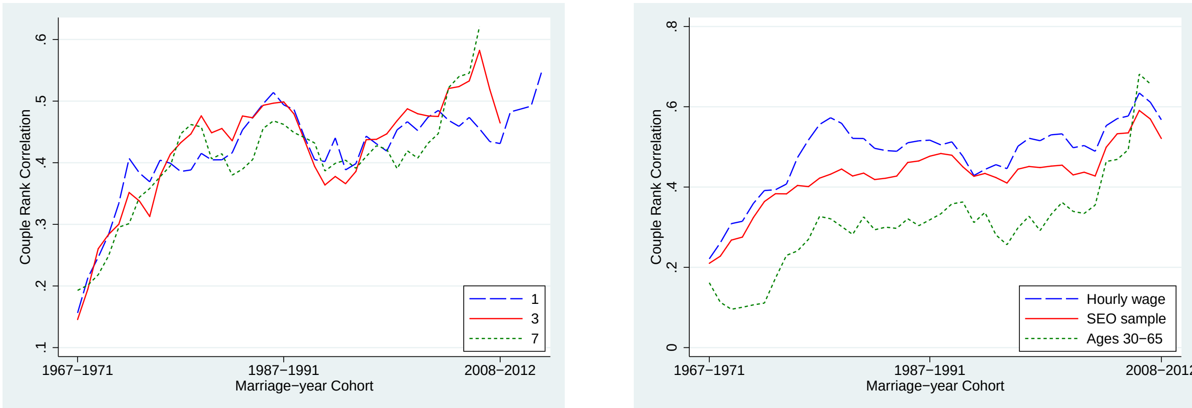
Note: The solid line in the left (right) panel, plotted on the left axis, displays the evolution of assortative mating across marriage-year cohorts, as measured by the couple rank correlation in full (residual) permanent income. The associated 95% bootstrapped confidence regions are depicted as the gray areas. The dashed line in the left (right) panel, plotted on the right axis, shows the within-cohort full (residual) family income inequality across families, as measured by the Gini coefficient. Residual permanent incomes are constructed by removing the effects of age, year, education, and sector of work from annual labor income. Two-earner families are used. *Source:* PSID.

a very high rate of labor force participation unlike an average woman of prime working age around 1970.

Figure 3.1 graphs the evolution of assortative mating and family income inequality across the cohorts. The solid line in the left panel, plotted on the left axis, shows that the assortative mating based on permanent income, as measured by permanent-income correlation of couples, increased from 0.19 in the 70s cohort to more than 0.4 in the 90s cohort. This substantial increase in assortative mating, interestingly, coincides with a strong upward trend in family income inequality (dashed line, right axis) across these cohorts. The Gini coefficient in family income increased from 0.18 in the 70s cohort to more than 0.26 in the 90s cohort. Interestingly, both the level of assortative mating and family income inequality level off after the 90s cohort.

The right panel analyzes the evolution assortative mating based on residual permanent income and residual family income inequality. Three findings stand out. First, the couple correlation drops down significantly in each cohort, and thus a large fraction of assortative

Figure 3.2: Trends in Assortative Mating under Alternative Specifications



(a) Number of Observations Used

(b) Other Specifications

Note: The left panel draws the evolution of assortative mating when different number of observations are used in permanent income calculation. The right panel displays the evolution of assortative mating when SEO sample is included; when hourly wage rather than annual wage; and, when only observations after age 30, in stead of 18, are used in permanent income construction. *Source:* PSID.

mating disappears with the age, education, and sector controls. This is mainly due to the well-known strong marital sorting in education. Second, these controls explain almost half of the rise in family income inequality as well, which is well-known in the literature (Katz and Murphy 1992; Lemieux 2006). Third, and most important, although these controls explain a significant fraction of the level of assortative mating, they don't explain the rise in assortative mating at all, which increased at a similar magnitude both based on full and residual permanent income. Therefore, the rise in assortative mating seems to be due to the residual part of the permanent income.

High-earner and/or more socially-connected individuals have a motive to help their spouses in labor market both through human capital accumulation and by finding well-paid jobs through informal networks. Changes in the strength of this motive over time might have affected the trends in assortative mating. This is especially worrisome since I use wage observations just after marriage, where presumably this motive is at its strongest level. One can test the relevance of this motive by comparing the evolution of assortative mating under alternative number of observations used in permanent income construction. This is because spousal help, in one way or another, takes time and should not reflect itself in the first year of marriage as much as few years after marriage. The left panel of Figure 3.2 shows trends in assortative mating are similar whether just first wage observation or a few more observations are used; the trends in assortative mating isn't likely to be driven by possible changes in the spousal-help motive.

The right-panel of Figure 3.2 provides other robustness checks on assortative mating trends. The solid line shows trends are similar when SEO sample is included into the analysis. The dashed line shows that trends are similar when hourly wage, in stead of annual income, is used in permanent income correlation. Therefore, labor supply margin is unlikely a key factor in the trends. Finally, the trends might have been affected by increasing observation age across cohorts caused by increase in marriage age over time. To address that, I reestimate permanent incomes by using the first five observations after age 30, when most of the individuals in all the cohorts are already married. As shown by the dotted line, trends are similar; therefore, increasing observation age doesn't seem to explain the trends.

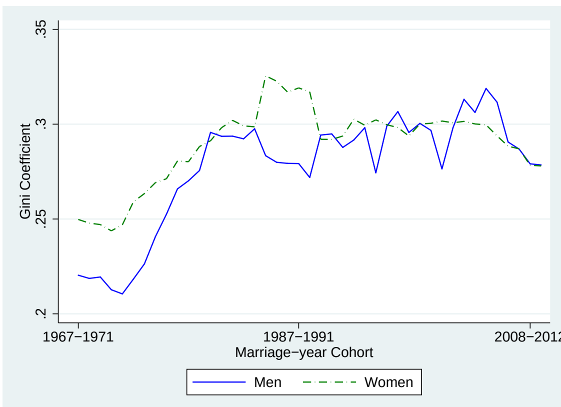
3.1 A Statistical Decomposition of Family Income Inequality

An increase in family income inequality, by construction, must be due to an increase in permanent-income inequality, assortative mating, or both. The top-left panel in Figure 3.3 shows a strong upward trend in permanent-income inequality across the cohorts.[5] Not accounting for this trend would bias the role of assortative mating in the increase in family income inequality. I therefore use the empirical copula approach to completely separate the impact of assortative mating from the changes in permanent-income distribution.

Let $\theta^c_{m,i}$ and $\theta^c_{w,i}$ denote permanent incomes of man m and woman w in family i of cohort c, and let $F^c_m(\theta_m)$ and $F^c_w(\theta_w)$ be marginal distributions of permanent incomes of men and

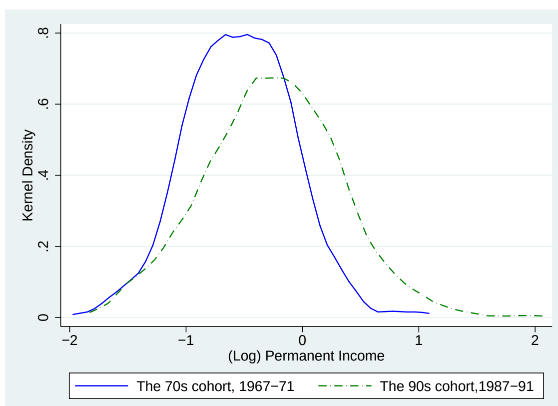
5. Gottschalk and Moffitt (1994) document the time trends in permanent income inequality over time.

Figure 3.3: Trends in Permanent-Income Inequality



(a) Permanent-income Inequality

(b) Permanent-income Distribution of Men



(c) Permanent-income Distribution of Women

Note: The top-left panel displays the evolution of permanent-income inequality, as measured by the Gini coefficient, across the cohorts. The top-right and bottom panels graph kernel density distributions of the permanent income for men and women. Solid (dashed) lines show the distributions for the 70s (90s) cohort. The Epanechnikov kernel with smoothing parameter 0.05 is used in the density estimations. *Source:* PSID.

women respectively. Then, one can specify the joint c.d.f. of $\theta_{m,i}$ and $\theta_{w,i}$ in cohort c as

$$F_{(\theta^c_{m,i},\theta^c_{w,i})}(\theta_m,\theta_w) = \mathcal{C}^c\Big(F^c_m(\theta_m), F^c_w(\theta_w)\Big)$$

where $\mathcal{C}^c$, the copula, is the joint c.d.f. of the ranks of $\theta^c_{m,i}$ and $\theta^c_{w,i}$ in their marginal distributions in cohort c.

The family income distribution can be decomposed into two components: the joint distribution of permanent-income ranks of couples (the copula) $\mathcal{C}^c\Big(F^c_m(.), F^c_w(.)\Big)$, and the marginal distributions of permanent income $F^c_m(.)$ and $F^c_w(.)$.[6] The impact of assortative mating thus can be measured by keeping the copula fixed at its form in the 70s cohort while letting the marginal distributions of permanent income vary across cohorts.

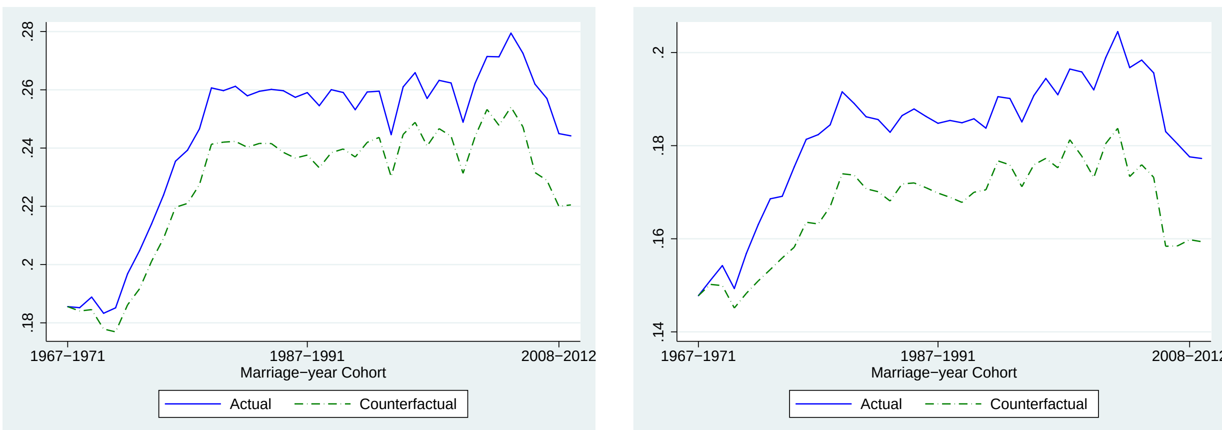
Figure 3.4 displays the findings. The left and right panels decompose the full and residual family income inequality respectively. Solid lines show the actual evolutions of inequality, while the dashed lines show the counterfactual evolutions by holding the empirical copula distribution fixed at its initial form while letting the permanent-income distribution vary. The changes in the dashed lines, thus, are purely due the changes in marginal distributions of full and residual permanent income. Clearly, these changes account for most of the increase in family income inequality. However, the differences between dashed and solid lines are sizable. The left panel shows the rise in the Gini coefficient would be almost one-third lower from the 70s cohort to the 90s cohort under the counterfactual scenario, and the right panel shows that the rise in the residual part of family income inequality would be almost 40% lower across these cohorts. The increase in the assortative mating thus accounts for a significant amount of the increase in family income inequality.

6. The copula $\mathcal{C}^c$ in cohort c can be approximated by its empirical counterpart

$$\hat{\mathcal{C}}^c(u) = \frac{1}{n+1}\sum_{i=1}^{n}\mathbb{I}\Big\{\frac{n\hat{F}^c_m(\theta^c_{m,i})}{n+1} \le u_m, \frac{n\hat{F}^c_w(\theta^c_{w,i})}{n+1} \le u_w\Big\},$$

where $u = (u_m, u_w) \in [0,1]^2$, $\mathbb{I}\{.\}$ is an indicator function, n is the number of families in cohort c, and $\hat{F}^c_m(.)$ and $\hat{F}^c_w(.)$ are the empirical marginal distributions of permanent incomes in cohort c.

Figure 3.4: Actual and Counterfactual Trends in Family Income Inequality



(a) Full

(b) Residual

Note: The left (right) panel displays the actual and counterfactual trends in full (residual) family income inequality. The Gini coefficient is used as the measure of inequality. The empirical copula approach is used to compute the counterfactual trends. The solid lines show the actual evolution of family income inequality. In the dashed lines, I keep the empirical copula distribution fixed at its initial form but let the permanent-income distribution vary across the cohorts. *Source:* PSID.

CHAPTER 4

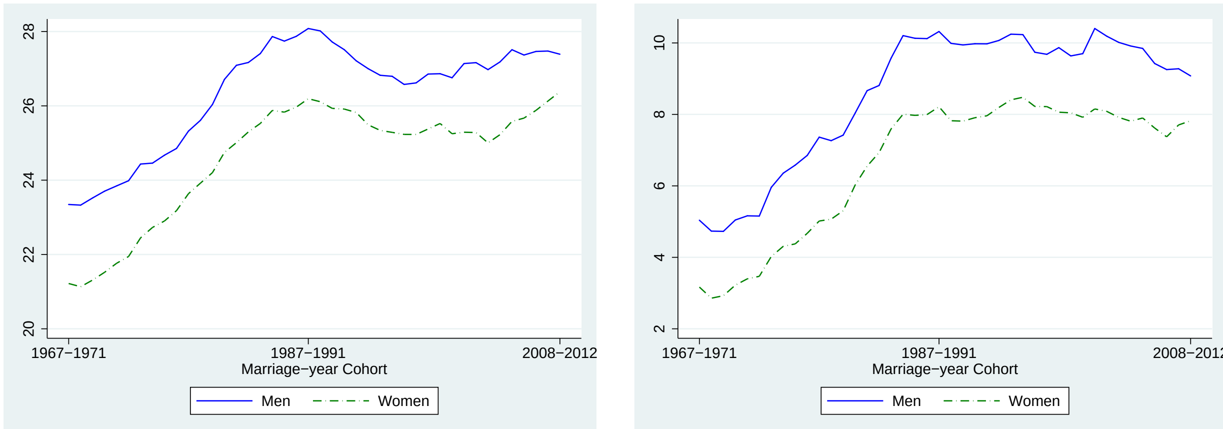
EMPIRICAL FINDINGS ON THE RELATIONSHIP BETWEEN MARRIAGE AGE AND THE ASSORTATIVE MATING

I have shown via a decomposition approach that the trend in assortative mating explains almost one-third of the increase in family income inequality. That approach, however, is silent on the mechanisms behind the increase in assortative mating. I argue that the increase in assortative mating can be explained by the factors that increase marriage age. Here, I provide some reduced-form evidence on the indirect effect of these factors on the assortative mating through shifting marriage age. I quantify this effect in the next section with a structural model.

Figure 4.1 graphs across cohorts, the evolution of the average age at marriage and the average years of work experience before marriage. The left panel shows men (women) started marriage at age 23 (21) on average in the 70s cohort, whereas the average marriage age in the 90s cohort was 28 (26). As shown in the right panel, this remarkable increase in marriage age fully translated into years of work experience. Men (woman) had only 5 (3) years of work experience on average before marriage in the 70s cohort but 10 (8) years in the 90s cohort. Work experience of men increased as much as their marriage age due to the flat trend in educational attainment of young men from the early 1971s until the 1991s (Bauman 2016). The educational attainment of young women increased significantly during this time, which seems to be offset by the earlier labor market entry of women due to the decrease in child bearing and fertility (Smith and Ward 1989). Figure 4.2 graphs the joint distribution of the marriage age of couples in the 70s and 90s cohort. It shows the strong marital sorting along age in the 70s cohort continues to hold in the 90s cohort. More importantly, the marriage age in all the quantiles of the marriage-age distribution increases significantly, although the increase in the upper quantiles is somewhat larger than in the lower quantiles.

I argue this considerable increase in marriage age can explain a part of the increase in

Figure 4.1: Mean Age at Marriage and Experience before Marriage

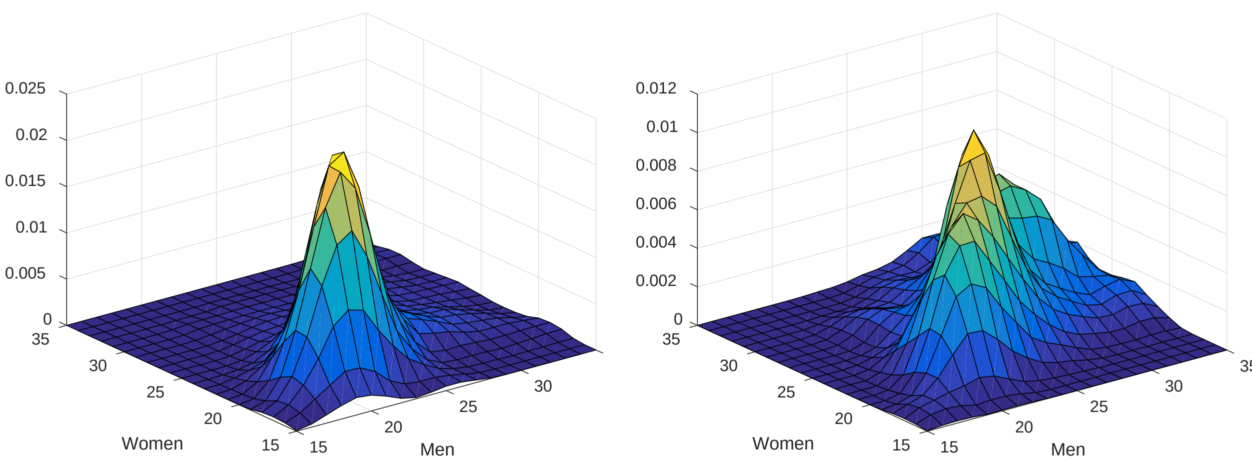


(a) Mean Age

(b) Mean Experience

Note: In the left panel, the solid (dashed) line displays the mean age at marriage for men (women) across the cohorts. In the right panel, the solid (dashed) line shows the average years of work experience before marriage for men (women) across the cohorts.

Figure 4.2: Kernel Density of Marriage Age



(a) The 70s cohort, 1967-71

(b) The 90s cohort, 1987-91

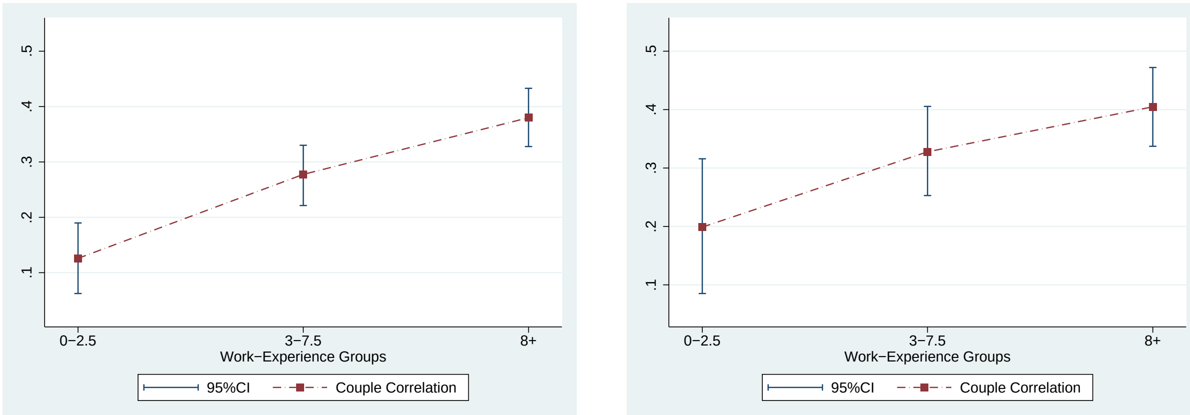
Note: The joint distribution of marriage age of couples is displayed for the 70s and 90s cohort in the left and right panel, respectively. The joint distributions are estimated by using the Epanechnikov kernel with smoothing parameter 0.04.

assortative mating. As Figure 4.1 shows, individuals in the 70s cohort married too early before spending much time in the labor market. Therefore, this cohort faced a large degree of uncertainty over their future incomes when they married because this uncertainty is high during the initial years of work (Boar 2018). This large uncertainty might have caused weak sorting along permanent income in the marriage market. However, with five years of increase in average experience, the 90s cohort might have faced much lower uncertainty at marriage time thanks to the quick resolution of this uncertainty with work experience. This reasoning might explain why the 90s cohort has stronger marital sorting.

Before fleshing out this story with a model, I first provide some reduced-form evidence on the link between marriage age and assortative mating. To do so, I divide couples into groups according to their average years of work experience before marriage and calculate couple correlation in permanent income within each group. I choose three groups due to the small sample size. Figure 4.3 shows the estimates of the correlation together with the 95% bootstrapped confidence bands. The left panel uses all the couples in my benchmark sample. Couple correlation is around 0.13 for couples with an average of 2.5 or less years of work experience before marriage, however, couples with an average of 8 or more years of experience have a 0.4 correlation and the difference is statistically significant. This finding, together with the large increase in work experience shown in the right panel of Figure 4.1, shows the increase in marriage age can potentially explain most of the trend in assortative mating. Due to a small sample size and broad experience categories, I postpone quantifying the impact of the marriage age on assortative mating to the next section.

One might worry this finding is purely driven by the fact the group with the most experience includes disproportionately more couples from the later cohorts, which are shown to have higher levels of assortative mating. One way to address this concern is to use only the couples that were formed between 1991 and 2012, because no significant trend exists in assortative mating after 1990. The right panel of Figure 4.3 shows findings for this sample. The couple correlation in this new sample is around 0.2 for couples with an average of 2.5 or

Figure 4.3: Couple Correlation in Permanent income by Experience



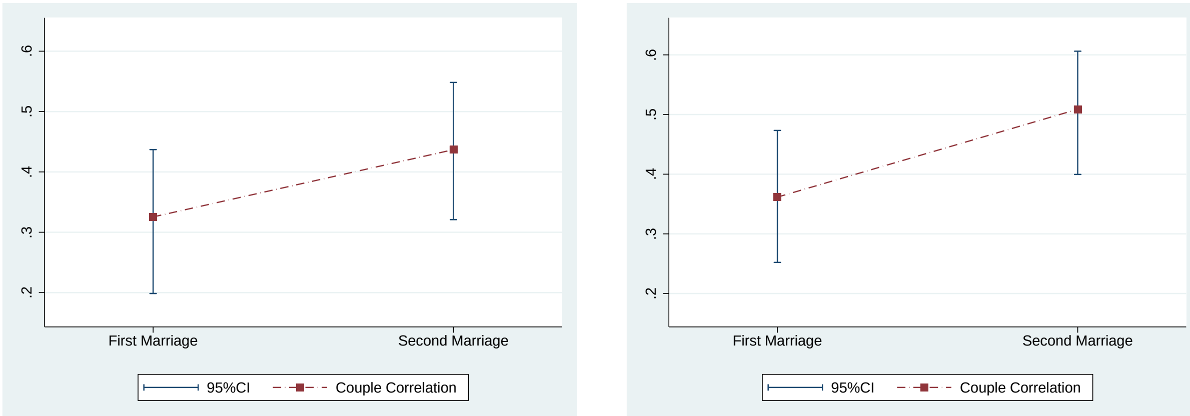
(a) All cohorts, 1967-2012. (b) Couples formed between 1991 and 2012.

Note: This figure displays couple rank correlation in permanent income for three experience categories. Couples are classified into these categories according to their average years of work before marriage. The left panel uses all the cohorts in the benchmark sample, 1967-2012, whereas the right panel uses only the couples formed between 1991 and 2012. The bands show 95% bootstrapped confidence intervals.

less years of experience and around 0.4 for couples an average of 8 or more years of experience. Although confidence intervals are broader due to the smaller sample size especially for the least experienced group, the difference between the lowest and highest experience categories remains large and statistically significant.

Figures A.4, A.5, A.6 and A.7 in Appendix A provide some robustness checks on this finding. As shown in Figures A.4 and A.5, the strong relationship between assortative mating and experience continues when hourly income is used instead of annual income and when SEO subsample of PSID is included. Moreover, couples formed at older ages might be different in particular characteristics than couples formed at younger ages, which might be the main driver of the strong relationship between marriage age and assortative mating. To address this concern, I look at the relationship between marriage age and couple correlation in residual part of permanent income, which is constructed by removing the effects of gender, education and work sector from permanent income. As shown in Figure A.6 in Appendix A, the strong relationship still holds with these controls. Moreover, most of the observations come from after marriage due to the design of PSID, which might bias my findings due to the large increase in marriage age. I address this concern in Figure A.7 in Appendix

Figure 4.4: Assortative Mating in First and Later Marriages



(a) Annual income (b) Hourly income

Note: This figure displays the degree of assortative mating in first and later marriages. The left panel displays permanent income correlation between spouses, whereas the right panel displays spousal correlation in the permanent income that is constructed by using hourly incomes rather than annual incomes. The bands show 95% bootstrapped confidence intervals.

A by constructing permanent incomes and residual permanent incomes by using income observations of individuals when they are between 30 and 45 years old. I still find a strong relationship between years of work experience before marriage and the degree of assortative mating.

Unobserved heterogeneity might obscure the true relationship between assortative mating and marriage age. One way to deal with unobserved characteristics that affect choice of marriage age is to leverage the individuals who married more than once. In Figure 4.4, I check whether these individuals display stronger sorting in their later marriages than in their first marriages. Couple correlation in permanent income is around 0.32 in their first marriages and 0.47 in their later marriages as shown in the left panel, and the difference is statistically significant. As shown in the right panel, there is a similar difference in couple correlation when hourly income is used in permanent income construction. This exercise still doesn't provide the ideal counterfactual scenario because divorces might have changed marital preferences of these individuals in a different way than that would happen if they simply postpone their first marriages. However, it shows that individuals display stronger sorting when they get married later, which is another strong evidence in favor of my view that the increased marriage age contributed to the increase in the degree of assortative mating.

CHAPTER 5

MODEL

The strong association between marriage age and assortative mating in Figure 4.3 motivates a deeper analysis on why this association exists and how much of the increase in assortative mating can be explained by the increase in marriage age. Here, I provide a framework to give substance to the mechanism outlined in the previous section, and quantify its effect on assortative mating. I build on the job-matching model of Jovanovic (1979), which I enrich by introducing the marriage market. Marriage age is exogenous in the model, and hence the role I attach to marriage age is better interpreted as the cumulative effect of all the exogenous factors that caused the increase in marriage age.

Imagine a discrete-time economy that is populated by single and married individuals. A large and equal number of single men and women enter the economy in each period. Each individual i is exogenously assigned to an education level e_i at birth. I assume four education categories: less than high school, high school, some college, and college. For simplicity, I don't model the choice of marriage age and simply assume each individual i draws a marriage age a_i according to its gender at birth from an exogenous distribution. My counterfactual analysis looks at the effects of changing this distribution on the assortative mating.

Individuals maximize the discounted sum of future utility flows, and they discount the future at rate β. They are subject to death with a constant probability δ. I further assume married couples draw same mortality shock for simplicity, and hence the economy has no widow/widower. The economy additionally has no saving technology, and individuals consume what they earn. Momentary utility of a single individual i at time t is

$$\frac{w_{i,t}^{1-\theta} - 1}{1-\theta},$$

where $w_{i,t}$ is the income of individual i at time t and θ is the relative risk aversion.

I assume utility is a public good in marriage and depends on consumption and love. More specifically, contemporaneous utility of a married household (i, j) at time t is

$$\frac{\left(b_{i,j}(w_{i,t} + w_{j,t})\right)^{1-\theta} - 1}{1-\theta},$$

where bliss shock $b_{i,j}$ measures how much pair (i, j) love each other and is constant through marriage.

5.1 Labor Market

Individuals inelastically supply one unit of labor in the labor market in each period. Production requires a match of one individual and one firm, and only labor as the input. At the beginning of each period t, individuals decide to quit or stay in their jobs. If individual i quits, he/she immediately meets with a new firm and draws a match-specific productivity $\gamma_{i,t}$ from a normal distribution with mean μ_i and variance σ^2. The individual-specific part μ_i incorporates the return to education and also heterogeneity in innate ability, and is drawn from a normal distribution with mean μ_{e_i} and variance σ_μ^2. Then, he/she produces output $e^{\gamma_{i,t}+\nu_{i,t}}$ at the end of the period, where $\nu_{i,t}$ is drawn from a normal distribution with mean zero and variance σ_ν^2. All distributional assumptions are common knowledge and μ_i is observable, but $\gamma_{i,t}$ is not observable. Individuals observe output and update their beliefs about the match-specific productivity in a Bayesian fashion. I assume income is decided before production and is set equal to the expected output in that period. Match-specific productivity is constant through tenure.

5.2 Marriage Market

All individuals who reach their marriage ages meet in a centralized marriage market in each period. A bliss shock $b_{i,j}$ realizes for every male and female pair (i, j) in the market, which is drawn from a log-normal distribution with mean zero and variance σ_b^2. Individuals prefer a partner with higher future income potential and also with a higher bliss shock. I assume the labor market history of every individual i is public knowledge and can be accessed by a potential spouse to construct beliefs about future utility flows from marrying i. Individuals use these beliefs and bliss shocks to create marriage-preference order for individuals on the other side of the market.

I restrict attention to a set of stable matchings, in which there is no pair of man and woman who are willing to abandon their partners and match each other. Utility is not transferable across married couples in the model, and the set of stable matchings in the marriage market thus has the lattice structure with two extreme matches: the "men-optimal" and the "women-optimal".[1] Findings are very similar between the men-optimal and women-optimal matches, I therefore report only the results under men-optimal matching. I use the Gale-Shapley's deferred-acceptance algorithm to solve for the men-optimal stable matching in the marriage market.

No divorce occurs in the model, hence matched couples stay together until death.

5.3 Optimization Problem of Married and Single Individuals

Now I can lay out the optimization problem for married and single individuals. Let $V^M\big(b_{i,j}, \mu_i, \mu_j, \hat{\gamma}_i, \hat{\gamma}_j, ten_i, ten_j\big)$ be the value of a married couple (i, j) with bliss shock $b_{i,j}$, individual-specific productivities μ_i and μ_j, expected match-specific productivities $\hat{\gamma}_i$ and $\hat{\gamma}_j$, and tenure ten_i and ten_j at the beginning of a period after job quit/stay decisions are

1. The men-optimal matching is the matching that all men weakly prefer compared to other stable matchings. The women-optimal matching is the same except for women.

made. This value function solves the Bellman equation

$$
\begin{aligned}
V^M\big(b_{i,j},\mu_i,\mu_j,\hat{\gamma}_i,\hat{\gamma}_j,ten_i,ten_j\big) = \frac{\Big(b_{i,j}\Big(w(\hat{\gamma}_i,ten_i)+w(\hat{\gamma}_j,ten_j)\Big)\Big)^{1-\theta}-1}{1-\theta}+ \\
\beta(1-\delta)\mathbf{E}\Bigg[\max\Big\{\underbrace{V^M\big(b_{i,j},\mu_i,\mu_j,\hat{\gamma}_i',\hat{\gamma}_j',ten_i+1,ten_j+1\big)}_{\text{Both stay}}, \\
\underbrace{V^M\big(b_{i,j},\mu_i,\mu_j,\mu_i,\hat{\gamma}_j',0,ten_j+1\big)}_{i\text{ quits, }j\text{ stays}}, \\
\underbrace{V^M\big(b_{i,j},\mu_i,\mu_j,\hat{\gamma}_i',\mu_j,ten_i+1,0\big)}_{i\text{ stays, }j\text{ quits}},\underbrace{V^M\big(b_{i,j},\mu_i,\mu_j,\mu_i,\mu_j,0,0\big)}_{\text{Both quit}}\Big\}\Bigg],
\end{aligned}
$$

where $w(\hat{\gamma}_i,ten_i)$ and $w(\hat{\gamma}_j,ten_j)$ are the incomes of i and j, which are equal to the expected outputs in the current period.[2] After realizations of outputs at the end of the period, the couple (i,j) update their expected match-specific productivities in their current jobs to $\hat{\gamma}_i'$ and $\hat{\gamma}_j'$. They then decide whether to quit their current jobs. The value of marriage doesn't depend on the value of being single since there is no divorce option in the economy.

Similarly, let $V^S\big(\mu_i,\hat{\gamma}_i,ten_i,age_i,age_i^M\big)$ be the value from being single for individual i at age age_i, with individual-specific productivity μ_i, expected match-specific productivity $\hat{\gamma}_i$, tenure ten_i, and marriage age age_i^M, at the beginning of a period after job quit/stay

2. Note that tenure also enters into the income function. This is because mean-preserving changes in the distribution of match-specific productivity affects the expected output due to the Jensen's inequality.

decision is made. This value function solves the Bellman equation

$$
\begin{aligned}
V^S\left(\mu_i, \hat{\gamma}_i, ten_i, age_i, age_i^M\right) &= \frac{w(\hat{\gamma}_i, ten_i)^{1-\theta} - 1}{1-\theta} + \beta(1-\delta) \\
\Bigg(\mathbb{I}_{\left\{age_i+1<age_i^M\right\}} \mathbf{E}\Bigg[\max\Big\{ & \underbrace{V^S\left(\mu_i, \hat{\gamma}_i', ten_i+1, age_i+1, age_i^M\right)}_{i \text{ stays}}, \\
& \underbrace{V^S\left(\mu_i, \mu_i, 0, age_i+1, age_i^M\right)}_{i \text{ quits}} \Big\} \Bigg] \\
+ \mathbb{I}_{\left\{age_i+1=age_i^M\right\}} \mathbf{E}\Bigg[\max\Big\{ & \underbrace{V^M\left(b_{i,j}, \mu_i, \mu_j, \hat{\gamma}_i', \hat{\gamma}_j, ten_i+1, ten_j\right)}_{i \text{ stays}}, \\
& \underbrace{V^M\left(b_{i,j}, \mu_i, \mu_j, \mu_i, \hat{\gamma}_j, 0, ten_j\right)}_{i \text{ quits}} \Big\} \Bigg] \Bigg),
\end{aligned}
$$

where the indicator function $\mathbb{I}_{\left\{age_i+1<age_i^M\right\}}$ takes the value of one if individual i won't reach his/her marriage age in the next period and zero otherwise. On the other hand, if individual i reaches his/her marriage age in the next period, the indicator function $\mathbb{I}_{\left\{age_i+1=age_i^M\right\}}$ takes the value of one and the individual match with a spouse according to the Gale-Shapley procedure mentioned previously.[3]

5.4 Calibration

Table 5.1 outlines the calibration. The length of a period is one year. I set discount rate β to 0.96 as in Prescott (1987). Death rate δ is set to 1/48 so that individuals in the economy live for 48 years on average.[4] Relative risk aversion θ is set to 2. I choose the next four parameters σ, σ_ν, σ_μ, and σ_m to target the key moments in Table 5.2.

3. More specifically, each individual creates marriage-preference order according to the value from marrying individuals on the other side of the market. They use all the available information–that is, realization of bliss shock, as well as information on tenure, individual productivity and expected match-specific productivity–to calculate value from marrying a person.

4. The length of work life is 48 years for a person who enters the labor market at age 18 and retires at 65.

Match-specific parameters σ and σ_ν determine how fast an individual uncovers his/her productivity in a match. Because the job-quit decision depends on the speed of learning, the persistence of income shocks is mainly governed by these two parameters. I pin down these parameters by targeting persistence-related moments in the data as in Karahan and Ozkan (2013). I estimate the following residual-income model:

$$\begin{aligned} y^i_{h,t} &= \alpha_i + z^i_{h,t} + \phi_t \epsilon^i_h, \\ z^i_{h,t} &= \rho_{h-1} z^i_{h-1,t-1} + \pi_t \eta^i_h, \end{aligned} \tag{5.1}$$

where $y^i_{h,t}$ is the residual income of person i at time t with h years of work experience, which is constructed by regressing the logarithm of income on a cubic polynomial in years of experience, four education dummies, and the full set of time fixed effects. The three terms on the right-hand side of the income equation are individual-specific, persistent, and transitory components of residual income, respectively. The second equation shows how the persistent component evolves over time. As in Karahan and Ozkan, I allow persistence parameter ρ_h to be experience specific. The innovation to permanent component η^i_h is iid and experience specific, and π_t allows its variance to be time dependent. The transitory shock ϵ^i_h is also iid and experience specific, and ϕ_t captures time dependency in its variance. I estimate this model with the minimum-distance estimator by minimizing the distance between the empirical covariance structure of residual incomes and their theoretical counterparts implied by the residual-income process above. This estimation is standard in the literature, and thus I omit its details.[5] I target the persistence moments from the initial 15 years of work life because most marriages take place during that period. I estimate average persistence ρ_h to be 0.87 and average variance of persistent shocks η^i_h to be 0.027. I then choose the parameters σ and σ_ν so that the model produces the same persistence moments with the data during the initial 15 years of work life. To calculate these moments in the model, I simulate the

5. Minimum-distance estimation is discussed in length by Guvenen (2005) and Karahan Ozkan (2013).

Table 5.1: Calibration of Parameters

	Parameter	Value
Discount rate	β	0.96
Death probability	δ	1/48
Risk aversion	θ	2
Standard deviation of match productivity	σ	0.68
Standard deviation of productivity shock	σ_ν	0.47
Standard deviation of individual effect	σ_μ	0.05
Standard deviation of bliss shock	σ_b	0.19
Education returns	μ_e	$\{0, 0.227, 0.368, 0.654\}$
Education shares for men		$\{0.058, 0.341, 0.220, 0.379\}$
Education shares for women		$\{0.065, 0.362, 0.263, 0.308\}$

Table 5.2: Model Estimation Moments

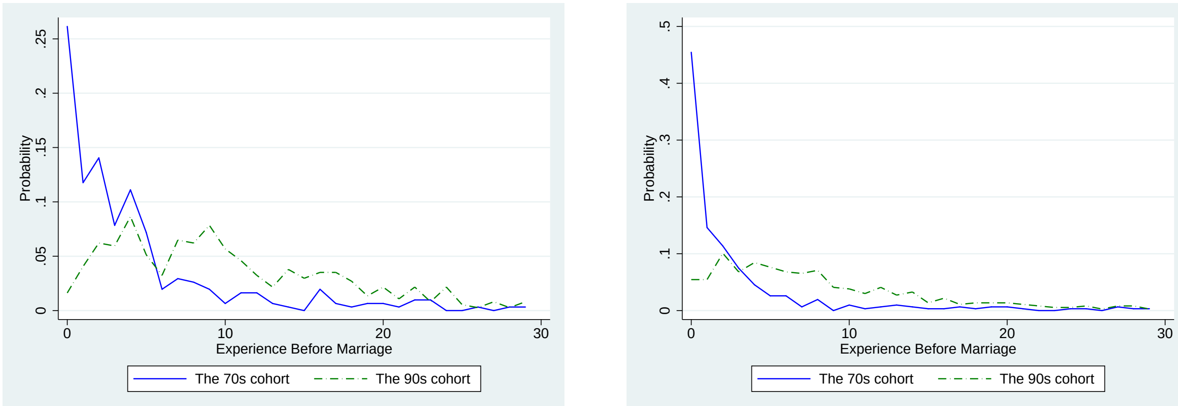
Moment	Data	Model
Gini coefficient for permanent income	0.215	0.216
Average persistence of shocks (first 15 years)	0.87	0.87
Average variance of persistence shocks (first 15 years)	0.027	0.026
Rank correlation in permanent income	0.11	0.112

model to create residual-income observations and then estimate the above residual-income process with a minimum-distance estimator without the time fixed effects ϕ_t and π_t.

The standard deviation of individual effect σ_μ is chosen to target permanent-income inequality in the data, which is 0.215, as measured by the Gini coefficient, for the 70s cohort. The match-specific component creates significant variation in the permanent income, which is why the individual fixed effect is estimated to be small relative to the match-specific component. Finally, the parameter σ_b determines the importance of love relative to income in spouse selection, and it was chosen to set the couple rank correlation in permanent income to 0.11.

Remaining parameters of the model are directly taken from the data. The returns to education are obtained from regressing the logarithm of income on a cubic age polynomial, four education dummies, and the full set of time fixed effects. The 70s cohort is used to obtain population shares of education groups. The marriage-age distributions in the model

Figure 5.1: Experience before Marriage



(a) Men (b) Women

Note: This figure displays the probability distribution of years of work experience before marriage. In the left-panel, the solid (dashed) line shows the distribution for men in the initial (final) cohort. The right-panel shows the distributions for women.

are obtained by the distributions of years of work experience before marriage in the data, because individuals start working immediately at birth in the model. The solid (dashed) lines in Figure 5.1 display these distributions for the initial (final) cohort. I use the distributions for the 70s cohort in the benchmark calibration, and the counterfactual exercise below uses the distributions for the 90s cohort instead. As shown in Figure A.8 in Appendix A, there is a bit of heterogeneity in the distributions of work experience across the education groups especially in the 70s cohort. However, I find similar results when I allow the distribution of work experience to be different across the education groups.

Figures C.1 and C.2 in Appendix C compare the educational homogamy in the data and model. Although education doesn't directly affect who matches with whom in the model, the model produces strong sorting along educational attainment. This is because education is a good predictor of future incomes in the model and thus enters into marital preferences indirectly. Moreover, educational homogamy in the data and model are very similar, which is a success of the model.

Table 5.3: Counterfactual Analysis

	Couple Rank Correlation	
	Data	*Model*
70s cohort, 1967-71	0.11	0.112
90s cohort, 1987-91	0.37	0.301

5.5 Counterfactual Analysis: Increase in Marriage Age

Here, I look at the effect of an exogenous change in marriage-age distributions on assortative mating. Holding all else fixed, I re-estimate the model by using the distributions for the 90s cohort, shown by the dashed lines in Figure 5.1, instead of the distributions for the 70s cohort (the solid lines). Table 5.3 summarizes my findings. Couple rank correlation in permanent income increases from 0.112 to 0.303. This amount accounts for almost 75% of the increase in the correlation from the 70s cohort to the 90s cohort documented in the previous section. Why does marriage age have a substantial effect on assortative mating?

In the model, individuals change jobs frequently during the first few years of their careers to find more productive jobs, this causing a considerable uncertainty in permanent income in the initial years of work. If individuals marry early, the available information on future incomes becomes noisy in the marriage market due to this large uncertainty, which leads to a weak sorting along permanent income. However, individuals find more productive jobs as they progress in their careers, which lowers their incentives to quit their current jobs and makes their future incomes more predictable. Uncertainty in permanent income, thus, resolves quickly with work experience in the model. Therefore, if individuals delay marriage, information on future incomes become less noisy in the marriage market and the sorting along permanent income thus becomes stronger.

This exercise shows that the increase in marriage age can explain most of the trend in the assortative mating and thus a significant part of the increase in family income inequality.

5.6 Uncertainty in the Data and Model

One might worry the large role of marriage age on assortative mating in the model arises due to an exaggeration of the level of income uncertainty and of the speed of its resolution with work experience. In fact, I don't target any uncertainty-related moments in the calibration although the degree of uncertainty in incomes and the speed of its resolution with work experience play crucial roles in my findings.

To address this concern, I compare the income uncertainty produced in the model with that in the data. Due to the large variation in income uncertainty by sector of work, documented by Boar (2018), I forecast future incomes for sectors separately. To do so, I first construct 17 sectors by aggregating industry-occupation pairs as in Boar (2018). Then I run the following regression for each sector s, work experience j, and horizon h :

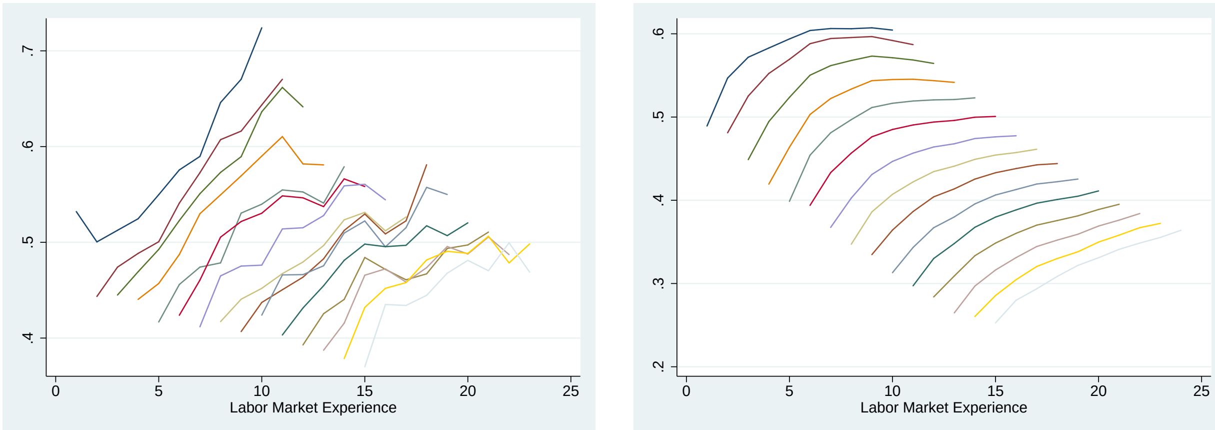
$$w^i_{j+h} = \theta_0 + \theta_1 X^i_j + \theta_2 t_{j+h} + \epsilon^i_{j,j+h}, \tag{5.2}$$

where dependent variable w^i_{j+h} is the logarithm of the hourly income of person i at experience $j+h$. The variable X^i_j is meant to capture all information available at experience j, and it includes current and lagged income, a cubic polynomial in experience, education dummies, and gender. Economic growth in incomes is captured by the time trend t_{j+h}. I use the residuals $\epsilon^i_{j,j+h}$ from this regression to construct forecast errors $\tilde{\epsilon}^i_{j,j+h}$ by the equation

$$\tilde{\epsilon}^i_{j,j+h} = \tilde{w}^i_{j+h}(e^{\epsilon^i_{j,j+h}} - 1), \tag{5.3}$$

where $\tilde{w}^i_{j+h}$ is the forecast of hourly income at experience $j+h$. As in Boar (2018), I calculate the standard deviation of $\tilde{\epsilon}^i_{j,j+h}$ using all observations in sector s and normalize it by the average of $\tilde{w}^i_{j+h}$ over all individuals at sector s to make it unit-of-measure independent. I call this ratio income uncertainty at experience j in horizon h at sector s. I then take the weighted average of this uncertainty over sectors to make it economy-wide, thus providing

Figure 5.2: income Uncertainty in the Data and Model



(a) Data (b) Model

Note: Each line in the figure shows, for a given year of work experience, the relative standard deviation of income forecast (the income uncertainty) in the 1- to 10-year-ahead horizon. For example, the leftmost line in each panel corresponds to the 1- to 10-year-ahead income forecast made in the first year of work, and the rightmost line corresponds to the forecast made in the 15th year of work. The left panel uses the data for income forecasts and the right panel uses simulated data from the model.

the level of income uncertainty at forecast horizon h for a given year of work experience j.

The left panel of Figure 5.2 graphs the level of income uncertainty in 1- to 10-year ahead horizons for the initial 15 years of work experience. An individual in his/her initial year of work experience faces more than 0.5 of a standard deviation in uncertainty about the next year's income and more than 0.7 at the 10-year horizon. But this uncertainty resolves quickly with work experience. An individual with 15 years of work experience faces less than 0.4 of a standard deviation in uncertainty about the next year's income and less than 0.5 at the 10-year horizon.

I construct income uncertainty in the model by simulating the model with a large number of individuals and then following the procedure above as if everyone is in the same sector, because the model contains no sectors. Results are shown on the right panel of Figure 5.2. As in the data, uncertainty is higher in the early years of work and it is increasing with the forecast horizon. Surprisingly, the model creates similar income-uncertainty levels with the data, although I don't target any uncertainty-related moments in the calibration. For example, an individual in his/her initial year of labor market experience faces around 0.6

of a standard deviation in income uncertainty in the data on average over the 1- to 10-year horizons, and about 0.55 in the model. An individual with 15 years of work experience faces with 0.45 of a standard deviation in income uncertainty on average over the 1- to 10-year horizons in the data but about 0.35 in the model. Admittedly, the uncertainty resolution with work experience is somewhat higher in the model than in the data. I believe this difference might be due to the overestimation of income uncertainty in the data at higher experience levels. Although many years of work experience are available for these individuals, my forecast equation only considers the most recent few years of work experience and dismisses previous income information entirely, which might have significant predictive power regarding future incomes and can decrease forecast errors significantly. Although using entire work experience in the forecasting equation seems like the optimal way to overcome this problem, it is not practical at higher experience levels with PSID data, due to the small number of observations.

CHAPTER 6
CONCLUSION

This paper investigates the evolution of assortative mating based on permanent income in the U.S. since the 1970s; quantifies its impact on rising family-income inequality; and, finally, tries to understand the factors behind this evolution. It documents a significant increase in assortative mating, as measured by couple's permanent-income correlation, between families formed around 1970 and that formed around 1990. I then show that changes in the degree of assortative mating accounts for a sizable amount of the increase in family income inequality across these family cohorts. This finding shows focusing on the time trends in permanent-income inequality is not enough to understand the mechanics of increasing family income inequality. Note, this finding does not rule out a feedback mechanism. It might be that increasing family income inequality incentivized individuals to care more about their spouse's incomes, causing a higher degree of marital sorting along permanent income, which in turn mechanically increased family income inequality.

However I then argue that the increase in the marriage age can explain most of the increase in assortative mating. I first show a positive association between the degree of assortative mating and years of work experience previous to marriage. This finding is complemented with a structural model that quantifies the impact of increased marriage age on assortative mating. I show that the increase in marriage age can explain most of the increase in assortative mating and thus accounts for a significant part of the increase in family income inequality.

It is important to keep in mind that marriage age is not exogenous as assumed in the model. A large literature already documents the exogenous factors behind the increase in marriage age. The effect I attributed to the marriage age in my analysis, thus, should be understood as the indirect effect of all these factors on assortative mating through increasing marriage age. Going forward, an interesting extension of the model would be to allow individuals to choose when they marry. With this extension, one can discuss the link between these factors and assortative mating in a more transparent way and might even be able to quantify the role of each of these factors separately.

Another interesting extension of my analysis could be an examination of fiscal policy implications of assortative mating. Under the current U.S. tax system, dual-earner couples with similar incomes are generally subject to significantly higher tax rates than those with unequal incomes (Pomerleau, 2015; Lin and Tong, 2012). Assortative mating, thus, affects federal tax revenues even when its effect on inequality is ignored. It would be interesting to measure how large would be the impact of the increase in assortative mating on federal tax revenues.

Finally, my model and analysis only cover the impact of increased marriage age on the current generation. It seems likely to have a larger impact in the long-run due to the intergenerational mechanisms this paper overlooks. An increase in the degree of assortative mating in a generation, caused by an increase in marriage age, will increase the permanent income inequality among the children of this generation. This occurs because of the transfer of labor market ability from parents to kids by genetics and time spent together, as well as by the increasing disparity in human capital investment on the children across families with the increase in family income inequality. Based on my findings, these intergenerational mechanisms needs increased attention, particularly since I documented large increase in the degree of assortative mating.

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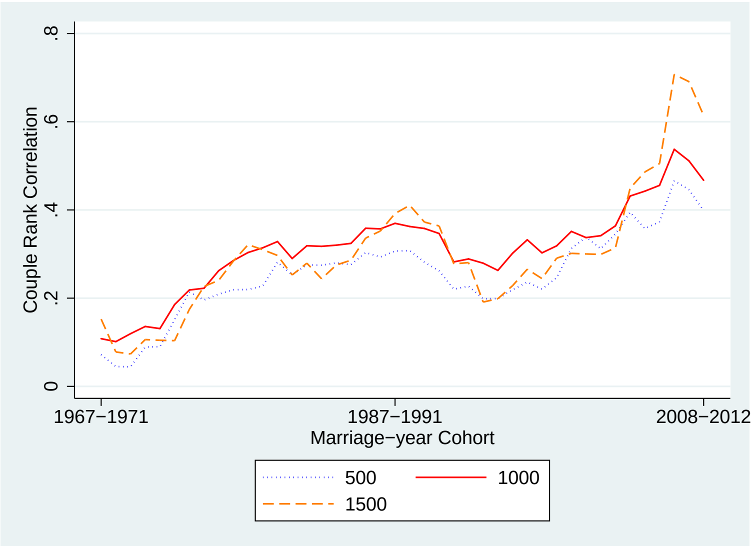
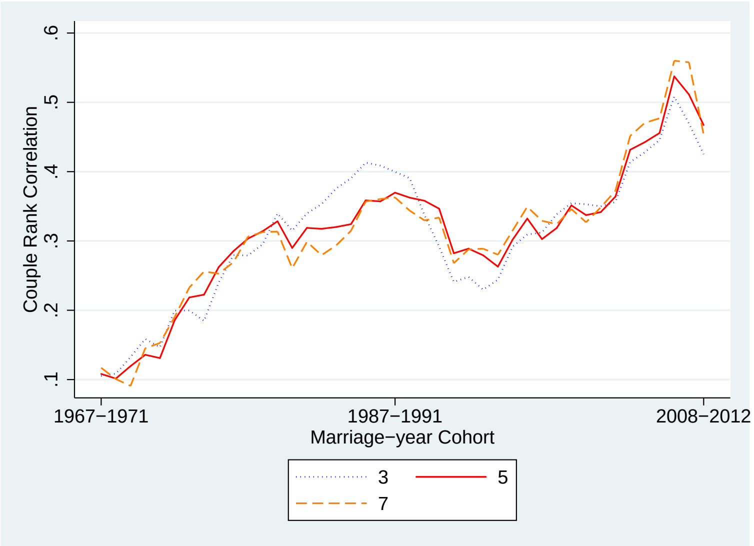
APPENDIX A

ADDITIONAL RESULTS AND ROBUSTNESS EXERCISES

Figure A.1: Assortative Mating Trend by Alternative Minimum Hours and Observations Restrictions



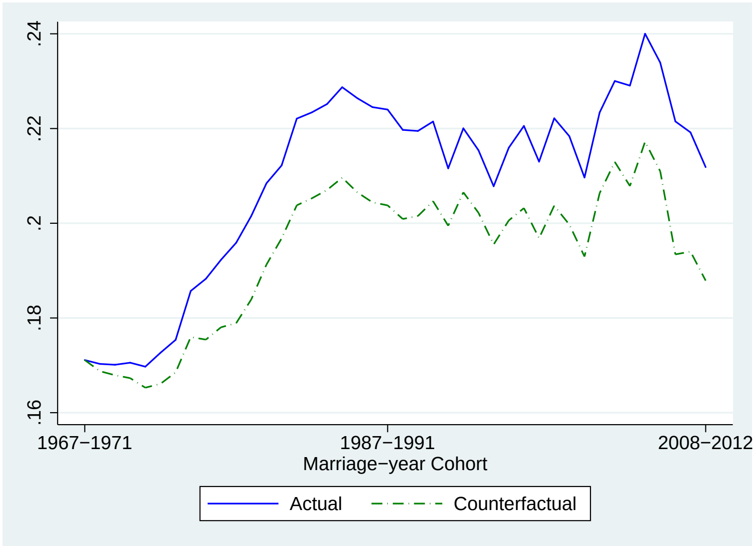
(a) Minimum Hours



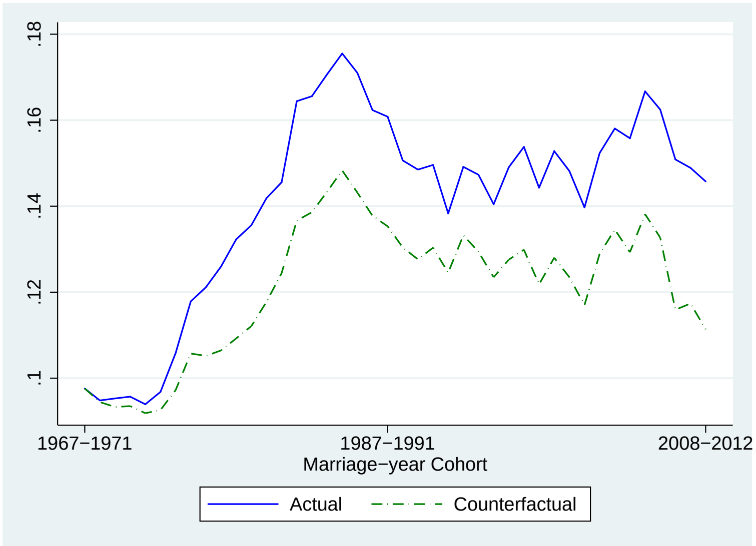
(b) Number of Observations

Note: The top panel displays couple correlation in permanent income by imposing different restrictions on minimum hours of work in sample selection: 500, 1000 (the benchmark) and 1500 hours. The bottom panel displays correlation by imposing different restrictions on number of observations: 3, 5 (the benchmark) and 7 observations.

Figure A.2: Actual and Counterfactual Trends in Family income Inequality using Annual income



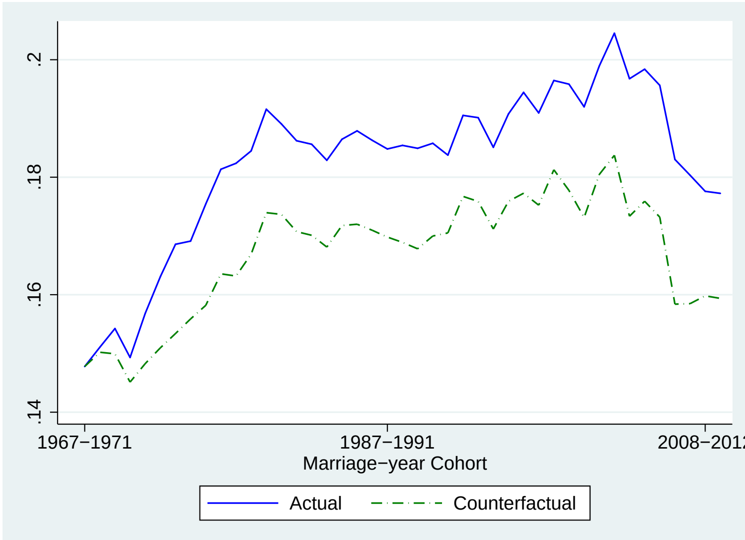
(a) Gini Coefficient



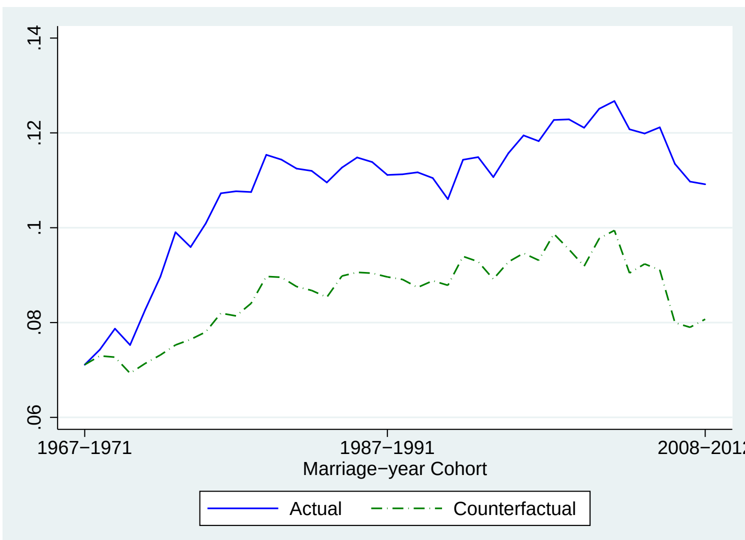
(b) Variance

Note: This figure displays the actual and counterfactual trends in family income inequality by using hourly income rather than annual income in permanent income estimation. The Gini coefficient (the variance of logarithm) is used as the measure of inequality in the left (right) panel. The empirical copula approach is used to compute the counterfactual trends. The solid lines show the actual evolution of family income inequality. In the dashed lines, I keep the empirical copula distribution fixed at its initial form but let the permanent-income distribution vary across the cohorts.

Figure A.3: Actual and Counterfactual Trends in Family income Inequality using Residual income



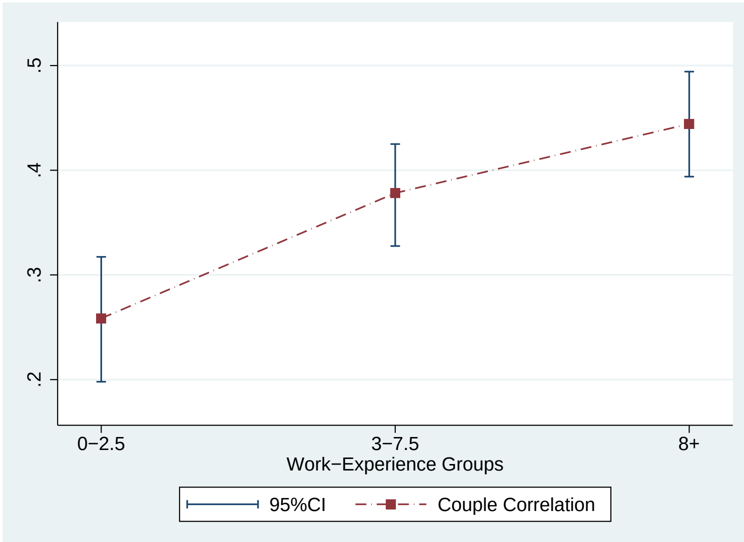
(a) Gini Coefficient



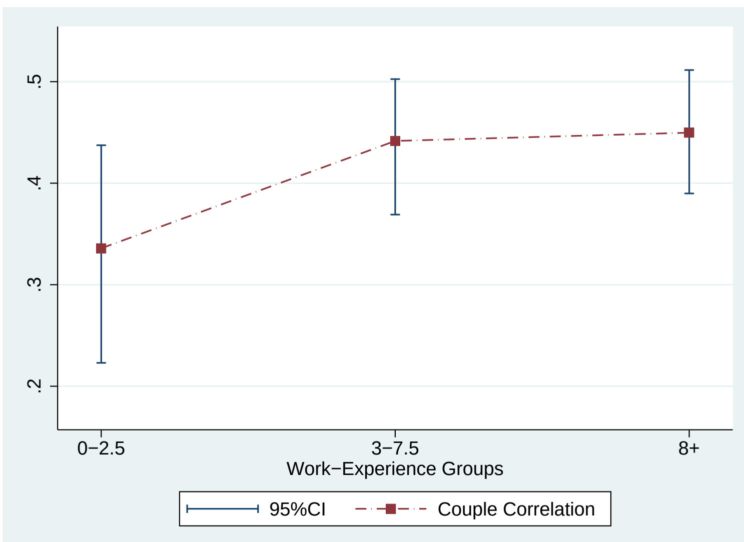
(b) Variance

Note: This figure displays the actual and counterfactual trends in family income inequality by using residual part of the permanent income. I reestimate the regression equation with gender, education and sector controls, and calculate residual permanent income by taking average residual for a person. Family income is defined as the sum of residual permanent incomes of both spouses. The Gini coefficient (the variance of logarithm) is used as the measure of inequality in the left (right) panel. The empirical copula approach is used to compute the counterfactual trends. The solid lines show the actual evolution of family income inequality. In the dashed lines, I keep the empirical copula distribution fixed at its initial form but let the permanent-income distribution vary across the cohorts.

Figure A.4: Couple Correlation in Permanent income by Experience



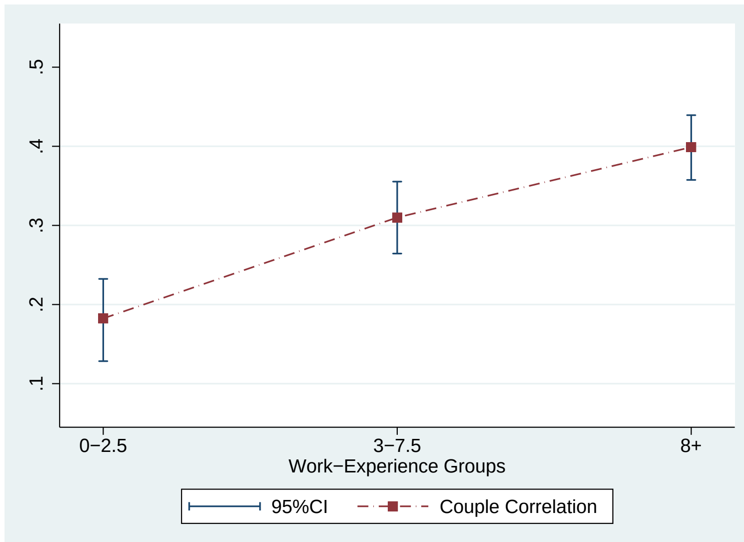
(a) All cohorts, 1967-2012.



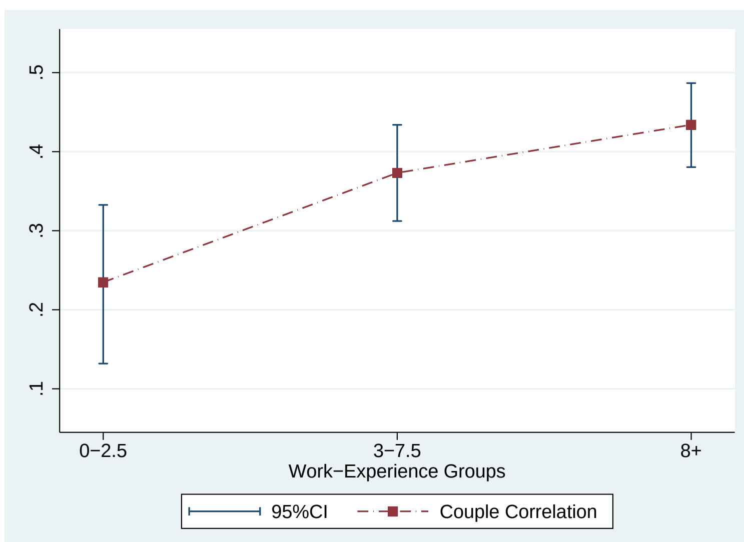
(b) Couples formed between 1991 and 2012.

Note: This figure displays couple rank correlation in permanent income using hourly incomes rather than annual incomes for three experience categories. Couples are classified into these categories according to their average years of work before marriage. The left panel uses all the cohorts in the benchmark sample, 1967-2012, whereas the right panel uses only the couples formed between 1991 and 2012. The bands show 95% bootstrapped confidence intervals.

Figure A.5: Couple Correlation in Permanent income by Experience



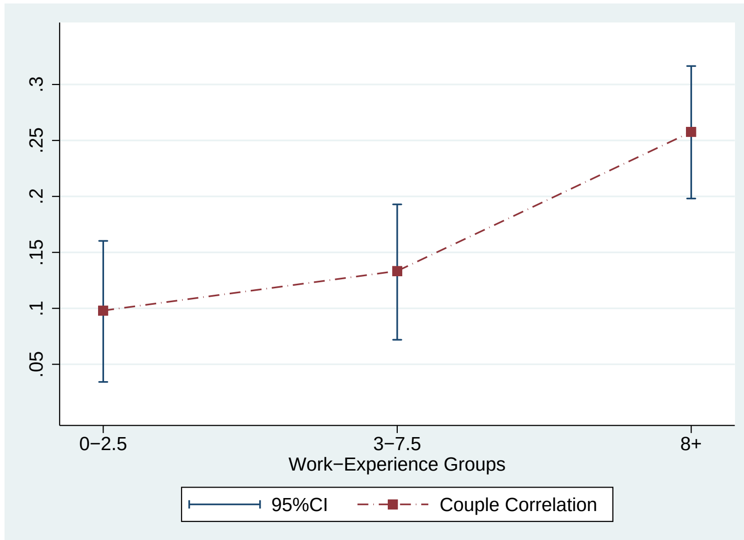
(a) All cohorts, 1967-2012.



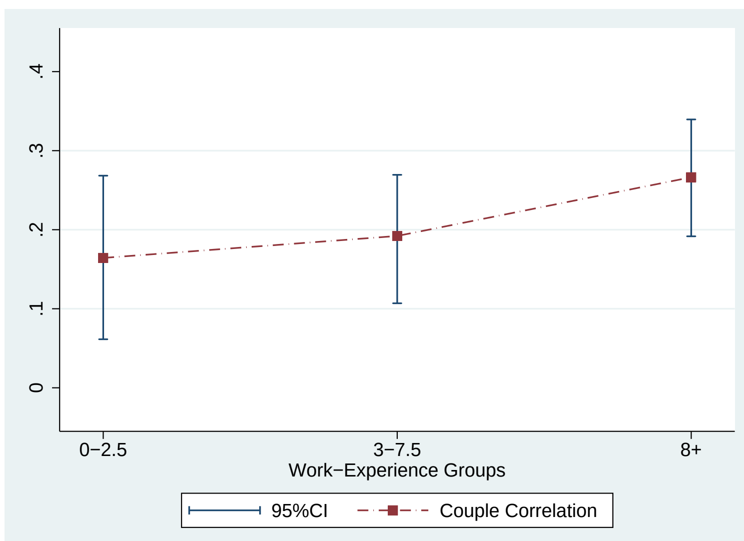
(b) Couples formed between 1991 and 2012.

Note: This figure displays couple rank correlation in permanent income by including SEO panel of PSID for three experience categories. Couples are classified into these categories according to their average years of work before marriage. The left panel uses all the cohorts in the benchmark sample, 1967-2012, whereas the right panel uses only the couples formed between 1991 and 2012. The bands show 95% bootstrapped confidence intervals.

Figure A.6: Couple Correlation in Residual Permanent income by Experience



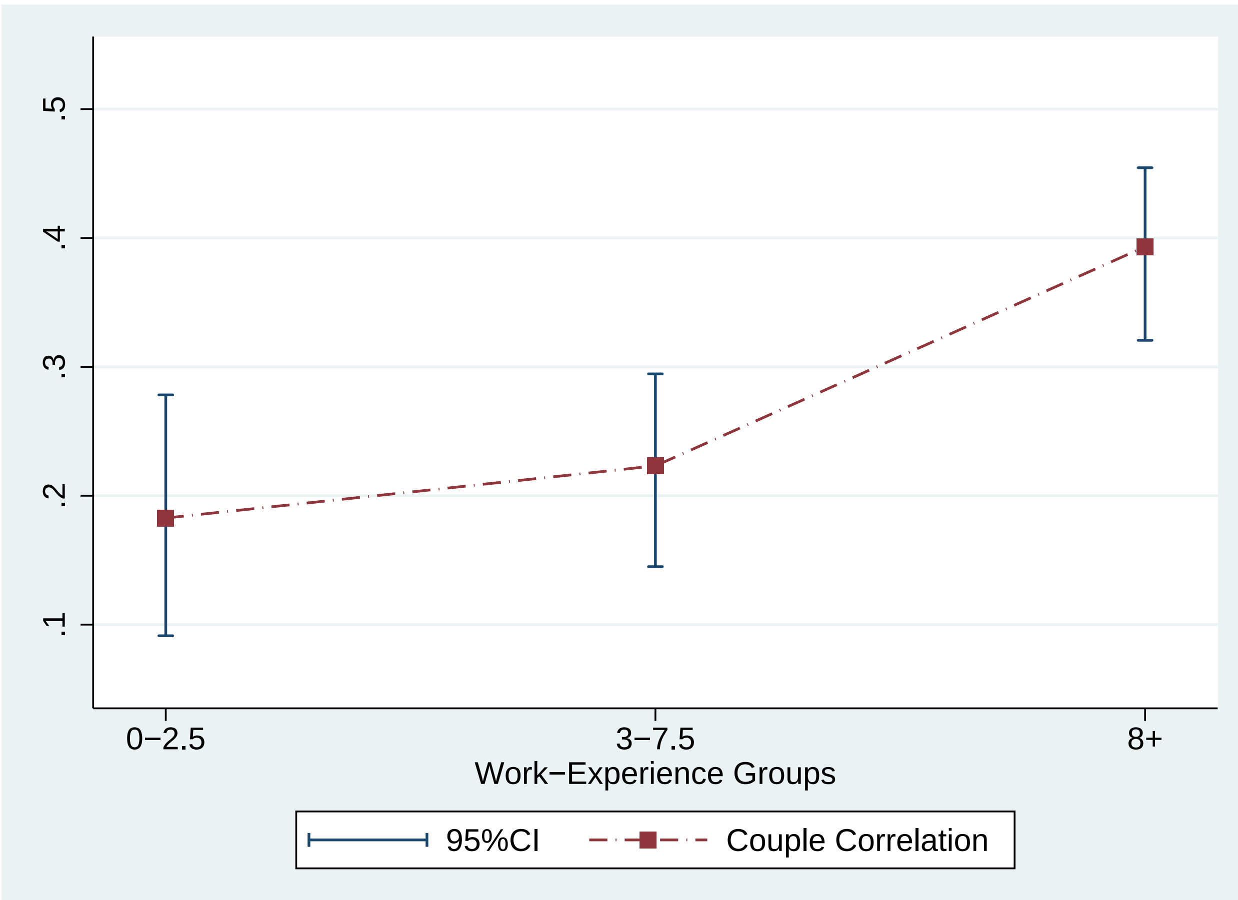
(a) All cohorts, 1967-2012.



(b) Couples formed between 1991 and 2012.

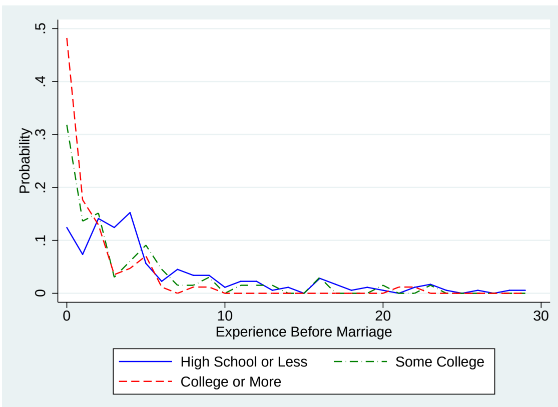
Note: This figure displays couple rank correlation in residual part of permanent income for three experience categories. Couples are classified into these categories according to their average years of work before marriage. The left panel uses all the cohorts in the benchmark sample, 1967-2012, whereas the right panel uses only the couples formed between 1991 and 2012. The bands show 95% bootstrapped confidence intervals.

Figure A.7: Couple Correlation in Permanent income by Experience

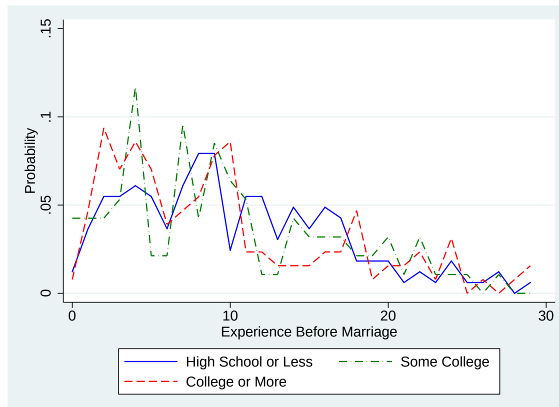


Note: This figure displays couple rank correlation in permanent income for three experience categories. Couples are classified into these categories according to their average years of work before marriage. Permanent incomes are constructed by using income observations from individuals when they are between 30 and 45 years old. The bands show 95% bootstrapped confidence intervals.

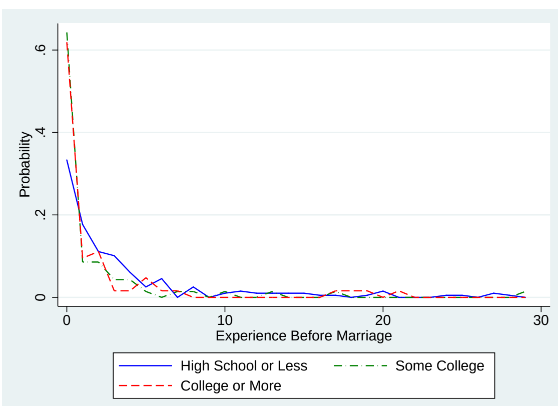
Figure A.8: Distribution of Work Experience before Marriage by Education



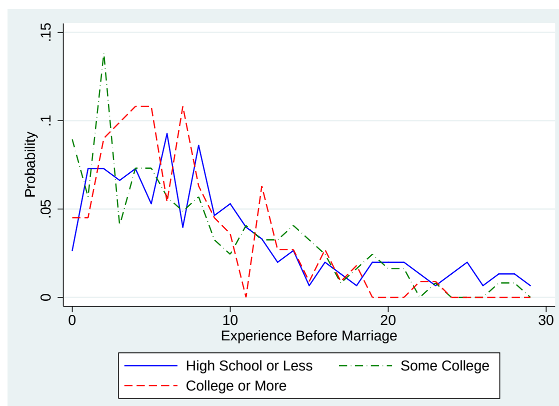
(a) Men in the 70s cohort



(b) Men in the 90s cohort



(c) Women in the 70s cohort



(d) Women in the 90s cohort

Note: This figure displays the probability distribution of years of work experience before marriage for three education categories: high-school or less, some college, and 4-years of college or more. The top-left (top-right) panel shows the distributions for men in the 70s (90s) cohort. The bottom-left (bottom-right) panel displays the distributions for women in the 70s (90s) cohort.

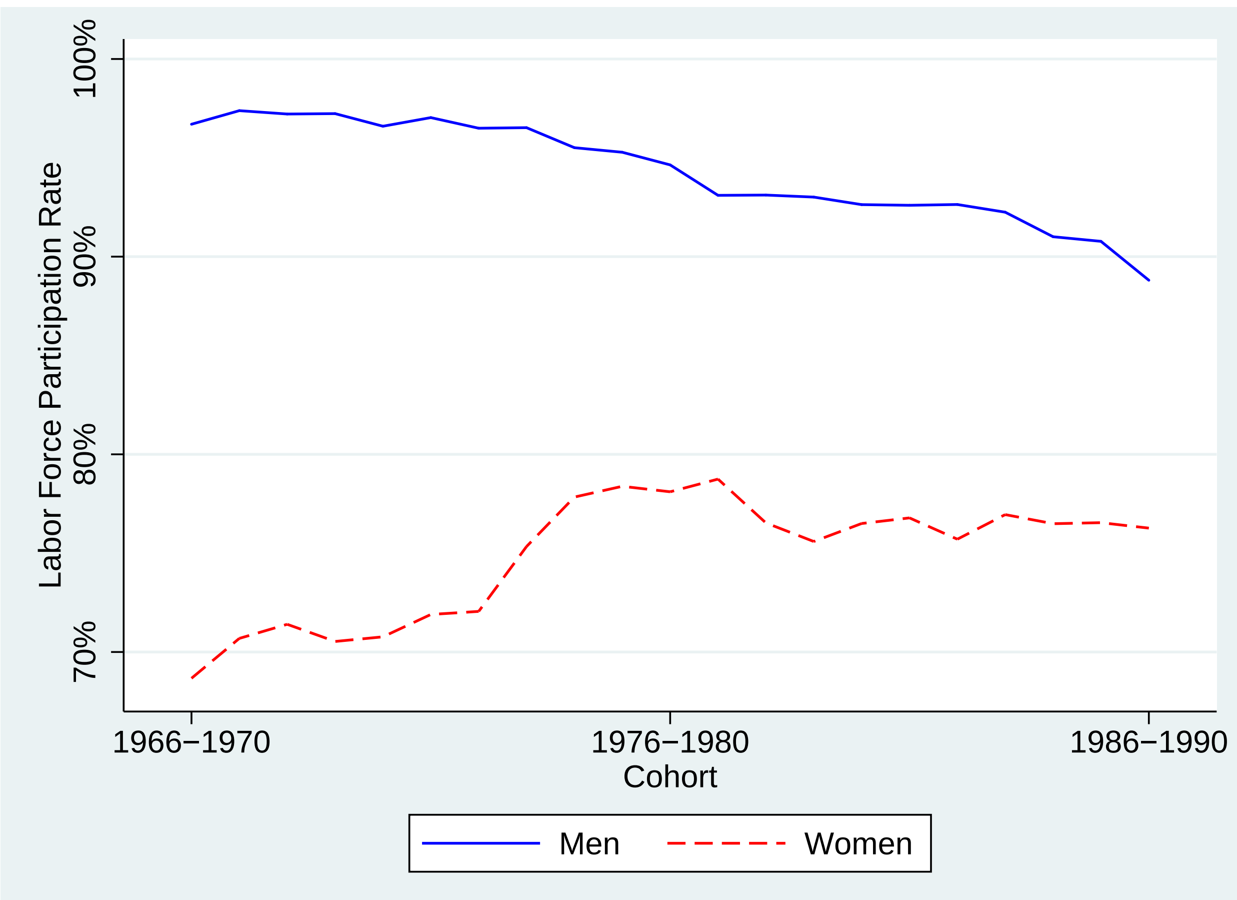
APPENDIX B

CHANGES IN LABOR FORCE PARTICIPATION

There are significant changes in labor force participation over time. In Figure B.1, I present the labor force participation for family cohorts by gender. An individual is assumed to be participating in labor market if he/she worked more than half of their prime working-age years. Labor force participation of women increased from 68% in the 70s cohort to 76% in the 90s cohort, while labor force participation of men decreased from 97% to 89%.

Could these changes in labor force participation play a role in the increase in the as-

Figure B.1: Labor Force Participation by Gender

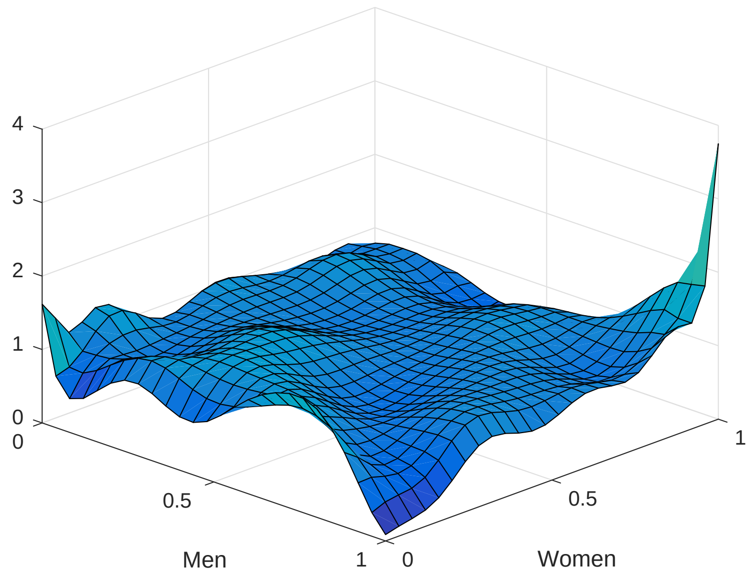


Note: This figure displays the labor force participation rate across family cohorts. Labor force participation in a cohort is calculated as the population share of individuals who worked more than half of their prime working-age years. The solid (dashed) line shows the evolution of labor force participation for men (women).

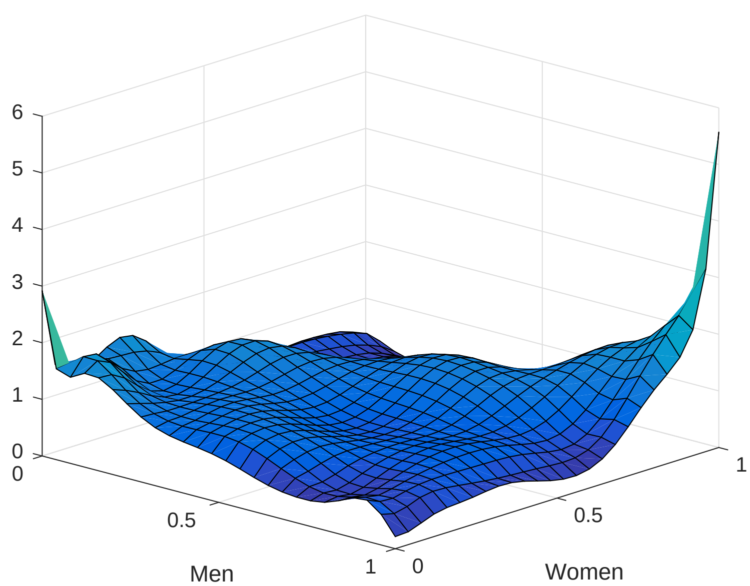
sortative mating? This could happen only if the labor force participation (LFP) increased relatively more for the demographic groups that have relatively higher permanent income correlation between spouses. One potential source of heterogeneity in LFP changes might be educational attainment. However, Juhn and Potter (2006) show that LFP changed at similar magnitudes for different education groups. Moreover, as shown in Bauman (2016), educational attainment didn't change much for young men from the early 1971s until 1991s; it did increase a bit for young women from 1971s to 1991s, but the change was small relative to post-1991. Therefore, compositional changes in two-earner families in terms of educational attainment were unlikely to lead to sizable changes in the degree of assortative mating.

Mulligan and Rubinstein (2008) argue that less able women participated relatively more in the labor force during the 1971s, with this reversing in the subsequent decades. This change in the composition of working female population can increase the degree of assortative mating if the degree of assortative mating is relatively higher for more able women. In Figure B.2, I draw the joint rank distribution (the copula) of couples' permanent incomes to check the heterogeneity in the degree of sorting with women's ability. Although there is a strong sorting, especially in the 90s cohort, as evidenced by the relatively large mass on the diagonal, there is no significant differences in the level of sorting between high- and low-ability woman. Moreover, in Figure B.3, I present the probability of a couple being in the same permanent income quintile (decile) conditional on the permanent income quintile (decile) of woman. It shows that these conditional probabilities are slightly higher for relatively less-able women. The degree of this is small enough to conclude that the compositional changes in the female labor force argued by Mulligan and Rubinstein (2008) were unlikely to be important factors behind the increase in assortative mating.

Figure B.2: Empirical Copula Density of Permanent income



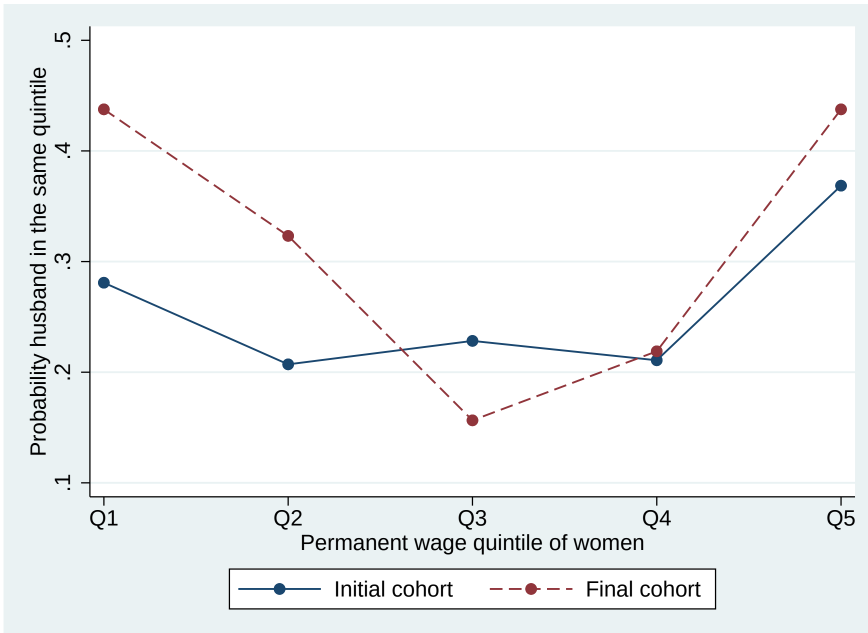
(a) The 70s cohort, 1967-71.



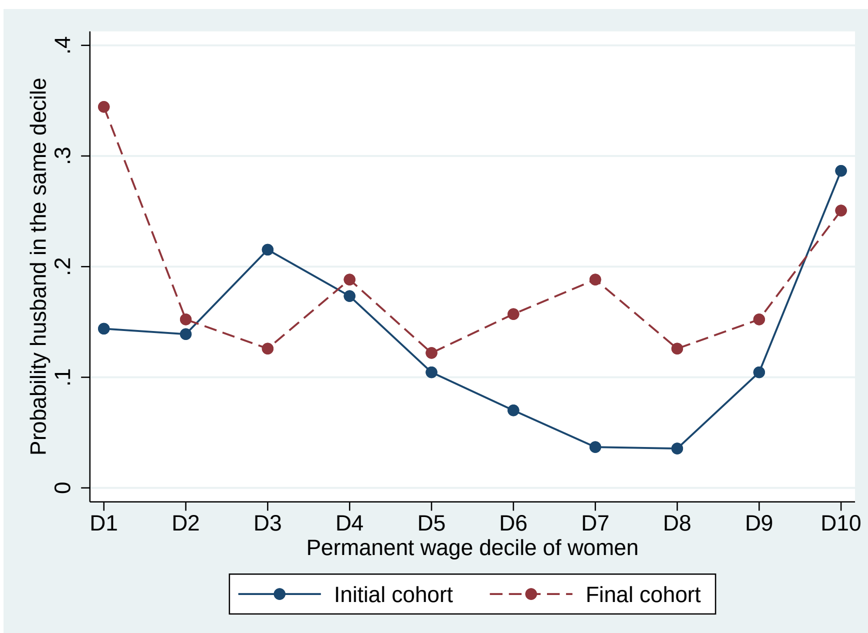
(b) The 90s cohort, 1987-91.

Note: The joint rank distribution (the copula) of couples' permanent income is displayed for the 70s and 90s cohort in the top and bottom panel, respectively. The joint distributions are estimated by using the Epanechnikov kernel with smoothing parameter 0.04.

Figure B.3: Probability of a couple being in the same quintile and decile



(a)



(b)

Note: The top (bottom) panel shows the conditional probability of a couple being in the same permanent income quintile (decile) given the permanent income quintile (decile) of the woman. The solid (dashed) line uses the couples from the 70s (90s) cohort.

APPENDIX C

ADDITIONAL FINDINGS IN THE MODEL

Table C.1: Educational Homogamy in the Data and Model

Wives' Education / **Husbands' Education**	HS-	HS	Col-	Col
HS-	69.0% / 67.7%	21.9% / 22.1%	6.8% / 7.3%	2.1% / 2.6%
HS	32.4% / 29.1%	36.0% / 37.9%	23.8% / 23.2%	7.6% / 9.6%
Col-	13.3% / 11.5%	34.7% / 23.6%	37.9% / 41.4%	13.9% / 23.3%
Col	4.1% / 2.2%	12.1% / 11.6%	27.9% / 25.8%	55.8% / 60.3%

Note: The values below (above) the diagonal in each cell gives the conditional probability of the wife's education category in the data (model) given the husband's education category. The data values are calculated by using the 70s cohort. Four education categories are used: less than a high school graduate, high school graduate, some college, and college graduate.

Table C.2: Educational Homogamy in the Data and Model

Husbands' Education / **Wives' Education**	HS-	HS	Col-	Col
HS-	41.4% 37.2%	50.3% 49.2%	5.6% 9.5%	2.5% 3.9%
HS	14.9% 11.1%	63.1% 58.3%	15.2% 20.7%	6.7% 9.8%
Col-	5.9% 4.3%	58.8% 35.7%	23.3% 36.3%	11.8% 23.5%
Col	2.0% 0.8%	23.6% 17.2%	19.6% 22.2%	54.5% 59.6%

Note: The values below (above) the diagonal in each cell gives the conditional probability of the husband's education category in the data (model) given the wife's education category. The data values are calculated by using the 70s cohort. Four education categories are used: less than a high school graduate, high school graduate, some college, and college graduate.