Changes in Assortative Matching and Educational Inequality: Evidence from Marriage and Birth Records in Mexico

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June 20, 2021

Abstract

Over the past three decades, educational attainment in Mexico has grown substantially, and changing demographic trends have resulted in lower birth and marriage rates. Increasing educational attainment may affect marriage patterns through the growing supply of partners with higher education levels and changing preferences over their partner's education level. In this paper, we use national administrative records on births and marriages to quantify changes in the relative education levels within married and non-married couples. Our findings suggest two main patterns. First, assortativeness is higher when focusing on non-adjacent versus adjacent education categories. That is, it is more common for a college graduate to partner with a secondary-school educated partner rather than a partner with only a primary-school education. Second, assortativeness among college graduates has grown considerably over time. Our findings hold across both marriage records as in the birth records, indicating a parallel increase in assortativeness regardless of marital status. These findings suggest that changes in martial sorting patterns have exacerbated inequality over time.

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We thank Matthew Braaksma and David Lam for helpful comments. We also thank conference participants at the Population Association of America annual meeting. All errors are our own.

1 Introduction

In recent decades, Mexico has experienced both increases in per-capita income and declines in income inequality (Lustig et al., 2013). Despite these gains, income inequality remains considerably higher in Mexico compared to other OECD countries (OECD, 2016). Educational attainment has similarly grown over time, however, a large share of the population still has less than a primary education. If couples sort by educational attainment, then the marriage market may amplify inequality across households.[1] Inequality due to assortativeness has the potential impact future generations through intergenerational transfers of human capital.[2]

In this paper, we study educational sorting using administrative marriage and birth records. To better understand the Mexican context, we begin by documenting demographic trends in marriage, divorce, and fertility rates, as well as trends in educational attainment. We establish several stylized facts. First, we find that over the past three decades marriage rates have declined across all education levels, with men and women marrying later on average. Second, similar to marriage patterns, the birth rate in Mexico has converged across education levels. Finally, we observe a significant increase in educational attainment, especially among women; by 2007, among newly married couples, the spouse with greater education was more likely to be the wife

Unlike the above descriptive trends, measuring how assortative matching has changed over time is not straightforward. The main challenge is that the marginal distributions of education for men and women have changed over time, and in particular, the distributions have become more similar. As a result, the prevalence of same-education couples has mechanically increased. We, and the literature at large, are primarily interested in identifying how preferences for same-education partners have evolved over this time period, *after accounting for these mechanical changes*. Several methods have been developed to overcome this measurement challenge. We primarily rely on Chiappori et al. (2020)'s Separable Extreme Value (SEV) index, which measures assortativeness using an underlying structural model building upon Choo and Siow (2006). The key idea behind the model and the resulting index is that sorting is determined by the utility spouses derive from matching with a particular type of partner. As a result, one can connect changes in preferences for a same-education partner to changes in assortativeness. Since changes in preferences are precisely what we wish to capture, the use of the model to measure assortativeness is preferable to alternative methods.[3] Nonetheless, we also employ Shen (2020)'s Perfect-Random Normalization measure of assortativeness in the Appendix as a robustness check. The Perfect-Random normalization has the

[1] A large literature examines the relationship between educational assortative matching and income inequality across households. Breen and Salazar (2011); Greenwood et al. (2014); Eika et al. (2019) are examples.

[2] Recent work on the impact of assortative matching on child outcomes and intergenerational mobility includes Beck and Gonzalez-Sancho (2009) and Kye and Mare (2012).

[3] Shen (2020) and Chiappori et al. (2020) discuss how other measures of assortativeness, such as the log-linear measure used in Schwartz and Mare (2005) or the likelihood approach in Eika et al. (2019), may lead to spurious conclusions regarding changes in assortativeness over time.

advantage of being an intuitive measure that also accounts for changes in the education distributions of men and women over time.

Using the above methodologies, we find that assortativeness has broadly increased over the past thirty years; it has become increasingly common in Mexico for partners of similar education levels to marry one another, even after accounting for the increases in men's and women's educational attainment. Moreover, we find that this result is especially strong among the highly educated.

The above results, however, mask important heterogeneity that underlies our summary measures. In particular, it is necessary to recognize that assortativeness is a local property (Chiappori et al., 2020), in the sense that it is possible for assortativeness to be high within one pair of education categories (e.g., college and secondary), but low within other pairs (e.g., primary and middle). In our context, we divide individuals into four mutually exclusive education categories; primary or less, middle, secondary, and college. Allowing for multiple education categories is especially important in Mexico, where a high share of the population have less than a middle-school education (see Figure 1). Using more local measures, we find that the level of assortativeness is considerably higher when focusing on non-adjacent versus adjacent education categories (i.e., primary-college versus secondary-college). This finding suggests that both men and women frequently match with partners who have a slightly lower or higher education, but not with one that's significantly different. Second, we find that the assortativeness of adjacent education categories has increased only slightly over the past three decades. However, we observe a large increase in assortativeness among college graduates. Moreover, this increase is greater when measuring assortativeness among college graduates and individuals in non-adjacent education categories.

The above results hold when using marriage records. We complement this analysis by replicating these measures using annual birth records, which allows us to examine both marital *and* parental matching. The benefit of using administrative birth records, which is not standard, is that it highlights the transmission of educational inequality across generations (Mare and Schwartz, 2006). While computing assortativeness using marriage records captures a portion of this relationship, birth records are a more direct measure as not every marriage results in children, and not every child has married parents. The difference between these two data sources is especially important in Mexico where it is increasingly common to have a first birth while cohabiting or being unmarried. However, the cost of using birth records is missing information on the father's education, which we discuss in Section A.3.

We find that the the patterns are remarkably similar regardless of whether we use birth or marriage records. Both the relative magnitudes of assortativeness in a given year, and the trends we observe over time are similar regardless of whether we measure assortativeness using birth or marriage records. If there is any meaningful difference, it is that births may be slightly less assortative, but this result depends on the pair of categories being considered. This similarity is perhaps unsurprising; childless couples in Mexico are rare, and it follows that marital and parental matching is similar. This result differs somewhat, however, from comparable work in the United States by Mare and Schwartz (2006), who find parental matches are more positively assortative than marriage matches. We investigate our results further by separating parents by their marital status, and examining whether assortativeness has evolved differently for married vs. non-married parents. Given the increase in non-martial cohabitation, one might expect differences by martial status. Nonetheless, we observe little difference by martial status, though the results are noisier due to there being fewer observations.

This paper makes several contributions to the existing literature. First, we measure the evolution of assortative matching in Mexico over the past 30 years, which adds to the cross-sectional approaches taken in Choi and Mare (2012) and Torche (2010). While studying changes over time in assortative matching in the United States and other high-income countries, less is known about the dynamics in a country like Mexico where educational attainment is rapidly growing, and the patterns are different for men and women. For example, in the United States, the gender gap in education between men and women has reversed (Goldin et al., 2006; Fortin et al., 2015; Van Bavel et al., 2018). While this reversal has also occurred in some Latin American countries, it has not in Mexico (Duryea et al., 2007; Ganguli et al., 2014). These differing patterns may have implications for the marriage market, and therefore inequality as well.

Our second contribution is to measure parental matching using administrative birth records. In Mexico, where a majority of births are currently to unmarried couples, measuring matching patterns among parents is necessary to understand trends in intergenerational mobility. We therefore compliment existing work by Mare and Schwartz (2006) and Shen (2020) who examine parental matching in the United States, and Krzyżanowska and Mascie-Taylor (2014) who study the relationship between assortative matching and fertility in the United Kingdom. Finally, we deviate from the existing literature by measuring assortative marriage matching using administrative records of new marriages and births. Having the full universe of new marriages allows us to detect immediate changes in the marriage market.

The rest of the paper is organized as follows. In Section 2 we provide an overview the related literature on assortativeness and discuss formal measures of assortative matching. Section 3 provides an overview of demographic trends in Mexico, and relates this to changes in assortative matching. We then present the results in Section 4. Section 5 concludes.

2 Assortativeness Matching

This study primarily relates to research on assortative matching and how it has evolved over time. The extent to which individuals with similar characteristics marry has interested economists, sociologists, and demographers as it is relevant to intergenerational mobility, inter- and intra- household inequality, and more generally to how couples within the marriage interact.[4]

2.1 Previous work on Assortative Matching

A large literature has measured changes in matching patterns over time in the United States. While past research in this area has suggested that assortativeness has increased continuously in recent decades (Schwartz and Mare, 2005; Hou and Myles, 2008; Mare, 2016; Eika et al., 2019), there is a growing consensus that this was not necessarily the case.[5] Gihleb and Lang (2016) highlight the measurement difficulties inherent in such exercises, and demonstrate that results are often sensitive to how education categories are chosen. More recent work by Shen (2020), building upon work by Liu and Lu (2006), has discussed the importance of differential changes in education rates by gender, and how this may also lead to incorrect conclusions. Shen (2020) suggests a measure of assortativeness that avoids these complications and finds that assortativeness did not increase. Finally, the more structural literature has consistently found little change in assortativeness over time in the United States (see, e.g., Siow (2015) and Chiappori et al. (2017)).

We are not the first study to examine assortative matching in Mexico. Choi and Mare (2012) study the relationship between US-Mexico migration and assortative matching and find that migration results in more heterogeneous couples as migration alters the pool of available spouses.[6] Similar work by Solís et al. (2007) studies the relationship between migration and assortative matching over time in Monterrey, Mexico. Finally, Torche (2010) also measures assortative matching using the 2000 Mexico census. We differ from these studies in several important ways. First, unlike Choi and Mare (2012) and Torche (2010), we examine how assortative matching has changed over time. Second, unlike Solís et al. (2007), we focus on all of Mexico, and not just a single state. Moreover, we account for changes in the marginal distributions of male and female education. We also examine parental matching, which adds to our understanding of the role of assortative matching in intergenerational mobility.

[4]See Kalmijn (1998) and Schwartz (2013) for an overview on research on assortative matching.

[5]Research in this area also includes Mare (1991) and Qian (1998), among others.

[6]Related work by Raphael (2013) examines how heterogeneous sex ratios driven by state-specific US-Mexico migration affects female welfare in Mexico.

2.2 Measuring Assortative Matching

The extent of assortative matching is determined by the number of individuals with similar characteristics (in our case education) marrying one another. While this concept is simple to understand, there are several measurement challenges that researchers need to overcome. First, changes in the distributions of men's and women's education over time make intertemporal comparisons of assortativeness challenging (Shen, 2020). If these distributions grow more similar over time (as has been the case in Mexico), that mechanically increases the maximum degree of sorting. We wish to measure preferences for homogamous unions after accounting for changes in the underlying male and female education distributions.

A second challenge is defining education categories. Gihleb and Lang (2016) demonstrate that grouping college graduates with those with post-graduate degrees leads to different conclusions about how assortativeness has changed over time in the United States. This problem is more relevant in our context where education levels vary from post-college degrees to individuals with less than a primary education. We address this by using four education categories to flexibly measure assortative across the education distribution.

We begin by introducing the notation we use to measure assortativeness. We then discuss Chiappori et al. (2020), who provide a way of computing assortativeness that is robust to changes in gender-specific education rates across time, and is therefore ideal for the Mexican setting.[7] The added benefit of Chiappori et al. (2020) is that it connects the level of assortativeness with an underlying structural, marriage matching model.

Three parameters will govern our measures of assortativeness. Let m and n be the proportion of male and female college graduates, respectively. Let r denote the proportion of marriages where both spouses are college graduates. For now, we consider only two types of education levels (college and high school), but in our empirical analysis, we use four education categories: college, secondary, middle, and primary or less. If there were perfect assortative matching, then r would equal the minimum of m and n. If the matching were random, then r would equal the product of m and n.[8] Where r falls in this interval determines the extent of assortative matching observed in the population. Table 1 illustrates the degree of assortative matching in matrix form. Panel A provides the notation for the observed values. Panel B illustrates the case of random matching, and Panel C presents the case of perfect matching, when there are an equal number of men and women with college degrees (i.e., $m = n$).

Chiappori et al. (2020) discuss two properties that any measure of assortative matching must satisfy. The first property, *Monotonicity*, requires that assortativeness is increasing in r when m and

[7] In the Appendix, we provide an alternative measure of assortativeness following Shen (2020).

[8] If there were perfect negative assortative matching, r would equal $|m-n|$.

Table 1: Assortative Matching in a Two-Education Market

Panel A: Observed

	College	High School
College	r	$m-r$
High School	$n-r$	$1+r-m-n$

Panel B: Random

	College	High School
College	mn	$m(1-n)$
High School	$n(1-m)$	$(1-m)(1-n)$

Panel C: Perfectly Assortative

	College	High School
College	n	0
High School	0	$1-n$

Note: In the above tables, r denotes the share of marriages where both spouses have a college degree, and m and n denotes the number of men and women with a college degree, respectively. In Panel C, we assume the education distributions for men and women are identical.

n are fixed. This intuitive property simply means that the level of assortative matching is higher if there are more couples that both have the highest education level. It follows that assortativeness is increasing in the number of non-college educated couples, given by $1-m-n+r$. The second property, *Perfectly Assortative Matching*, states that the maximum level of assortativeness occurs when there are no couples of mixed education levels (when $m=n$). While these properties seem obvious, they are necessary to deal with the complexities of changing distributions of education levels over time.

2.3 The Separable Extreme Value Model

We use the Separable Extreme Value (SEV) model following Chiappori et al. (2020) to measure assortativeness. As in Choo and Siow (2006), this model requires frictionless marital matching and a transferable utility setting. Men match with women, and each match generates a marital surplus that is divided among spouses. The matching is stable if there is no man and woman who would prefer to divorce their spouse and marry each other. With this being the case, we can infer the deterministic utility each spouse derives from being married by observing matching patterns, which we then use to infer the level of assortativeness.

Suppose there are X men, who are denoted by the subscript i, and Y women denoted by the subscript j in a marriage market. Men and women maximize their utility, and can either remain single or get married. A match generates a surplus s_{ij} that is divided among the spouses. With Transferable Utility, this gain is additively separable between spouses. Let u_i be the man's utility from marriage, and v_j the utility of the woman. Then $s_{ij}=u_i+v_j$.

Under the SEV model, there are a small (relative to the size of X and Y) number of types of individuals $I\in\{1,...,N\}$. In our context these will be levels of education, and for simplicity we assume that $N=2$ for now. The marriage surplus when man i matches with woman j is given by: $s_{ij}=Z^{IJ}+\gamma_{ij}$ where Z^{IJ} is the deterministic component of the surplus which only depends on individual education levels, and γ_{ij} is unobserved preference heterogeneity that reflects each spouse's utility from marriage outside of what is driven by observable characteristics. Let the surplus for a man to remain single be given by $s_{i0}=\epsilon_i^0$ and similarly for women $s_{0j}=\nu_j^0$. Normalizing the deterministic part of the surplus to zero for singles means that we can interpret the matrix $Z=[Z^{IJ}]$ as the influence of education on matching patterns. With two levels of education, the *supermodular core* of Z is given by $S=Z^{11}+Z^{22}-Z^{12}-Z^{21}$. We can therefore think of S as a measure of complementarity. Moreover, the greater S is, the more gains there are from marrying a same-education level spouse. It follows that S will be a natural measure of positive assortative matching.[9]

[9]The final two key assumptions of the SEV model is that the random component of the surplus γ_{ij} is additively separable between individual-

Following Chiappori et al. (2020), the supermodular core in the two-education case is written as follows:

$$S = Z^{11} + Z^{22} - Z^{12} - Z^{21} = 2\ln\left(\frac{r(1+r-m-n)}{(n-r)(m-r)}\right) \tag{1}$$

This result can then be used write the SEV assortativeness index that we use in our analysis:

$$I_{SEV}(m,n,r) = \ln\left(\frac{r(1+r-m-n)}{(n-r)(m-r)}\right) \tag{2}$$

which can again be computed easily as r, m, and n are observable. One can understand this index by noting the sorting matrix given in Panel A of Table 1. In effect, the SEV index is the sum of the logs of the diagonal elements of the sorting matrix (i.e., the homogamous matches) minus the sum of the logs of the off-diagonal elements (i.e., the heterogamous matches). Stated differently, a sorting matrix exhibits more assortative matching if there are more marriages along the main diagonal. When the matching is random, $I_{SEV} = 0$. If there is positive assortative matching, then $I_{SEV} > 0$. Finally, when there is negative assortative matching, $I_{SEV} < 0$. In the Appendix, we provide additional details regarding the model derivation in Section A.4, as well as example sorting matrices and their resulting SEV index in Section A.5.

In the Appendix, we also present an alternative measure of assortativeness, the Perfect-Random Normalization of Shen (2020), which normalizes the case of random matching, ($r = mn$) to zero and perfect matching ($r = min\{m,n\}$) to one. The index that ranks assortative matching is then given as follows where $m \geq n$:

$$I_{PRN}(m,r,n) = \frac{r-mn}{n-mn} \tag{3}$$

This normalization can be understood using Table 1. The numerator is scaled by the random matching case (Panel B), while the denominator reflects the distance between the perfect matching case (Panel C) and the random matching case (Panel B).

3 Demographic Trends in Mexico

Before we formally compute assortative matching, we document demographic trends in Mexico, with a focus on measures that pertain to the marriage market. Specifically, we measure changes in marriages, divorces, and births by educational attainment. We use vital statistics data from the National Institute of Statistics and Geography (INEGI). The data include the full universe of

specific preference terms, with $\gamma_{ij} = \epsilon_i + \nu_j$, and that these terms are independent of each other and Type I Extreme Value. However, the error terms do not have to follow a Type 1 Extreme Value distribution for identification (Galichon and Salanié, 2015). This assumption is standard and made out of convenience. For more discussion of how this distributional assumption see Chiappori et al. (2020).

marriages, births, and divorces from 1993 to 2019.[10] We combine this administrative data with census data to show the transformation in educational attainment as well as to compute divorce, marriage, and birth rates. We discuss the data in more detail in Section A.3 of the Appendix.

Changes in marriage, divorce, and fertility are closely connected to changes in educational attainment. We therefore first examine changes in the distribution of education across census years in Figure 1 for adults age 25 to 54. In 1990 the majority of the adult population had no more than a primary education. Today, the majority has at least a primary education, with more individuals attaining a middle school, high school, or college degree. Past research on changes in assortative matching have focused on the shift from high school to college education. In Mexico, the majority of the increase in educational attainment has been from less than a primary education to a primary education or above. This difference motivates how we measure assortativeness in Section 4.

One important insight from Figure 1 is that the growth of men and women's educational attainment has followed a mostly similar pattern. While the gender gap in education has converged over time, it has not reversed among the age 25 to 54 population, as has been the case in the other settings (Goldin et al., 2006; Duryea et al., 2007).

We show demographic trends by education in Figure 2. Panel A presents marriage rates, where we divide the number of new marriages of individuals with education e in year t by the total population in that year with that education level (divorce and marriage rates by education will be computed similarly). We restrict the sample to individuals age 15 to 54. Several patterns emerge. First, marriage rates are highest among individuals with a college or high school education. Second, marriage rates have been falling sharply, particularly among those with more education. Because some of these patterns may be driven by age-specific educational attainment, we also show marriage rates by age in Figure A2. We see that the marriage rate has fallen sharply across individuals younger than 25. Men and women are delaying marriage, though not necessarily enough to counteract an overall decline in marriage rates. This can be seen as well in Figure A3, which plots the frequency of marriage by the age of the wife and husband. Together, these figures demonstrate that couples that were previously forming, no longer are.

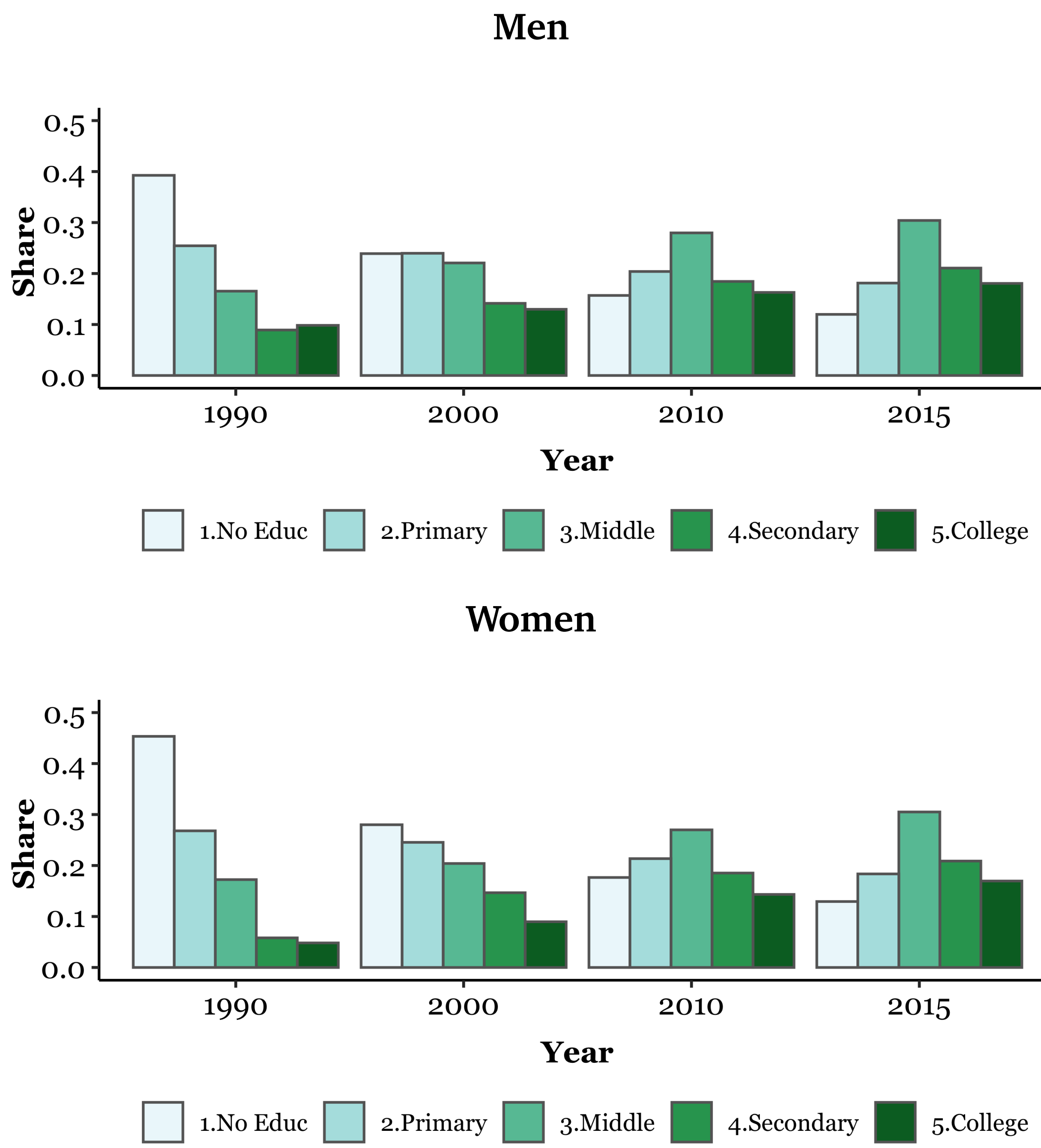
We next examine divorce rates, as recent work by Liu (2018) has demonstrated that more liberalized divorce laws may increase assortativeness.[11] Panel B of Figure 2 shows that divorce has risen at all education levels, with divorce being most common among the highly educated.[12] This dramatic shift in the marriage market may have implications for assortativeness. Moving to birth rates, we see that couples are having fewer children. However, we do not see the same difference

[10]Births registered in a given year sometimes correspond to an earlier birth year. That is, children born in year t may be registered and therefore included in year $t+1$ data. As a result, we limit our attention to the years 1993 to 2018 to minimize the number of missing births in our analysis.

[11]If a high-educated spouse can unilaterally divorce their low-educated partner, the gains from marrying up and leaving the labor market may decline.

[12]See Hoehn-Velasco and Penglase (Forthcoming) for a detailed discussion of divorce in Mexico.

Figure 1: Educational Attainment, Ages 25-54



Source: Mexican IPUMS data.
Notes: Less than primary education is less than 6th grade. Primary education is between 6th and 8th grade. Middle school education is 9th grade to 11th grade. Secondary education is 12th grade to 15 years of education. College is greater than 15 years but not missing education. Population includes those between 25 and 54.

by education category as we see with marriage and divorce rates, at least since 1995.

In the Appendix, we also show the birth rate by marital status in the first graph of Figure A1. The birth rate is declining most dramatically for married couples while increasing for cohabitating couples. The birth rate for cohabitating couples surpassed the birth rate for married couples in 2009. This corresponds with a demographic shift towards married and divorced individuals shown in Figure 1. This trend highlights the importance of measuring assortative matching among parents, and not just among married couples. Given that intergenerational mobility is one of the primary reasons we are interested in assortative matching, accounting for non-marital births is essential.

We conclude by examining which types of couples are marrying and having children. That is, do the majority of couples have the same level of education? And how has this changed over time? Table 2 presents the sorting matrix for new marriages for couples where at least one partner is age

Table 2: Observed Marital Matching (1993 and 2018)

		Wife's Education			
		College	Secondary	Middle	Primary or Less
Panel A: 1993					
Husband's Education	College	7.2%	2.9%	2.9%	0.8%
	Secondary	1.9%	6.7%	6.1%	2.1%
	Middle	1.4%	3.5%	19.1%	9.8%
	Primary or Less	0.5%	1.2%	7.1%	26.8%
				Sum of Diagonal: 59.8%	
Panel B: 2018					
Husband's Education	College	21.3%	5.3%	1.8%	0.4%
	Secondary	5.5%	16.0%	6.2%	1.1%
	Middle	2.5%	6.8%	16.7%	3.2%
	Primary or Less	0.5%	1.6%	4.4%	6.4%
				Sum of Diagonal: 60.4%	

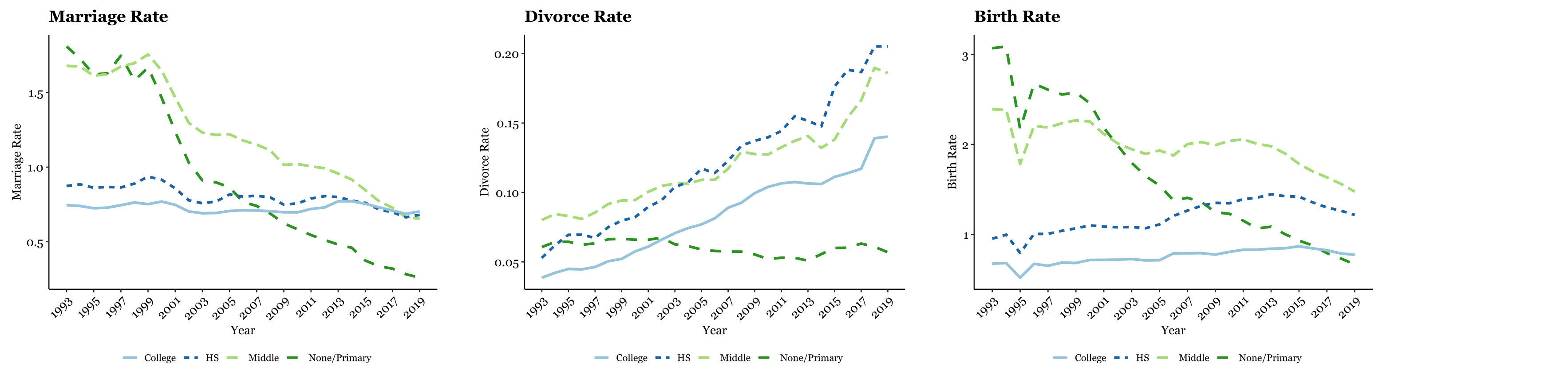
Source: Mexican INEGI data.
Notes: Primary or less is defined as less than 8 years of schooling or less. Middle is 9th to 11th grade. Secondary is 12 to 15 years of education. The sample includes marriages where at least one spouse is age 15 to 54.

Table 3: Observed Parental Matching (1993 and 2018)

		Wife's Education			
		College	Secondary	Middle	Primary or Less
Panel A: 1993					
Husband's Education	College	5.8%	2.7%	2.8%	0.8%
	Secondary	1.5%	5.6%	6.2%	2.4%
	Middle	1.1%	3.3%	16.8%	10.3%
	Primary or Less	0.5%	1.3%	8.1%	30.5%
				Sum of Diagonal: 58.8%	
Panel B: 2018					
Husband's Education	College	12.2%	3.9%	1.3%	0.2%
	Secondary	4.5%	15.0%	7.4%	1.3%
	Middle	2.3%	9.3%	21.1%	4.6%
	Primary or Less	0.5%	2.4%	6.1%	7.8%
				Sum of Diagonal: 56.2%	

Source: Mexican INEGI data.
Notes: Primary or less is defined as less than 8 years of schooling or less. Middle is 9th to 11th grade. Secondary is 12 to 15 years of education. The sample includes births where at least one parent is age 15 to 54. Births are limited to first births.

Figure 2: Marriage, Divorce, and Birth Rates by Education



(A) Marriage Rates (B) Divorce Rates (C) Birth Rates

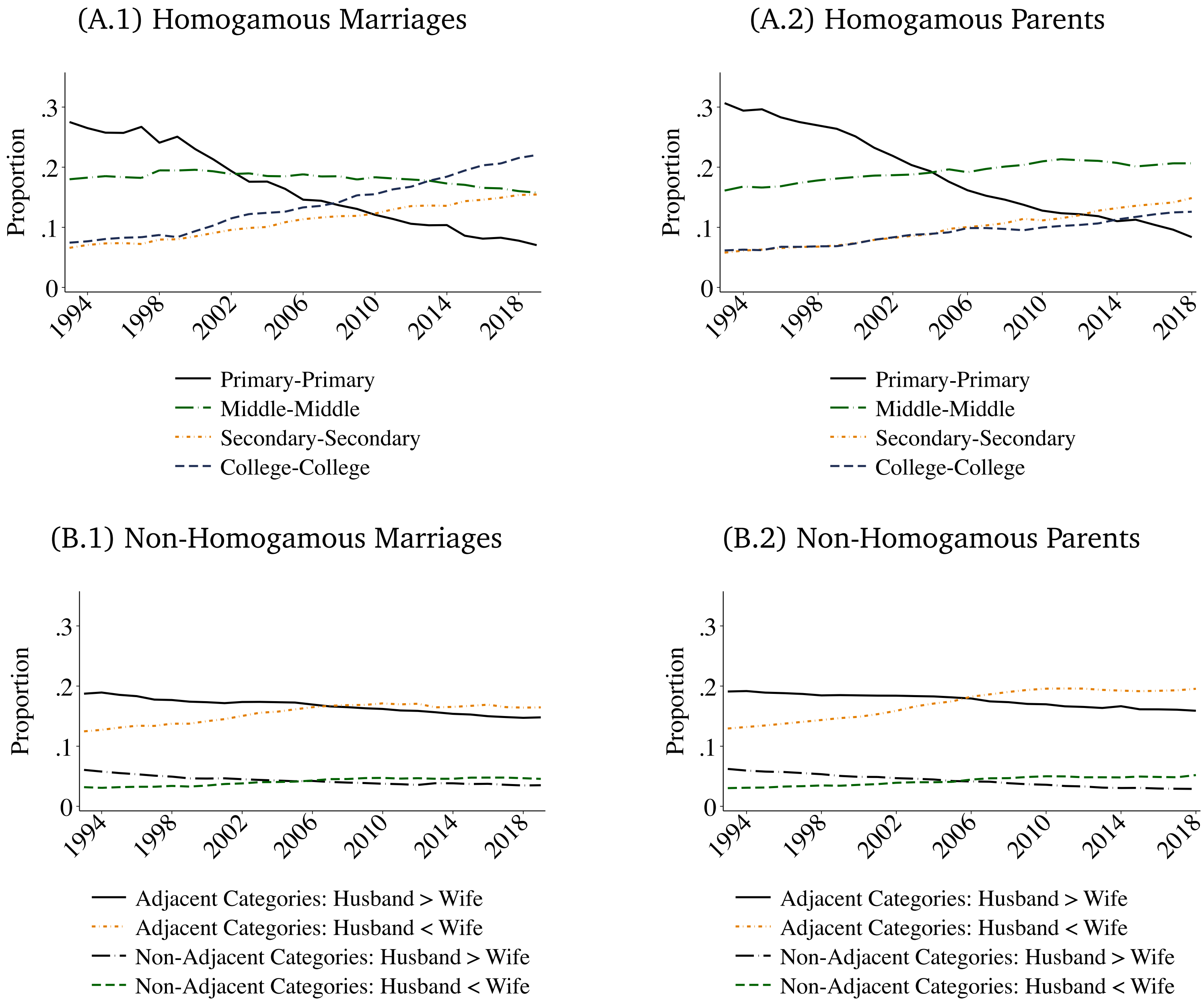
Sources: INEGI marriage, divorce, and birth statistics. Mexican IPUMS data.
Notes: The rates are per 1,000 women 15-54 with each level of education. Less than primary education is either *sin escolaridad*, or education *1 a 3 ãnos* and *4 a 5 ãnos*. Primary education is *primaria completa*. Middle school education is *secundaria*. Secondary education is *preparatoria*. College is greater *professional*. Technical education is grouped with secondary.

15 to 54, while Table 3 does the same for *first* births.[13] We select 1993 and 2018 as those are the earliest and latest waves of the INEGI data that are available. Here, we again see that education has increased, but also that the share of homogamous couples (the sum of the diagonal elements) is relatively constant; in 2018, men and women had equal education levels in 60.4 percent of new marriages compared to 59.8 percent in 1993. Among parents, there was a decline from 58.8 percent in 1993 to 56.2 percent in 2018. The largest change is in the frequency of wives and mothers having more education than their partners. Summing the cells in the lower triangle of each matrix, we calculate that in 1993, 15.6 percent of marriages consisted of a more educated wife, while in 2018 that number increased to 21.3 percent. Among parents, the increase is even larger; mothers had more education than fathers in 15.9 percent of first births in 1993, whereas in 2018 that number has grown to 25.1 percent. Thus, while the frequency of homogamous marriages has remained flat, there has been a meaningful shift towards marriages and births where the wife or mother is more educated.

We present these results differently in Figure 3. In the top sub-figures, we plot changes in equal-education marriages and births by level of education. Unsurprisingly, we see that both the share of primary-primary marriages and births have declined dramatically, while college-college marriages and births have increased. In the bottom sub-figures, we plot non-homogamous marriages and births, where the partners have different education levels. We separately plot adjacent and non-adjacent marriages and births, where adjacency is defined by whether the difference in educational attainment across partners is “close" (i.e., adjacent) or not (i.e., non-adjacent). The trends suggest that adjacent-category matches are significantly more common than non-adjacent ones. Moreover, we again observe that in 1993, men typically had more education than their wife, and that by 2006, this was no longer the case. This pattern is even more pronounced among parental matches.

[13]We use data on non-first births in the Appendix. We restrict our attention here to first births as we are interested in matching among parents, and do not want to count the same couple multiple times.

Figure 3: Matching Patterns (1993-2018)



Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panel A, we plot the proportion of all marriages where couples have equal educational attainment. Each line represents the share of couples who both have education i. In Panel B, we plot the proportion of marriages where couples have different educational attainment. Adjacent categories are defined as pairs of categories that are either directly above or below education category i (e.g., college and secondary are adjacent). Non-adjacent categories are defined as pairs of categories that are different, but not directly above or below education category i (e.g., college and primary are non-adjacent).

4 Assortative Matching Over Time

In Section 3, we document demographic trends, including changes in the frequency of homogamous marriages (Tables 2 and 3, and Figure 3). These results, by themselves, do not demonstrate how assortative matching has changed over time. The reason for this is that educational attainment has changed, and importantly, this change has not been identical for men and women. The descriptive results therefore confound changes in assortativeness coming from changes in the marginal distributions of education for men and women with changes in the underlying matching function. The more formal tools discussed in Section 2.2 help solve these issues, which we employ now.

We first describe the matching measures in more detail in Section 4.1. We then discuss the results using marriage and birth-records data in Sections 4.2 and 4.3, respectively. We conclude by discussing the implications of the results in Section 4.4.

4.1 Assortative Measures

The marriage matching matrix given in Tables 2 and 3 consist of four education categories. We provide two ways of grouping these four categories to compute measures of assortativeness using Equation (2). First, we focus on measuring assortativeness among 2×2 sub-matrices of the larger 4×4 matching matrix given in Table A1. This method results in six pairs of education categories in total.[14] Second, we select a single category k, merge the other three categories (i.e., category $\neg k$), and compare the single to the merged category. This second method results in four measures of assortativeness in total.

The motivation for the 2×2 grouping is that, as discussed in Chiappori et al. (2020), assortativeness is a local property; college graduates may frequently match with partners with a secondary education, but rarely match with partners with only a primary school degree. In this case, assortativeness would be high when comparing primary-college pairs, but low when considering secondary-college ones. With four education levels, there are six 2×2 sub-matrices along the main diagonal. This allows us to determine if there were differential changes in assortativeness at high and low levels of education, and if there were differences in adjacent pairs (i.e., college and secondary) and non-adjacent pairs (i.e. college and primary school). The benefit of using the merged categories, on the other had, is that it allows us to compute a summary measure of assortativeness following Eika et al. (2019) and Shen (2020).

4.2 Marriage Matching

We begin by examining assortative marriage matching using administrative records of new marriages. In Panels A.1 of Figure 4 we plot adjacent 2×2 education categories, while Panel B.1 presents the non-adjacent 2×2 ones. Several patterns are worth noting. First, the level of assortativeness is always positive, and somewhat flat across most pairs; there has not been any clear monotonic rise or fall in assortativeness over time.[15] Nonetheless, assortativeness has increased among certain pairs of education categories, particularly among pairs which include college graduates. This result suggests that in 2018, college graduates were less likely to match with partners with lower education levels compared to 1993, after accounting for increases in educational attainment. This finding is

[14]For example, to measure assortativeness among college graduates and those with a middle school degree, we compute r_1 (the share of college-college matches), r_3 (the share of middle-middle matches), f (the share of college-educated men matching with middle school-educated women), and d (the share of college-educated women matching with middle school-educated men). The SEV index for this pair is then computed as $I_{SEV} = \ln(\frac{r_1 r_3}{(f-r_1)(d-r_1)})$, which is comparable to the SEV Index given in Equation (2). Note that r_1, r_2, d, and f are defined in Table A1.

[15]Across all assortative measures we present, we find positive assortative matching, which contradicts theoretical predictions from Becker (1973, 1981) of negative assortative matching.

consistent with what has been observed in other contexts (e.g., Chiappori et al. (2020) and Shen (2020) in the United States).

The results also suggest that across all years, the level of assortativeness is significantly higher when we consider non-adjacent pairs of education categories (note that the y-axis range is different in Panel B). For example, the SEV index is above six when examining the level of assortativeness between college graduates and those with a primary education or less. This result means that greater the "distance" between education categories, the less matching there is across pairs.

In Panel C of Figure 4, we present the merged education categories, where we measure assortativeness between, e.g., individuals with a college degree, and those without. We also follow Eika et al. (2019) and Shen (2020) and compute weighted averages of assortativeness across these measures, where the weights are determined by the diagonal values given in Table A1. Again, the results are mostly flat, though there appears to be a slight increase.

We next present the numerical values of the SEV index for the first and last years of data in our sample in Table 4. These results follow Figure 4, but are limited to the years 1993 and 2018. Here, we can more easily compare long-term trends in assortativeness for different pairs of education categories and observe the magnitude of any changes. Panel A provides SEV measures for the 2×2 sub-matrices of the 4×4 matching matrix given in Table A1. Again, we can see that assortativeness has been largely constant, *except among college graduates*. For all education pairs that include college graduates, the SEV index has increased by at least 0.292. As a point of comparison, in the United States Chiappori et al. (2020) finds that the SEV index has increased by 0.580, 0.216, and 0.470 for college graduate pairs involving individuals with some college, a high school degree, and high school dropouts, respectively.[16]

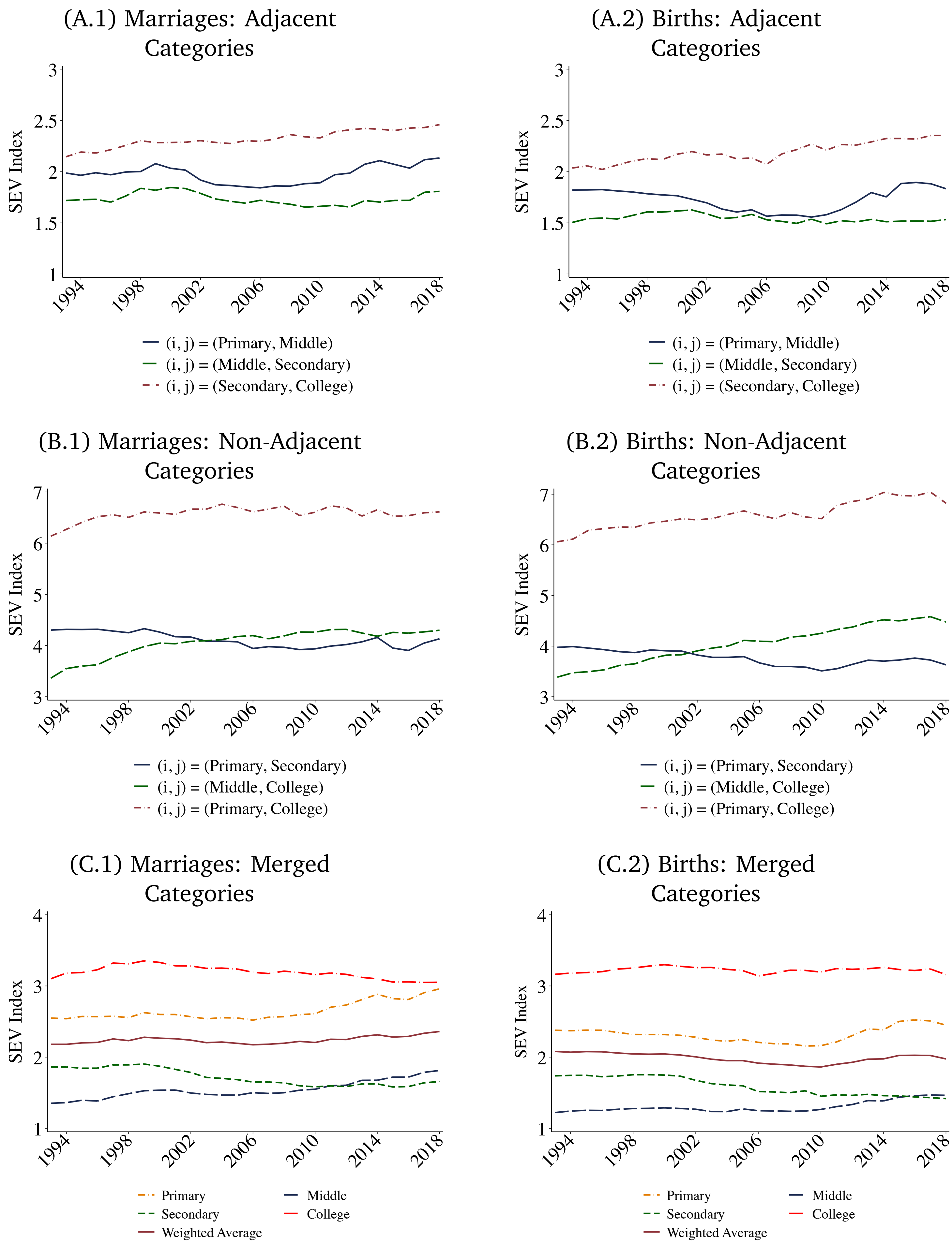
Interestingly, when we examine the merged categories, it appears assortativeness among college graduates has declined. However, what this suggests is that an increasing share of the population has a secondary degree, and we know from Panel A that assortativeness is relatively low when comparing secondary-college matches. The difference in results for comparisons involving college graduates across Panels A and B highlights the local nature of assortativeness.

4.3 Parental Matching

In addition to measuring assortativeness among married couples, we also examine parental matching using administrative birth records. As discussed in Section 3, there are differential trends in birth and marriage rates across education levels. There may then be differential trends in non-marital childbearing across education levels as well. It is therefore necessary to measure assortativeness

[16] Chiappori et al. (2020) measure assortativeness across 1930-1939 and 1970-1974 birth cohort.

Figure 4: Assortative Marriage and Parental Matching



Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panels A and B, each figure plots assortative matching for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value index. Panel A plots adjacent education categories while Panel B plots non-adjacent categories. In Panel C, each line is a comparison of education i with the combined remaining three education categories. The weighted average curve is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

Table 4: Changes in Assortativeness 1993-2018

	Marriages			Births		
	1993	2018	Difference	1993	2018	Difference
Panel A: 2 by 2 Comparisons	(1)	(2)	(3)	(4)	(5)	(6)
(i,j) = (Primary, Middle)	1.986	2.133	0.147	1.821	1.833	0.012
(i,j) = (Middle, Secondary)	1.718	1.807	0.089	1.504	1.531	0.028
(i,j) = (Secondary, College)	2.145	2.459	0.314	2.035	2.353	0.317
(i,j) = (Primary, Secondary)	4.302	4.132	-0.171	3.975	3.630	-0.345
(i,j) = (Lower Secondary, College)	3.363	4.298	0.935	3.386	4.477	1.091
(i,j) = (Primary, College)	6.138	6.613	0.475	6.060	6.823	0.763
Panel B: Merged Categories						
Primary	2.549	2.960	0.411	2.378	2.449	0.072
Middle	1.352	1.813	0.461	1.221	1.463	0.242
Secondary	1.860	1.657	-0.203	1.737	1.417	-0.320
College	3.101	3.052	-0.049	3.164	3.159	-0.004
Weighted Average	2.180	2.360	0.180	2.080	1.975	-0.104
Observations	496,358	358,423		635,126	510,713	

Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panel A, each row provides the assortative matching measure for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value Index. In Panel B, each line is a comparison of education category i with the combined remaining three education categories. The weighted average measure is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

among both married couples, and among parents as they may be different. Moreover, given that intergenerational mobility is a primary reason we study assortative matching, focusing on parental matching is, by itself, relevant. Before proceeding with the results, it is important to note that missing data is an especially relevant concern in the birth records data. Missing education, especially among fathers, is close to 25 percent depending on the year (see Figure A6). To determine the severity of this problem, we place bounds on the maximum and minimum potential assortativeness depending on the characteristics of the couples with missing data. We discuss this in more detail in Section A.3 in the Appendix.

We repeat our analysis in Section 4.2 using the universe of first births in Mexico. We begin by measuring assortativeness across the 2×2 sub-matrices of the 4×4 matching matrix given in Table A1. Panel A of Figure 4 presents assortativeness across adjacent categories, while Panel B does the same for non-adjacent categories. We see that the overall trend in assortativeness across both adjacent and non-adjacent education categories is similar to what we observed using the marriage records data. Moreover, the level of assortativeness is also largely similar whether or not we focus on marital or parental matching. In Table 4 the changes in assortativeness among the 2×2 comparisons are remarkably similar to what we find in the marriage records. All changes are in the same direction, and the magnitudes of the SEV changes are similar. For example, when we measure assortativeness among secondary and college graduates, we find that the SEV index has increased by 0.292 using marriage records, and 0.291 using birth records.

In the birth records, we know the martial status of the child's parents. This allows us to determine if we observe differential patterns in assortativeness across married and unmarried parents. On the left-hand side of Figure 5, we show the assortativeness measures for births to married parents, and the right-hand side displays assortativeness for unmarried ones. We provide the first and last year estimates for these figures in Table 4. We find that assortativeness is mostly higher (five of the six comparisons in Panel A) among married parents, but there is no systematic difference in trends over time. Why might assortativeness differ across married and unmarried parents? It's possible that marriage rates are simply higher when examining same-educated parents relative to parents with different education levels. A definitive reason is difficult to determine without more information on the couples.

The above analysis focuses on first births, as we do not want to count parental matches twice. Nonetheless, we may alternatively want to look at matching from the perspective of the child that results from the match, and ask how common it is for children to be born to parents of the same education level. To do this, we compare our measures of assortativeness between first births (i.e., the main results) and non-first births. This comparison sheds light on whether fertility rates are higher among positive or negative-assortative marriages; if we observe higher assortativeness among non-first births, that suggests that negative-assortative matches have more children.

The results are presented in Figure A5 and Table A3 in the Appendix. We first discuss the local measures presented in Panels A and B of Figure A5. Among comparisons involving college graduates, assortativeness is greater for first births, and has increased by more over time compared to later births. This suggests that negative-assortative matches involving college graduates have more children. This finding is consistent with the college-educated spouse specializing in market work, and the spouse with less than a college degree specializing in child care. The greatest difference in assortative measures is found in comparisons involving the primary-middle school $2x2$ sub-matrix. Among first births, there is little change in assortativeness over time. However, when looking at non-first births, we see a large decline.

Panel C of Figure A5 presents the merged categories. We hesitate to interpret these results too strongly as they are influenced by which parents are placed in the comparison group. Specifically, when we focus on first births, secondary and college educated individuals are a higher proportion of the merged category, and therefore there is more assortativeness (as can be seen in the local measures where those education levels tend to be more assortative). When we shift to focusing on later births, lower education couples comprise a larger share of the merged category, which will skew the results to be less assortative. For this reason, we prefer using the more local measures, consistent with the advice of Chiappori et al. (2020).

4.4 Discussion

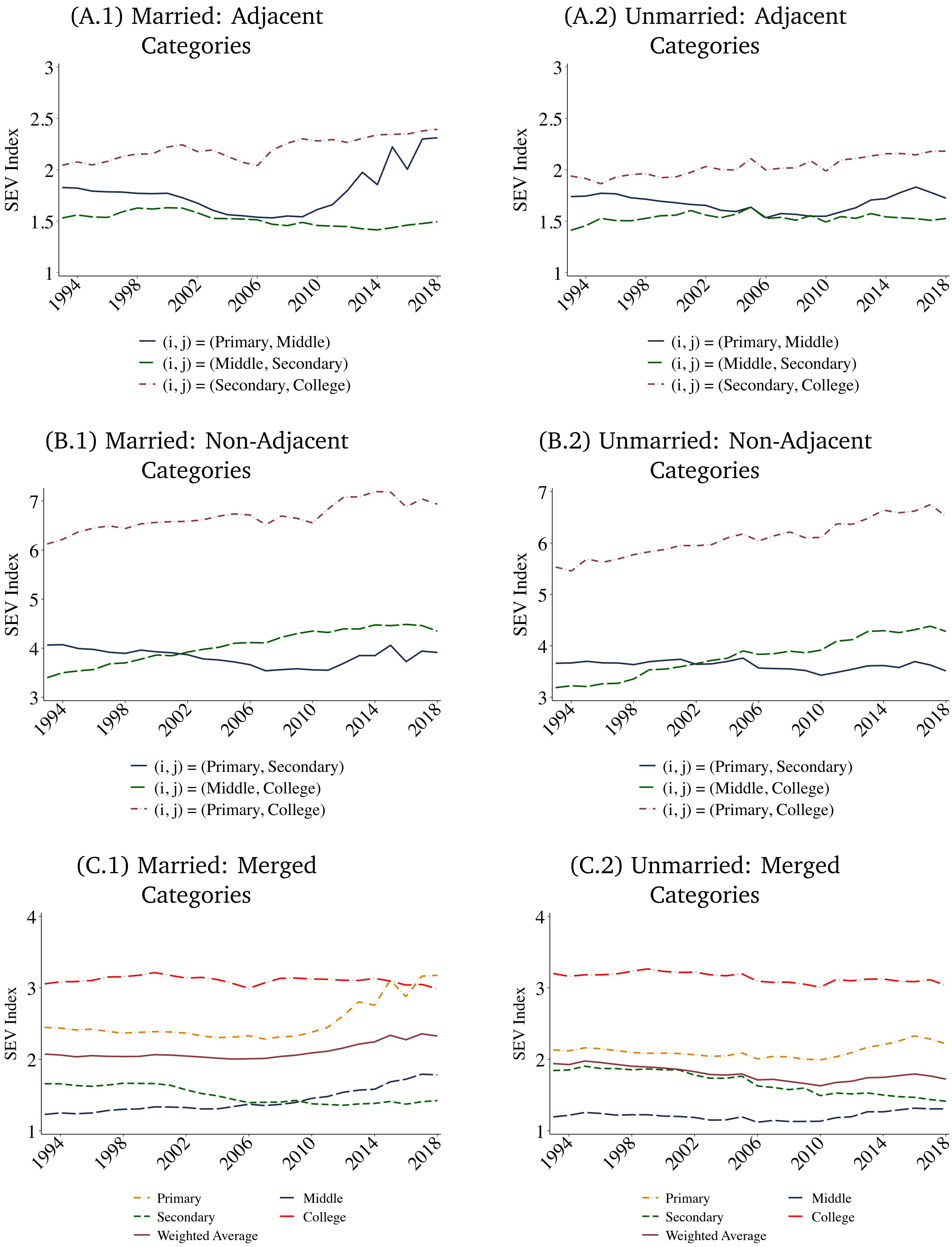
To this point, we've established three main results: 1.) assortative matching is highest in non-adjacent education categories, 2.) over time, assortativeness has increased the most among college graduates, and 3.) the patterns in assortativeness do not depend on whether we use marriage records or birth records. We now discuss potential explanations for these findings and their implications.

There are several potential reasons assortativeness may have increased. First, there may have been reductions in the search costs to finding a spouse due to increased female labor force participation. If women, particularly high-educated women, are entering the labor market, there are less search frictions in terms of finding a similarly-educated spouse. Given that female labor force participation has grown over the past three decades (Gasparini and Marchionni, 2017), it is not surprising that assortativeness has increased. This mechanism is consistent with recent work by Mansour and McKinnish (2018), who demonstrate that individuals in the United States who share the same occupation are significantly more likely to match with a same-occupation spouse.[17]

Changes in legislation governing the marriage market may have also resulted in an increase

[17] Online dating could similarly reduce search frictions (Hitsch et al., 2010). It is unclear, however, how important online dating is for increased assortative matching in Mexico as internet access is less widespread relative to the United States.

Figure 5: Assortative Parental Matching (Married vs. Non-Married)



Notes: Vital Statistics Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panels A and B, each figure plots assortative matching for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value index. We plot married parents on the left, and unmarried (single and cohabiting) parents on the right. Panel A plots adjacent education categories while Panel B plots non-adjacent categories. In Panel C, each line is a comparison of education i with the combined remaining three education categories. The weighted average curve is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

Table 5: Changes in Assortativeness 1993-2018 (Married vs. Non-Married)

	Married Parents			Unmarried Parents		
	1993	2018	Difference	1993	2018	Difference
Panel A: 2 by 2 Comparisons	(1)	(2)	(3)	(4)	(5)	(6)
(i,j) = (Primary, Middle)	1.827	2.311	0.483	1.739	1.724	-0.015
(i,j) = (Middle, Secondary)	1.531	1.495	-0.035	1.411	1.526	0.115
(i,j) = (Secondary, College)	2.044	2.393	0.349	1.939	2.182	0.243
(i,j) = (Primary, Secondary)	4.063	3.912	-0.151	3.661	3.512	-0.149
(i,j) = (Lower Secondary, College)	3.398	4.347	0.948	3.187	4.280	1.093
(i,j) = (Primary, College)	6.124	6.937	0.812	5.533	6.521	0.987
Panel B: Merged Categories						
Primary	2.446	3.175	0.729	2.131	2.217	0.086
Middle	1.229	1.782	0.553	1.195	1.307	0.112
Secondary	1.659	1.423	-0.235	1.843	1.413	-0.430
College	3.055	2.987	-0.068	3.200	3.031	-0.169
Weighted Average	2.073	2.325	0.252	1.941	1.723	-0.218
Observations	404,003	147,120		221,463	358,133	

Notes: Vital Statistics Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panel A, each row provides the assortative matching measure for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value Index. In Panel B, each line is a comparison of education category i with the combined remaining three education categories. The weighted average measure is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

in assortativeness. Over the past 30 years, Mexico has liberalized its divorce laws, and unilateral divorce is now legal in all 32 states. Recent work by Hoehn-Velasco and Penglase (Forthcoming) has found that these laws resulted in a large increase in divorce rates, which suggests the marriage market was affected more generally. If divorce is easier, this lowers the gains to specializing in home production, since leaving the labor market may have a negative effect on future income, should a divorce occur. Given that this type of specialization is likely most common in negative-assortative marriages, we may expect assortativeness to increase due to liberalized divorce laws.[18] This mechanism is explored in Liu (2018), who finds that the introduction of unilateral divorce in the United States increased the correlation in both income and education among spouses. A similar pattern may be present in Mexico.

Finally, changes in gender-specific migration patterns may have contributed to the growth in assortativeness. Men in Mexico are much more likely to migrate than women. Migration affects both the marriage outcomes of the migrant, but also the matching patterns of the “sending" community. Choi and Mare (2012) find evidence that return migrates are more likely to marry outside their education category, and attribute this change to increased income. Moreover, Choi and Mare (2012) find that in communities where migration is common, there is less assortative matching. It is therefore plausible that the decline in Mexico-U.S. migration over the past decade, explains some of the increase in assortativeness.

Our results suggest that the results are largely independent of whether we use administrative records of newly formed marriages, or birth records; Looking at Table 4, the signs of the differences in Panel A are constant across columns (3) and (6). One reasons for this, is that the assortativeness of married parents is largely similar to that of unmarried parents (see Table 5). Given the prevalence of cohabitation, the importance of marriage on fertility behavior may be minimal compared to other contexts. However, an important caveat to the similar results is that they occur when we use *first* births to measure parental matching. As shown in Figure A5 and Table A3, the results slightly differ when looking at non-first births. This suggests that there are minimal differences in the probability of having children, conditional on matching, but the number of children a couple has depends on the characteristics of the couple.

5 Conclusion

We study educational assortative matching in Mexico. Knowing who marries whom is essential for understanding the causes of inequality across households. If both high and low educated individuals only match within the same education category, the marriage market has the potential

[18]While divorce rates increased, additional work by Hoehn-Velasco and Penglase (2021) found no corresponding changes in women’s labor supply, suggesting the effect may not be large.

to increase income inequality. Moreover, since education is highly correlated across generations, positive assortative matching may exacerbate inequality across time.

Using administrative records on marriages and births, we quantify changes in assortative matching over the past three decades. We focus both on marriage matching, as well as *parental* matching. This distinction is especially important in a country like Mexico, where not every couple formally marries. To measure assortativeness, we rely on recent work by Chiappori et al. (2020) who demonstrate how one can identify changes in assortativeness over time in such a way that accounts for mechanical increases in homogamous marriages due to converging distributions of male and female education.

Our findings suggest three main patterns. First, we find a moderate increase in average assortativeness across the period considered. Moreover, the increase is greatest among college graduates. Second, the level of assortativeness is considerably higher when focusing on non-adjacent versus adjacent education categories; individuals who do marry outside their education category are most likely to do so with someone with a similar education level. This suggests that the incidence of college-educated individuals marrying those with less than a high school degree has declined, but this change in assortativeness does not hold when looking at the frequency of college graduates marrying those with a high school degree. Finally, we find that the overall patterns are consistent whether we use data on newly formed marriages, or from birth records. Our results have implications for understanding between-household inequality and child human capital development.

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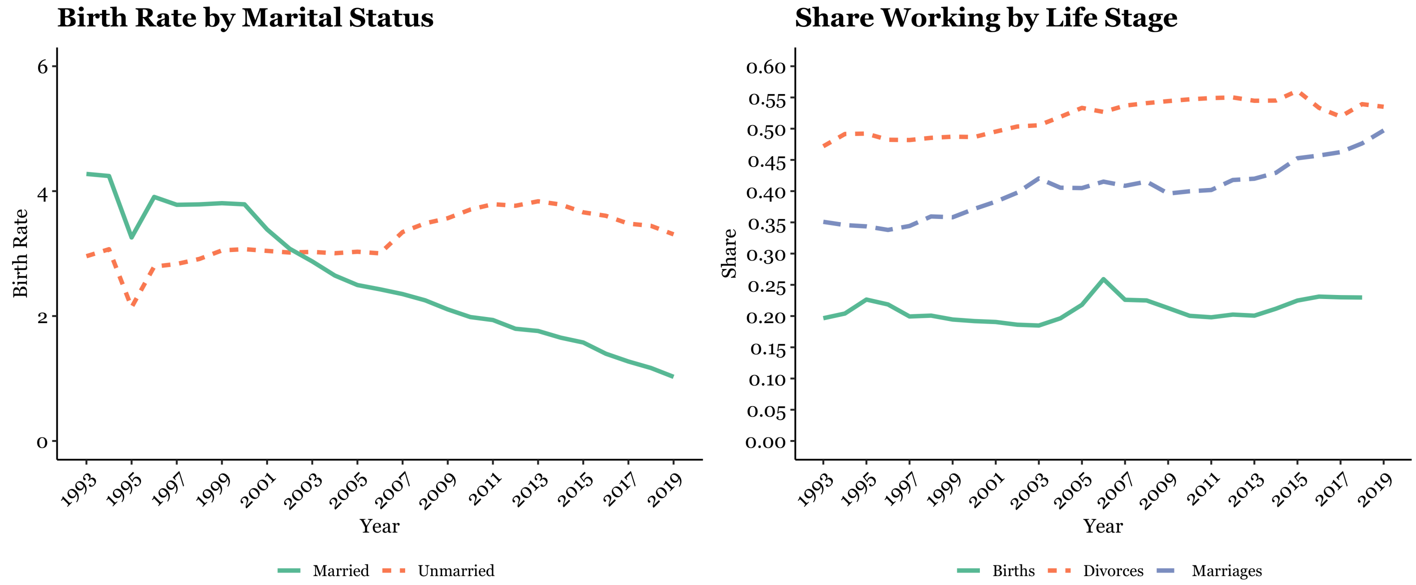
A Appendix

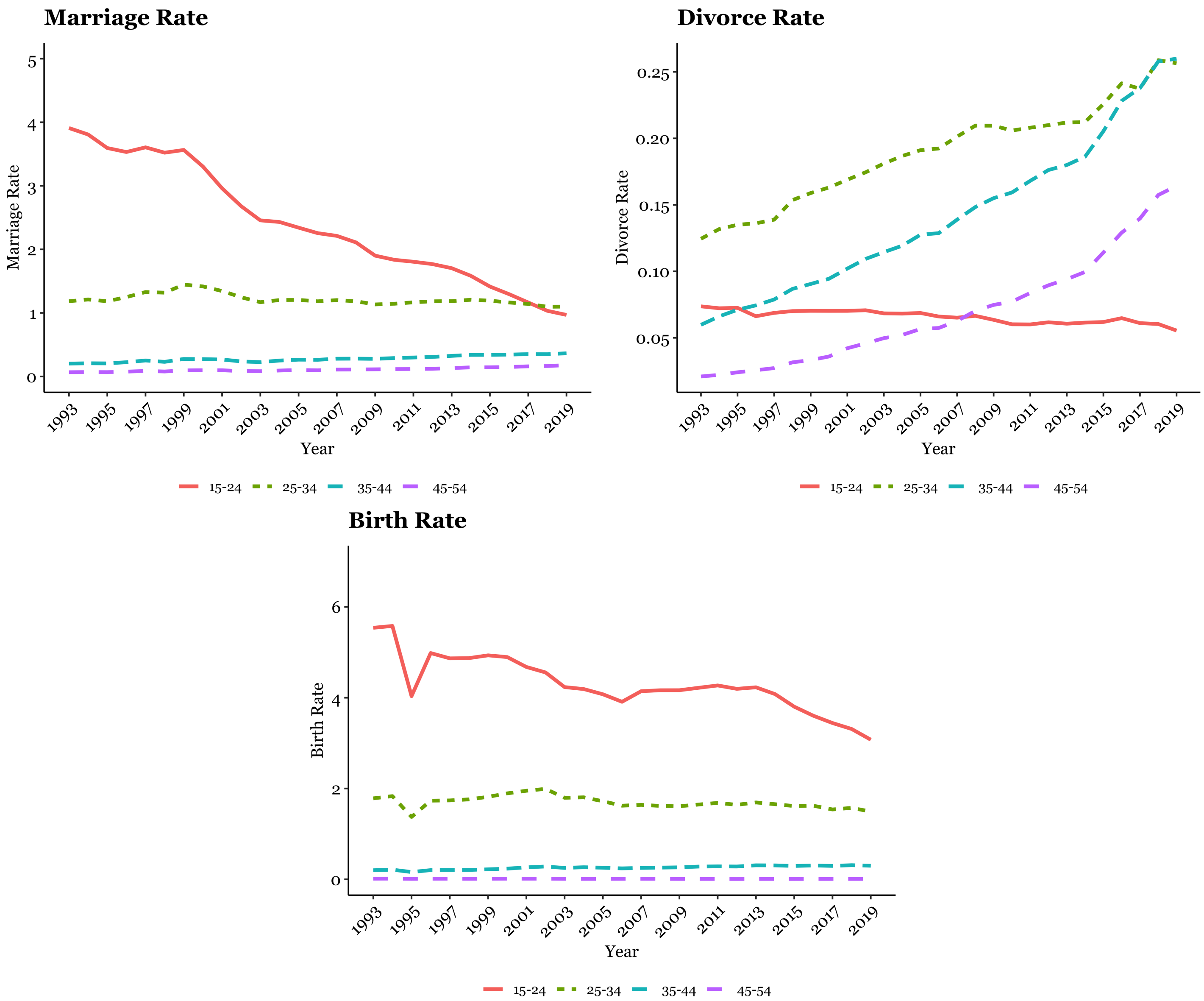
A.1 Additional Figures

Figure A1: Birth by Marital Status and Work Status during Life Stages



Sources: INEGI marriage, divorce, and birth statistics. Mexican IPUMS data. Notes: Rates are per 1,000 persons between 15 and 54.

Figure A2: Divorce, Marriage, and Birth Rates by Age

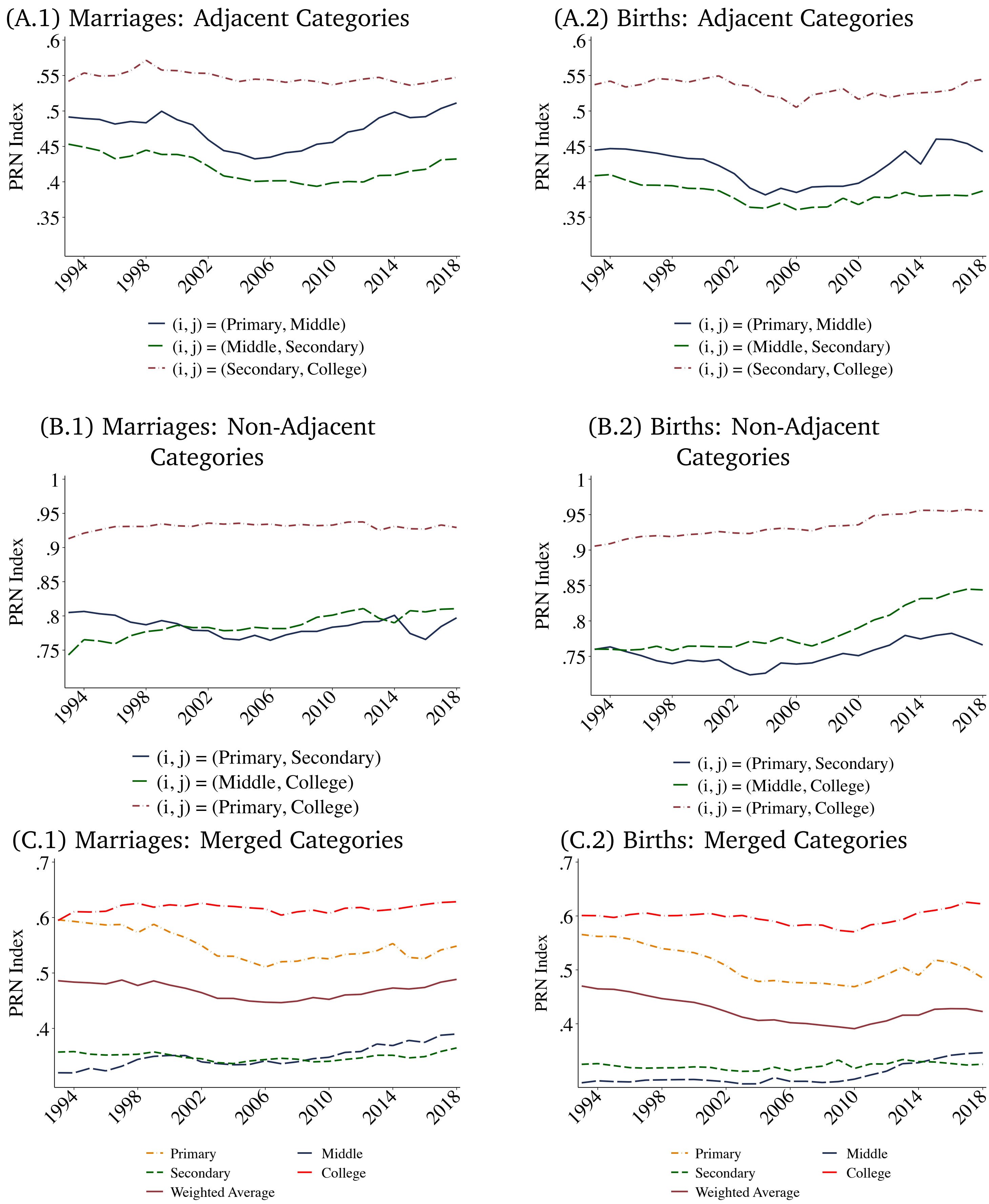


Sources: INEGI marriage, divorce, and birth statistics. Mexican IPUMS data. Notes: Rates are per 1,000 persons between 15 and 54. Less than primary education is either *sin escolaridad*, or education *1 a 3 ãnos* and *4 a 5 ãnos*. Primary education is *primaria completa*. Middle school education is *secundaria*. Secondary education is *preparatoria*. College is greater *professional*. Technical education is grouped with secondary.

Figure A3: Age of Matching Over Time (Marriages and First Births)

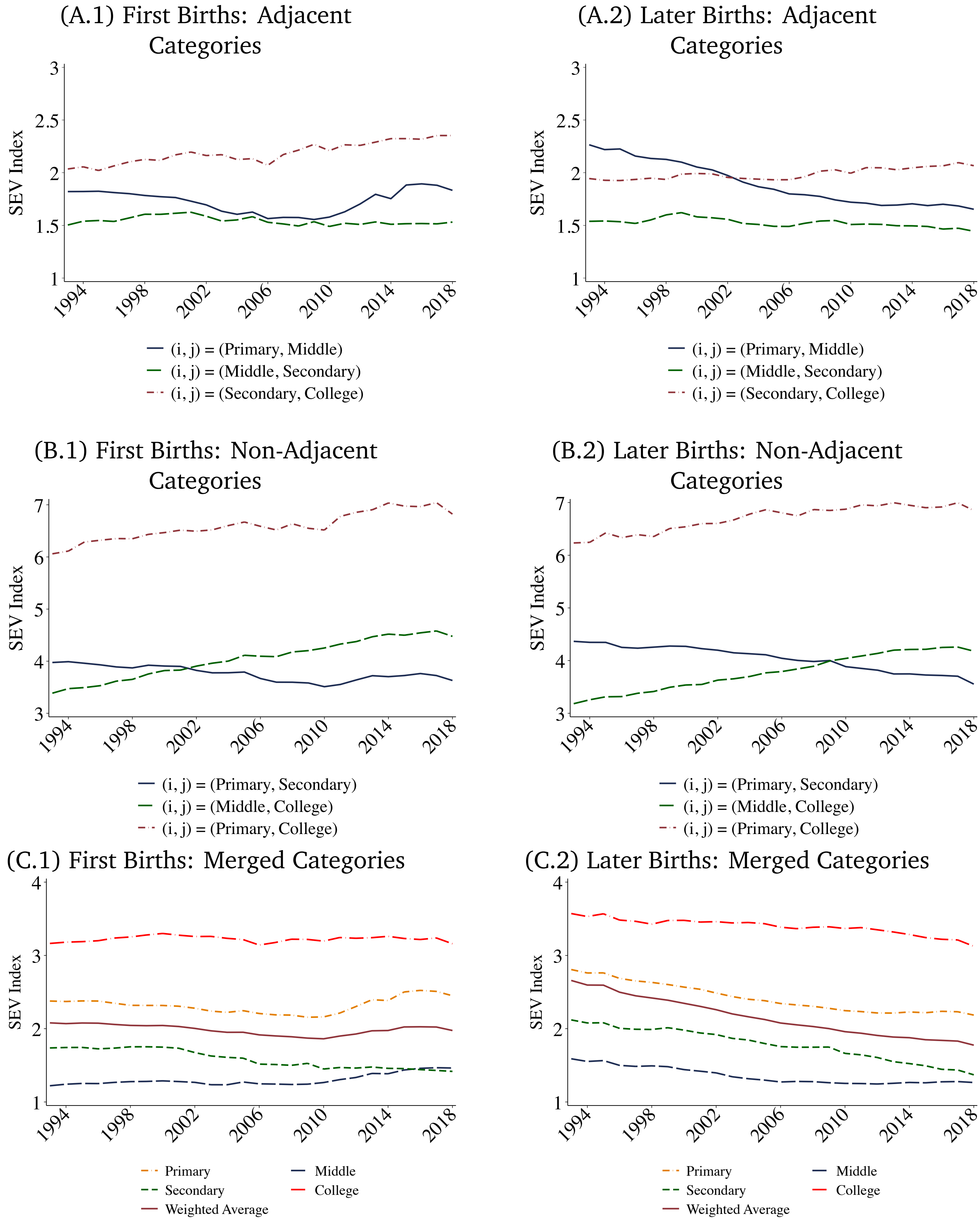
Notes: Vital Statistics Marriage and Birth Records. The sample includes marriages and first births where both spouses or parents are age 15 to 50.

Figure A4: Assortative Marriage and Parental Matching (Perfect-Random Normalization)



Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panels A and B, each figure plots assortative matching for the diagonal 2×2 sub-matrices of the full sorting matrix using the Perfect-Random Normalization. Panel A plots adjacent education categories while Panel B plots non-adjacent categories. In Panel C, each line is a comparison of education i with the combined remaining three education categories. The weighted average curve is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

Figure A5: Assortative Parental Matching (First vs. Later Births)



Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panels A and B, each figure plots assortative matching for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value Index. We plot first births on the left, and non-first births on the right. Panel A plots adjacent education categories while Panel B plots non-adjacent categories. In Panel C, each line is a comparison of education i with the combined remaining three education categories. The weighted average curve is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

A.2 Additional Tables

Table A1: Assortative Matching in a Four-Education Market

	College	Secondary	Middle School	Primary or Less
College	r_1	a	c	$n_1 - r_1 - a - c$
Secondary	b	r_2	d	$n_2 - b - r_2 - d$
Middle School	f	e	r_3	$n_3 - f - e - r_3$
Primary or Less	$m_1 - r_1 - b - f$	$m_2 - a - r_2 - e$	$m_3 - c - d - r_3$	$1 + r_1 + r_2 + r_3 + a + b + c + d + e + f - (m_1 + m_2 + m_3 + n_1 + n_2 + n_3)$

Notes: In the above tables, m_j are the shares of men who have graduated college, secondary school, and middle school, respectively. n_j gives the corresponding values for women. r_1 denotes the share of marriages where both spouses have a college degree, r_2 denotes the share of marriages where both spouses have a secondary school degree, and r_3 is the share where both have a middle school education. a, b, c, d, e, and f denote the shares of couples with different pairs of unequal education levels.

Table A2: Changes in Assortativeness 1993-2018 (Perfect-Random Normalization)

	Marriages			Births		
	1993	2018	Difference	1993	2018	Difference
Panel A: 2 by 2 Comparisons	(1)	(2)	(3)	(4)	(5)	(6)
(i,j) = (Primary, Middle)	0.492	0.511	0.020	0.445	0.442	-0.002
(i,j) = (Middle, Secondary)	0.453	0.432	-0.021	0.409	0.387	-0.022
(i,j) = (Secondary, College)	0.542	0.547	0.006	0.537	0.545	0.008
(i,j) = (Primary, Secondary)	0.805	0.797	-0.008	0.760	0.766	0.006
(i,j) = (Lower Secondary, College)	0.743	0.811	0.068	0.760	0.844	0.084
(i,j) = (Primary,, College)	0.913	0.929	0.016	0.906	0.955	0.049
Panel B: Merged Categories						
Primary	0.596	0.548	-0.047	0.566	0.485	-0.081
Middle	0.320	0.390	0.070	0.290	0.346	0.056
Secondary	0.357	0.365	0.007	0.325	0.325	0.000
College	0.595	0.628	0.034	0.601	0.622	0.021
Weighted Average	0.486	0.488	0.002	0.470	0.423	-0.047
Observations	496,358	353,423		635,126	510,713	

Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panel A, each row provides the assortative matching measure for the diagonal 2×2 sub-matrices of the full sorting matrix using the Perfect-Random Normalization. In Panel B, each line is a comparison of education category i with the combined remaining three education categories. The weighted average measure is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

Table A3: Changes in Assortativeness 1993-2018 (First vs. Later Births)

	First Births			Later Births		
	1993	2018	Difference	1993	2018	Difference
Panel A: 2 by 2 Comparisons	(1)	(2)	(3)	(4)	(5)	(6)
(i,j) = (Primary, Middle)	1.821	1.833	0.012	2.265	1.653	-0.612
(i,j) = (Middle, Secondary)	1.504	1.531	0.028	1.538	1.444	-0.094
(i,j) = (Secondary, College)	2.035	2.353	0.317	1.944	2.067	0.122
(i,j) = (Primary, Secondary)	3.975	3.630	-0.345	4.366	3.554	-0.811
(i,j) = (Lower Secondary, College)	3.386	4.477	1.091	3.183	4.179	0.997
(i,j) = (Primary, College)	6.060	6.823	0.763	6.234	6.850	0.616
Panel B: Merged Categories						
Primary	2.378	2.449	0.072	2.807	2.186	-0.621
Middle	1.221	1.463	0.242	1.590	1.266	-0.324
Secondary	1.737	1.417	-0.320	2.120	1.370	-0.750
College	3.164	3.159	-0.004	3.571	3.125	-0.447
Weighted Average	2.080	1.975	-0.104	2.658	1.775	-0.883
Observations	635,126	510,713		1,265,354	778,435	

Notes: Vital Statistics Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. In Panel A, each row provides the assortative matching measure for the diagonal 2 × 2 sub-matrices of the full sorting matrix using the Separable Extreme Value Index. In Panel B, each line is a comparison of education category i with the combined remaining three education categories. The weighted average measure is computed by averaging the assortative index across educational levels, where the weights are determined by diagonal value of the matching table given in Table A1.

A.3 Data

We use national administrative records for births, marriages, and divorces from the Instituto Nacional de Estadística y Geografía (INEGI). The data includes an individual record for each record throughout Mexico over 1993-2018. These characteristics provided by INEGI for each record include the geographic location and the education levels of the couple.

We primarily rely on the birth records to measure assortativeness. The advantage of the birth records is that it details the information for married couples, cohabitating couples, as well as single women. We use records for first births to women in all 31 states as well as Mexico City. This allows us to look at assortativeness for all household arrangements, including those that are not formally cohabitating and would not appear in household surveys. We also utilize the INEGI marriage and divorce records, which collects similar information on education levels. These records include information over each marriage and divorce that occurred in Mexico, along with the characteristics of the couple.

There are several data limitations that require our attention. First, several states poorly reported education levels. Four states were particularly problematic for education reporting in the vital statistics records, as they defined education differently across years and contained excessive amounts of missing data.[19] To deal with this issue, we eliminate these four states from our analyses. In total, we focus on 27 states and Mexico City.

Even with omitting the four states with inconsistent and incomplete data, missing education levels is still a concern. The education level of one or both spouses is at times missing, and importantly this is not likely to be random; individuals with lower education may be more likely to leave certain categories of the marriage or birth certificate blank. A related problem in the birth records is that the father's information is often missing, and this is again likely to be correlated with age and education.

To examine the extent of this problem, we begin by plotting the percentage of missing education values in the marriage and birth records by year in Figure A6. Missing data in the marriage records is given in Panel A, while Panel B presents missing data in the birth records. We separately plot records where the husband/father's education is missing, the wife/mother's education is missing, and finally when either are missing. Several patterns emerge. First, missing data is considerably lower in the marriage records, especially among men. Roughly 10 percent of marriage records have a missing education value for either the husband or wife. In the birth records, this figure increases to more than 10-15 percent among mothers and more than 20 percent for fathers.[20] Second, Figure A6 shows that the number of missing values is higher in more recent years than it was in the 1990s. This is particularly concerning for us as we are interested in how assortative matching has evolved over time.

There is no obvious reason for the high number of missing values or for why the have grown over

[19] The four omitted states are México, Michoacán, Nayarit, and Querétaro.

[20] In the United States, Shen (2020) finds that around 20 percent of birth records have missing information on the fathers education. Our data is therefore comparable in quality.

time. There are systematic differences across states, which suggests that state collection procedures may be driving the high number of missing values. Unfortunately, we can only speculate regarding what the actual education levels are for these observations. If they are random, then our estimates are robust. However, if they are correlated with education, i.e., if individuals with lower educational attainment are less likely to report their education level, this may affect our conclusions.

To address the missing data issue, we examine the sensitivity of the results to several different assumptions regarding the characteristics of the problem records. Consider a marriage where the wife's education is observed, but the husband's education is not. We first assume that every missing husband has an identical education level as the wife. This will result in the maximum level of assortativeness, or the "upper bound". We next assume that every missing husband has a different level of education compared to the wife. This will result in the minimum level of assortativeness possible, or the "lower bound". Finally, our preferred estimate, which is, in effect, what we do in our main analysis, is to assume that the missing data is random, and that the problem marriage record follows an identical pattern as the non-missing data. We make these assumptions only for when one of the two spouses has non-missing data.

We present the results in Table A4. In the interest of clarity, we limit our attention to the first and last years of the data. Panel A provides the results for marriages, while Panel B does the same for births. In columns (1) and (3), we report the main estimates that were calculated in the main text. In columns (2) and (4) we present the lower and upper bound of our assortativeness estimates based on whether couples with missing education levels are all homogamous, or instead non-homogamous. We find the bounds for the marriage records are not wide, which is perhaps unsurprising given that it is rare for only one spouse's education level to be observed. On the other hand, it is quite common to observe only the mother's education in the births records. As a result, the lower and upper bounds provided in Panel B are quite wide. Nonetheless, we wish to emphasize that the intervals are highly conservative, and the goal is only to place a bound on the assortative measures. For completeness, we repeat the analysis using our alternative measure of assortativeness in Table A5.

Table A4: Impact of Missing Data on Assortative Measures

	1993		2018	
	Estimate	[Lower bound, Upper bound]	Estimate	[Lower bound, Upper bound]
Panel A: Marriages	(1)	(2)	(3)	(4)
(i,j) = (Primary, Middle)	1.986	[1.950-2.022]	2.133	[2.116-2.159]
(i,j) = (Middle, Secondary)	1.718	[1.678-1.770]	1.807	[1.795-1.828]
(i,j) = (Secondary, College)	2.145	[2.093-2.211]	2.459	[2.358-2.517]
(i,j) = (Primary, Secondary)	4.302	[4.207-4.345]	4.132	[4.083-4.158]
(i,j) = (Lower Secondary, College)	3.363	[3.264-3.423]	4.298	[4.086-4.356]
(i,j) = (Primary, College)	6.138	[5.869-6.188]	6.613	[5.854-6.675]
Observations	496,398	502,609	358,423	363,783
Panel B: Births				
(i,j) = (Primary, Middle)	1.821	[0.903-2.269]	1.833	[0.731-2.354]
(i,j) = (Middle, Secondary)	1.504	[0.567-2.027]	1.531	[0.590-2.028]
(i,j) = (Secondary, College)	2.035	[1.084-2.481]	2.353	[1.309-2.747]
(i,j) = (Primary, Secondary)	3.975	[1.885-4.453]	3.630	[1.608-4.150]
(i,j) = (Lower Secondary, College)	3.386	[1.854-3.802]	4.477	[2.202-4.872]
(i,j) = (Primary, College)	6.060	[2.846-6.431]	6.823	[2.803-7.241]
Observations	635,126	726,159	510,713	585,381

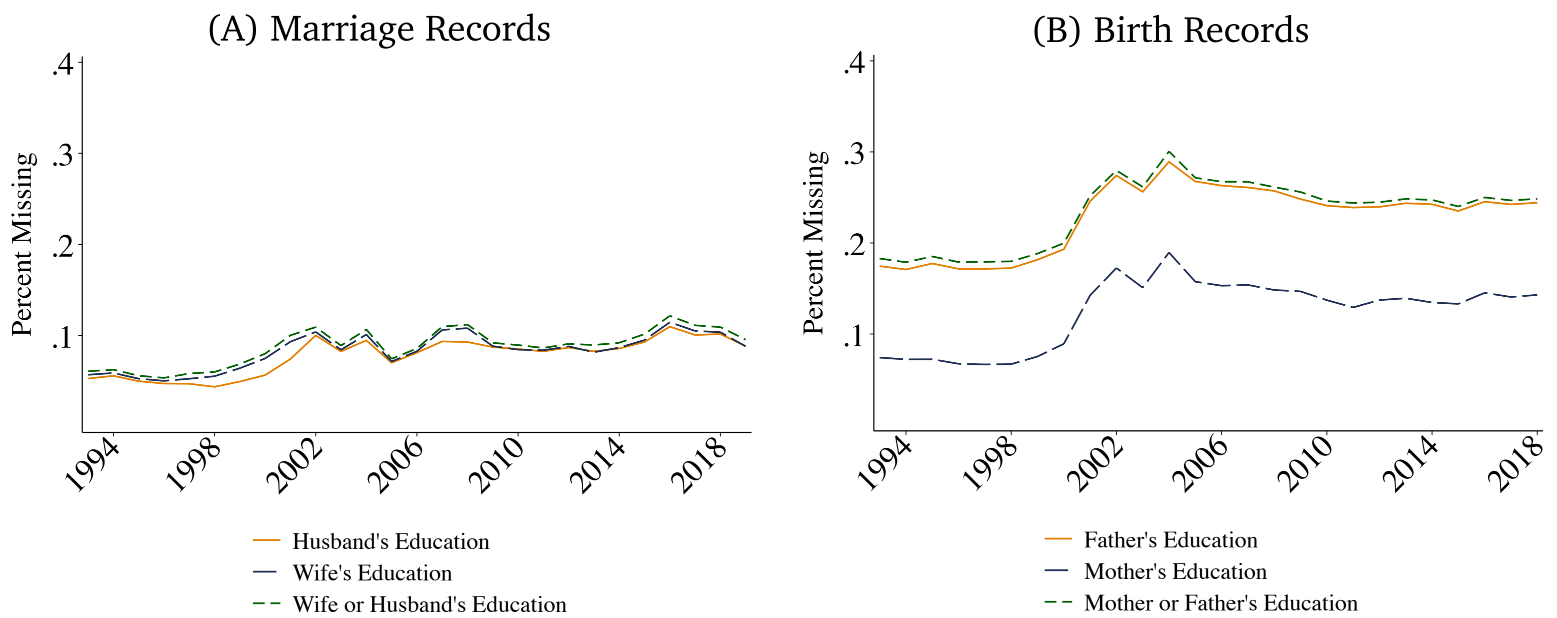
Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. Each row provides the assortative matching measure for the diagonal 2×2 sub-matrices of the full sorting matrix using the Separable Extreme Value Index. The lower bound of assortativeness is calculated by assuming that all missing education levels for one partner is *different* than the observed education level for the other partner. The upper bound of assortativeness is calculated by assuming that all missing education levels for one partner is the *same* as the observed education level for the other partner. The bounds do not account for couples where both partners have missing educational attainment.

Table A5: Impact of Missing Data on Assortative Measures (Merged Categories)

	1993		2018	
	Estimate	[Lower bound, Upper bound]	Estimate	[Lower bound, Upper bound]
Panel A: Marriages	(1)	(2)	(3)	(4)
Primary	2.549	[2.499-2.580]	2.960	[2.770-2.992]
Middle	1.352	[1.311-1.391]	1.813	[1.810-1.845]
Secondary	1.860	[1.800-1.904]	1.657	[1.651-1.691]
College	3.101	[3.020-3.150]	3.052	[2.911-3.107]
Observations	496,398	502,609	358,423	363,783
Panel B: Births				
Primary	2.378	[1.967-2.729]	2.449	[2.019-2.867]
Middle	1.221	[0.657-1.640]	1.463	[1.095-1.878]
Secondary	1.737	[1.251-2.165]	1.417	[0.890-1.835]
College	3.164	[2.748-3.479]	3.159	[2.457-3.462]
Observations	635,126	726,159	510,713	585,381

Notes: Vital Statistics Marriage and Birth Records. Men and women are divided into four mutually exclusive education categories: 1. Primary or Less, 2. Middle, 3. Secondary, 4. College. Each row is a comparison of education category i with the combined remaining three education categories. The lower bound of assortativeness is calculated by assuming that all missing education levels for one partner is *different* than the observed education level for the other partner. The upper bound of assortativeness is calculated by assuming that all missing education levels for one partner is the *same* as the observed education level for the other partner. The bounds do not account for couples where both partners have missing educational attainment.

Figure A6: Missing Data by Year



Notes: Vital Statistics Marriage and Birth Records. The solid-orange line gives the percentage of marriage or birth records without the father's education by year. The blue, long-dashed line does the same for the mother's education. The blue-dashed line denotes the percentage of marriages or births by year where the education of either men and women are missing.

A.4 Separable Extreme Value Model

The goal of this section is to provide additional details of the Separable Extreme Value (SEV) model, and to provide the derivation of the resulting measure of assortative matching. The content of this section follows closely with Chiappori et al. (2020). All terms are defined as in the main text.

This is a frictionless marriage matching model of heterosexual couples. Denote men by the subscript i and women by the subscript j. Men and women each maximize their utility, where each potential marriage generates a surplus s_{ij} that is divided among the spouses. The model assumes Transferable Utility, so that the surplus is the sum of each spouses individual utility, with $s_{ij} = u_i + v_j$, where $u_i = U^{IJ} + \epsilon_i^J$, and $v_j = V^{IJ} + v_j^I$ represent the utility of men and women, respectively.

The SEV model relies upon a number of conditions. First, there must be a large number of men and women relative to the number of "types" of individuals (i.e., education categories), where the total number of types of men and women are given by I and J, respectively. Second, the surplus generated from a match must be composed of a deterministic component (Z^{IJ}) that does not vary across individuals, and a random term (γ_{ij}) that reflects unobserved individual preference heterogeneity, with $s_{ij} = Z^{IJ} + \gamma_{ij}$. Moreover, the utility for single individuals is normalized to zero and given by $s_{i0} = \epsilon_i^J$ and $s_{0j} = v_j^I$. The resulting matrix $Z = ([Z^{IJ}])$ then reflects individual preferences for different types of partners, and will be central to the SEV index measure of assortativeness.

For simplicity, assume there are two types of education categories for men and women; that is, $I = J = 2$. Then matrix Z will be a 2×2 matrix with a supermodular core (the sum of the diagonal elements minus the sum of the off-diagonal elements) of $S = Z_{11} + Z_{22} - Z_{12} - Z_{21}$. S is a measure of complementarity, and assortativeness will be increasing in S.

The third assumption is that the random term γ_{ij} is additively separable with $\gamma_{ij} = \epsilon_i^J + v_j^I$. These terms represent unobservable individual tastes for certain types of partners. Fourth, the SEV model assumes that these terms are Type 1 Extreme Value, which results in differences in utility across education partners following a logistic distribution.

With this setup, Chiappori et al. (2020) construct a measure of assortativeness, stated below in the following proposition and subsequent proof:

Proposition: Let m, n, and r be defined as they are in the main text. Then table (m, n, r) can be generated by any SEV model such that its supermodular core satisfies

$$Z^{11} + Z^{22} - Z^{12} - Z^{21} = 2\ln\Big(\frac{r(1+r-m-n)}{(m-r)(n-r)}\Big)$$

One of the structural matrices that would generate Table (m, n, r) is:

$$Z = 2\begin{pmatrix} \ln r & \ln(m-r) \\ \ln(n-r) & \ln(1+r-m-n) \end{pmatrix}$$

Proof:

The probability P^{IJ} of any woman with education $i \in I$ matching with a man of education J is given by

$$\begin{aligned} P^{IJ} &= Pr(U^{IJ} + \epsilon_i^J \geq U^{IK} + \epsilon_i^K)\ \forall\ K \\ &= Pr(\epsilon_i^J - \epsilon_i^K \geq U^{IK} - U^{IJ})\ \forall\ K \end{aligned}$$

The above equation simply says that if we observe a woman marrying a particular type of man, it must be the case that she derives more utility from that specific match relative to any available alternative.

Similarly, for men, let Q^{IJ} be the probability of a man $j \in J$ being matched with a woman in category I:

$$\begin{aligned} Q^{IJ} &= Pr(V^{IJ} + \nu_i^I \geq V^{IK} + \nu_i^K)\ \forall\ K \\ &= Pr(\nu_i^I - \nu_i^K \geq V^{KJ} - V^{IJ})\ \forall\ K \end{aligned}$$

Since the error terms are assumed to be Type 1 Extreme Value, the probabilities are given by (Choo and Siow, 2006):

$$P^{IJ} = \frac{\exp U^{IJ}}{\sum_K \exp U^{IK}} \quad \text{and} \quad Q^{IJ} = \frac{\exp V^{IJ}}{\sum_K \exp V^{KJ}}$$

Then, in the two-education case, the matching probabilities for women are given by:

$$P^{11} = \frac{r}{m} = \frac{\exp U^{11}}{\exp U^{11} + \exp U^{12}} \quad \text{and} \quad P^{12} = 1 - P^{11}$$

$$P^{21} = \frac{n-r}{m} = \frac{\exp U^{21}}{\exp U^{21} + \exp U^{22}} \quad \text{and} \quad P^{22} = 1 - P^{21}$$

And for men,

$$Q^{11} = \frac{r}{n} = \frac{\exp V^{11}}{\exp V^{11} + \exp V^{21}} \quad \text{and} \quad Q^{21} = 1 - Q^{11}$$

$$Q^{21} = \frac{m-r}{n} = \frac{\exp V^{12}}{\exp V^{12} + \exp V^{22}} \quad \text{and} \quad Q^{22} = 1 - Q^{12}$$

Chiappori et al. (2020) implement the following normalizations: $U^{11} = U^{21} = V^{11} = V^{12} = 0$. Note that alternative normalizations would alter the resulting values of Z^{IJ} but would not affect the measure of assortativeness.

Then,

$$
\begin{aligned}
U^{12} &= \ln\Big(\frac{m-r}{r}\Big)\\
U^{22} &= \ln\Big(\frac{1+r-m-n}{n-r}\Big)\\
V^{21} &= \ln\Big(\frac{n-r}{r}\Big)\\
V^{22} &= \ln\Big(\frac{1+r-m-n}{m-r}\Big)
\end{aligned}
$$

Recall that $Z^{IJ} = U^{IJ} + V^{IJ}$. Then,

$$Z^{11} = 0, \;\; Z^{22} = \ln\Big(\frac{(1+r-m-n)^2}{(m-r)(n-r)}\Big), \;\; Z^{12} = \ln\Big(\frac{m-r}{r}\Big), \;\; Z^{21} = \ln\Big(\frac{n-r}{r}\Big)$$

and the measure of assortativeness is:

$$S = Z^{11} + Z^{22} - Z^{12} - Z^{21} == 2\ln\Big(\frac{r(1+r-m-n)}{(m-r)(n-r)}\Big) \tag{A1}$$

The SEV Index can then be defined as:

$$I_{SEV} = \ln\Big(\frac{r(1+r-m-n)}{(m-r)(n-r)}\Big) \tag{A2}$$

A.5 Understanding Magnitudes of the SEV Index

To better understand how to interpret the magnitudes of the SEV Index, we provide a numerical examples of different sorting patterns, and what the resulting SEV index is for each of those cases. We limit our attention to two education categories (e.g., college and high school) for simplicity, and use the 2×2 measures discussed in Section 4.

To illustrate how to interpret the index, we fix values of m and n, which denote the share of men and women with a college degree as a percentage of men and women with a college or high school degree, respectively. We then vary r, which measures the share of marriages where both spouses have a college degree. As r increases, there is more assortativeness.

Suppose we observe 100 married couples. Further, suppose 40 men have a college degree ($m = 0.40$), 40 women have a college degree ($n = 0.40$),, and all other individuals have a high school education. Thus, there can be anywhere from 0 to 40 marriages where both spouses have a college degree. If the 40 college-educated men match with the 40 college-educated women, then the share of college-college matches is $r = 0.40$, and there is perfect assortative matching (i.e., $I_{SEV} = \infty$). If there are 16 college-college matches out of 100 ($r = 0.16$), then there is random matching, and $I_{SEV} = 0$. If there are no college-college matches, then there is perfect negative assortative matching and $I_{SEV} = -\infty$. Note that if we increase the share of college-college matches from 4 to 8 results in a different change in the SEV index compared to going from 16 to 20. That is, I_{SEV} does not increase linearly in r. Table A6 provides the magnitudes of the SEV index for different values of m, n, and r.

Table A6: Hypothetical SEV Index Values for Different Sorting Matrices

College-College Marriages (r) (1)	Share Men with a College Degree (m) (2)	Share Women with a College Degree (n) (3)	SEV Index $\ln(\frac{r(1+r-m-n)}{(m-r)(n-r)})$ (4)
0.00	0.40	0.40	$-\infty$
0.04	0.40	0.40	-2.60
0.08	0.40	0.40	-1.52
0.12	0.40	0.40	-0.71
0.16	0.40	0.40	0.00
0.20	0.40	0.40	0.69
0.24	0.40	0.40	1.42
0.28	0.40	0.40	2.23
0.32	0.40	0.40	3.26
0.36	0.40	0.40	4.84
0.40	0.40	0.40	∞

Notes: We illustrate how different values of r, m, and n correspond to different magnitudes of the SEV Index. All numbers are hypothetical. Column 1 provides the share of marriages where both spouses have a college degree. Column 2 and 3 give the share of men and women with a college degree. Column 4 gives the SEV index. The parameter r is bounded below by zero and above by the minimum of m and n.