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ABSTRACT

Marital Patterns and Income Inequality*

We investigate the role of marital patterns in explaining rising income inequality using a structural marriage matching model with unobserved heterogeneity. This allows us to consider both the extensive and intensive margins of the marriage market, i.e. who remains single and who marries whom. Using US data from 1962 to 2017, we show that marital patterns can explain about 1/3 of the rise in income inequality. The intensive margin (educational assortative mating) has only played a minor role (5%), the extensive margin being the main driver of the contribution of marital patterns (95%).

JEL Classification: C78, D1, D3, I24, J12

Keywords: marriage market, matching, singles, assortative mating

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1. Introduction

Most developed countries have witnessed a dramatic rise in income inequality over the last six decades (Piketty and Saez, 2003). As a result, the study of (the sources of) income inequality has been increasingly popular among economists, with plausible explanations coming from unexpected fields such as family economics. A recent stream of research (Eika, Mogstad, and Zafar, 2017; Ciscato and Weber, 2017) has indeed addressed the question: to what extent do marriage patterns and in particular education assortative mating explain between-household income inequality? To answer this question, researchers have relied on a battery of models and statistical techniques developed by economists, sociologists and demographers to measure education assortative mating (e.g. Schwartz and Mare (2005) in sociology or Liu and Lu (2006) in economics) and quantify its contribution to income inequality. All these techniques rely on producing counterfactual data for any given market in which, ceteris paribus, the observed education assortative mating has been replaced by a reference one. The bulk of this literature uses random matching as the reference which is computed as the product of the marginal distribution of married men and women by education. This requires to *take as given* the observed distribution of singles in that market. As a result, this reference measure of assortativeness depends crucially on implicit assumptions about (the evolution of) singles' utilities underlying the (evolution of the) distribution of singles. Since this approach is silent about the evolution of the extensive margin, it does not allow to quantify the role of singles in measures of assortativeness and inequality.

In this paper, we follow a recent literature in family economics that studies marriage as a matching market (Choo and Siow, 2006; Chiappori, Salanie, and Weiss, 2017) and take a structural approach to consider both the extensive and intensive margins of the marriage market, i.e. the "who remains single" effect and the "who marries whom" effect respectively. Our main contribution is to show that, using a simple structural approach such as the one developed in Choo and Siow (2006) (CS from now on), equilibrium is fully characterized by a set of nonlinear equations (Galichon, Kominers, and Weber, 2018), that can be used to construct various reference measures of assortativeness taking the "who remains single" effect into account. More precisely, our approach distinguishes between "fixed joint utility" references that pin down the joint utility of couples but allow the (reservation) utilities of singles to vary across markets so that the distribution of singles corresponds to the observed one in that market; and "fixed surplus" references that pin down the full joint surplus of couples. This distinction is of crucial importance since "fixed joint utility" and "fixed surplus" references do not impose the same restrictions on the utility, and hence the distribution, of singles. Using "fixed surplus" references, one produces counterfactuals that indicate the evolution of marital patterns merely due to observed changes in the distribution of types of men and women over time. In contrast, using "fixed joint utility" references, one produces counterfactuals that indicate the observed evolution of marital patterns due to both, observed changes in the distribution of types and the distribution of singles. The difference between these two series of counterfactuals therefore quantifies the "who remains single" effect whereas the difference between the "fixed joint utility" series of counterfactuals and observed data quantifies the "who marries whom" effect.

With this distinction in mind, we then introduce four references: two "fixed joint utility", one where the joint utility of couples is set to that of a chosen market ("reference market adjusted for singles") and one where the joint utility is set to 0 ("random"), and two "fixed surplus", one where the surplus of couples is set to that of a chosen market ("reference market") and one where the surplus of couples is set to 0 ("pure random"). We show that the random matching reference used in e.g. (Eika, Mogstad, and Zafar, 2017) is equivalent to the "random" reference, hence a "fixed joint utility" reference.

We bring the model to data for the US marriage market between 1962 and 2017 and compute four measures of education assortative mating based on the four references defined above, using 1962 as the reference market. We show that whether one chooses the random matching as reference or the "reference market" matters in terms of the evolution of associated measures of education assortativeness. For instance, while the "pure random" and "random" references both indicate a decline of assortativeness among College graduates, the "reference market" and "reference market adjusted for singles" both indicate an increase. We argue that the approach consisting of choosing an observed market as reference is more "realistic" since it is based on preferences measured in the data rather than some arbitrary values, 0, underlying the "random" matching reference.

Interestingly, whether the reference is "fixed joint utility" or "fixed surplus" matters for the measure of assortativeness when the reference is an observed market. When fixing the joint utility of couples to be at the level of the reference market ("reference market adjusted for singles") we find that for all educational levels, assortativeness rises, more so for the "below High-School" level. In contrast, when fixing the joint surplus of couples to be at the level of the reference market ("reference market"), we find that assortativeness rises for both some College and College graduates and declines for High-School graduates.

We then document the rise in between-household income inequalities as measured by the Gini coefficient, where households include both singles and couples. We find that the associated Gini coefficient rose from 0.38 in 1962 to 0.5 in 2017. Using the "reference market" as counterfactual, we find that inequality would have been lower in 2017 by almost 0.04 Gini points. This indicates that marital patterns can explain up to 1/3 of the observed increase in income inequality over the period. We further decompose this effect into the "who remains single" and "who marries whom" effects. Using the "reference market adjusted for singles" as counterfactual, we find that inequality would have been roughly similar to that observed in 2017. This indicates that the effect of marital patterns on rising income inequality is merely due to the "who remains single" effect (95%) whereas assortativeness in education, the "who marries whom" effect, only contributes very little (5%).

Relation to the literature. Our model of the marriage market is a frictionless matching model with perfectly transferable utility (TU). Early contributions to the TU matching literature include Koopmans and Beckmann (1957), Shapley and Shubik (1971) and Becker (1973). Recently, several papers extended this framework by adding unobserved heterogeneity in tastes, e.g. CS, Dupuy and Galichon (2014) and Galichon and Salanié (2015). Our setting relies heavily on the CS model, in particular its reformulation as a matching function equilibrium (Galichon, Kominers, and Weber, 2018).

We use the model to study educational assortative mating and income inequality between households. For a theoretical discussion of the connection between educational assortativeness and income inequality, see e.g. Fernandez et al. (2005). There is a substantial literature in economics, sociology and demography documenting trends in educational assortative mating, e.g Kalmijn (1991), Mare (1991), Schwartz and Mare (2005), Liu and Lu (2006), and Gihleb and Lang (2016). The effect on income inequality is studied in Burtless (1999), Greenwood et al. (2014) and more recently

Eika, Mogstad, and Zafar (2017). These papers rely on a purely statistical approach. One exception is Ciscato and Weber (2017) who make use of the continuous and multidimensional version of the Choo and Siow model developed by Dupuy and Galichon (2014). However, singles are excluded from their analysis.

Organization of the paper. The paper is organized as follows. Section 2 introduces our matching model and section 3 presents the computation of the various counterfactual experiments used to measure assortativeness and decompose income inequality. Section 4 presents the data and descriptive statistics, and section 5 documents trends in educational assortativeness in the US marriage market between 1962 and 2017. In section 6, we present and discuss the decomposition of (trends in) income inequality. Section 7 concludes. Additional computational details and results can be found in the appendix.

2. The matching model

2.1. **Set up.** A marriage market consists of men $i \in \mathcal{I}$ and women $j \in \mathcal{J}$ who meet on the market and may form heterosexual couples, holding the option to remain single. We assume that men and women can be grouped into *types*, each type containing individuals with similar observable (to the analyst) characteristics. The set of types for men is denoted $\mathcal{X}$ and the set of types for women is denoted $\mathcal{Y}$. A man i is then said to be of observable type x_i and woman j of observable type y_j. The set of types of both men and women is extended to include the option of remaining single, i.e. $\mathcal{X}_0 = \mathcal{X} \cup \{0\}$ and $\mathcal{Y}_0 = \mathcal{Y} \cup \{0\}$.

A matching μ is a vector $(\{\mu_{xy}\}_{xy \in \mathcal{X} \times \mathcal{Y}}, \{\mu_{x0}\}_{x \in \mathcal{X}}, \{\mu_{0y}\}_{y \in \mathcal{Y}})$, containing μ_{xy} the mass of marriages between type x men and type y women, μ_{x0} the mass of single men of type x and μ_{0y} the mass of single women of type y. The total mass of men of type

x is denoted $n_x = \sum_y \mu_{xy} + \mu_{x0}$ and the total mass of women of type y is denoted $m_y = \sum_x \mu_{xy} + \mu_{0y}$.

A couple composed of man i and woman j derives a joint utility of ϕ_{ij}, whereas, upon remaining single, man i and woman j would enjoy utility ϕ_{i0} and ϕ_{0j} respectively.

2.2. **The Choo and Siow model.** We follow CS's seminal contribution and consider a model with perfectly transferable utility in which a couple formed of a man i of type x and a woman j of type y derive a joint utility

$$\phi_{ij} = \phi_{x_i y_j} + \epsilon_{i y_j} + \eta_{x_i j},$$

where ϵ and η are interpreted as random tastes of man i for women of type y and of woman j for men of type x. The utility of being single for a man i of type x and a woman j of type y is defined similarly as $\phi_{x0} + \epsilon_{i0}$ and $\phi_{0y} + \eta_{0j}$ respectively.[1]

As shown in Galichon and Salanie (2015) and Chiappori, Salanie and Weiss (2017), men and women solve

$$\begin{aligned} u_i &= \max_{y \in \mathcal{Y}} \left(U_{xy} + \epsilon_{iy}, U_{x0} + \epsilon_{i0} \right) \\ v_j &= \max_{x \in \mathcal{X}} \left(V_{xy} + \eta_{xj}, V_{0y} + \eta_{0j} \right), \end{aligned}$$

where U_{xy} and V_{xy} are termed systematic or net (of transfers) utilities and $U_{x0} = \phi_{x0}$ and $V_{0y} = \phi_{0y}$, such that in equilibrium, the expected indirect utility of a man of type

[1] In a single market, the utility of being single can be normalized to 0 without loss of generality, interpreting ϕ_{xy} as the marital surplus. However, this normalization is not justified when comparing across markets unless the utility of being single does not vary across markets.

x and a woman of type y are respectively

$$\begin{aligned} G_x\left(U_{x.}\right) &= E\left[\max_{y\in\mathcal{Y}}\left(U_{xy}+\epsilon_{iy},U_{x0}+\epsilon_{i0}\right)|x_i=x\right] \\ H_y\left(V_{.y}\right) &= E\left[\max_{x\in\mathcal{X}}\left(V_{xy}+\eta_{xj},V_{0y}+\eta_{0j}\right)|y_j=y\right]. \end{aligned}$$

It follows that an equilibrium outcome can be defined as follows.

Definition 1. A triple (μ, U, V) is an equilibrium outcome if:

(1) the matching μ satisfies the accounting constraints

$$\begin{aligned} n_x &= \mu_{x0}+\sum_{y\in\mathcal{Y}}\mu_{xy} \\ m_y &= \mu_{0y}+\sum_{x\in\mathcal{X}}\mu_{xy}, \end{aligned}$$

(2) for each matched pair, the systematic utilities satisfy the feasibility conditions

$$\phi_{xy}=U_{xy}+V_{xy},$$

and,

(3) μ, U, and V are such that the market clears hence satisfying

$$n_x\frac{\partial G_x\left(U_{x.}\right)}{\partial U_{xy}}=\mu_{xy}=m_y\frac{\partial H_y\left(V_{.y}\right)}{\partial V_{xy}}.$$

2.3. **Reformulation as an aggregate matching function equilibrium.** As noted in Galichon and Weber (2017), equilibrium characterization is greatly simplified whenever the heterogeneities ϵ and η are drawn independently from type I extreme value distributions as in CS. Indeed, under this assumption, equilibrium is fully characterized by the set of nonlinear equations

$$\begin{aligned} n_x &= \mu_{x0} + \sum_{y \in \mathcal{Y}} M_{xy}(\mu_{x0}, \mu_{0y}) \\ m_y &= \mu_{0y} + \sum_{x \in \mathcal{X}} M_{xy}(\mu_{x0}, \mu_{0y}) \end{aligned} \tag{1}$$

where M_{xy} is the aggregate matching function

$$M_{xy}(\mu_{x0}, \mu_{0y}) = \sqrt{\mu_{x0}\mu_{0y}} \exp\left(\frac{\Phi_{xy}}{2}\right), \tag{2}$$

and $\Phi_{xy} = \phi_{xy} - \phi_{x0} - \phi_{0y}$ is the marital surplus of type (x, y) couples.

Theorem 1 ((Galichon, Kominers, and Weber, 2018; Galichon and Weber, 2017))**.** *An equilibrium exists and is unique.*

Interestingly enough, under specific surplus functions, the "random matching" as defined in the literature on assortative mating, is the equilibrium matching in the CS model, as pointed out in the following remark.

Remark 2.1 (Random matching)**.** Let the surplus function be $\Phi_{xy} = a_x + b_y$. Since there is no complementarity between the types of spouses in generating surplus, one might expect that, in this market, the equilibrium matches of men and women $\{\mu_{xy}\}_{xy \in \mathcal{X} \times \mathcal{Y}}$ will show no assortativeness yielding a "random matching". This intuition is actually correct. Indeed, using equation (2) one has

$$M_{xy}(\mu_{x0}, \mu_{0y}) = (\mu_{x0} A_x)^{1/2} (\mu_{0y} B_y)^{1/2}, \tag{3}$$

where $a_x = \log A_x$ and $b_y = \log B_y$.

The system of equations (1) then becomes

$$\begin{aligned} (\mu_{x0}A_x)^{1/2}\sum_y (\mu_{0y}B_y)^{1/2} &= \bar{n}_x \\ (\mu_{0y}B_y)^{1/2}\sum_x (\mu_{x0}A_x)^{1/2} &= \bar{m}_y, \end{aligned} \tag{4}$$

where $\bar{n}_x = n_x - \mu_{x0}$ and $\bar{m}_y = m_y - \mu_{0y}$.

Summing the first equation over x or the second over y gives

$$\left(\sum_y (\mu_{0y}B_y)^{1/2}\right)\left(\sum_x (\mu_{x0}A_x)^{1/2}\right) = \sum_x \bar{n}_x = \sum_y \bar{m}_y = N, \tag{5}$$

where N is the mass of couples.

Dividing each equation of system (4) by equation (5) obtains

$$\begin{aligned} \frac{(\mu_{x0}A_x)^{1/2}}{\sum_x (\mu_{x0}A_x)^{1/2}} &= \frac{\bar{n}_x}{N} \\ \frac{(\mu_{0y}B_y)^{1/2}}{\sum_y (\mu_{0y}B_y)^{1/2}} &= \frac{\bar{m}_y}{N}. \end{aligned}$$

Plugging these expressions into equation (3) obtains

$$M_{xy}(\mu_{x0}, \mu_{0y}) = N\left(\frac{\bar{n}_x}{N}\right) \times \left(\frac{\bar{m}_y}{N}\right), \tag{6}$$

so that the equilibrium matching in this case is indeed the "random matching".

The CS model has two important features that make it particularly suited for empirical work: straightforward identification of preferences and efficient computation of an equilibrium. These features are highlighted in the following remarks.

Remark 2.2 (Surplus identification)**.** Equation (2) can be inverted to yield

$$\Phi_{xy} = \log \frac{\mu_{xy}^2}{\mu_{x0}\mu_{0y}}. \tag{7}$$

This equation links the marital surplus on the left hand side to matching on the right hand side. The marital surplus of couples of type (x, y) is therefore nonparametrically point identified using data on a single cross-section of matches μ_{xy} and singles μ_{x0} and μ_{0y}.

Remark 2.3 (Equilibrium computation)**.** The proof of theorem 1 is actually constructive and provides a computationally efficient algorithm, called IPFP, to compute the equilibrium matching given surplus function Φ_{xy} and the distribution of types of men n_x and women m_y.

Algorithm 1. The IPFP algorithm works as follows

Step 0. Choose an initial value of $\mu_{0y} = m_y$, $\forall y$.

Step 2k+1. Solve for $\mu_{x0}^{(2k+1)}$ using

$$\mu_{x0}^{(2k+1)} = \left(\sqrt{n_x + C_x^2} - C_x\right)^2$$

where $C_x = \exp\left(\Phi_{xy}/2\right) \sum_{y\in\mathcal{Y}} \sqrt{\mu_{0y}^{(2k)}}/2$, $\forall x$.

Step 2k+2. Solve for $\mu_{0y}^{(2k+2)}$ using

$$\mu_{0y}^{(2k+2)} = \left(\sqrt{m_y + D_y^2} - D_y\right)^2$$

where $D_y = \exp\left(\Phi_{xy}/2\right) \sum_{x\in\mathcal{X}} \sqrt{\mu_{x0}^{(2k+1)}}/2$, $\forall y$.

The algorithm converges to the unique solution (μ_{x0}^*, μ_{0y}^*).

3. Counterfactuals

This section builds on the ideas introduced in remarks 2.2 and 2.3. The methodology is introduced in section 3.1 below, while sections 3.2 and 3.3 show how it can be used to measure assortativeness as well as account for the contribution of "who remains single" and "who marries whom" to income inequality.

3.1. Definitions.

Let $t = 1, ..., T$ index marriage markets and assume that, for each market, data consist of an observed matching

$$\mu^t = (\{\mu^t_{xy}\}_{xy \in \mathcal{X} \times \mathcal{Y}}, \{\mu^t_{x0}\}_{x \in \mathcal{X}}, \{\mu^t_{0y}\}_{y \in \mathcal{Y}}).$$

Following remark 2.2, for each market t, one identifies nonparametrically the associated surplus $\Phi^t = (\{\Phi^t_{xy}\}_{xy \in \mathcal{X} \times \mathcal{Y}})$ from the data μ^t using equation (7). As anticipated in remark 2.3, the model allows one to construct counterfactuals for each market t. In this paper, we define a counterfactual as follows:

Definition 2. A counterfactual for market t is a tuple $\left(\bar{\Phi}^t, \bar{\mu}^t\right)$ that consists of a given reference of the marital surplus $\bar{\Phi}^t$ that together with the distribution of types observed in data t, yield an equilibrium matching $\bar{\mu}^t$ computed using algorithm 1.

Below, we introduce two approaches: (i) a first approach in which counterfactuals are derived using a fixed surplus reference by pinning down the full surplus of couples and (ii) a second approach in which counterfactuals are derived using a fixed joint utility reference by pinning down the joint utility of couples, but allowing the (reservation) utilities of singles to vary across markets so that the distribution of singles corresponds to the observed one in that market.

3.1.1. *Fixed surplus references.* Within the fixed surplus references approach, we derive two series of counterfactuals $\left(\bar{\Phi}^t, \bar{\mu}^t\right)$ for each market t. The first series, labelled "reference market", is obtained setting the reference surplus function equal to that of data t', hence letting

$$\bar{\Phi}^t_{xy} = \Phi^{t'}_{xy}, \forall x, y \in \mathcal{XY}. \qquad (\text{"reference market"}) \tag{8}$$

The second series, labelled "pure random", is obtained by setting the reference surplus function equal to a constant, and in particular

$$\bar{\Phi}^t_{xy} = 0, \forall x, y \in \mathcal{XY}. \qquad (\text{"pure random"}) \tag{9}$$

Setting the constant to 0 makes sense in the context of our model since the associated equilibrium matching corresponds to the "pure random" matching case (i.e. consider remark 2.1 with $a_x + b_y = 0$). Indeed, in this case, there are no systematic components to induce men and women to marry, and, conditional on marriage, to choose one type of spouse over another. Matching is purely random as it is driven solely by the idiosyncratic component of utility.

Each of these two series of counterfactuals allows us to eliminate the "who marries whom" effect, by eliminating differences in the degree of assortativeness across markets, setting it equal to its level in the reference market t' or to zero depending on the types of counterfactuals. Note that in each series, the mass of singles in each counterfactual market is not restricted and can differ from that observed in the associated market.

3.1.2. *Fixed joint utility references.* Within the fixed joint utility references approach, we introduce two series of counterfactuals that aim at further controlling for the "who remains single" effect. To do so, we compute, for each counterfactual market of each series introduced above, the equilibrium matching that would prevail if in addition to having the same degree of assortativeness, the equilibrium mass of singles in each counterfactual market was imposed to be the same to that observed in market t, i.e. $\bar{\mu}^t_{x0} = \mu^t_{x0}$ and $\bar{\mu}^t_{0y} = \mu^t_{0y}$. These counterfactuals can be performed by specifying the surplus function as

$$\bar{\Phi}^t_{xy} = \Phi^{t'}_{xy} + a^t_x + b^t_y. \qquad \text{("reference market adjusted for singles")} \tag{10}$$

and

$$\bar{\Phi}^t_{xy} = 0 + a^t_x + b^t_y. \qquad \text{("random")} \tag{11}$$

Plugging either of these surplus functions into system 1, after simple algebra, one indeed obtains

$$\begin{aligned} \sum_y \exp\left(\frac{\kappa^t_{xy} + a^t_x + b^t_y}{2}\right) &= \bar{n}^t_x \\ \sum_x \exp\left(\frac{\kappa^t_{xy} + a^t_x + b^t_y}{2}\right) &= \bar{m}^t_y, \end{aligned} \tag{12}$$

where $\kappa^t_{xy} = \bar{\Phi}^t_{xy} - a^t_x - b^t_y + \log \mu^t_{x0}\mu^t_{0y}$, and $\bar{n}^t_x = n^t_x - \mu^t_{x0}$ and $\bar{m}^t_y = m^t_y - \mu^t_{0y}$ are respectively the mass of married men of type x and women of type y imposed by the fixed distribution of singles and the distribution of types in counterfactual market t. The system of equations (12) is the discrete version of the system that can be found in Dupuy and Galichon (2014). One can then solve this system for $\{a^t_x\}_{x\in\mathcal{X}}$ and $\{b^t_y\}_{y\in\mathcal{Y}}$, up to a normalization $a^t_{x_0} = 0$. The vectors $\{a^t_x\}_{x\in\mathcal{X}}$ and $\{b^t_y\}_{y\in\mathcal{Y}}$ can be thought of as the utilities of being single in market t, i.e. $\{\phi^t_{x0}\}_{x\in\mathcal{X}}$ and $\left\{\phi^t_{0y}\right\}_{y\in\mathcal{Y}}$.

Remark 3.1. The $\{a_x^t\}_{x\in\mathcal{X}}$ and $\{b_y^t\}_{y\in\mathcal{Y}}$ can also be interpreted as taxes on marital surplus. These taxes introduce distortion while preserving the supermodularity of the surplus function. As a result, they affect directly who remains single and only indirectly distort who marries whom. In our counterfactuals, we are able to fix the distribution of singles by implementing such tax systems.

3.2. **Measuring assortativeness.** To measure assortativeness, the literature has taken different routes. The most common approach relies on the so-called "random matching" counterfactual. To obtain the mass of each type of couples under "random matching", one simply discard singles and compute the product of the marginal distribution of types among married men and women multiplied by the observed number couples. Note that "random matching" can be recovered in our model using the "random matching" counterfactual in equation 11. Regardless of the method used, we get the counterfactual matching μ^R (and the counterfactual number of couples N^R). Then, for any type of couples (x, y), the measure of assortativeness reads

$$S^R(x, y) = \frac{\mu_{xy}}{N}\frac{N^R}{\mu_{xy}^R}. \tag{13}$$

The random counterfactual approach raises a number of concerns. First, this measure is purely data-driven and by construction, likely to become very large for types whose proportions in the population become small. This casts some doubts on the reliability and comparability of the estimates when group sizes are small. Second, singles are excluded from the analysis and the marginal distributions of types are taken conditional on being married. Therefore, if marriage rates change at a different pace across types, the results are likely to be biased. Third, the random counterfactual relies on the somehow extreme assumption that the joint utility is uniformly zero. As a result, the measure does not behave well as illustrated in the following examples. Consider a marriage market with 90 men and women with a high school degree and 10 men and women with a college degree. Assume that all college degree men and women marry together. We observe that 10% of all marriages occur between college educated men and women, when this proportion should be 1% if marriage was random. The measure of assortativeness is very high and equal to 10 for college educated couples. Let us assume that after a few years, there are now 50 men and women with a high school degree and 50 men and women with a college degree. Again, all college degree men and women marry together, so that they account for 50% of all marriages. This proportion should be 25% under the random counterfactual, so that the measure indicates a decrease in assortativeness. Fourth, measures based on the random counterfactual raise a deeper interpretation problem. Indeed, the model underlying the random case is one where the joint utility is assumed to be zero, but where taxes are implemented every year so that the predicted mass of singles of each type coincides with the observed one. In other words, the surplus that serves as a reference to construct the random counterfactual is not fixed; it changes every year.

We therefore propose an alternative approach to compute assortativeness which consists in comparing the share of marriages of a certain type of couples among all couples, $\frac{\mu^t_{xy}}{N^t}$ (where N^t is the number of couples in market t), to the share of marriages of that type under the "reference market" counterfactual (see equation 8) where the reference market is that of $t' = 1962$. We compute the counterfactual matching μ^C (and obtain the counterfactual number of couples, N^C). Then, for any pair xy, we construct the measure

$$S^C(x, y) = \frac{\mu_{xy}}{N} \frac{N^C}{\mu^C_{xy}}. \tag{14}$$

Note that comparing the two measures gives

$$\begin{aligned} S^C(x,y)/S^R(x,y) &= \frac{\mu^R_{xy}}{\mu^C_{xy}} \frac{N^C}{N^R} \\ &= \frac{\left(\frac{\bar{n}_x}{N^R}\right) \times \left(\frac{\bar{m}_y}{N^R}\right)}{\mu^C_{xy}/N^C}. \end{aligned}$$

Throughout the paper, we will closely inspect the diagonal elements of the S^C and S^R matrices. In addition, we provide two "aggregate" measures, defined as follows:

$$S^R_a = \frac{\sum_{x=y} \mu_{xy}}{N} \frac{N^R}{\sum_{x=y} \mu^R_{xy}}. \tag{15}$$

and

$$S^C_a = \frac{\sum_{x=y} \mu_{xy}}{N} \frac{N^C}{\sum_{x=y} \mu^C_{xy}}, \tag{16}$$

3.3. **Inequality decomposition.** We investigate to what extent changes in marital patterns contributed to rising income inequality in the US between 1962 and 2017. To do so, we propose to compare the "observed" Gini coefficient (case **O**) to i) the Gini coefficient under the "reference market" counterfactual (case **C**) where the reference market is that of $t' = 1962$ and ii) the Gini coefficient under the "reference market adjusting for singles" counterfactual (case **C'**) where again the reference market is that of $t' = 1962$.

Note that the difference in inequality between the observed (case **O**) and the "reference market" counterfactual (case **C**) is the sum of two components: (i) the "who marries whom" effect, which captures the impact on inequality of differences in assortativeness among couples between observed and counterfactual situations, and (ii) the "who remains single" effect, which captures the impact on inequality of differences in the relative proportion of couples and singles between the observed and counterfactual situations. The role played by singles in generating inequality can then be isolated by using the second counterfactual, the "reference market adjusted for singles" counterfactual (case **C'**).

Precisely, we proceed through the following steps: [2]

Step 1. Use the observed matching $\mu_t^{\mathbf{O}}$ in each year t and obtain the Gini coefficient, denoted $g_t^{\mathbf{O}}$.

Step 2. Use the "reference market" counterfactual matching $\mu_t^{\mathbf{C}}$ (where the reference market is that of $t' = 1962$), and obtain the Gini coefficient, denoted $g_t^{\mathbf{C}}$.

Step 3. Use the "reference market adjusted for singles" matching $\mu_t^{\mathbf{C}'}$ (where the reference market is that of $t' = 1962$), and obtain the Gini coefficient denoted $g_t^{\mathbf{C}'}$.

Following the above discussion, we see that the "who marries whom" and the "who remains single" effects can be decomposed using step 3: indeed, the resulting Gini coefficient, $g_t^{\mathbf{C}'}$, is net of the "who remains single" effect, i.e. of any composition effect due to changes in the number of couples relative to singles.

We expect both of these effects to be positive, i.e. $g^{\mathbf{C}} < g^{\mathbf{C}'} < g^{\mathbf{O}}$, since (i) among couples, there is likely less education assortative mating under the "reference market" counterfactual than in year t (see figure 2) and (ii) there are likely more singles in year t than under the "reference market" counterfactual (see the left panel of figure 7).

Table 1 contains a summary of the main counterfactual experiments that are used throughout the paper.

[2]For each of the matchings associated to steps 1-3, we generate a random sample using the procedure described in algorithm 2 in appendix A. The Gini coefficient measuring income inequality can then be computed for each of these (counterfactual) samples.

Table 1. Summary of counterfactual experiments

Label	Approach	Serie/Case	Reference	a_x^t, b_y^t
O	-	"Observed"	-	-
C	"fixed surplus"	"Reference market"	Φ^{1962}	$a_x^t = b_y^t = 0$
R'	"fixed surplus"	"Pure random"	0	$a_x^t = b_y^t = 0$
C'	"fixed joint utility"	"Reference market adjusted for singles"	Φ^{1962}	chosen to fit (μ_{x0}^t, μ_{0y}^t)
R	"fixed joint utility"	"Random"	0	chosen to fit (μ_{x0}^t, μ_{0y}^t)

- **O - C**: "total" effect
- **O - C'**: "who marries whom" effect
- **C' - C**: "who remains single" effect

4. Data

We analyze the US marriage market between 1962 to 2017 using the CPS march supplements data. For each year, we select heterosexual couples in which the husband is aged between 26 and 60 years old and the wife between 24 and 58 years old.[3] In addition, we select single men aged 26-60 and single women aged 24-58. We exclude all couples and singles with missing information on age, labor income (from wages, salary and self employment) and education. In our application, we define four types corresponding to four education levels: below high school degree ("BHS"), high school degree ("HSG"), some college ("SC"), and college graduates (and above) ("C").

Table 2. Descriptive statistics

	1962		1980		2013	
	Women	Men	Women	Men	Women	Men
Age	39.53	42.56	38.96	41.68	41.73	43.76
College degree	0.07	0.13	0.15	0.24	0.40	0.37
Income	6897.58	46064.24	15044.83	59357.73	30872.60	65841.07
Participation rate	0.41	0.98	0.64	0.96	0.73	0.92

Notes: the table provides descriptive statistics for some selected years (1962, 1980 and 2013). Our sample include single and married men aged 26 to 60 and single and married women aged 24 to 58. Only couples are used in this table.

[3]This age selection differs from that in Eika, Mogstad, and Zafar (2017) who select all couples in which at least one partner is aged between 26 and 60.

Descriptive statistics on couples are reported in table 2 for selected years. Our sample differs slightly from Eika, Mogstad, and Zafar (2017) because of the differences in the age restriction imposed, but the difference is minimal.

[Figure 1 about here.]

In figure 1, we compute the share of each type of men and women, single or married, on the marriage market between 1962 and 2017. The figure depicts the dramatic decrease in the share of men and women with less than high school degree, and the increase in the share of men and women with some college education or a college degree. These are major structural changes that are fully taken into account on our model.

5. Assortativeness in the US, 1962 - 2017

[Figure 2 about here.]

We start by computing the aggregate measure of assortativeness from equations 15 and 16. This is displayed in figure 2.[4] According to both measures S_a^C and S_a^R, assortativeness in educational attainment has steadily increased in the US between 1962 and 2017. Obviously, the measure S_a^C is equal to one in 1962 since our counterfactual is assuming that the marital surplus has not changed over time. Our results indicate that in 2017, the share of perfectly assortated couples observed in the data is 20% higher than what would have been the case if the surplus had not changed since 1962. One also notices that the measure S_a^R is higher than S_a^C starting from 1962 and over the whole period, indicating that a non negligible degree of assortative mating already occurred in 1962 compared to random matching.

[4]Figure 10 in appendix B shows results using other measures using the "pure random" counterfactual and the "reference market adjusted for singles" counterfactual. The patterns are are very similar.

[Figure 3 about here.]

[Figure 4 about here.]

Next, we investigate what forces are driving the trend at the aggregate level. We do so with the help of figures 3 and 4. In figure 3, we plot our measure of assortativeness for each element on the diagonal using the reference market counterfactual (left panel) and the pure random counterfactual (right panel). Similarly, figure 4 shows our measure of assortativeness for each element on the diagonal using the reference market adjusted for singles counterfactual (left panel) and the random counterfactual (right panel).

[Figure 5 about here.]

It is also useful to compare the left panels of figures 3 and 4, that is, to compare measures using the reference market counterfactual and the reference market adjusted for singles counterfactual, respectively. Interestingly, the second measure shows a clear increasing trend for all elements on the diagonal and in particular a large increase for BHS whereas the first measure indicates a stagnant or moderate increase for BHS. The main explanation is that the reference market counterfactual induces a lot of individuals, of all types, to marry (as can be seen in figure 5 in 1962, with little difference across types). In contrast, the reference market adjusted for singles implements each year increases in the reservation utilities inducing individuals to remain singles. Although marriage rates by type were similar in 1962 and have been declining for all types since, there is some divergence across types. In particular, the reference market adjusted for singles counterfactual will induce relatively more BHS individuals to remain single in 2017 than any other type. Consequently, over time,

[4]By marriage rates, we denote the share of men (resp. women) that are married in our sample, for each type x (resp. for each type y).

this counterfactual predicts relatively fewer marriages between BHS individuals than the reference market counterfactual.

As a final example let us consider college education. The measure for college education using the random counterfactual is very high between 1962 and the early 1990s. One of the mechanism at play here is that in this period college educated women married relatively less frequently than other types of women. That is, married college educated women accounted for a small share of all married women in this period. Hence, the random counterfactual predicts very few marriages involving college graduate women, in particular marriages between two college graduates.

We now have the main elements to discuss the main finding from comparing figures 3 and 4: the driving forces of increased assortativeness at the aggregate level are dramatically different whether we consider the reference market counterfactual (our preferred approach) or the random counterfactual. While our measure using reference market counterfactual suggests that the trend is mainly driven by increased assortativeness for some college couples and college couples, the measure based on the random counterfactual concludes that most of the increase in aggregate assortativeness can be attributed by rising assortativeness for below high school couples and high school degree couples. These differences can be explained by two assumptions underlying the random matching counterfactual. First, the joint utility from marriage is zero, therefore the random counterfactual predicts relatively (and unrealistically) few assortative marriages, especially so when types become small in size in the population. Second, it assumes that each year, the surplus is not fixed over time but rather distorted by changes in the reservation utilities of individuals such that the mass of singles is equal to that observed in the data.

6. Inequality

6.1. **Main results.** In this section, we document the rise in observed between-household income inequality as measured by the Gini coefficient. We compare the observed level of inequality to what would have happened under the various counterfactuals summarized in table 1, over the period 1962-2017. We use the "reference market" as our main counterfactual experiment, which allows us to determine how inequality would have changed in year t had the surplus remained constant since 1962. Following the methodology described in section 3.3, for various matchings μ (observed or counterfactual), we generate a sample of households and compute the resulting income inequality.

[Figure 6 about here.]

The main results are displayed in figure 6.[5] Over the period 1962 - 2017, the actual Gini coefficient increased by 0.12 points from about 0.38 to 0.5. Had the surplus remained constant since 1962 as in the "reference market" counterfactual, our model would predict that the Gini coefficient would have increased by 0.085 from 0.38 to 0.465. Under this counterfactual, the evolution of the Gini coefficient is only driven by factors external to the marriage market except for changes in the distribution of types which are assumed exogenous to our model. This allows us to conclude that marital patterns can explain about 1/3 of the observed increase in income inequality over the period considered.

We further decompose this effect into the "who remains single" and "who marries whom" effects. To do so, we make use of the "reference market adjusted for singles" counterfactual. Under this counterfactual, inequality would only have been slightly

[5]Figure 11 in appendix B present the results with confidence intervals.

lower, which indicates that assortativeness in education contributed only very little to the rise in income inequality between households. Most of the effect is therefore attributed to the "who remains single" effect. Indeed, the difference between the "reference market" counterfactual and the "reference market adjusted for singles" counterfactual is merely due to changes in the reservation utilities of singles so that the predicted mass of singles of each type fits the observed one, keeping the joint utility to its 1962 level. The resulting increase in inequality is therefore driven by changes in "who remains single". Conversely, the difference between the "reference market adjusted for singles" counterfactual and the observed data is only due to changes in the joint utility over time. The resulting small increase in inequality is therefore driven by the "who marries whom" effect.[6] To summarize, in the period 1962-2017, marital patterns contributed to an increase in income inequality of about 0.035 Gini points which represents about 1/3 of the observed increase in inequality. The contribution of marital patterns is composed for 5% of the "who marries whom" effect the remaining 95% coming from the "who remains single" effect.

6.2. **Discussion.** We discuss our main results by looking at three separate questions. First, we discuss the role of singles in increasing inequality. Second we compare our results to the use of other counterfactuals. And finally, we discard singles entirely to focus on inequality between couples.

[Figure 7 about here.]

Since the effect of marital patterns on inequality merely comes from the "who remains single" effect, this suggests that the observed distribution of singles is very different of the one predicted under the "reference market" counterfactual. This is

[6]These differences (**C' - C** and **O - C'**), as well as the total effect of marital patterns on inequality (**O - C**), are displayed, with confidence intervals, in appendix B, figure 12.

corroborated by figure 7. The left panel shows that, in 2017, our sample of households contains 40% of singles, but this proportion falls to 27.5% in the "reference market" counterfactual. To explain the decrease in the number of singles under the counterfactual, we look at the evolution of the (expected) marital surplus since 1962 (right panel of figure 7). The figure clearly indicates that the marital surplus has dropped dramatically since 1962; therefore, since under the "reference market" counterfactual this surplus is kept constant to its 1962 level, this means that more individuals are pushed into marriage in the counterfactual than in the observed data, hence reducing the relative proportion of singles in the counterfactual.

[Figure 8 about here.]

Next, we compare our main results to those obtained using other counterfactuals. In particular, we replicate our results using the "pure random" case as the main counterfactual. We also make use of the "random" case to perform our decomposition exercise. The results are displayed in the right panel of figure 8, the left panel showing our main results for comparison. Under the "pure random" counterfactual, the Gini coefficient would have dropped in 2017 by approximatively the same amount as before when comparing the observed case and the "reference market" counterfactual. This is due to the fact that under the "pure random" counterfactual there are actually more couples (as shown in figure 7a), which decreases inequality. However, the "who marries whom" effect now plays a larger role, as shown by the Gini coefficient under the "random" counterfactual. This is due to the absence of assortativenesss under this counterfactual, while under the "reference market" counterfactual, there is as much assortativeness as observed in 1962. Another interesting finding in figure 8 is that, in the 1960s and 1970s, the Gini coefficient under the "pure random" counterfactual is much higher than the observed one. Indeed, figure 7b suggests that the marital surplus was relatively higher in that period; therefore assuming a surplus of zero, as is the case in the "pure random" counterfactual, induces many people out of marriage into singlehood,[7] causing an increase in inequality.

[Figure 9 about here.]

Finally, we perform the same analysis as before but discarding singles to focus only on between-couples income inequality and the "who marries whom" effect. Our results are displayed in figure 9. The left panel is the counterpart of our main results from figure 6 but without singles. Obviously, inequality is much lower than in our previous analysis since we do not account for singles here. Using the "reference market adjusted for singles" counterfactual, we show that once again the Gini coefficient would be lower than the observed one. As before, the "who marries whom" effect is at play here. It is interesting to note, however, that inequality under the "reference market" counterfactual would be higher than the observed one. This is because changing the surplus to its 1962 level has both a direct effect (through the supermodularity of the surplus) and indirect effect (by changing the marginal distribution of types conditional on marriage) on "who marries whom". On the right panel, we do the same exercise using the random counterfactuals ("pure random" and "random"). The effect captured by most of the literature (in particular, Eika, Mogstad, and Zafar (2017)) corresponds to the difference between the observed Gini coefficient and the Gini coefficient under the "random" counterfactual. Here, our results indicate that income inequality would drop by roughly 0.02 points in 2017. We shall point out that under the "pure random" counterfactual, inequality would drop as well, but to a lesser extent. This is because, as in the case with the "reference market" counterfactual,

[7]Figure 7a confirms that in the 1960s and 1970s, the proportion of singles on the marriage market was about 20%, but this proportion rise to 40% under the "pure random" counterfactual.

setting the counterfactual surplus to 0 influences "who marries whom" indirectly through its effect on the marginal distribution of types conditional on marriage.

7. Conclusion

In this paper, we use a structural model of the marriage market to study the effect of marital patterns on the evolution of between-household income inequality in the United States between 1962 and 2017. We rely on the Choo and Siow model, reformulated as an aggregate matching function equilibrium, to generate a battery of counterfactual experiments. These counterfactuals are in turn used to construct measures of assortativeness, and study the effect of educational assortative mating on inequality.

The main feature of our approach is that singles are fully integrated in the model. This means that we are able to decompose the total effect of marital patterns on inequality into "who marries whom" and "who remains single" components. We first show that assortativeness in education has been steadily increasing in the US between 1962 and 2017, merely so because of individuals with college education. Then, we show that, had the marital surplus remained constant over time, inequality would have been lower in 2017 by almost 0.04 Gini points. Marital patterns can therefore explain up to 1/3 of the observed increase in income inequality over the period considered. We then show that most of this effect comes from the "who remains single" component (95%), and that assortativeness in education contributed only very little (5%).

We believe that our model could be extended in several ways. With large datasets, it is possible to have more refined types, for example using both education levels and quantiles of potential income. The model could also be used to study assortativeness in race over the same period. This is left for future research.

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Appendix A. Generating a matching

For any aggregate matching $\mu = (\{\mu_{xy}\}_{xy \in \mathcal{X} \times \mathcal{Y}}, \{\mu_{x0}\}_{x \in \mathcal{X}}, \{\mu_{0y}\}_{y \in \mathcal{Y}})$ (whether this is the observed matching or a counterfactual one), we must generate a matching between our sample of men $i \in \mathcal{I}$ and women $j \in \mathcal{J}$ in order to compute inequality. We propose to do so using the following algorithm

Algorithm 2. For a given matching μ, and for any $k \in \{1, ..., |\mathcal{X}||\mathcal{Y}| + |\mathcal{X}| + |\mathcal{Y}|\}$,

Step 0. Initialize Z to be an empty vector. Initialize the pool of available men to be all the men in our sample. Initialize the pool of available women to be all the women in our sample.

Step 1. Fix N to be equal to the k^{th} entry of the vector μ.

Step 2.1. If the k^{th} entry corresponds to single men of type x, draw a random sample of N men of type x (without replacement) from the pool of available men, and append their income to the vector Z. Remove these men from the pool of available men.

Step 2.2. If the k^{th} entry corresponds to single women of type y, draw a random sample of N women of type y (without replacement) from the pool of available women, and append their income to the vector Z. Remove these women from the pool of available women.

Step 2.3. If the k^{th} entry corresponds to couples of type xy, draw a random sample of N men of type x and N women of type y (without replacement) from the pool of available men and women. Sort these N men and N women in a random order. Match man 1 with woman 1, etc., up to matching man N to woman N. Append the sum of their income to the vector Z. Remove these men and women from the pool of available men and women.

Step 3. Repeat steps $1 - 3$ for each $k \in \{1, ..., |\mathcal{X}||\mathcal{Y}| + |\mathcal{X}| + |\mathcal{Y}|\}$.

We then use the full vector Z to compute the Gini coefficient. Note that this procedure is very easy to implement and extremely fast. Therefore, we can repeat it R times and compute inequality for each of the Z^r vectors. This allows us to obtain confidence intervals on our measure of inequality.

Appendix B. Other results

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

Appendix C. Further remarks

Remark C.1 (No assortative mating)**.** Consider the case where the marital surplus is $\Phi_{xy} = a_x + b_y$. Recall that, as shown in Galichon and Salanie (2017), the equilibrium matching μ corresponds to the optimal matching and therefore solves

$$\max_{\mu \in \mathcal{M}} \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \Phi_{xy} \mu_{xy} + \mathcal{E}(\mu)$$

where the term $\mathcal{E}(\mu)$ is an entropic penalization.[8]

Since in our particular case, the surplus is neither supermodular nor submodular, the market exhibits no assortative mating. Interestingly, the equilibrium matching associated with these additive preferences solves the program

$$\max_{\mu \in \mathcal{M}} \mathcal{E}(\mu) - \sum_{x \in \mathcal{X}} a_x \mu_{x0} - \sum_{y \in \mathcal{Y}} b_y \mu_{0y}.$$

This program maximizes entropy subject to a penalization for forming singles, with a penalty weight of a_x for single men of type x and b_y for single women of type y. When $a_x = b_y = 0$, that is when the matching surplus is 0, this program maximizes entropy: the equilibrium matching is one that maximizes entropy. It follows that the natural concept to measure the absence of assortativeness in this model is that of entropy.

[8]Under the Choo and Siow assumptions that unobserved heterogeneity if Type I Gumbel distributed reads as

$$\mathcal{E}(\mu) = -2 \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \omega(\mu_{xy}) - \sum_{x \in \mathcal{X}} (\omega(\mu_{x0}) - \omega(n_x)) - \sum_{y \in \mathcal{Y}} (\omega(\mu_{0y}) - \omega(m_y))$$

where $\omega(x) = x \log x$.

List of Figures

[9]By marriage rates, we denote the share of men (resp. women) that are married in our sample, for each type x (resp. for each type y).

Figure 1. Type distribution in the marriage market, 1962 - 2017.

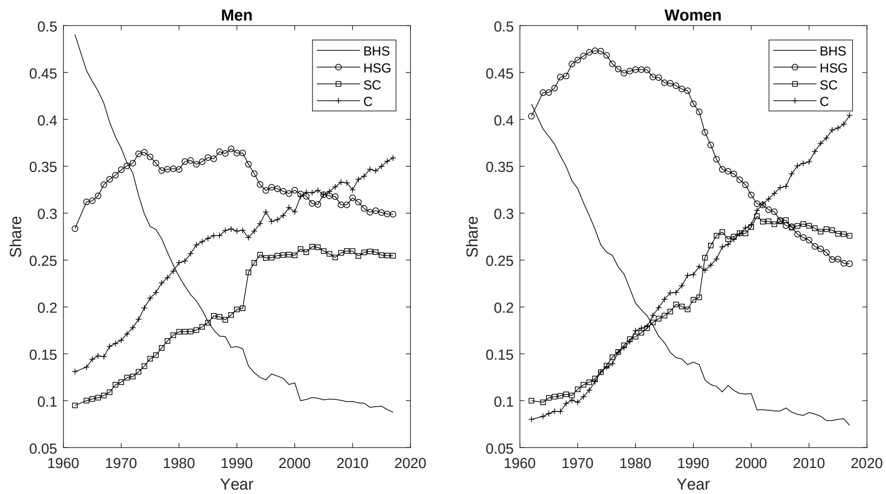


Figure 2. Aggregate measure of assortativeness, 1962 - 2017.

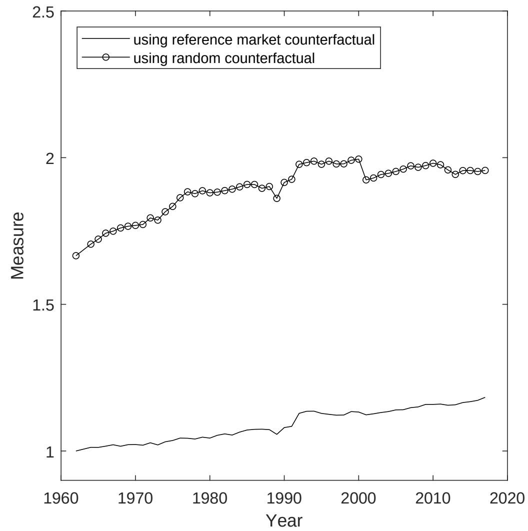


Figure 3. Measures of assortativeness (diagonal elements): “fixed surplus”reference, 1962 - 2017.

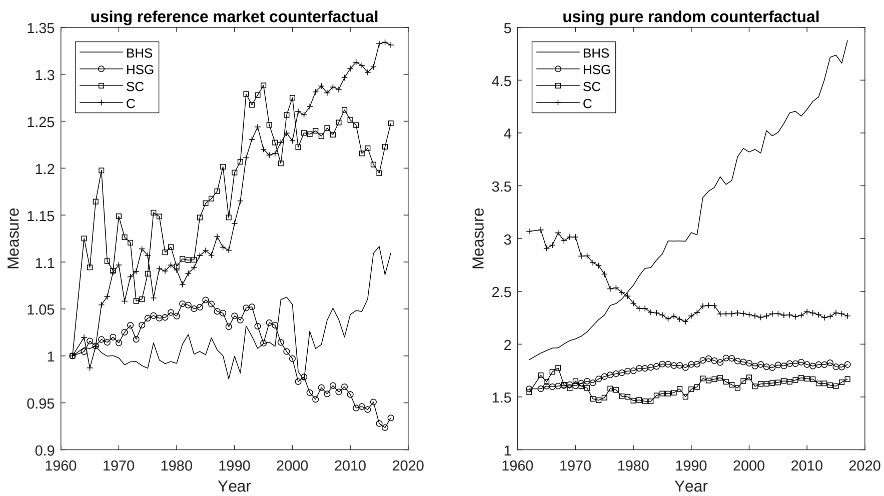


Figure 4. Measures of assortativeness (diagonal elements): "fixed joint utility"reference, 1962 - 2017.

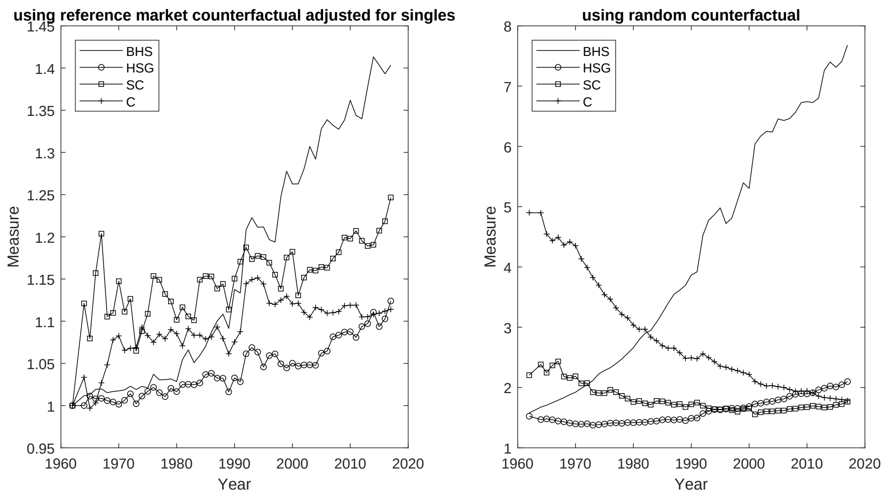


Figure 5. Observed marriage rates[10], by type, 1962 - 2017.

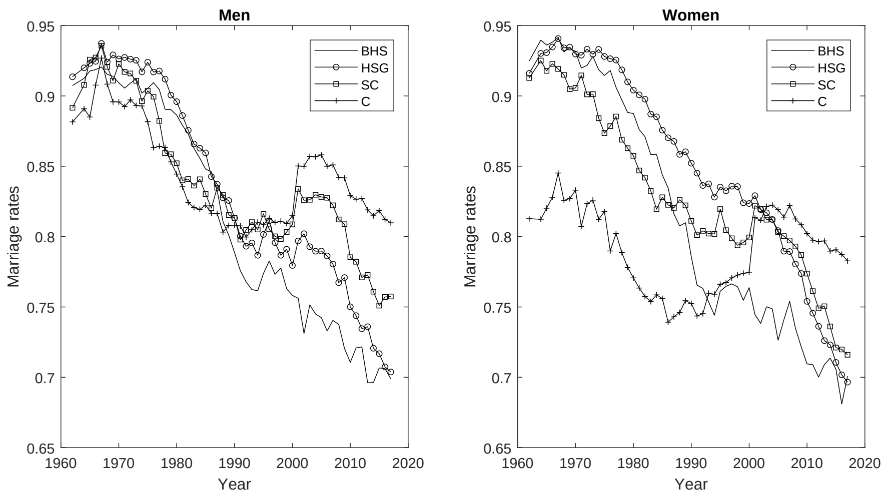


Figure 6. Trend in income inequality, 1962 - 2017

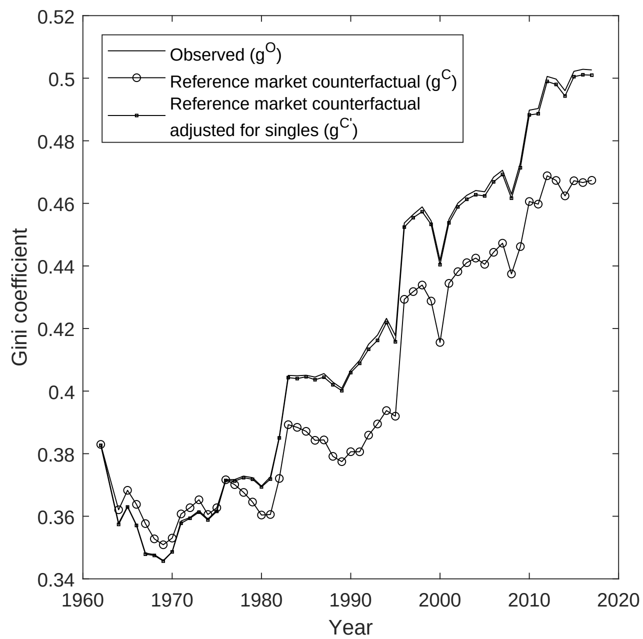
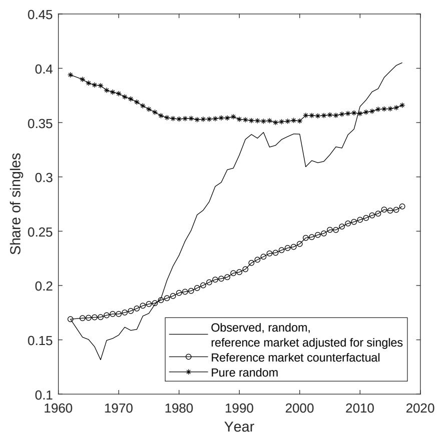
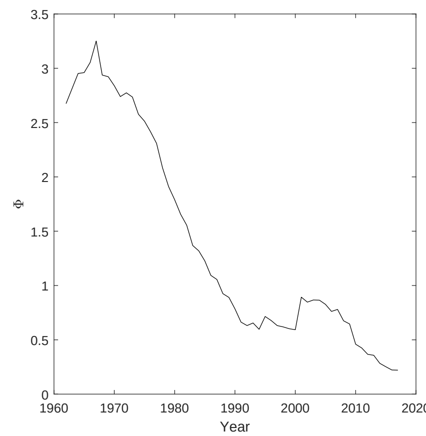


Figure 7. Share of single-headed households and expected surplus, 1962 - 2017



(a) Observed and counterfactual shares of single-headed households, 1962 - 2017



(b) Weighted average of the marital surplus, 1962 - 2017

Figure 8. Trends in income inequality: all counterfactuals, 1962 - 2017

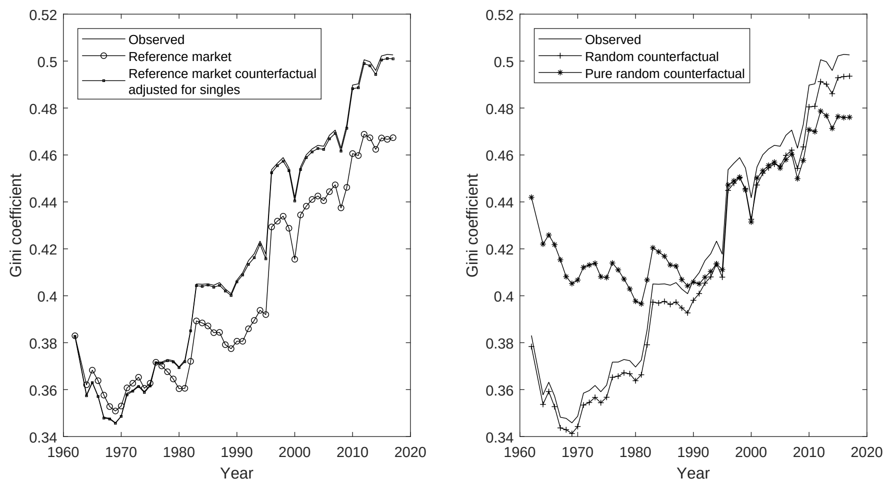


Figure 9. Trends in income inequality: all counterfactuals, couples only, 1962 - 2017

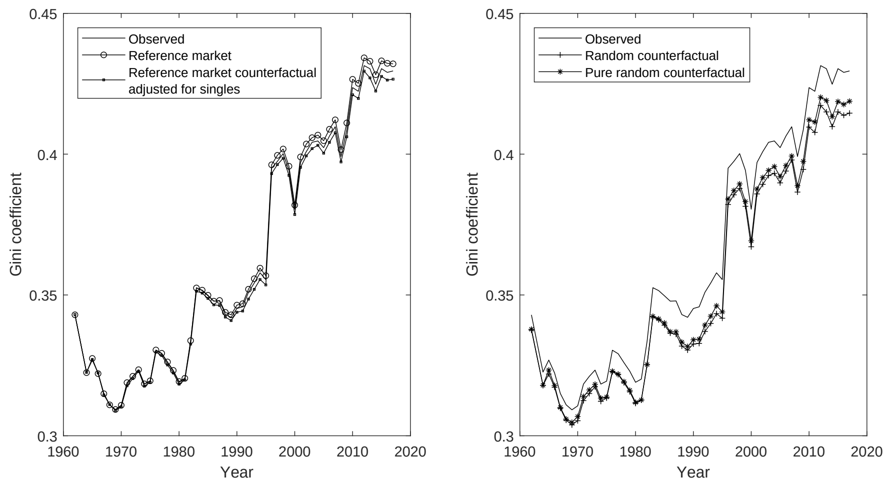


Figure 10. Aggregate measures of assortativeness, 1962 - 2017.

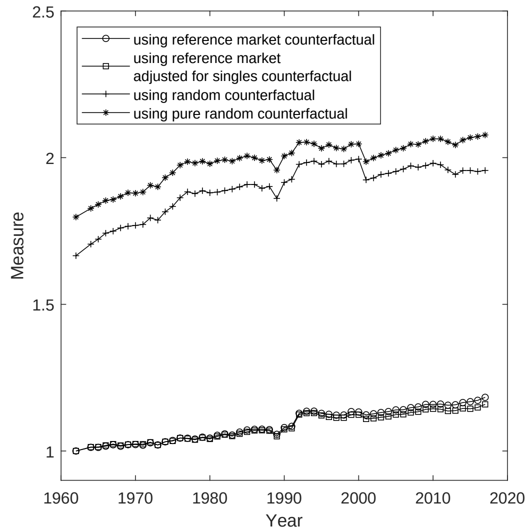


Figure 11. Trend in income inequality (with confidence intervals), 1962 - 2017

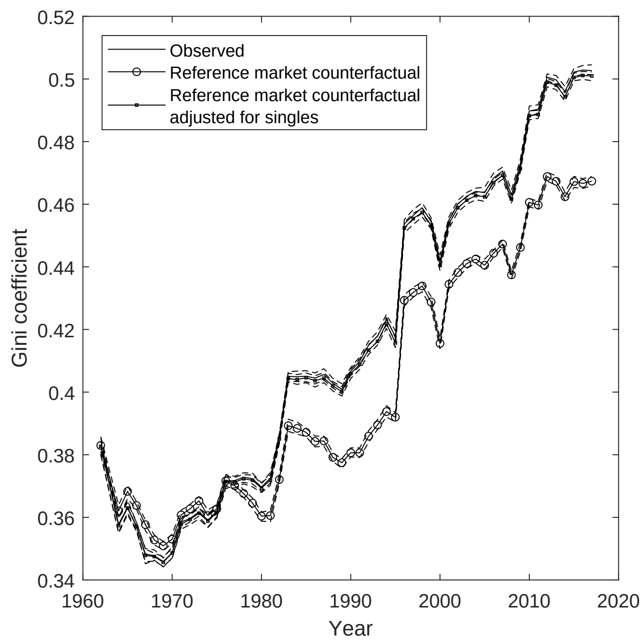


Figure 12. Trend in income inequality (differences), 1962 - 2017