Assortative Mating and Household Income Inequality in Argentina

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Abstract

This paper uses the decomposition method of (Greenwood et al., 2014) to assess the contribution of Assortative Mating to household income inequality in Argentina. For this purpose, the Gini coefficient and contingency tables for spouses' educational attainment are estimated to simulate the outcomes of random mating. Unlike Greenwood, we do not use **IPUMS** data due to the lack of availability of income data in the Argentine census; we resort instead to household surveys for 21 years.

We find that Assortative Mating plays a minor role in the determination of household income inequality; despite explaining about 5% of household income inequality, results have very little robustness to changes in parameters and are also at odds with values of several sorting indicators which show a very modest increase.

JEL Classification: D31, C15, J12

Keywords: assortative mating, income distribution, female labor supply, gender wage gap.

Contents

1 Introduction

The determinants of family income distribution have attracted considerable attention in the last fifteen years, but most empirical analyses have focused on advanced economies; there are few studies on this topic in emerging economies such as Argentina. Most papers on the determinants of household income inequality have studied the following three aspects:

1. **Wage gap and labor participation**: Starting in the mid-twentieth century, female labor participation has increased significantly in Western countries, and neither Argentina nor the remaining Latin American countries were the exception. This increase strongly impacted Fertility, intra-family income distribution, marriage, and divorce rates (Killingsworth and Heckman, 1986).

2. **Fertility**: As a consequence of supplying more work hours in the market, women have tended to give birth to fewer children. Therefore, married women can no longer raise the same number of children as their mothers or grandmothers.

3. **Assortative mating**: According to this theory, long-term human mating decisions are influenced by several factors related to the degree of similarity between both spouses; among them are educational attainment, labor income, ethnic background, religion, etcetera.

Following Schwartz (2010), until the 1950s, marriage was an economic relationship between two persons with complementary income sources. Typically, males supplied their labor in the market while females provided public goods at home (cooking, cleaning, child-rearing). This pattern of labor division has changed since the 1960s, as evidenced by changes in the sign of the correlation coefficient of spouses' earnings from negative to positive. From this date on, high-earning males tended to marry high-earning females. Consequently, spouses began to resemble each other in several observable characteristics besides earnings (such as educational attainment or age.)

2 Literature Review

In his pioneering work on the economics of the family, Becker (1991) argued that an optimal mating level is reached when it is impossible to change the combination of spouses to improve one person's welfare without hurting others. There is a negative assortment when benefits arise from specialization, that is, when one of the spouses supplies hours of work in the market while the other produces public goods at home. On the other hand, there is positive mating when there are no benefits from specialization; that is, productivity is maximized when both spouses supply work hours in the market.

Mare, 1991 is another early study on educational Assortative Mating; he argues that educational attainment and marriage age affect a person's chance of finding someone with similar characteristics because the educational system forces homogeneity in age and social class. This homogeneity structures students' acquaintances, increasing their likelihood of marrying someone with similar traits later in their lives. According to his theory, marital sorting may increase or decrease educational homogamy (marriages between two individuals with similar observable characteristics) depending on the relative strength of two opposing forces:

- Both the increase in women's participation and the closing of the wage gap have altered expectations of men and women about marriage; if women can now attain higher income and education levels, they may now seek partners more similar to them in these aspects. Therefore there will be an increasing sorting measured using income or education levels.

- As a consequence of pursuing a career, men, and women marry at later ages than their parents or grandparents; this means they may lose a large part of their acquaintances from high school or university, this, an amount of their “social capital”, (the pool of individuals where they are supposed to meet their spouses). If this assertion is true, sorting should decrease rather than increase in time, Mare, 1991 shows evidence that the first effect is more significant and, therefore, Assortative Mating is increasing.

Later, Cancian and Reed (1999) used decomposition methods to analyze the effects of assortative mating on household income inequality using the coefficient of variation (CV) of total household income as a measure of inequality. This coefficient is preferred to other statistics, such as the Gini or Theil indices because neither can be decomposed linearly into their components. Later works have continued this line of analysis, using other methods, they can be classified according to the following taxonomy:

Parametric decompositions : this is the method described in the previous paragraph; it uses the coefficient of variation as a measure of income inequality; despite an important shortcoming, it tends to assign greater weight to transfers between individuals with a high-income differential. Nevertheless, it is used because it can be decomposed linearly without resorting to more advanced statistical techniques. Recent work by (Campos-Vázquez, Hincapié, and Rojas-Valdéz, 2012) uses this method to study household income inequality in Mexico; also, Funes Leal (2015) does a similar analysis for Argentina. A second drawback of this decomposition is the fact that it uses a summary statistic and not a distribution function as a counterfactual.

Non-parametric decompositions : a different decomposition method was developed by DiNardo, Fortin, and Lemieux (1996), it is based on simulating counterfactual distributions using a set of covariates; these simulated distributions are obtained by means of a re-weighting approach, then income inequality measures are estimated for both on the original Distribution and the counterfactual Distribution. Daly and Valletta (2006) decomposed several inequality and poverty indicators for the United States[1] using data from the *Current Population Survey* in an attempt to measure the impact of the growing dispersion of male labor income on the household income distribution. Next, (Eika, Mogstad, and Zafar, 2014) used it to study the effects of assortative mating on income inequality for the United States and Norway using the correlation between educational attainment levels as a mating measure.

Semi-parametric decompositions : this method is a combination of the previous two, Greenwood et al. (2014) use a semi-parametric form to decompose the Gini coefficient of household income with IPUMS[2] data for the United States. Their decomposition method splits the data into many groups and computes the Gini coefficient for each using their average income and size. Then, several counterfactual scenarios are estimated using individual mating patterns and female labor participation rates.

3 Some stylized facts

3.1 Gini indices

To characterize the trend of income inequality in Argentina, we can split our 21-year time span into several periods; we will use two of these classifications; the first one, in this section, makes use of two

[1] Median, standard deviation, coefficient of variation, quantile ratios, Gini and Theil coefficients, mean log deviation and poverty ratio ($FGT(0)$)

[2] International Public Use Microdata Samples

clearly defined periods: one that began in 1991-1992 and finished with the 2001-2002 crisis, it was characterized by a growing inequality in labor income due to larger returns to skilled labor, greater trade liberalization, growing labor force and increasing unemployment. The other period started in late 2002 and was characterized by a declining trend in income inequality (a phenomenon observed throughout Latin America), much slower-growing female labor participation and lower unemployment. The second periodization will be described later, using four different periods to increase the number of observations and dampen business cycle effects.

The most widely used measure of income inequality by the literature is the Gini coefficient (Cowell and Flachaire, 2015), defined as:

$$G(y) = -1 + 2\int_0^{\infty} \frac{y}{\mu(F)} dF(y) \tag{1}$$

Where y is a measure of income (total household income in this case), $F(y)$ is the cumulative Distribution of y, and $\mu(F)$ is the mean of y. As measured by this index, income inequality fell from an average of 0.5 in the 1992-2002 decade to roughly 0.42 in the following decade. Figure 1 plots the estimated value of the Gini index per year along with its bootstrapped confidence intervals[3] with $R = 500$ replications. Let $\hat{G}_i$ for $i = 1, \ldots, R$ be the estimated value for the Gini index in each replication, $\bar{G} = \frac{1}{R}\sum_{i=1}^{R} \hat{G}_i$ the average value estimated over all replications, then the bootstrapped standard errors will be:

$$SE(\hat{G}) = \sqrt{\frac{1}{R-1}\sum_{i=1}^{R}\left(\hat{G}_i - \bar{G}\right)^2} \tag{2}$$

Using these standard errors, we can compute confidence intervals for the Gini Index of per capita household income (total household income divided by the number of family members); this are the shaded lines in Figure 1.

Figures 2(a) and 2(b) plot Gini indices and confidence intervals for both subsamples of males and females. Throughout this paper, Total income is defined in the same way as in **SEDLAC** database[4], this is, as the sum of both labor and non-labor income of all household members. Labor income is all payments received by wage earners from their main and secondary sources of income. Non-labor income, by contrast, is equal to the sum of payments originated in pensions, capital benefits, and transfers (unemployment insurance, scholarships, etc.).

The behavior of male income inequality closely resembles the aggregate because it is by far its main component. But female income inequality has a very different trend compared to that of males; despite showing higher levels in the 1990s and much lower values in the 2000s, it can be observed that the value of the Gini index is significantly higher than that of either their counterpart or the aggregate, this behavior is related to much lower female labor participation, especially in the 1992-2001 period.

In the same vein, female income inequality of female income decreased by a higher rate than males; this is also related to female labor participation since it had a large increment in this period. Finally it must be mentioned that the **Encuesta Permanente de Hogares (EPH)**, Argentina's oldest continuous household survey, had a methodology modification in the third quarter of 2003[5]. The new survey was improved in a number of ways that had a sizable impact on our inequality measures. It remains an open question whether the degree to which this modification had a noticeable impact on our estimates of the levels of inequality or not; however, it can be argued that the rate of variation

[3]See James et al. (2013) for a comprehensive introduction to the bootstrap.

[4]Socio-Economic Database for Latin America and the Caribbean (`http://sedlac.econo.unlp.edu.ar`)

[5]For the year 2003, we use the "old" EPH ("EPH Puntual") for the first and second quarters and the "new" EPH ("EPH Contínua") for the third and fourth quarters.

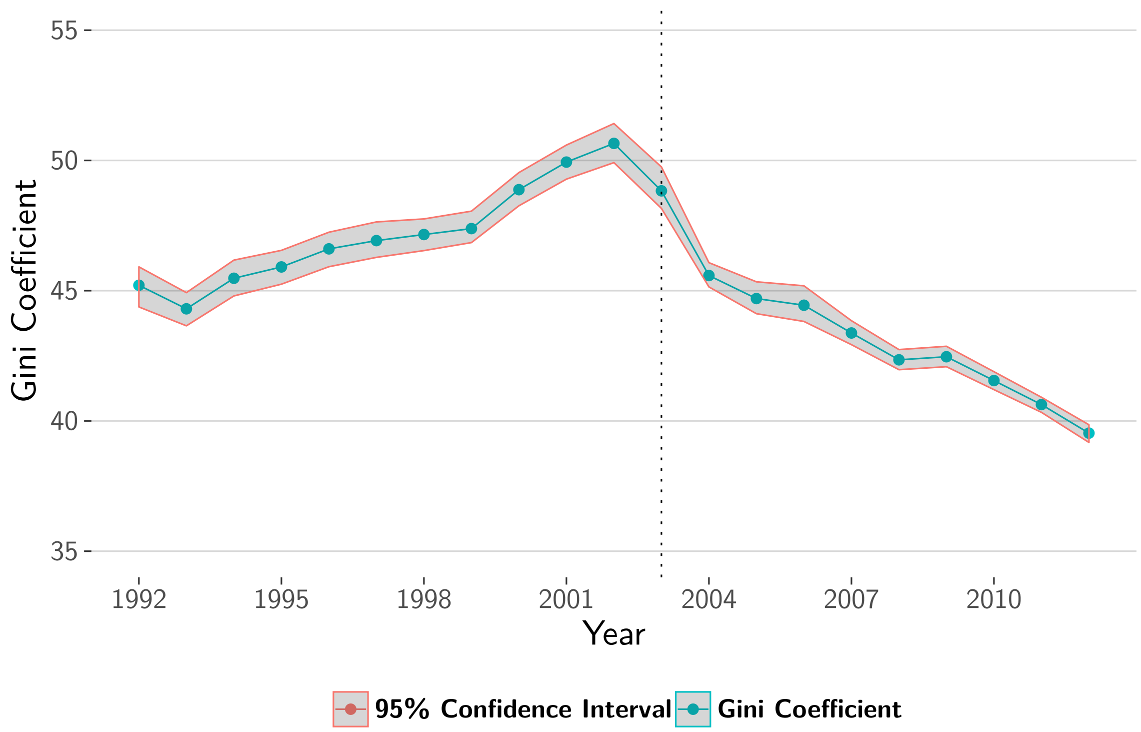


Figure 1: Gini Index of real per capita household income and bootstrap confidence intervals

of inequality has not been affected, most Latin American countries experienced a sizable reduction in their income inequality in the first decade of the XXI century, and Argentina is not an exception. A dotted vertical line was included in all plots to mark the year 2003, when the survey methodology was modified.

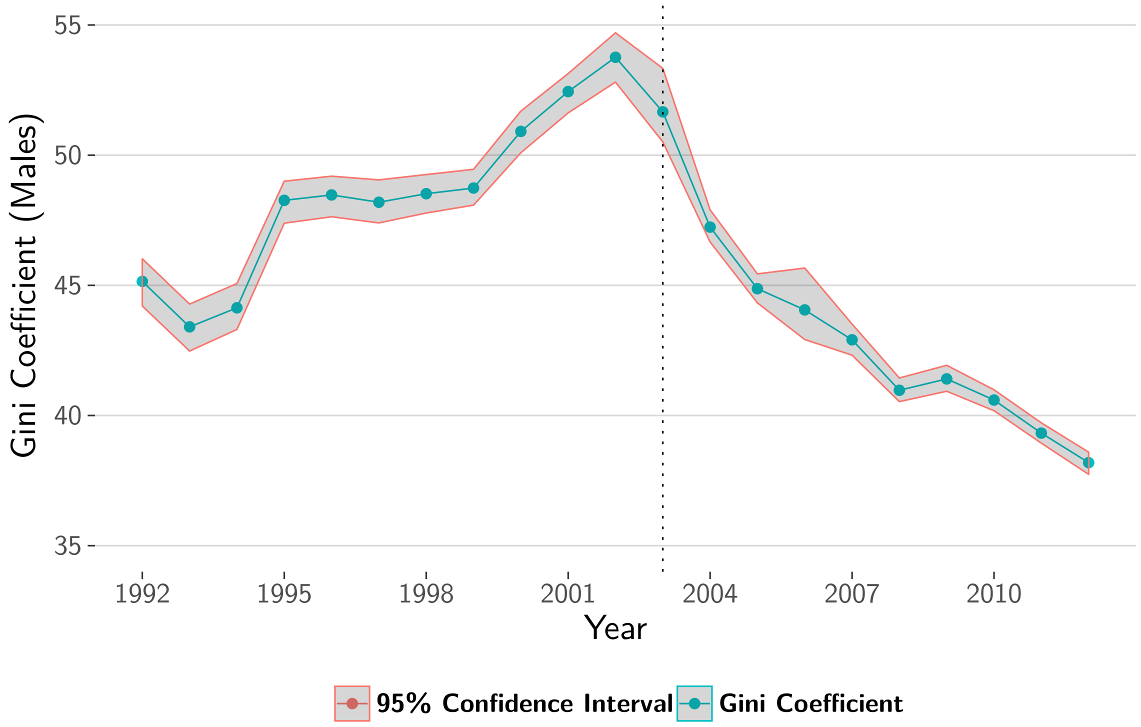
3.2 Income distributions

Another way to look at the evolution of income inequality is using a histogram of the variable; unfortunately, they make the distribution constant on each interval, causing discrete jumps at every end. One way to overcome this difficulty is employing a smoothing function, called a "kernel function," to estimate a distribution $\hat{f}(y_0)$ at every point in its support. In addition, given that the dDistributionof any income variable is highly asymmetric since there usually are many households with low incomes and a comparatively small number of households with high incomes, we need to make the dDistributionsymmetric, but preserving the orderings, therefore, we use a logarithmic transformation given that its monotonicity preserves these orderings.

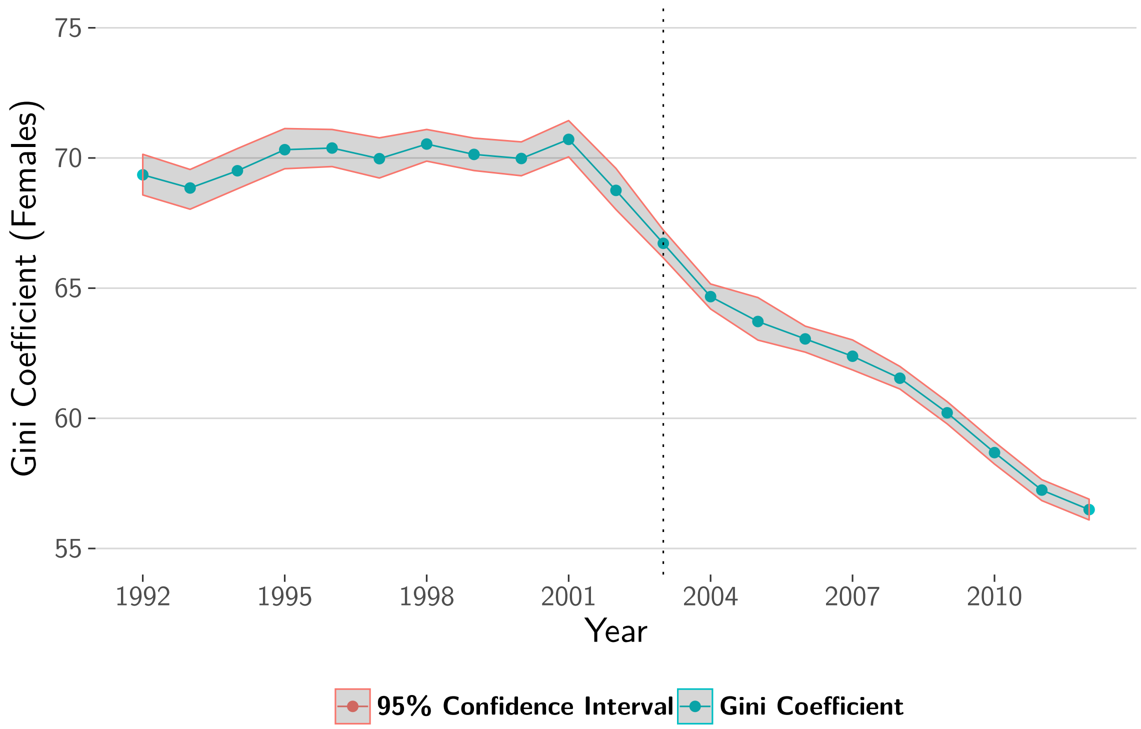
The kernel function method developed by Rosenblatt and Parzen (Pagan and Ullah, 1999) approximates the true distribution of income $(f(y))$ using a function defined as:

$$\bar{f}(y_0) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{h}K\left(\frac{y_i - y_0}{h}\right) \tag{3}$$

$K(.)$ is the kernel function; it measures how close an arbitrary observation y_i is from y_0, there is a large number of possible kernel functions, but two functions are widely used: normal and Epanechnikov(Cowell and Flachaire, 2015), we will use the later:



(a) Gini coefficient for male total income



(b) Gini coefficient for female total income

Figure 2: Decompositions of total household income

$$K\left(\frac{y_i - y_0}{h}\right) = \begin{cases} \frac{3}{4}\left[1 - \left(\frac{y_i - y_0}{h}\right)^2\right] & \text{if } \left|\frac{y_i - y_0}{h}\right| < 1 \\ 0 & \text{if } \left|\frac{y_i - y_0}{h}\right| \geq 1 \end{cases} \tag{4}$$

It is also necessary to determine what value of the parameter h to use; it is called the "bandwidth" and, according to Gasparini, Cicowiez, and Sosa Escudero (2013), the chosen value is even more important than the kernel function itself. To avoid further complications, we will use Scott's method, which selects the optimal bandwidth (h^*) as:

$$h^* = 1.06\sigma n^{-1/5}$$

Where n is the sample size and σ is an estimator of the standard deviation of $\log(y)$. In Figure 3, the dDistributionof real total household income is plotted (in 2012 prices) using an adult-equivalent correction (explained in the following section). We used values for the first and last year (1992 and 2012) and one intermediate year (2002) because the year had the lowest average per capita income due to the 2001-2002 economic crisis.

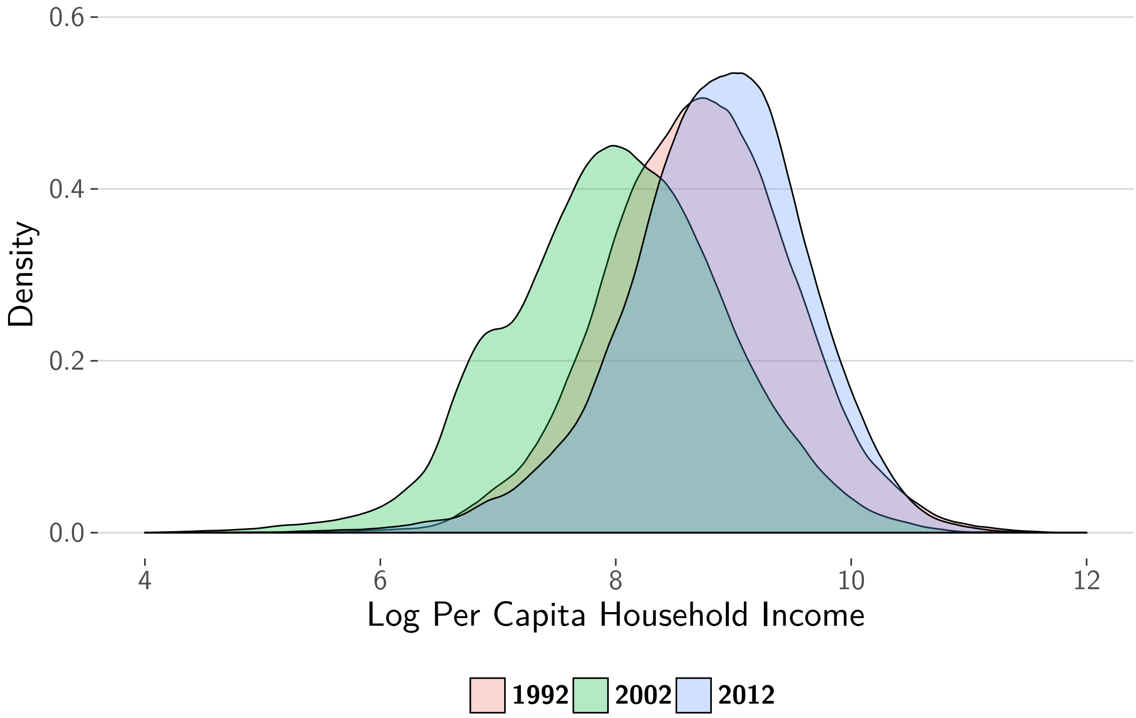


Figure 3: DistributDistributioneal total household income (2012 prices)

First, the overlapping distributions show how the 2001-2002 crisis impacted on individual incomes: there was a significant decrease in both mean and median income relative to its 1992 values; nevertheless, in the following period, both recovered steadily. Second, it must be recalled that using a log scale distorts variations in levels; for example, total household income fell from ARS 7806.78 (USD 1715.77) in 1992 to ARS 4208.77 (USD 925) in 2002 then it increased again to ARS 9062.95 (USD 1991.86) in 2012[6]. In other words, income almost halved as an effect of the crisis, but it

[6] All magnitudes are measured in 2012 ARS

reversed its trend to reach a 16% higher value relative to 1992.

In Figure 4, estimated distributions of total male and female income are plotted using Epanechnikov kernel functions and optimal bandwidth parameters shown above.

Figures 4(a) and 4(b) plot distributions of total male and female income for the same period; we can note the following:

- Both distributions (for males and females) are remarkably similar in shape because the log transformation drops all observations with zero income, thus reducing the gender wage gap.
- The 2002 financial crisis triggered a series of social protection policies which had a greater impact on females due to their lower average wages; this is evidenced in 2002 when the distributDistributionog income became bi-modal and remained this way but with a progressively smaller "peak" at lower wages.
- The male-female wage gap has decreased throughout the period, but the distributiDistribution total income is still asymmetric compared to that of males; it clearly has a larger density in the left tail.

4 Assortative mating and educational attainment

4.1 Introduction

This section aims to replicate the method used by (Greenwood et al., 2014), a microeconometric decomposition exercise to evaluate the impact of assortative mating on income inequality as measured by the Gini index. The theory behind this exercise is described in Greenwood et al. (2015) where individuals' mating and labor supply decisions are modeled in a utility maximization setting, and authors also provide a number of equilibrium and stable matching conditions.

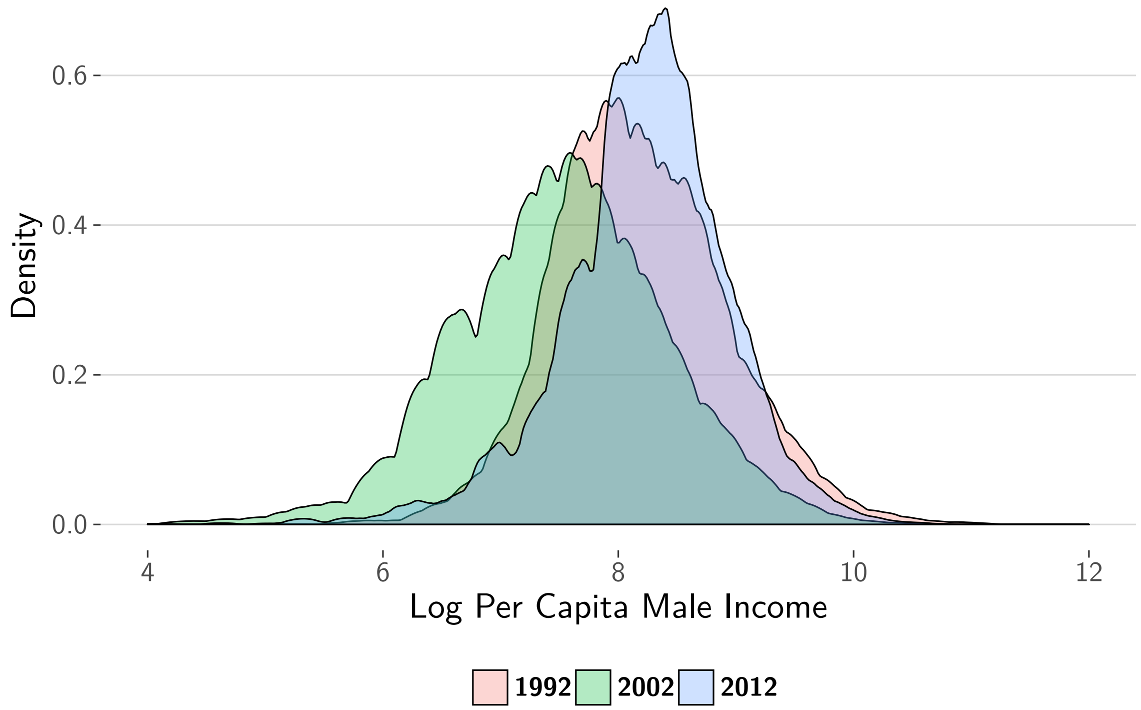
According to (Greenwood et al., 2014), if couples were formed randomly, the Gini index for 2005 would have fallen from 0.43 to 0.34 using American Community Survey data. On the other hand, Eika, Mogstad, and Zafar (2014), using data from the Current Population Survey and a different decomposition method (that of DiNardo, Fortin, and Lemieux (1996)) found a more modest decrease in inequality due to assortative mating, from 0.403 to 0.384. Another method was used by Hryshko, Juhn, and McCue (2014), who also found a much lower decrease in inequality with social security data from the United States[7], according to this authors, values of the Gini index fall from 0.295 to 0.290 in 2004, they also replicate this experiment with data from the Panel Study of Income Dynamics (PSID), finding a decrease from 0.273 to 0.264.

4.2 Simulation method

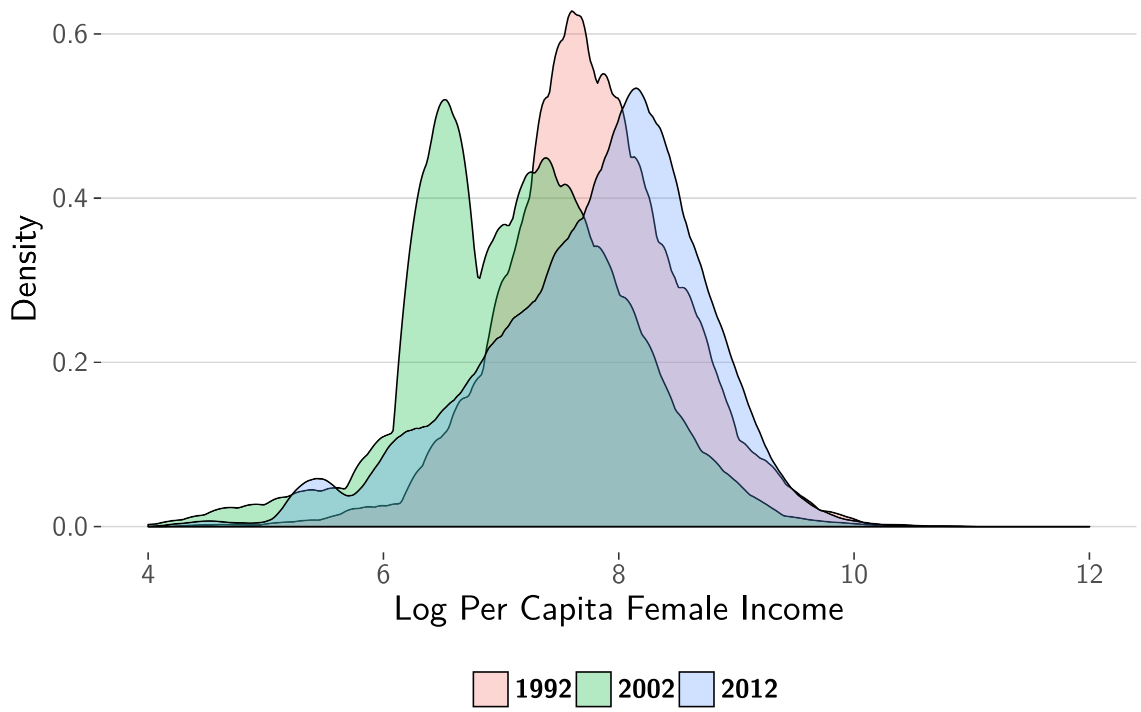
The semi-parametric decomposition method used is based on contingency tables, that is the joint distributionDistributionnal classes for both spouses, to simulate outcomes resulting from random mating. It is useful at this point to use the taxonomy proposed by Harmenberg (2014), according to whom there are two competing approaches for studying assortative mating with microeconometric decompositions. The first method, called *addition approach*, computes the income from each "pseudo-household" by adding up spouses' incomes; the second one, called *imputation approach*, imputes the pseudo-income assuming that it is distributed in a similar way as actual income for households with similar observable characteristics.

Let:

[7] Data from the Survey of Income and Program Participation Panels (SIPP-SSA)



(a) Distribution of log total income - males



(b) Distribution of log total income - females

Figure 4: Distributions of log total income by gender (2012 prices)

x_m, x_f : individual characteristics for males and females (educational attainment, labor participation, number of children, etc.)

y_m, y_f : individual income of both spouses, such that total income for household i is defined as $y_i = y_{mi} + y_{fi}$.

$f(z_i)$: true distribution of variable z_i

Under the addition approach, attributes x_m, x_f are kept constant for all couples; this means that the following distribution is estimated:

$$(f(y_m|x_m) * f(y_f|x_f))\, f(x_m, x_f) \tag{5}$$

This method assumes that $m(f)$ are randomly distributed, such that $y_m|x_m$ and $y_f|x_f$ are independent.

Under non-conditional randomization, attributes are kept constant and the expression is reduced to:

$$f(y_m) * f(y_f) \tag{6}$$

The imputation approach computes the following expression: $f(y|x_m, x_f) * f(y_m) * f(y_f)$ and household income is calculated with its observable characteristics.

Both approaches have advantages and disadvantages; the addition approach avoids wasting information by randomizing existing populations but fixes labor supply and income since both are exogenous to the decision of starting a household. The imputation approach considers labor supply and income when creating a household but wastes potentially useful information because observable attributes do not allow perfect imputation.

(Greenwood et al., 2014) use a form of the imputation method because they approximate the income distribution using empirical quintiles and all combinations of educational levels; finally, they compute the counterfactual distributionDistributionmbination of educational levels. With these data, they use an estimated distribution of educational levels as weights and aggregate the income distribution by quintiles along all education levels to obtain the new household income distribution.

The decomposition method requires a re-estimation of the Gini index using a large number of groups based on marital status, educational attainment, labor participation, and number of children.

$\mathcal{M}_{E_H}$: husband educational level index, $E_H \in \{P-, P, S-, S, U-, U\}$ where each category represents, primary incomplete, primary complete, secondary incomplete, secondary complete, higher education (university and/or technical degrees) incomplete and higher education complete.

$\mathcal{M}_{E_W}$: wife educational level index, $E_W \in \{P-, P, S-, S, U-, U\}$.

$\mathcal{M}_{LFP_H}$: husband labor participation index, $LFP_H \in \{WORK_H, \sim WORK_H\}$, where the first category refers to those who participate in the labor market, while the second refers to those who don't.

$\mathcal{M}_{LFP_W}$: wife labor participation index, $LFP_W \in \{WORK_W, \sim WORK_W\}$.

$\mathcal{M}_{KIDS}$: index for number of children $KIDS \in \{0, 1, 2, 2+\}$, here the last category is for couples with more than two kids.

The full set of indices is, then:

$$\mathcal{M} = \bigcup_{E_H, E_W, LFP_H, LFP_W, KIDS} (\mathcal{M}_{E_H} \cap \mathcal{M}_{E_W} \cap \mathcal{M}_{LFP_H} \cap \mathcal{M}_{LFP_W} \cap \mathcal{M}_{KIDS}) \tag{7}$$

Therefore, for married couples, we have a total of $6 \times 6 \times 2 \times 2 \times 4 = 576$ groups.

For non-married households, we have the following group indices:

$\mathcal{M}_{MARSTAT}$: index for individual's marital status,
$MARSTAT \in \{NMAR_M, NMAR_F, DIV_M, DIV_F\}$, and its categories are single men, single women, divorced men, and divorced women.

$\mathcal{M}_E$: index for educational level, $E \in \{P-, P, S-, S, U-, U\}$

$\mathcal{M}_{LFP}$: index for labor force participation, $LFP \in \{WORK, \sim WORK\}$.

$\mathcal{M}_{KIDS}$: index for number of children: $KIDS \in \{0, 1, 2, 2+\}$.

The full set of indexes for non-married couples is:

$$\mathcal{M} = \bigcup_{MARSTAT,E,LFP,KIDS} (\mathcal{M}_{MARSTAT} \cap \mathcal{M}_E \cap \mathcal{M}_{LFP} \cap \mathcal{M}_{KIDS}) \tag{8}$$

For single and divorced households, the number of groups is $4 \times 6 \times 2 \times 4 = 192$, so adding up, we end up with $576 + 192 = 768$ groups.

4.3 Data: sources and description

We use data from the Encuesta Permanente de Hogares (EPH) for years 1992 to 2012 instead of using IPUMS data as Greenwood et al. (2014) for two reasons: first, Argentine population censuses do not gather any kind of income data, and consequently they cannot be used for distributional analyses and, second, even if this was possible at the time of writing this document the full dataset from the latest population census (2010) had not been uploaded into the IPUMS website yet.

The *Encuesta Permanente de Hogares* underwent a very significant methodological improvement in 2002, consisting of the following modifications[8]:

- Survey frequency changed from bi-annually to quarterly.
- Sampling methodology was modified from a simple stratified sample to a rotating panel; for this reason, the survey is called "continuous-EPH" from then on.
- The questionnaire was heavily modified as a side effect; some compatibility between the old and the new EPH was lost in important questions such as length of unemployment spell and others related to income sources.
- The number of urban areas in the survey increased to make the survey representative of all urban population (roughly 90% of Argentina's total population.)

These changes in methodology, however, are not likely to have a large impact on our results because all estimations are based on aggregates on a group level and unchanged family characteristics (employment status, age, education, and total income.) Nevertheless, this greater frequency from 2003 onward increases the number of observations per year by a factor of two.

For our analysis, we group years in four blocks; the rationale for doing this is twofold: avoiding business cycle effects on labor participation and incomes and also increasing the size of our sample[9], much smaller than those of IPUMS. The blocks are listed below, but our analysis will be centered on periods 1 and 4 since the effect of assortative mating on inequality can only be measured in the long run:

[8] Beccaria and Groisman, 2008.

[9] This is similar to Bredemeier and Juessen (2013)

- Period 1: 1992-1996
- Period 2: 1997-2002
- Period 3: 2003-2007
- Period 4: 2008-2012

4.4 Data cleaning

To perform the analysis, we must first perform a series of manipulations. First, we drop all family members other than the head, his or her spouse, and all children under 18 years old. Next, we keep only families with both a head and a spouse between 24 and 55 years old to capture the smallest possible number of students and pensioners.

The next step is to categorize households according to the taxonomy previously described according to the marital status and gender of its members. Here is where we depart from Greenwood et al. (2014) because we use six education levels instead of five; we do this because the former classification would leave the highest level ("postgraduate education") with very few observations, especially in period 1, due to a relatively lower average education level in Argentina compared to that of the United States.

The fourth step involves estimating an adult-equivalent total household income; once again, we depart from the original study because we do not use the OECD equivalence scales[10]. We use instead the equivalence scale from Argentina's National Statistics Office (INDEC):

Table 1: Adult equivalence Table (INDEC)

Age	Sex	Adult-equivalent Value
Under a year old	Both	0.33
1 year		0.43
2 years		0.50
3 years		0.56
4 to 6 years		0.63
7 to 9 years		0.72
10 to 12 years	Males	0.83
13 to 15 years		0.96
16 to 17 years		1.05
10 to 12 years	Females	0.73
13 to 15 years		0.79
16 to 17 years		0.79
18 to 29 years	Males	1.06
30 to 59 years		1.00
60 years and over		0.82
18 to 29 years	Females	0.74
30 to 59 years		0.74
60 years and over		0.64

Source: Bergés (2011).

We also need to identify persons who supply their work in the labor market; for this end, we create a dummy variable equal to 1 if the person is employed and 0 otherwise. Finally, we generate

[10] On this scale, an adult male has a weight equal to 1, an adult female has a weight equal to 0.5, and all children under 14 years old have a weight equal to 0.3.

another categorical variable for the number of children (no children, one child, two children, and more than two children).

5 Assortative Mating Indicators

The model of Greenwood et al. (2014) seeks to answer the next two questions:

1. Is there any evidence of increased Assortative Mating in households from 1992-2012?
2. What is the contribution of Assortative Mating to household income inequality?

Question number 1 can be answered by looking at a series of indicators, but question number 2 requires a more sophisticated analysis; hence we will employ a simulation method.

5.1 Indicator 1: Regression Coefficients

This indicator is based on estimating this equation:

$$EDU_{it}^{f} = \alpha + \beta EDU_{it}^{m} + \sum_{t \in \mathcal{T}} \gamma_t * EDU_{it}^{m} * \text{year}_{st} + \sum_{t \in \mathcal{T}} \theta_t * \text{year}_{st} + \epsilon_{it} \quad \epsilon_{it} \sim N(0, \sigma) \tag{9}$$

Where:

EDU$_{it}^{f}$**, EDU**$_{it}^{m}$: are education levels of males (m) and females (f) that constitute household i in year t.

year$_{st}$: are year dummies $t = 1992, \ldots, 2012$ such that year$_{st} = 1$ if $s = t$ and year$_{st} = 0$ otherwise.

Coefficient β measures the strength of the association between spouses' education levels in the base year (1992), while coefficients γ_t measure the relative contribution of husbands education relative to that of their wives for all years after the base year, therefore they measure the degree of Assortative Mating. Coefficients θ_t are used to control for the exogenous increase in education levels of both males and females.

Figure 5 shows a slight upward trend in the range; however, coefficients are not significant at 5% because their confidence intervals contain the value of zero for most years. The strength of Assortative Mating is higher in the second half of the period but much smaller than that for the United States, partly due to the smaller period and higher frequency; as explained previously, assortative mating is a structural phenomenon with very little year-to-year variation.

5.2 Indicator 2: Kendall's Tau

Kendall's tau is a rank correlation coefficient used to measure the strength of a correlation between two categorical variables, in this case, the education level of spouses. This coefficient (Kendall, 1970) is defined as:

$$\tau = \frac{S}{\frac{n(n-1)}{2}} \tag{10}$$

S is the difference between the number of concordant pairs (P) and the number of discordant pairs (Q), a pair of observations is called *concordant* if both husband and wife attained the same education level and *discordant* otherwise, then: $P + Q = \frac{n(n-1)}{2}$, and:

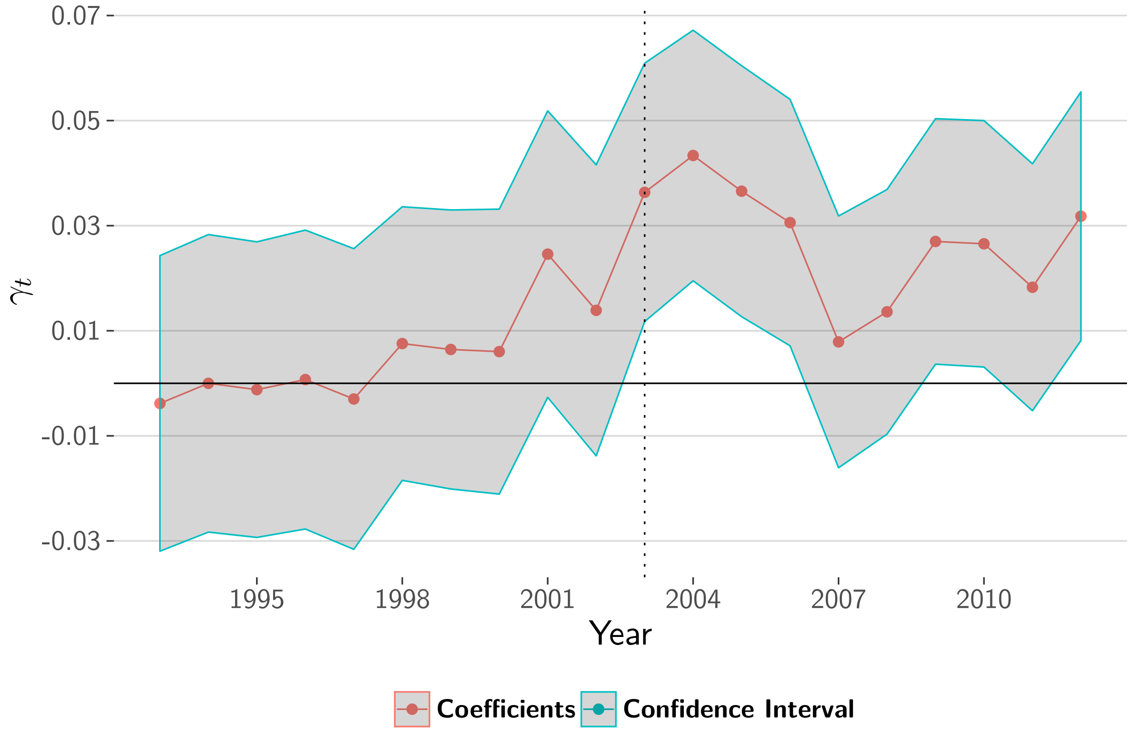


Figure 5: Increase in Assortative Mating

$$\begin{aligned}\tau &= \frac{P-Q}{\frac{n(n-1)}{2}} \\ &= 1-\frac{2Q}{\frac{n(n-1)}{2}} \\ &= \frac{2P}{\frac{n(n-1)}{2}}-1\end{aligned}$$

Kendall's tau is normally distributed (Worner, 2006), in the range $[-1, 1]$, but this may not be the case if there is a large number of *ties* (pairs that are neither concordant nor discordant.) In the presence of ties, a continuity correction accounts for them as described in Kendall, 1970, p. 58.

Confidence intervals for this statistic are computed using Fisher's **Z-score**:

$$Z = \frac{1}{2}\left[\log(1+\tau) - \log(1-\tau)\right]$$

Its standard error is equal to $SE(Z) = \sqrt{\frac{1}{n-3}}$, where n is the number of couples in the sample. We can use these standard errors to estimate confidence intervals, given that the Z-sore has a normal distribution.

Following Worner, 2006, and given that the values of Kendall's tau are bounded between -1 and 1, positive values for the coefficient indicate that both categorical variables increase together, but a negative value mean can be interpreted as a correlation coefficient. Also, absolute values of this coefficient can be interpreted as probabilities; for example, a value of -0.25, means that, if we select a random couple, there is a probability of 0.25 that both spouses do not have the same education levels.

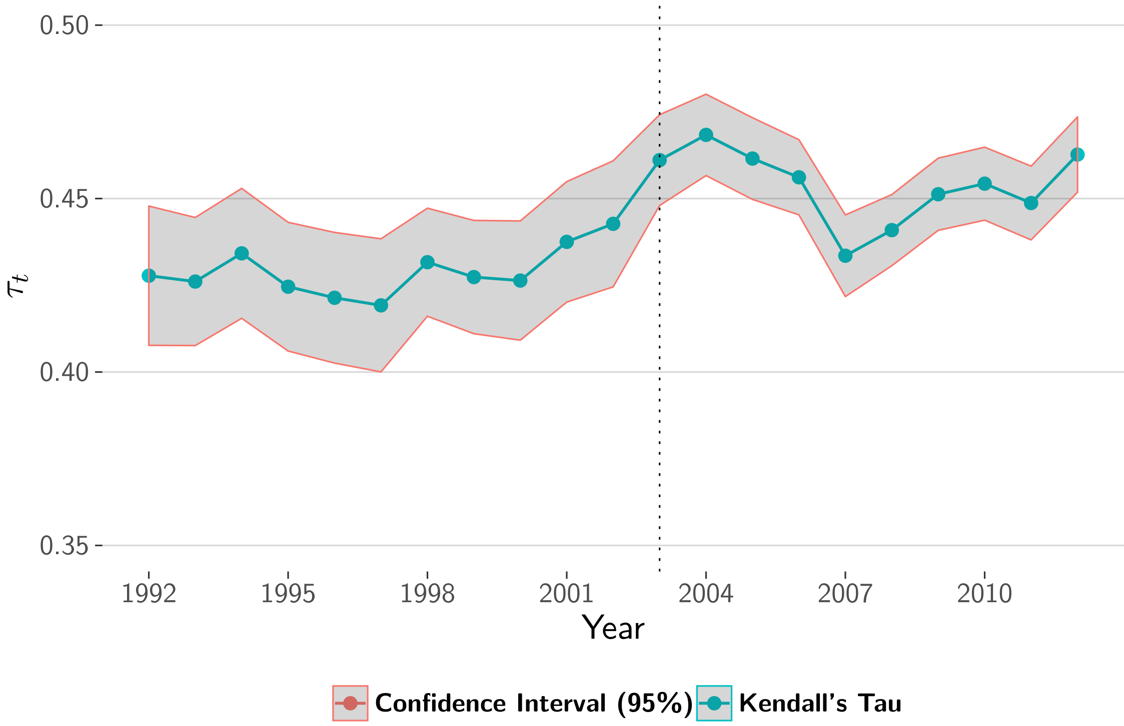


Figure 6: Rank correlation coefficient for couples' education attainment

There is no consensus on what is a "high" or a "low" value for Kendall's tau, but it is possible to use this informal rule:

$$\begin{aligned} \pm 0.01 \leq \tau < \pm 0.3 &\quad \text{weak correlation} \\ \pm 0.3 \leq \tau < \pm 0.7 &\quad \text{moderate correlation} \\ \tau \geq \pm 0.7 &\quad \text{strong correlation} \end{aligned}$$

In Figure 6, values of Kendall's tau and confidence intervals for spouses' educational attainment are plotted. Its trend is similar to that of the regression coefficients, but their significance is somewhat higher; the value of τ was almost constant throughout the 1990s. In the 2000s, it had a slight increase again, but it does not deviate further than 0.46, having started at 0.42; according to the categories above, it can be stated that the correlation is moderate, but showing no clear signs of increasing, unlike the U.S. data from Greenwood et al., 2014.

5.3 Indicator 3: Relative sum of diagonals

Our third indicator of Assortative Mating originates in the association matrix of couples' educational attainment if a^t_{ij} is the cell for the husband's educational level i and wife's j in year t. Then, the sum of all diagonal entries in matrix $\mathbf{A}$ (values with $i = j$) can be defined as: $\sum_{i=1}^{6} a^t_{ii}$.

On the other hand, let r^t_{ij} be the equivalent cell in a matrix $\mathbf{R}$, defined as the internal product of row and column totals of association matrix $\mathbf{A}$. This matrix is the simulated association matrix if mating was random. Let $\sum_{i=1}^{6} r^t_{ii}$ be its sum of diagonals, then we define:

$$\delta_t = \frac{\sum_{i=1}^{6} a^t_{ii}}{\sum_{i=1}^{6} r^t_{ii}} = \frac{tr(\mathbf{A})_t}{tr(\mathbf{R})_t} \tag{11}$$

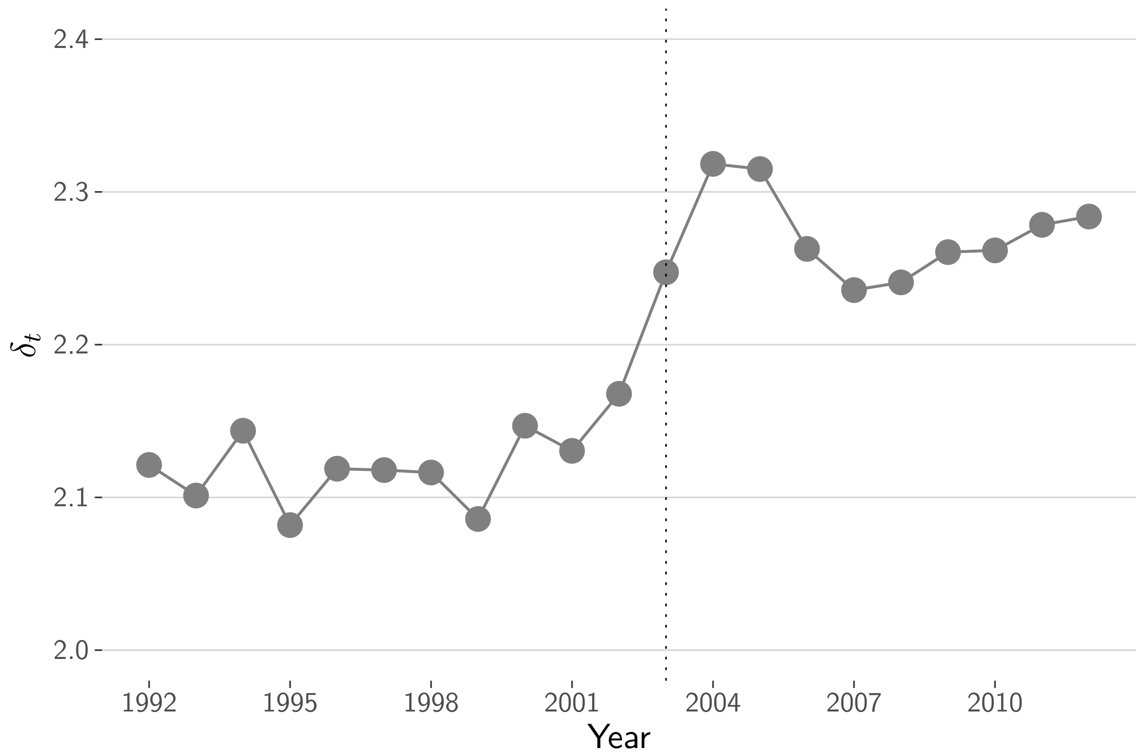


Figure 7: Ratio of sums of diagonal entries of association matrices by year

$tr(\mathbf{A})$ y $tr(\mathbf{R})$ are the traces of both observed and simulated association matrices.

In Figure 7, values for δ_t per year are plotted; its value is greater than one in the entire series span, implying positive Assortative Mating. Nevertheless, its behavior resembles that of indicators 1 and 2 in both levels and rates of variation.

5.4 Indicator 4: Contingency tables

The final Assortative Mating indicator used is an association or contingency table, the joint distribution of all six couples' educational levels by period. In this case, the Distributioneriods 1992-1996 and 2008-2012 are shown below:

Table 2: Contingency table for period 1992-1996

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	$\mathbf{0.165}$	0.040	0.041	0.055	0.008	0.005
P	0.037	$\mathbf{0.044}$	0.005	0.012	0.000	0.001
S-	0.027	0.004	$\mathbf{0.082}$	0.034	0.032	0.014
S	0.059	0.011	0.047	$\mathbf{0.067}$	0.015	0.011
U-	0.002	0.000	0.024	0.006	$\mathbf{0.062}$	0.015
U	0.004	0.000	0.019	0.010	0.021	$\mathbf{0.018}$
Marginal dist.	0.296	0.099	0.217	0.185	0.138	0.065

Source: Household surveys (EPH).

Tables 2 and 3 show the joint distribution of each combination of educational levels in period 1 (1992-1996) aDistribution012). In most cases, the highest value of the association matrix coincides with that in the main diagonal, it can also be seen that frequencies of the combinations from the

Table 3: Contingency table for period 2008-2012

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	**0.104**	0.017	0.040	0.041	0.011	0.007
P	0.019	**0.017**	0.004	0.009	0.001	0.001
S-	0.025	0.003	**0.116**	0.033	0.060	0.028
S	0.033	0.006	0.046	**0.062**	0.020	0.018
U-	0.003	0.000	0.024	0.005	**0.110**	0.024
U	0.003	0.000	0.021	0.007	0.041	**0.035**
Marginal dist.	0.188	0.045	0.252	0.158	0.243	0.114

Source: Household surveys (EPH).

highest education levels increase in period four relative to period one. This shows that the average educational level has increased, especially for women; in particular, the frequency of wives with the highest level of education almost doubled between both periods.

6 Inequality indices

Our second stated objective in this paper is to assess the impact of Assortative Mating on income inequality. Two inequality indicators are used to achieve this: the Gini index and Lorenz curves.

Let:

f_{ij} : fraction of type i households in income percentile j: $f_{ij} = \frac{N_{ij}}{N}$, where N is the sample size and N_{ij} is the size of group (i, j).

r_{ij} : income of households i relative to mean household income of the entire population: $r_{ij} = \frac{y_{ij}/N_{ij}}{Y/N}$, y_{ij} is total household income of group (i, j) and Y is the household income for the whole sample.

s_j : share of aggregate income for percentile j: $s_j = \sum_i f_{ij} r_{ij}$.

I_p : cumulative share of percentile p: $I_p = \sum_j^p s_j = \sum_j^p \sum_i f_{ij}$

We depart again from Greenwood et al., 2014 since we are using survey instead of census data, this implies that our sample size will be much smaller; one way to mitigate its impact is reducing the number of percentiles from 10 to 5 (that is, from deciles to quintiles), this allows us to reduce the number of groups without affecting results significantly. However, the analysis will also be carried out with deciles in the "robustness checks" section; let these quintiles be: $j \in \{0.1; 0.2; 0.3; 0.4; 0.5\}$, then we will have just $768 \times 5 = 3840$ groups, instead of $768 \times 10 = 7680$ groups.

Lorenz curves are defined as the plot of (p, I_p), where $p = \sum_j^p \sum_i f_{ij}$, and $I_p = \sum_j^p \sum_i f_{ij}$. The Gini coefficient equals twice the area under the Lorenz curve and a $45°$ line:

$$g = 2 \int_0^1 |I_p - p| dp, \quad \text{with: } 0 \leq g \leq 1 \tag{12}$$

Consequently, both indices are functions of f_{ij} and r_{ij}:

$$l_p = Lorenz_p\left(\{f_{ij}\}, \{r_{ij}\}\right) \tag{13}$$
$$g = Gini\left(\{f_{ij}\}, \{r_{ij}\}\right) \tag{14}$$

Since we have a very large number of groups, we will use the decomposition formula devised by Rao (1969), which decomposes the coefficient in any arbitrary number of groups, denoted by n:

$$g = \sum_{p=1/n}^{1-1/n} \left[pI_{p+1} - \left(p + \frac{1}{n} \right) I_p \right] \tag{15}$$

Thus, to plot the Lorenz Curve we need to split the interval $[0, 1]$ into n equally spaced line segments: $j \in \mathcal{J} = \{\frac{1}{n}, \ldots, 1 - \frac{1}{n}\}$, the value of n is the number of quantiles used ($n = 4$: quartiles, $n = 5$: quintiles, $n = 10$: deciles, $n = 100$: percentiles.)

In Figure 8, Lorenz curves and Gini coefficients for periods 1992-1996 and 2008-2012 are plotted. Inequality had a very small variation because these numbers were calculated as an average of years when inequality grew (period 1) and later decreased (Period 4.) In the first period, the poorest 20% earned less than 5% of total income, while the richest 20% earned almost 50% of total income. In the latter period, this shares decreased but not significantly, since now the lowest quintile gets a little over 5% of total income, while the highest quintile gets about 47% of total household income[11].

Finally, if we compare the observed inequality with the level that arises after imposing random matching, we can see that it falls nearly 6.3 points in period 1 and 3.3 points in period 4.

7 Counterfactual experiments

The counterfactual experiments carried out are based on two population characteristics: the joint distribution of education levels of spouses and female labor participation. GinDistributionts are calculated after changing these distributions.

Another way to express the Gini coefficient is (Cowell and Flachaire, 2015):

$$G = 1 - 2 \int_0^1 L(F; q) dq \tag{16}$$

$L(F, q)$ is the q-th ordinate of the Lorenz curve, which depends on the distribution of a function of income F, in this way:

$$L(F, q) = \frac{C(F, q)}{\mu(F)} \tag{17}$$

$\mu(F)$ is the average income (a function of its distribution), and $C(F, q)$ is the cumulative income functional defined as:

$$C(F, q) = \int_{\underline{y}}^{\bar{y}} y dF(y) \tag{18}$$

Joining both terms, we obtain an expression for the Gini coefficient:

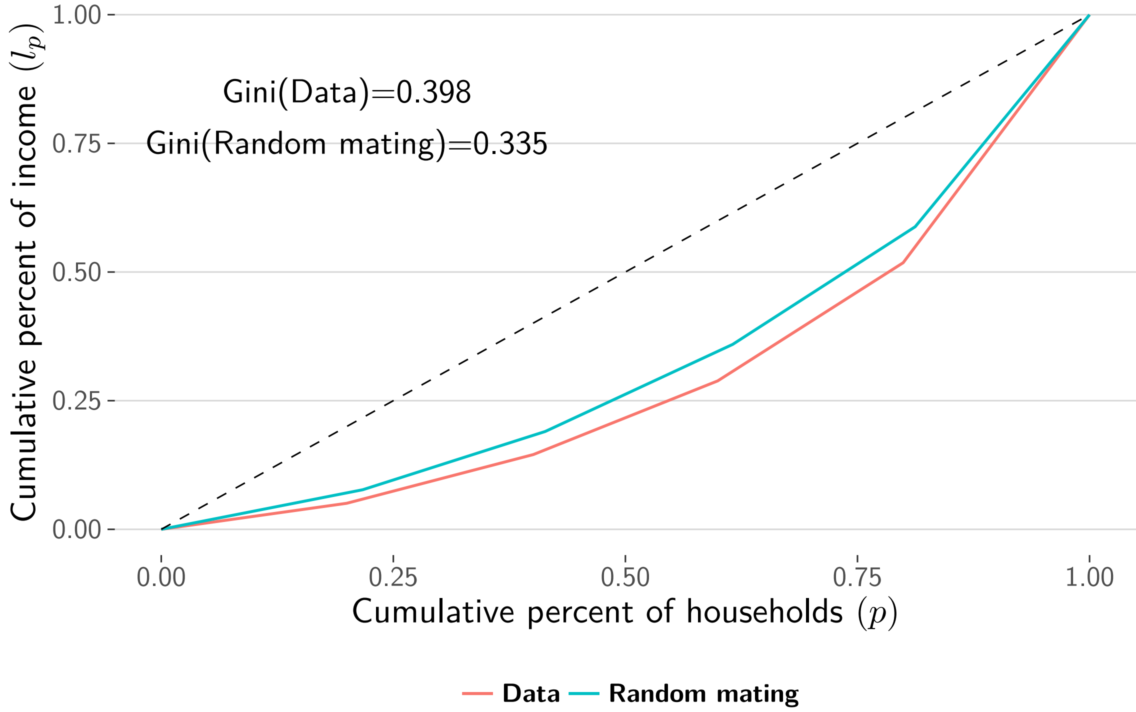
$$G = 1 - \frac{2}{\mu(F)} \int_0^1 \int_{\underline{y}}^{\bar{y}} y * f(y, E_H, E_W, LFP_W) dy dq \tag{19}$$

Finally, replacing both conditional and marginal distributions, we get, for $t = 1, 4$:

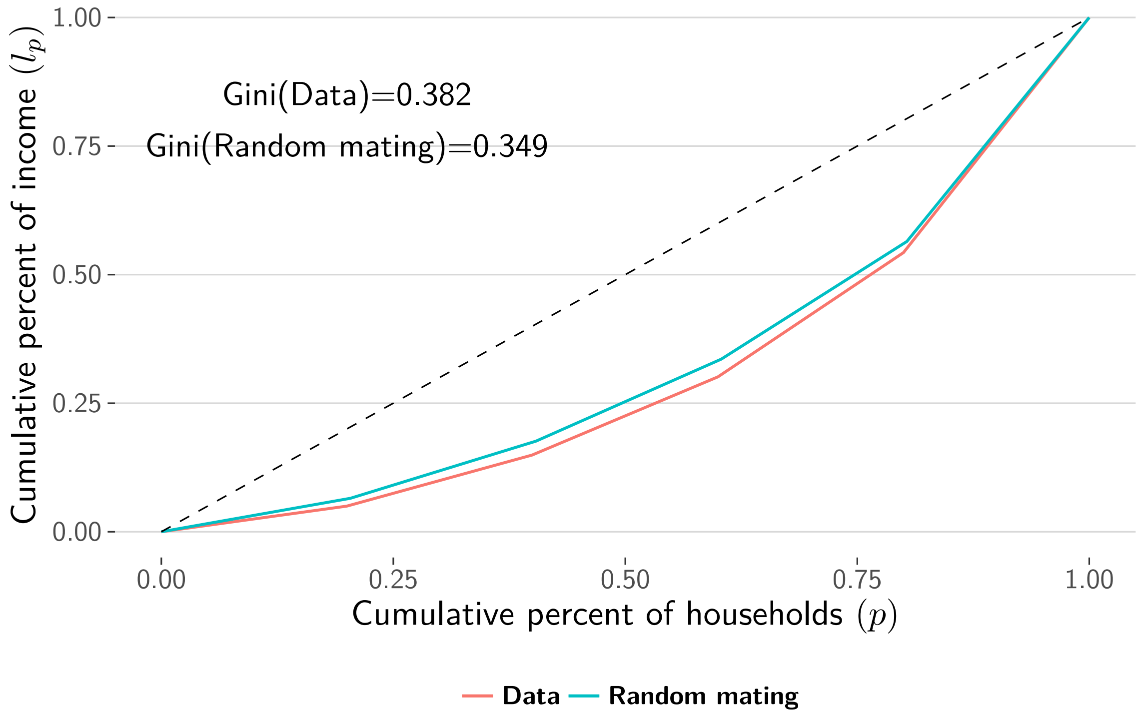
$$G_t = 1 - \frac{2}{\mu(F)_t} \int_0^1 \int_{\underline{y}_t}^{\bar{y}_t} y * f^t(y/E_H, E_W, LFP_W) * g^t(E_H, E_W/LFP_W) * h^t(LFP_W) dy dq \tag{20}$$

With:

[11]"Total household income" always refers to household income with an adult-equivalent correction.



(a) 1992-1996



(b) 2008-2012

Figure 8: Lorenz curves: data versus random mating

$$f(y, E_H, E_W, LFP_W) = f(y/E_H, E_W, LFP_W) \times g(E_H, E_W, LFP_W) \quad (21)$$
$$g(E_H, E_W, LFP_W) = g(E_H, E_W/LFP_W) \times h(LFP_W) \quad (22)$$

All counterfactual experiments depend upon changes in spouse's educational attainment distributions $f(E_H, E_W)$ and changes in female labor participation as a function of quintiles of household income $f(LFP_W)$.

7.1 Random mating

The first counterfactual experiment simulates the result that would have arisen if mating was completely random and then estimates inequality indicators from this scenario. Let $\mathcal{M} = 1, \ldots, 576$ be the index used to identify married couples, $\mathcal{S} = 577, \ldots, 768$ the index for single and divorced persons, then our counterfactual experiment departs from replacing the f_{ij} for $(i,j) \in \mathcal{M}$ observed for those that would be observed if mating was random: $\tilde{f}_{ij}$ for $(i,j) \in \mathcal{M}$, finally, counterfactual Lorenz curves and Gini coefficients will be:

$$l_p = Lorenz_p\left(\{f'_{ij}\}, \{r_{ij}\}\right) \quad (23)$$
$$g = Gini\left(\{f'_{ij}\}, \{r_{ij}\}\right) \quad (24)$$
$$\{f'_{ij}\} \equiv \{\tilde{f}_{ij}\}_{\mathcal{M}} \cup \{f_{ij}\}_{\mathcal{S}} \quad (25)$$

In terms of joint distributions, the Gini coefficient for periods $i = 1, 4$ is now:

$$G_i^{RM} = 1 - \frac{2}{\mu(F)_i} \int_0^1 \int_{\underline{y}_i}^{\bar{y}_i} y f^i(y/E_H, E_W, LFP_W) g_R^i(E_H, E_W/LFP_W) h^i(LFP_W) dy dq \quad (26)$$

$g_R^i(E_H, E_W/LFP_W)$ is the counterfactual joint distribution of education levels assuming random mating, such that differences in Gini coDistributionan only be attributed to changes in the distribution of the education level distribution.

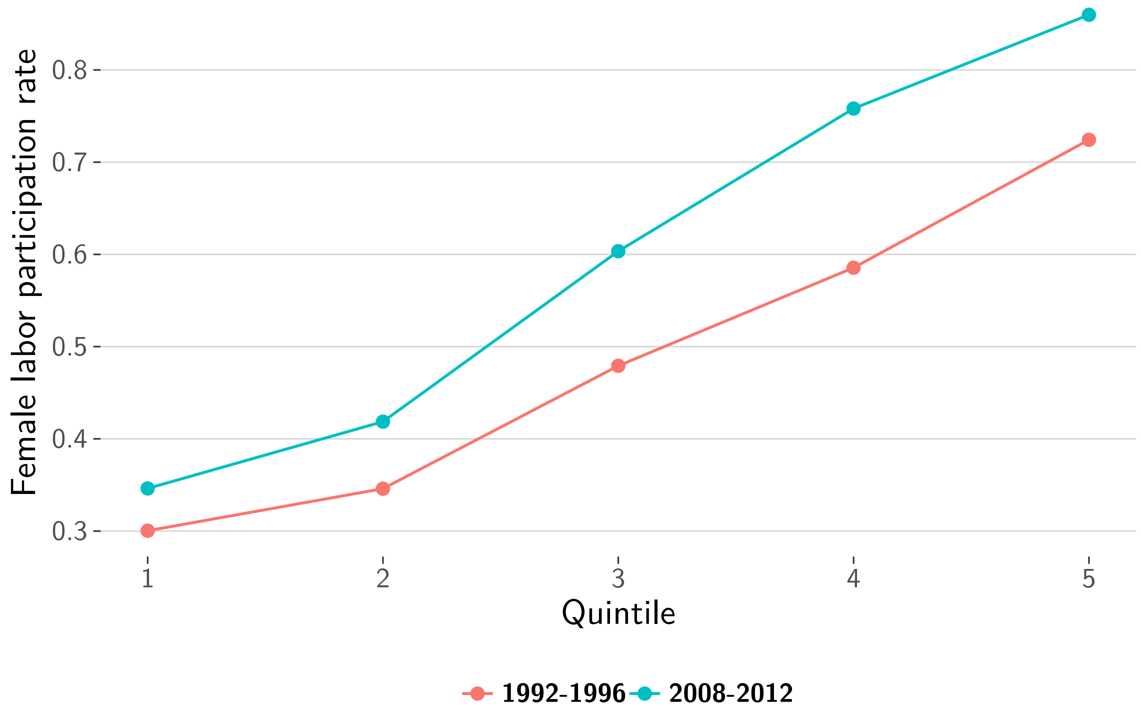
After modifying mating patterns, we seDistributione inequality falls; this result is in line with those of Greenwood et al. (2014), but the effect of random mating is higher in the period 1992-1996 than in 2008-2012 (6.3 points versus 3.3.) This contrasts with the slight increase in Assortative Mating shown in the previous section. Contingency tables of this simulation exercise are shown in the appendix (Tables 6 and 7).

7.2 Female labor participation

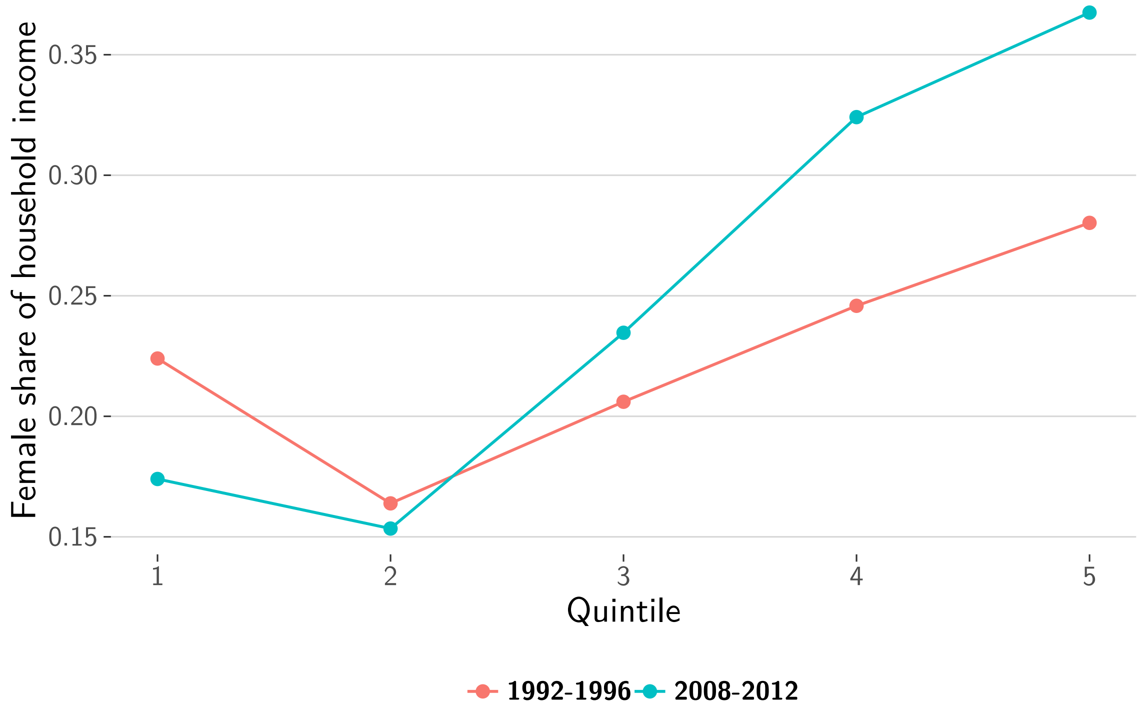
Another driver of inequality is female labor participation, especially married women; at first glance, it should reduce intra-household income inequality, but this effect may not be linear along quantiles. Similarly, a greater female share of household income (due to the former) must not be necessarily linear.

The effect of Assortative Mating depends on women being employed; in figure 9(a), it is shown that this is more frequent in the 2008-2012 period than in the 1992-1996 period. This increase in participation is larger the higher the quintile of income distribution. This effect is also present in the share of females in household income 9(b) since it is also greater the higher the quintile.

The next counterfactual experiment randomizes mating in both periods, but now women in period 1(4) participate in the labor market according to that of period 4(1). This is equivalent to changing



(a) Female labor participation



(b) Female share of household income

Figure 9: Married female labor participation: 1992-1996 versus 2008-2012

both conditional and marginal distributions of education levels as well as the marginal distribution of female labor participation:

$$G_t^{RM+\Delta LFP} = 1 - \frac{2}{\mu(F)_t} \int_{\underline{y}_t}^{\bar{y}_t} y * f^t(y/E_H, E_W, LFP_W) * g_R^t(E_H, E_W/LFP_W) h^s(LFP_W) dydq \tag{27}$$

Where $s = 4$ if $t = 1$ and $s = 1$ if $t = 4$, this way, the aggregate effect is due to variations in two distributions: the joint distribution of education levels and that of female labor participation by quintile of income.

This variation inDistributionr participation decreases inequality in the first period from 0.398 to 0.334, and reduces inequality in the fourth period from 0.382 to 0.348, Greenwood et al. (2014) argue that the source of this change is the diversification of household income between husbands and wives.

Almost the entire reduction in inequality is due to random mating because the effect of female labor participation is negligible. These results are at odds with those of Greenwood, who finds that female labor participation reinforces that of random mating. Contingency tables for this experiment are Tables 8 and 9, and their respective Lorenz curves are plotted as 10(a) and 10(b) in the appendix.

7.3 Standardized contingency tables

The last counterfactual experiment is similar to the first one, but we now take into account the fact that simulated contingency tables under random mating do not control for the increase in husbands' and wives' education levels from 1992-1996 to 2008-2012. This increase affects marginal distributions estimated from these contingency tables; as a solution to this issue, we use **Standardized Contingency Tables** in which their marginal distributions are all equal to $1/6$ by means of an algorithm by Sinkhorn and Knopp using a standardization method proposed by Mosteller, 1968 and summarized in Greenwood et al., 2014, p. 6, but in our case the desired marginal distribution is $(1/6, 1/6, 1/6, 1/6, 1/6, 1/6)$.

In terms of our notation for the Gini coefficient, this experiment can be expressed as:

$$G_t^{ST} = 1 - \frac{2}{\mu(F)_t} \int_0^1 \int_{\underline{y}_t}^{\bar{y}_i} y * f^t(y/E_H, E_W, LFP_W) * g_E^t(E_H, E_W/LFP_W) * h^t(LFP_W) dydq \tag{28}$$

$$G_t^{ST+\Delta LFP} = 1 - \frac{2}{\mu(F)_t} \int_0^1 \int_{\underline{y}_t}^{\bar{y}_i} y * f^t(y/E_H, E_W, LFP_W) * g_E^t(E_H, E_W/LFP_W) * h^s(LFP_W) dydq \tag{29}$$

We also repeat the outcome resulting from variations in female labor participation, as in experiment 2, we label this as experiment 3 (where we impose a standardized contingency table) and 4 (where we impose both a standardized contingency table and female participation of the opposite period) standardized contingency tables and Lorenz curves for this exercise are also shown in the appendix (Tables 10 and 11 and Figures 11(a), 11(b), 12(a) and 12(b)).

7.4 Results

Results from simulations are summarized in Table 4; they are similar to those found for the United States because most of them decrease the Gini coefficient by about 4 or 5 points. With random mating (experiment 1), inequality falls 6.3 and 3.3 points in periods 1 and 4, respectively; if we also

Table 4: Gini coefficients for counterfactual experiments

Experiment	1992-1996 (1)	2008-2012 (4)
Data	39.8	38.2
Random mating in 1	33.5	
Random mating in 4		34.9
Random mating in 1 and ΔFLP	33.4	
Random mating in 4 and ΔFLP		34.1
Standardized table in 1 with marginals from 4	34.6	
Standardized table in 4 with marginals from 1		35.1
Standardized table in 1 with marginals from 4 and ΔFLP	34.5	
Standardized table in 4 with marginals from 1 and ΔFLP		34.2

Source: Own estimations based on Greenwood et al., 2014.

allow variations in female labor participation (experiment 2), inequality falls in a similar amount (6.4 points for period 1 and 4.1 points for period 4.)

Experiments 3 and 4, as mentioned, are similar to 1 and 2, but using standardized contingency tables, with the standardized table only (experiment 4), inequality falls 5.2 points in period 1 and 3.1 points in period 4. Finally, in experiment 4, we add variations in female participation to the standardized contingency table to find variations of 5.1 points and 4 points in periods 1 and 4.

Results summarized in the table show that assortative mating plays an important role in income inequality because it explains about 3 to 6 points of it, along the same lines as those found by Greenwood et al. (2014) for the U.S.

There is an ongoing discussion regarding the importance of assortative mating on income inequality; the former paper is on one side (those who argue that there is a large impact on inequality), and on the other side, we find the results by Eika, Mogstad, and Zafar (2014) and Hryshko, Juhn, and McCue (2014) who argue the contrary. These differences in results can be accounted for by the fact that these papers use different databases, decomposition methods, and different time spans. Nevertheless, it can be argued that methodological differences explain these results; this will be explored in the following section.

7.5 Robustness checks

Our experiments' results depend on how we parametrize the distribution of income and the number of groups we use since we deviate from the analysis of Greenwood et al. (2014) in those items. These changes were Distributionce the number of groups. Otherwise, many of them would have had zero observations, making them useless for the analysis.

We can, instead, carry out the analysis using either the same number of quantiles or an equivalent number of groups as Greenwood et al. The first robustness check consists of using deciles instead of quintiles of household income distribution, regardless of the large number of groups that will be left without observations; now we have $768 \times 10 = 7680$ groups.

The second robustness check is based on the exact opposite modification since we now decrease the number of groups, dropping the variable for the number of children while using income quintiles for grouping again. This modification reduces the number of groups to $128 \times 5 = 640$. After performing these checks, we can assess how robust this methodology is to changes in the number of groups, Greenwood et al., 2014 do not perform such calculations.

These checks show a number of discrepancies with respect to baseline estimations (Table 4):

- Gini coefficients estimated with observed data increase in 2.8 points (period 1) and 2.7 points (period 4) if the number of quantiles is doubled; on the other hand, they also increase in 0.5 points (period 1) and 0.1 (period 4) when we decrease the number of groups. These variations

Table 5: Robustness checks: Gini coefficients

Simulation	**Change in quantiles**		**Change in groups**	
Experiment	**1992-1996**	**2008-2012**	**1992-1996**	**2008-2012**
Data	42.6	40.9	40.3	38.3
Random mating in 1	35.2		38.9	
Random mating in 4		36.8		40.0
Random mating in 1 + ΔFLP	35.0		38.6	
Random mating in 4 + ΔFLP		35.8		37.6
Standardized table in 1	36.3		40.1	
Standardized table in 4		37.0		40.8
Standardized table in 1 + ΔFLP	36.2		39.9	
Standardized table in 4 + ΔFLP		36.0		38.4

Source: Own estimations based on Greenwood et al., 2014.

cast a shadow of doubt on the decomposition algorithm because it should not experience significant variations with respect to the number of quantiles, particularly in the first check.

- Results from experiments also differ substantially because the imposition of random mating causes an **increment** in inequality for period 4; however, if we also allow variations in female labor participation, it cancels out this increase. This result is also valid with a standardized contingency table.

- Finally, a reduction in the number of groups makes all variations smaller, while an increase in groups causes the exact opposite; this means that results are not only not robust but also an increasing function of the number of groups.

8 Discussion

The outcome of our simulations and robustness checks carried out in previous sections are in stark contrast with respect to the four indicators of Assortative Mating we estimated earlier. The latter shows that this phenomenon can explain up to six points of income inequality, as measured by the Gini coefficient, while all indicators show an insignificant increase in the strength of Assortative Mating over the period.

As mentioned earlier, Harmenberg, 2014 shows that the method used in this paper tends to exaggerate the impact of Assortative Mating on the Gini coefficient compared to other methods. We improve his explanation, showing that this is actually a consequence of the grouping strategy: the higher the number of groups, the higher the impact estimated.

There are other likely causes for these discrepancies, but their importance is relative to what assumption we think is violated:

Time span : perhaps the most important drawback of our data is the time span we use (21 years) vis-à-vis the one used by Greenwood et al. (45 years); the starting year was chosen because data from years before 1992 has serious issues related to income measurement due to the high inflation from the 1980s and a much smaller sample due to the surveying of less urban areas and problems with survey frequencies. As mentioned, we could not use IPUMS data since the Argentine Population Census does not survey household income data. Finally, to increase our sample, we joined five consecutive years into two periods (1992-1996 and 2008-20012.)

Method : both Hryshko, Juhn, and McCue (2014) and Eika, Mogstad, and Zafar (2014) found a much smaller impact of Assortative Mating, even with a larger time span than this paper; this also questions Greenwood's method as the likely cause for the discrepancies.

Nature of Assortative Mating : changes in mating patterns are expected to be slow; that is, year-to-year variations in any indicator should not be very large (that is the rationale for using census data with a 10-year frequency). Even taking frequency into account, we see that mating patterns in Argentina do not change substantially; it could be argued that mating had already experienced a large degree of sorting before 1992, therefore, it only increased slightly, and its contribution to inequality is not substantial.

9 Concluding remarks

This paper aimed to assess the importance of Assortative Mating on income inequality in Argentina between 1992 and 2012 because this topic has received very little attention in Argentina and Latin America as a whole. The evidence we found suggests that Assortative Mating plays a minor role in the determination of income inequality; two findings in this paper support this conclusion:

- We used four indicators of Assortative Mating used by different authors; all showing little variation in the period 1992-2012.
- A simulation exercise was performed with household survey data; despite finding evidence of a significant contribution of Assortative Mating to inequality, inequality measured with the Gini coefficient falls by more than 3 points after imposing random mating, but these results are not robust to variations in the number of groups.

Evidence supporting Greenwood's hypothesis of a large impact of sorting on household income inequality is, in our view, little, for the reasons pointed out before, they contradict the results from all simple Assortative Mating indicators, and counterfactual experiments are not robust to modifications in the number of groups used. Taken as a whole, these findings weaken the results of Greenwood et al. (2014) while supporting those of Eika, Mogstad, and Zafar (2014) and Hryshko, Juhn, and McCue (2014), who postulated a much smaller contribution of Assortative Mating on income inequality.

These seemingly discouraging findings (at least from a researcher's point of view) are positive if we think of them from a policymaker's point of view because, in case its impact was large, it could not be mitigated with any public policy in a direct way, unlike other sources of inequality.

There is still plenty of room to continue research in this area since we still need to assess what would happen if we apply this method to data from other Latin American countries or if we use a different decomposition method.

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10 Appendix: contingency tables

Table 6: Contingency table for 1992-1996 with random mating

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.094	0.031	0.068	0.059	0.044	0.020
P	0.030	0.010	0.021	0.018	0.014	0.006
S-	0.058	0.019	0.042	0.036	0.027	0.012
S	0.063	0.021	0.045	0.039	0.029	0.014
U-	0.032	0.011	0.023	0.020	0.015	0.007
U	0.022	0.007	0.016	0.014	0.010	0.005

Source: Household surveys (EPH).

Table 7: Contingency table for 2008-2012 with random mating

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.041	0.010	0.056	0.035	0.054	0.025
P	0.010	0.002	0.013	0.008	0.013	0.006
S-	0.050	0.012	0.067	0.042	0.065	0.030
S	0.035	0.008	0.047	0.029	0.045	0.021
U-	0.031	0.008	0.042	0.026	0.040	0.019
U	0.020	0.005	0.027	0.017	0.026	0.012

Source: Household surveys (EPH).

Table 8: Contingency table for 1992-1996 with random mating and FLP for 2008-2012

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.068	0.039	0.018	0.032	0.004	0.006
P	0.037	0.105	0.005	0.017	0.001	0.002
S-	0.018	0.006	0.058	0.032	0.028	0.025
S	0.035	0.015	0.030	0.056	0.012	0.018
U-	0.003	0.001	0.027	0.009	0.084	0.044
U	0.006	0.001	0.029	0.021	0.039	0.072

Source: Household surveys (EPH).

Table 9: Contingency table for 2008-2012 with random mating and FLP for 1992-1996

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.071	0.036	0.019	0.031	0.004	0.006
P	0.037	0.102	0.006	0.020	0.001	0.002
S-	0.020	0.008	0.061	0.028	0.024	0.025
S	0.030	0.017	0.029	0.063	0.010	0.019
U-	0.004	0.001	0.025	0.009	0.087	0.041
U	0.005	0.002	0.027	0.016	0.041	0.075

Source: Household surveys (EPH).

Table 10: Standardized contingency table for 1992-1996

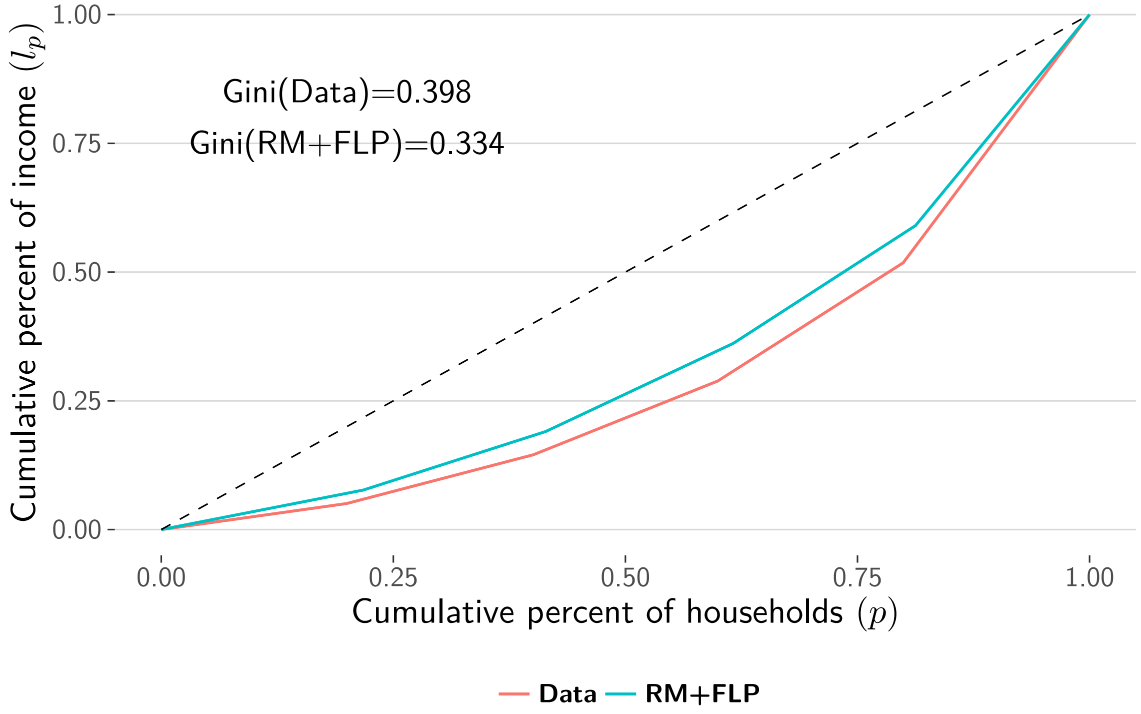
Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.101	0.019	0.039	0.043	0.011	0.008
P	0.020	0.018	0.004	0.008	0.001	0.001
S-	0.023	0.003	0.110	0.037	0.065	0.028
S	0.038	0.005	0.048	0.054	0.023	0.017
U-	0.002	0.000	0.027	0.006	0.105	0.026
U	0.003	0.000	0.023	0.010	0.038	0.034

Source: Household surveys (EPH).

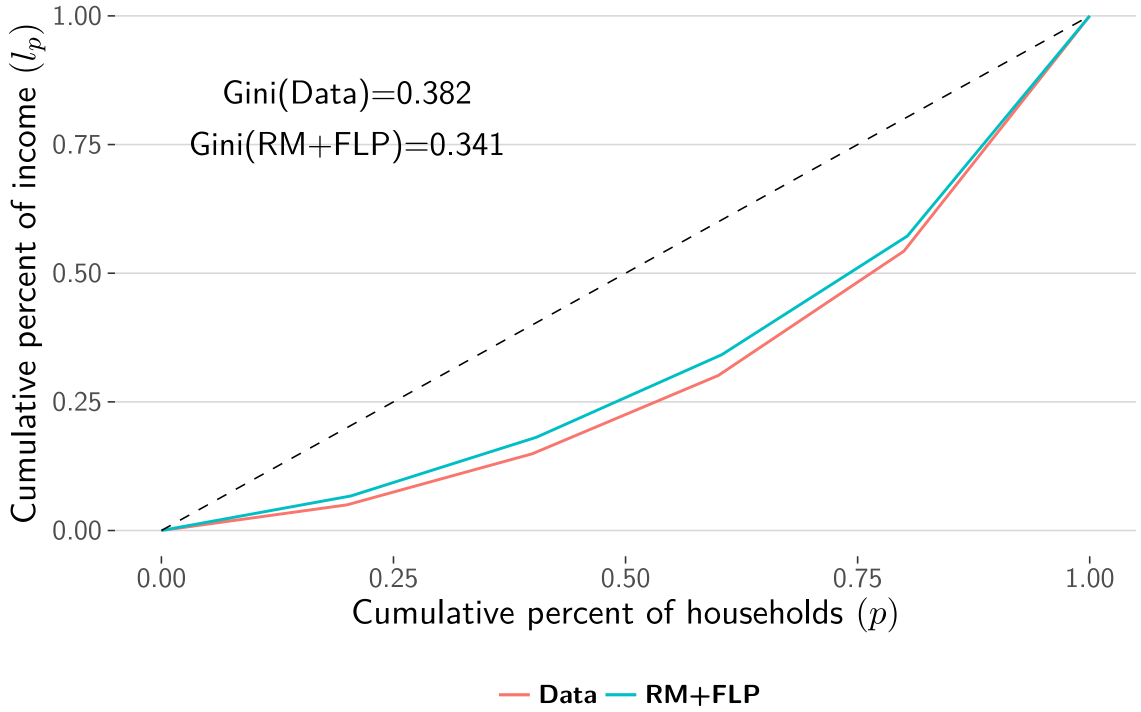
Table 11: Standardized contingency table for 2008-2012

Husband	Wife					
	P-	**P**	**S-**	**S**	**U-**	**U**
P-	0.172	0.037	0.041	0.053	0.008	0.005
P	0.037	0.043	0.005	0.013	0.001	0.001
S-	0.030	0.005	0.085	0.030	0.029	0.014
S	0.051	0.012	0.045	0.076	0.013	0.012
U-	0.004	0.000	0.021	0.005	0.064	0.014
U	0.004	0.001	0.017	0.008	0.023	0.020

Source: Household surveys (EPH).

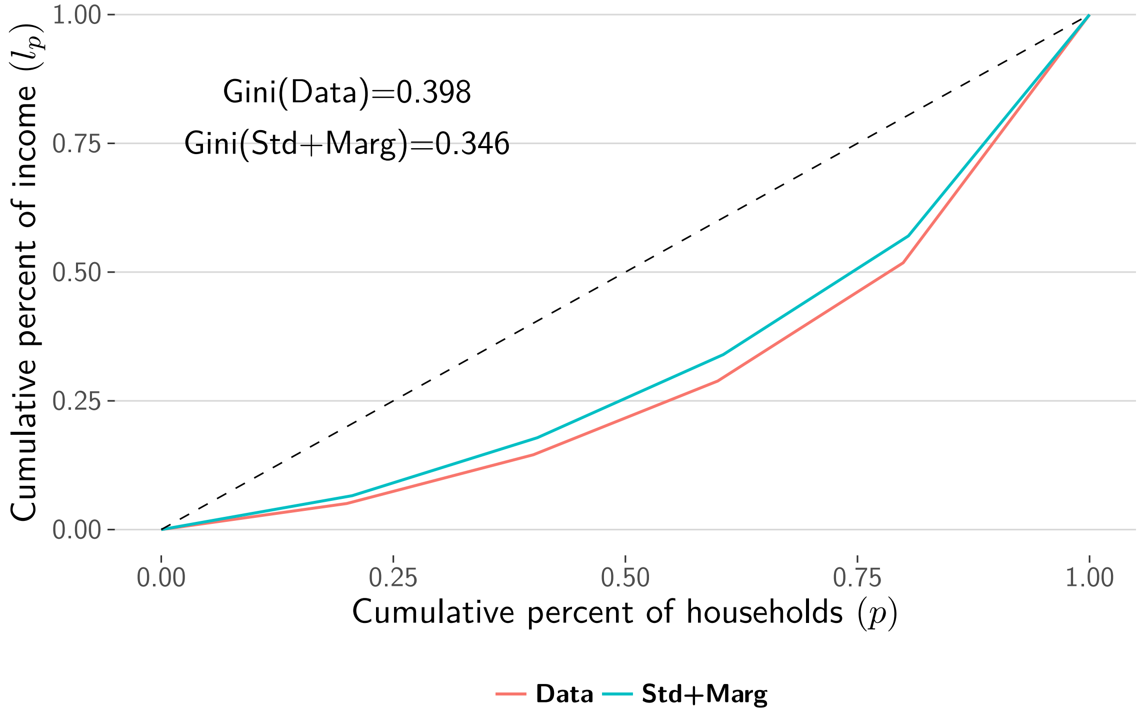


(a) Lorenz curve for experiment 2 (1992-1996)

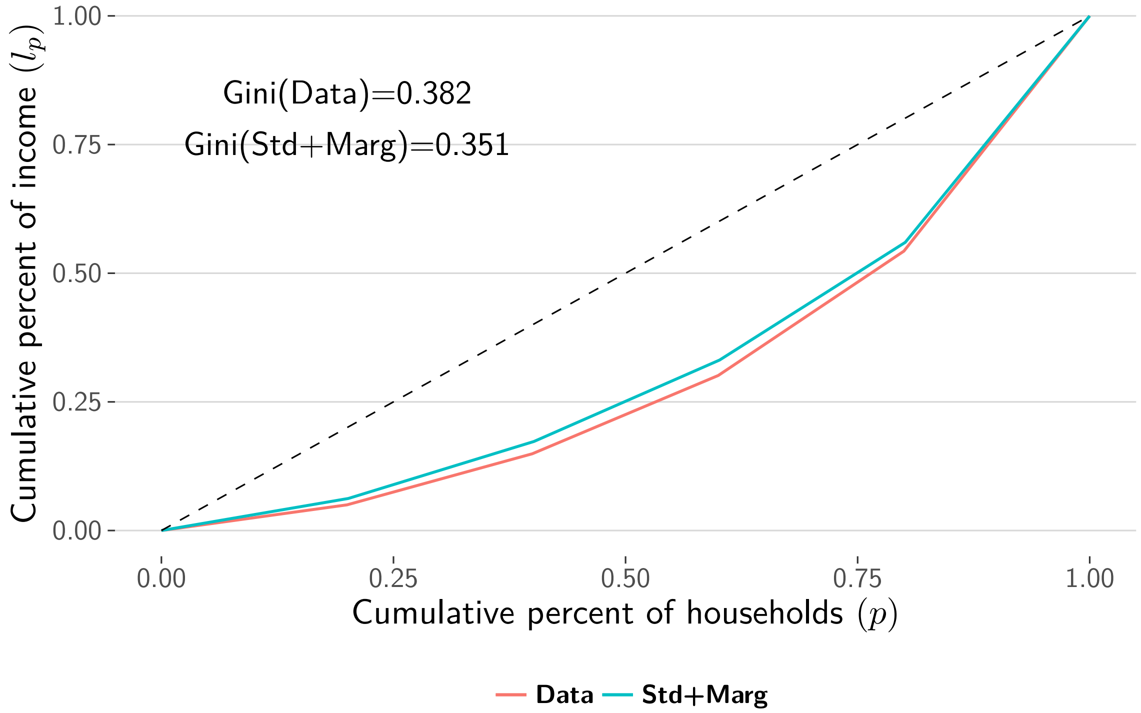


(b) Lorenz curve for experiment 2 (2008-2012)

Figure 10: Lorenz curves (counterfactual scenario 2)

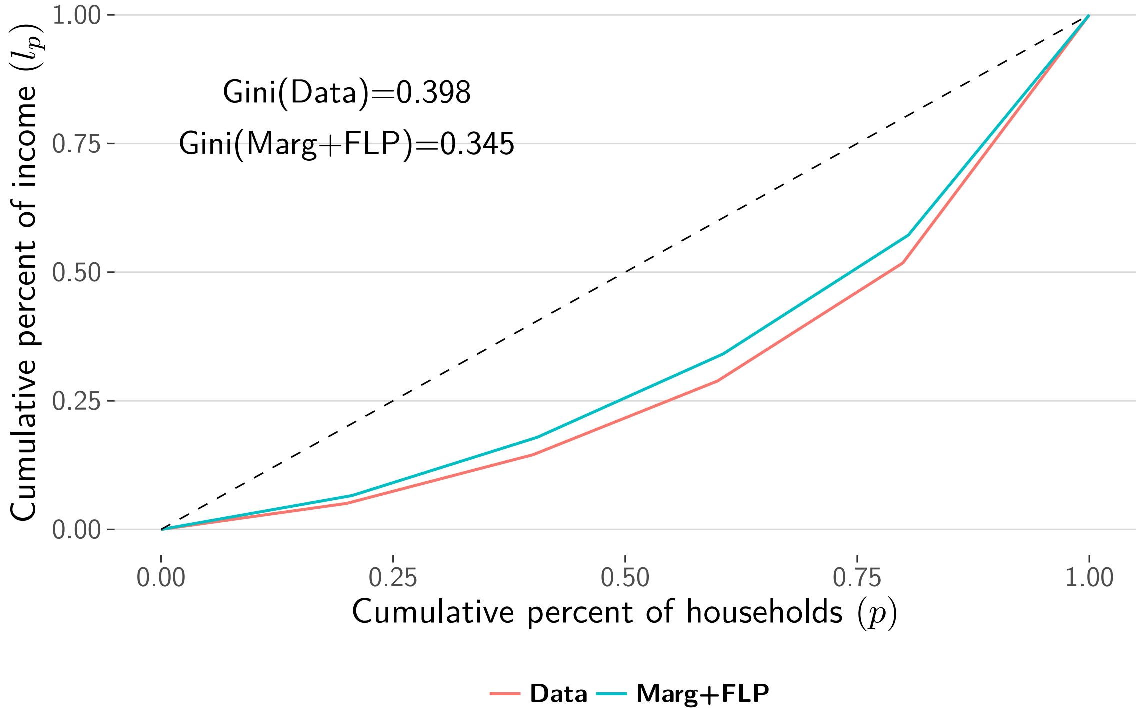


(a) Lorenz curve for experiment 3 (1992-1996)

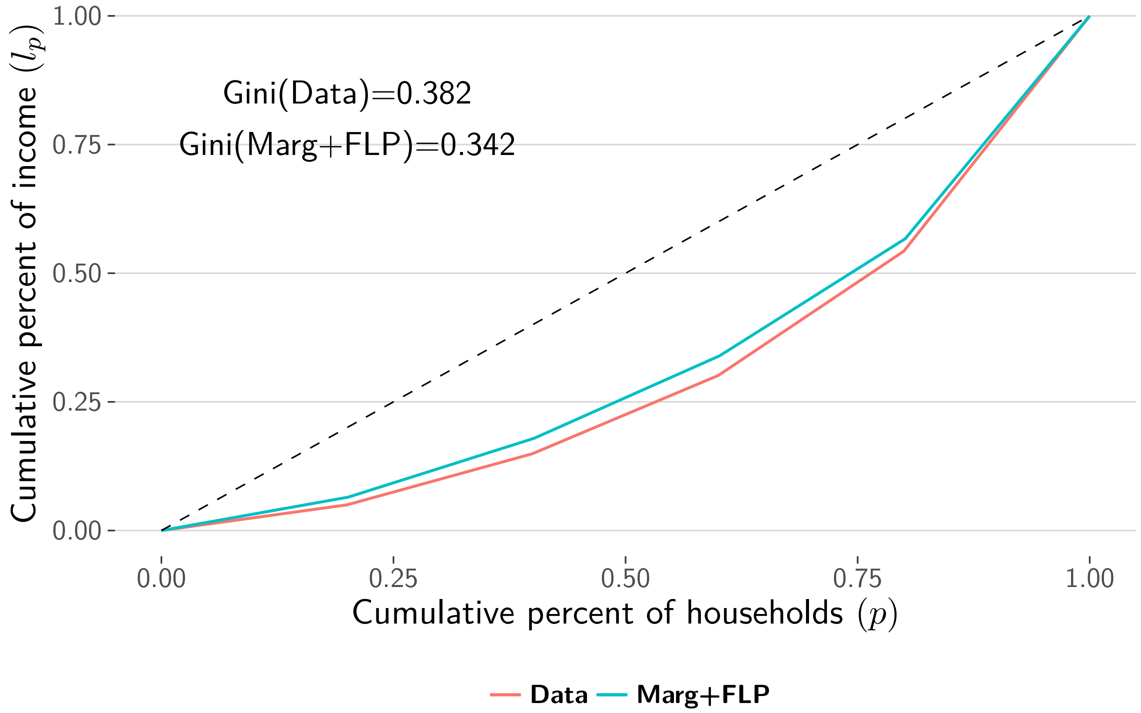


(b) Lorenz curve for experiment 3 (2008-2012)

Figure 11: Lorenz curves (counterfactual scenario 3)



(a) Lorenz curve for experiment 4 (1992-1996)



(b) Lorenz curve for experiment 4 (2008-2012)

Figure 12: Lorenz curves (counterfactual scenario 4)