Marital Matching and Women's Intergenerational Mobility in the Late-19*th* and Early-20*th*-Century U.S.

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Abstract

This paper characterizes the evolution of marital matching on age, nativity, and education as well as changes in women's intergenerational mobility during the late 19*th* and early 20*th* centuries. We find that age homogamy changed very little for women born in the 19*th* century, which makes the rapid transition to smaller within-couple age gaps in the 20*th* century a departure from a 100-year trend. As mass immigration to the U.S. transformed the nation, the likelihood that a woman had a father-in-law who was of similar nativity to her father decreased, suggesting that inter-marriage helped stir the U.S. melting pot. In the late 19*th* century, assortative matching on education changed little, even as educational attainment soared during the high-school movement. Lastly, between 1900 and 1940, women's intergenerational mobility increased, as measured by her husband's occupational standing relative to her father's. We conclude that, even as a dynamic marriage market reduced the importance of father's heritage and occupational standing, women's own educational attainment remained a powerful force in shaping their socioeconomic status.

Keywords: assortative matching, marriage homogamy, intergenerational mobility

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1. Introduction

Assortative matching, or marriage homogamy, measures the similarity of traits between a husband and wife. This statistic has long been of great interest to social scientists across disciplines, because it characterizes the functioning of the marriage market, including the scarcity or abundance of potential partners, the complementarity or substitutability of partners' traits in production (Becker, 1973, 1974; Lam, 1988) and consumption (Stevenson and Wolfers, 2007), and bargaining power and gender equity within marriage (Kalmijn, 1991, 1994; Shorter, 1977). Assortative matching also determines long-run economic outcomes, including income inequality between households (Kremer, 1997; Fernandez & Rogerson, 2001; Greenwood et al., 2014; Eika et al., 2019; Ciscato & Weber, 2020); the allocation of resources within households (Calvo et al., 2021); and intergenerational social and economic mobility of children (Aiyagari et al., 2000; Chadwick & Solon, 2002; Ermisch et al., 2006; Currie & Almond, 2011).

This paper describes the evolution of assortative matching in the 19*th* and early 20*th* centuries, an era characterized by rapid industrialization and economic growth, the dramatic expansion of public education, mass immigration, urbanization, the Great Depression, and war. We examine four dimensions of marital sorting, including by age, nativity, education, and occupational standing. Our analysis uses the full-count 1850-1940 Decennial Censuses (Ruggles et al., 2021) as well as newly released data from the Longitudinal Intergenerational Family Electronic Micro-database (LIFE-M) (Bailey et al., 2022a), which covers the late 19*th* and early 20*th* century for individuals born in Ohio. The LIFE-M data are fundamental to our analysis of the intergenerational mobility of women. The LIFE-M data contain high quality, longitudinal links of more than 260,000 girls from birth to adulthood, by relying on vital records that contain both women's birth ("maiden") and married surnames. The presence of both birth and marriage surnames allows us to locate both husbands and fathers, facilitating an analysis of women's social and economic mobility in samples many times larger than any other available for U.S. women born between 1865 to 1920. Using both sources of data allows us to compare estimates from linked samples to the census population, reweight the LIFE-M samples to resemble the population of married women, and adjust for selection into marriage by age.

Our results add new insights about the functioning of the marriage market in the 19*th* and early 20*th* centuries. Adjusting for the age composition of married women observed in the census, we find that age homogamy changed very little for women born over the 19*th* century. This stability contrasts with results in Rolf and Ferrie (2008), who find that age differences between husbands and wives increased sharply, from 2 to 5 years, for women born over the first thirty years of the 19*th* century. Our adjustment for the age composition of married women, however, shows that the age differences between husbands and wives were stable over the 19*th* century, rising slightly from around 4.5 to 5.2 years in the early 19*th* century and then returning to a 4.5-year age gap for the duration of the late 19*th* century. This considerable stability in age homogamy makes the transition to smaller within-couple age gaps in the 20*th* century exceptional rather than a return to antebellum U.S. marriage patterns.

A second finding is the significant decrease in marital matching on nativity in the mid- to late-19*th* century. As mass immigration to the U.S. transformed the nation, the likelihood that a woman was married to a man whose father was born in the same country as her father declined from 0.93 to 0.75—a decrease in nativity homogamy suggesting inter-marriage helped stir the U.S. melting pot. Then, between 1890 and 1940, rates of nativity homogamy stabilized in the nation overall. But this pattern was not universal. Among Ohio-born women, nativity homogamy *increased* from around 0.75 to 0.82 between 1885 and 1940, signaling an increase in segregation by father's country of origin in the rapidly industrializing economies of the Midwest.

Our analysis of assortative matching on occupation focuses on the Ohio-born women in the LIFE-M sample. The similarity of estimates in the LIFE-M sample to those from *unlinked* census samples for age and nativity lend credibility to the quality of the links and representativeness of the reweighted samples. The limitation of these data is that they only speak to patterns in Ohio—a limitation we are addressing with ongoing linking work to increase the number of states in the LIFE-M data.

In terms of assortative matching on education, we find that the intergenerational association of husbands' and wives' educational attainment changed little over the same period, despite the High School

Movement increasing the share of Americans graduating from high school, from 10 percent in 1910 to over 50 percent by 1940 (Goldin 1998). But the results for women's intergenerational mobility offer a different picture. After a period of stability in intergenerational mobility for birth cohorts born in the 30 years after the Civil War, we find that the intergenerational persistence between the occupational standing of a woman's husband and her father fell by roughly one third for cohorts born over the next 30 years. We also find that absolute measures of intergenerational mobility increase for the same cohorts, suggesting considerably more upward mobility for women whose father's occupation ranks in the bottom half of the income distribution.

These findings point to several important open questions in the literature, highlighting both areas of agreement and disagreement. Similar to findings using a name-based approach (Olivetti & Paserman, 2015), linked Massachusetts marriage records (Craig et al., 2019), and retrospective surveys (Jácome et al., 2021), our analysis implies that intergenerational persistence *fell* for women between 1915 and 1940. However, the magnitudes of our estimates of intergenerational persistence differ. Intergenerational persistence for Ohio-born women is *twice* what Craig et al. (2019) measure in Massachusetts for similar cohorts, suggesting considerably more persistence in socio-economic status in late-19*th* and early-20*th* century Ohio. This finding is robust to using correlation coefficients or rank-rank coefficients. However, our estimates of intergenerational persistence are lower than in Olivetti & Paserman (2015), who use names rather than occupation, and Jácome et al. (2021) who use a hybrid of current household income and retrospective reports of father's occupation. Both the levels and trends in intergenerational mobility for women in the LIFE-M Ohio data differ from those in the Census Tree, leaving important puzzles for future work.

This work contributes a novel historical perspective to a growing body of work examining assortative matching and women's intergenerational mobility in the U.S. in the 19*th* century (Olivetti & Paserman, 2015; Craig et al. 2019; Buckles et al., 2023; Althof et al., 2023) and the late 20*th* century (Aiyagari et al., 2000; Charles et al., 2013; Greenwood et al., 2014; Eika et al., 2019). It also contributes historical context for understanding changes in marital matching on nativity to modern studies focusing on the rise in interracial/interethnic marriages (Schoen & Thomas, 1989; Gilbertson, 1996; Kalmijn, 1998; Qian, 1997). Finally, it adds to recent studies using alternative approaches to studying assortative matching on socio-economic status by considering separately assortative matching on fathers' occupational standing and women's own educational attainment (Olivetti and Paserman 2015, Craig et al. 2019, Jácome et. al. 2021).

2. An Overview of Assortative Matching and Women's Intergenerational Mobility in U.S. History

Assortative matching and women's intergenerational mobility has been difficult to study in U.S. history, due largely to data limitations. Data linking in historical data have tended to focus on fathers and sons, largely because men can be linked using their full first and last names (Ferrie, 1996; Long & Ferrie, 2013; Feigenbaum, 2018; Song et al., 2020; Abramitzky et al., 2021; Ward, 2021; Collins & Wanamaker, 2022; Tan, 2022). Census linking projects have been limited in their ability to follow women over time, because women change their surnames at marriage. Moreover, the availability of large, systematically linked data has expanded the possibilities for studying generational changes for men in the late 19th and early 20th centuries.

As an example, the Early Indicators Project, led by Dora Costa, provides an important longitudinal perspective on economic outcomes for men during the middle and late 19*th* century (Wimmer 2003). The data consist of 39,340 Union Army (UA) soldiers, approximately 6,200 of whom were "Colored Troops." These data measure the date of death and provide rich information on disability, health, use of medical care, and pension receipt for men reaching retirement age in the late 19th century. Through links to the 1850 and 1930 censuses, the UA data also include socio-demographic and economic variables. An important limitation of the UA data is that they consist of men only (because women did not serve as soldiers in the Civil War) and most were Northern born.

The Minnesota Population Center (MPC)'s Linked Representative Samples (LRS) merge the full-count 1880 Census to the 1850-1930 Census one-percent samples (Ruggles et al. 2010). This combines economic (e.g., occupation, literacy, labor-force participation, home ownership) and demographic (e.g., age, birthplace, race, marital status, number of children) outcomes for around 500,000 people, including both men and women, across the life course. Although large in scale, important limitations of these data are that most women cannot be linked between their birth and married families (due to surname changes) and intergenerational coverage consists of at most two generations of men (primarily father-son pairs).

More recently, MPC released the Multigenerational Longitudinal Panel (MLP), which uses supervised machine learning to link millions of individuals between every pair of adjacent censuses from 1850 to 1940 (Helgertz et al., 2020). The resulting sample sizes range from around 6 million individuals linked between the 1850 and 1860 censuses and 52 million individuals linked between the 1930 and 1940 censuses. MLP's linking strategy is implemented in two steps. First, men are linked between adjacent censuses as individuals. In this step, MLP exploits rich training data and contextual information in the linking process (e.g., place of residence, co-resident individuals), in addition to names and basic demographics. This strategy increases match rates while reducing the likelihood of false matches, but the final linked sample overrepresents men who do not move and who have the same household members. In the second step, the procedure links household members living with the men linked in the first step. This second step helps link women who are co-residing with their spouses and daughters living with their fathers. As in the LRS, Census data limitations make it nearly impossible to link women who change households or their names at marriage, which means that MLP contains a selected set of women.

Concurrent to the development of MLP, Abramitzky et al. (2020) released census links under the Census Linking Project (CLP), which also links millions of men between every available pair of censuses from 1850 to 1940. Building on the linking approaches in Abramitzky, Boustan, and Eriksson (2012) and Abramitzky, Mill, and Pérez (2019), CLP uses unsupervised machine learning based on name, race and time/place of birth information in the census. (Note that the difference between supervised and unsupervised machine-learning methods is that the latter do not use training data to control error rates or optimize performance, resulting in much smaller linked samples and higher error rates.) CLP does not link women.

Recent studies have addressed these data limitations in several ways. Olivetti and Paserman (2015) take the creative approach of using children's first names to impute their childhood socioeconomic status. For example, they find that, in the 1850 Census, fathers of children named *Edward* had higher occupational rank on average than fathers of *Jesse*. Using this information, they compute intergenerational mobility for daughters and sons by correlating imputed occupational status of fathers in childhood and own (or husband's) occupational status in the 1850-1940 Decennial Censuses. They find that both father-son and father-daughter intergenerational elasticities remained stable around 0.31-0.35 for fathers and sons and 0.34-0.40 for fathers and daughters in the 19*th* century. The elasticities increased to around 0.49 for both father-son and father-daughter pairs observed between 1900 and 1920, then declined to 0.43 for father-son pairs and to 0.37 for father-daughter pairs between 1920 and 1940.

A more direct approach by Craig et al. (2019) uses a supervised machine-learning approach to link Massachusetts marriage certificates to the 1850, 1880, and 1910 Censuses to examine the socio-economic mobility of women in terms of the occupational standing of their husbands and fathers. They linked 10,852 couples (17 percent of all marriage records) at an error rate of 13 percent for the marriage cohorts of 1850-1880, and 20,413 couples (16 percent of all marriage records) at an error rate of 9 percent for the marriage cohorts of 1880-1910.[1] They find intergenerational mobility for women, based on either the occupational income scores or occupational wealth scores of the father and husband, is higher than for men for the 1850-1880 cohorts.[2] Between the first and second cohorts, women and men's mobility increases, but larger increases for men lead rates of intergenerational mobility to converge between the two cohorts.

Buckles et al. (2023) combine Census information with a rich and unique set of records on FamilySearch.org, one of the largest, user-created genealogical platforms, to create the "Census Tree." FamilySearch.org information is largely generated by its users, who search the website's trove of information (e.g., vital records, newspapers, cemetery documents, census records) to link their own

[1] The results are based on the latest available online appendix in 2019 (accessed November 12, 2022).
[2] Craig et al. (2019) calculates occupational wealth score based on the value of real and all property reported in the 1870 Decennial Census 1 percent sample.

family's records. The Census Tree combines these user links (which they estimate to be correct around 95% of the time) with machine links (which they estimate to be correct around 86-89% of the time) to produce a large intergenerational database containing both men and women (Price et al., 2021). Because the final Census Tree differs from the population (in particular, they are less mobile from their birth state, Price et al., 2021, Table 7), Buckles et al. (2023) estimate inverse-propensity scores to reweight the data to match the Census population following the procedure in Bailey et al. (2020). Their intergenerational mobility estimates for men and women use a variety of occupation scores and an instrumental-variables strategy to account for measurement error in occupational status (Solon 1992, Ward 2023). Their results show that intergenerational persistence for men and women is almost identical, falling from around 0.85 to 0.64 between the cohorts of 1840 and 1890 and remaining roughly constant through the cohort of 1910.

More recently, Jácome et al. (2021) pool multiple retrospective surveys from the second half of the 20*th* century to characterize the long-run evolution of intergenerational income mobility. Although these surveys are not drawn from the early 20*th* century, they contain information on cohorts that were born between 1900 and 1920, which overlaps with the youngest cohorts in our analysis sample. An important feature of these survey data is that it contains a fairly representative set of women as adults, who report retrospectively on their fathers' occupations. They find that intergenerational income persistence fell, and relative intergenerational mobility rose, for men and women born between the 1910s and 1940s.

Finally, Bailey et al. (2022b) use supervised machine learning and rich features in the Social Security Application Records (SS-5) to link over 1.7 million men and women born in the U.S. in 1910-1919 and their parents to the 1940 Census at a 3-percent error rate. The SS-5 records contain detailed information on applicants (full birth and married names, sex, race, exact date of birth, state or country of birth) as well as the full names of both parents. These features allow the analysis to identify parent-child relationships and create nationally representative samples containing all states. The limitation of these records is that they contain very few records before the birth cohorts of 1900, which limits their historical perspective. Importantly for this paper, Bailey et al. (2022b) find a high degree of intergenerational persistence in education for both women and men, born from 1910-1989.

The estimates of rising occupational mobility and stable rates of educational mobility in Jácome et al. (2021) and Bailey et al. (2022b) serve as important points of reference for our estimates of women's occupational and educational mobility.

3. New Data to Measure Assortative Matching and Women's Intergenerational Mobility

This paper uses the 1850-1940 Decennial Censuses as well as the Longitudinal Intergenerational Family Electronic Micro-database (LIFE-M) to construct estimates of marital matching. This section describes the 1850-1940 Decennial Censuses and LIFE-M data; our analysis samples for age, nativity, education, and occupational homogamy; and our methods to reweight the data.

A. The Full-Count 1850-1940 Decennial Censuses

For our analysis of age homogamy, we use the 1850-1940 Decennial Censuses from the Minnesota Population Center's (MPC) Integrated Public Use Microdata Series (IPUMS, Ruggles et. al., 2021). We restrict the analytic sample to women who (1) were born in the U.S., (2) were of marriageable age (20-60) at the time of enumeration, and (3) were co-residing with their husbands. Because we focus on assortative marriage in the U.S., we exclude foreign-born women from our analysis. This choice also increases comparability of the census with the LIFE-M data, because foreign-born individuals are not included in the LIFE-M sampling frame of U.S. birth certificates. In addition, many foreign-born women married in their country of origin before immigrating, and these marriage outcomes may reflect the dynamics of marriage markets outside the U.S. Note that although all daughters are U.S.-born, many have fathers who are immigrants. The sample sizes for women meeting these sample criteria in the Census and LIFE-M data are presented in Table 1, panel B.

For our analysis of marital matching on nativity, we use the full-count 1880-1930 Censuses, in which all individuals report their fathers' birthplaces directly to the census enumerator. This allows us to consider changes in nativity homogamy for a census population without the need to link individuals.[3] The sample sizes and link rates for women meeting these sample criteria are presented in Table 1, panel C.

For our analysis of marital matching on education, we use only the 1940 Census, which was the first census in which individuals reported their educational attainment. This analysis is restricted to husbands and wives residing together at the time of enumeration. See Table 1, panel D.

B. The Longitudinal, Intergenerational Family Electronic Micro-database (LIFE-M)

For each of these analyses, we supplement the census data with the newly available LIFE-M database, which links millions of birth records to other vital records (death and marriage records) and the historical censuses, with the goal of minimizing linking errors while maximizing link rates.[4] The project's supervised learning models target Type I error rates below 3 percent, which are further reduced through cross-checks across multiple record links. The LIFE-M data is particularly useful for examining women's intergenerational outcomes, because vital records contain rich information on women's birth (or "maiden") names, their parents' names, and their spouses' names and allows women to be tracked from their birth to marriage families (Bailey et. al., 2022). The large sample of linked women allows us to study the evolution of marriage outcomes for women across birth cohorts. We restrict our analysis to the LIFE-M women who were (1) born in Ohio between 1865 and 1920 (a narrower time frame than our restriction on the census data, due to available data), (2) of marriageable age (20-60) when observed in the censuses, and (3) co-residing with their husband in the linked censuses. The decennial census data provide the target population for our reweighting of the linked samples (Bailey et al. 2020). Our methodology for this reweighting is discussed in later sections.

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[3] This question is not available prior to 1880. In the 1940 Census, only a sample-line person was asked for their father's birthplace. This means that a woman who is the sample-line respondent will report her own father's birthplace. However, her spouse, who is not a sample-line respondent, will not. Therefore, we cannot observe both father and father-in-law's birthplace for women who do not co-reside with their fathers-in-law, which is a selected sample. For instance, in the 1940 Census, among 1,255,870 women satisfying our data restrictions and being the sample-line respondent, only 24,927 women (2 percent) co-resided with their fathers-in-law.

[4] LIFE-M does not link birth records to the 1890 or the 1930 Census. The full-count 1890 Census is not available, and the 1930 Census is planned for future work. Bailey et al. (2022b) present detailed information on data coverage and linking procedures for interested readers. This analysis excludes LIFE-M's North Carolina links, because of the limited sample sizes for our birth cohorts of interest.

C. LIFE-M Sample Sizes for Different Dimensions of Assortative Matching

Table 1 reports the number of women in the LIFE-M analytic samples for different measures of assortative matching, as well as the percentage of analogous population covered by the LIFE-M samples. LIFE-M samples generally link between 21 percent (or 79,122 women in the 1900 Census) to 30 percent (or 391,643 women in the 1940 Census) of the female population that satisfies our sample restrictions. If a woman is linked to more than one census, we include these links as separate observations in our data set. This data structure allows us to observe women from the same birth cohort at different ages across censuses and, therefore, model marriage patterns across ages.[5]

Panel B shows the sample for age homogamy, which is the least restrictive, because it only requires the age of a woman and her husband (no information about her father is needed). The sample for nativity homogamy in panel C requires the birthplaces of both a woman's father and her father-in-law. We observe the father's birthplace either from the couple's direct reports (for couples linked to the 1900, 1910, and 1920 Censuses) or through a father's own links to any census (where he reported his own birthplace).[6] Panel D shows couples linked to the 1940 Census to examine assortative matching by education.

The sample to estimate intergenerational mobility by occupation requires the most information, including both the occupations of a woman's father and her husband.[7] Whereas a husband's occupation is reported directly in the census in which he co-resides with his wife, we must additionally link women to their fathers to obtain fathers' occupations. As shown in Table 1, these additional data restrictions reduce sample sizes: the age sample contains 919,025 observations (panel B, column 5), while the intergenerational mobility sample contains 263,258 observations (panel E, column 5).

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[5] Because of the age limits we apply, women born after 1900 are only observed in the 1940 Census, because they were younger than 20 in 1920.

[6] An alternative measure of nativity homogamy compares the birthplaces of a woman's father and her husband. In that case, the analysis requires additional information on the father's birthplace, as the husband's birthplace is always reported in the censuses. See Appendix C.

[7] As an alternative measure of occupational homogamy, we also compare the occupations of a woman's father and father-in-law in Appendix D. In this case, the data require additional information on the father-in-law's occupation, which makes the analytic sample even more restrictive.

D. Representativeness of Linked Samples

One of the biggest concerns with linked samples relates to their representativeness (Bailey et al., 2020), especially because non-representative samples may lead to misleading inferences about population-level intergenerational mobility (Bailey et al. 2020, Jacome et al. 2021). To improve the representativeness of our samples, we create custom weights for each linked sample in Table 1 using inverse propensity scores for each birth cohort and census year (DiNardo et al., 1996; Heckman et al., 1998; Bailey et al., 2020). Appendix A describes this procedure in detail.

Table 2 presents descriptive statistics for the 1900 to 1940 Censuses (columns 1, 10, 15) as well as the unweighted and inverse-propensity-score weighted samples of the LIFE-M data (columns 2, 4, 6, 8, 11, 13, 16, 18). Differences between the target census population and the weighted LIFE-M samples are in columns 5, 9, 14, and 19, with standard errors listed beneath in parentheses. The unweighted samples are noticeably different in almost every characteristic, including individuals' birth year (due to the LIFE-M sampling frame) as well as other characteristics such as husband's occupational income score, co-residence with parents, out-of-birth-state migration, and urban residence, among others. In contrast, the weighted samples are more balanced in terms of these characteristics. Although some of the reweighted means are statistically different from the Census, this is due to very large sample sizes: the magnitudes of these differences are very small, especially relative to the unweighted sample differences. Similarity in observed characteristics does not guarantee balance in unobserved characteristics, but the comparability in observed characteristics is reassuring. As an additional point of comparison, we later show that both the magnitudes and trends in our weighted LIFE-M linked samples closely track the results in the census across cohorts when available, whereas the unweighted samples do not (Appendix Figure A.1-A.4).

4. Statistical Methodology

We characterize historical trends in assortative matching in four main dimensions: age, nativity, education, and intergenerational occupational mobility. Ideal data for our analysis would include marital outcomes and educational and occupational histories for all individuals in the U.S. In practice, we observe only couples who are married and co-residing at a point in time, which means that observed married couples are often different from the population of married couples. Figure 1 shows this changing selection of the observed couples by age, which presents a key challenge for the analysis. Panel A depicts the average age difference between husbands and wives by the women's birth cohort in the 1850 to 1940 Censuses. Within each census year, the average age difference within a couple is largest when the cohort is younger and smaller when the cohort is older. For example, married women born in 1880 who were aged 20 in the 1900 Census (empty square markers) were more than six years younger than their husbands on average, whereas the same cohort of women aged 50 in the 1930 Census (empty circle markers) were less than four years younger than their husbands. This pattern reflects the fact that women who marry at younger ages disproportionately marry older men. It also reflects survival bias in marriages: women who are age 50 are much less likely to be married to a partner who is much older than them, because his mortality risk increases in age. Failing to adjust for this selection could severely bias estimates of age homogamy and, potentially, other measures of marital sorting.

To adjust for selection into marriage by age, we estimate the following linear regression model by Ordinary Least Squares (OLS),

$$Y_{it} = f_k + q(age_{it}) + \varepsilon_{it} \tag{1}$$

where the dependent variable, Y_{it}, is the marriage outcome of interest, either the husband-wife age difference or a binary variable for same nativity of husband and father, for woman i co-residing with her husband in the census year t.[8] We code "same nativity" if a woman's father and father-in-law were born in the same country or grouping of countries. Considering the border changes in many nations in the late 19*th* and early 20*th* centuries, we combine countries that are close to each other geographically and culturally that changed borders into the same country group. While this measure will overstate the share of father-father-in-law nativity homogamy in terms of individual countries, we are more confident that

[8] We also consider alternative measures, such as the absolute difference in age between husbands and wives and a binary measure of whether a woman is over three years younger than her husband. These results are reported in Appendix B and change the story of our main analysis little.

changes in this measure capture real differences in country and culture of origin rather than changes in national borders.[9] We group women into 5-year cohort bins, f_k, to reduce noise, and $q(age_{it})$ is a quartic function of the cohort's age in census year t. After estimating this model using the full-count 1850-1940 U.S. Decennial Censuses (except for the unavailable 1890 Census), we predict outcomes for each birth cohort at a common age—35, thereby adjusting the data for selection into or out of married co-residence at different cohort ages in the census. Standard errors are clustered for dependence at the birth cohort year level (Moulton 1986).

In addition, these Census estimates can be compared to those from the LIFE-M sample, which are weighted to reflect observed characteristics in the Census using inverse-propensity-score weights (Bailey et al. 2020). Our ability to compare estimates across these samples allows us to assess the quality of the LIFE-M sample as well as assess the external validity of Ohio relative to a nationally representative, unlinked source. Because the censuses are available, the LIFE-M sample is not necessary to examine age or nativity homogamy. However, the comparison of the LIFE-M estimates to census estimates is useful for analyses in which the census cannot be used, for example, for the intergenerational occupational mobility analyses.

Our analysis of marital matching on education builds on a large literature on intergenerational mobility (Black and Devereux, 2011; Chetty et al., 2014; Chetty et al., 2017; Deutscher and Mazumder, 2023). We measure the educational attainment of wives and their husbands in the 1940 Census, the first to report this outcome.[10] Because we only observe education in one Census, we cannot adjust by age as we do in the previous analysis. For this reason, the analysis uses women ages 30 to 60 to minimize the effects

[9] Appendix C describes these detailed country groups. We also consider an alternative measure of same-nativity marriage: whether the woman's father and husband had the same birth country group. Although closely related to the baseline measure, the two definitions capture marital sorting in different ways. For instance, if a U.S.-born daughter of a German immigrant married a U.S.-born son of another German immigrant, the marriage is a same-nativity marriage according to our baseline definition. However, it is regarded as a cross-nativity marriage using the second definition because the woman's father was born in Germany and her husband was born in the U.S. The baseline definition is thereby less affected by immigration shocks and better reflects the intergenerational persistence of nativity preference for partners. These alternative measures yield similar results and are presented in Appendix C.

[10] Censuses before 1940 ask about literacy but not educational attainment.

of selection into marriage by age. Following Greenwood et al. (2014, 2016) and Eika et al. (2019), we examine assortative matching using OLS to estimate the following linear model,

$$Educ_i^W = \sum_j \gamma_j D_j \times Educ_i + f_j + \varepsilon_i \tag{2}$$

where $Educ_i^W$ is the educational attainment for wife i; $Educ_i$ is her husband's educational attainment; D_j is a dummy variable for women born in year j; and f_j captures individual birth-year fixed effects. The cohort-specific slope coefficient γ_j is a measure of educational sorting for women of birth cohort j. To account for changes in the marginal distributions of education across time, we also present intergenerational educational correlation estimates, in which $Educ^W$ and $Educ$ in equation (3) are normalized to have a mean of 0 and a standard deviation of 1 within cohort groups. Because there are so many ties (identical values) for educational attainment, we do not use the rank-rank approach that is often used for income (Chetty et al., 2014). Standard errors are clustered for dependence at the birth cohort year level (Moulton 1986).

A third analysis uses only the LIFE-M sample to compute intergenerational occupational persistence between a woman's father and her husband using the occupational score of their occupation. We choose to associate a husband's occupation score rather than women's own, because few women participated in the labor market in this period. This measure has several other advantages as well. First, occupations are readily reported in all historical censuses, which allows us to consider a long period of time. Second, occupation captures a more permanent component of socio-economic status than income, because it does not experience transitory shocks and is less subject to measurement error. In addition, occupational scores are used in other studies of intergenerational mobility (Olivetti and Paserman, 2015; Craig et. al., 2019), which facilitates straightforward comparisons to important findings in the literature.[11]

[11] We choose to use the occupational income scores to facilitate comparisons with studies most related to our question of interest. Ongoing work examines the robustness of our results to using alternative occupational scores. Collins and Wanamaker (2022) generate occupational scores based on 1940 wage income information by 3-digit occupation, with some adjustments for self-employed workers and farm workers; these scores are computed separately by race and census division of residence. Song et al. (2020) use a status measure that is based on literacy/education by occupation. Ward (2021) addresses racial and regional inequality by using the "adjusted Song score" which is based on literacy/education by occupation, race, and region.

We estimate the following specification of intergenerational persistence by OLS,

$$log(OccScore)_i = \sum_k \gamma_k D_k \times log(ParentOccScore)_i + log(ParentOccScore)_i \times q\left(age_i\right) + f_k + \varepsilon_i \quad (3)$$

where $log(OccScore)$ captures the occupational standing of the husband of woman i, in the observed census year t, and $log(ParentOccScore)_i$ captures the occupational standing of the woman's father. We group women into 5-year cohort bins, where D_k is a dummy variable for women born in cohort k (k =1865-1867, 1868-1872, 1873-1877, ,..., 1912-1917, 1918-1920) and f_k is a set of cohort fixed effects. A quartic function of the woman's age in the census, $q\left(age_i\right)$, helps capture lifecycle bias and age-based selection into marriage.

The coefficient of interest, γ, is an estimate of intergenerational persistence, or how fathers' occupational standing is associated with the occupational standing of their daughters' husbands. A higher value of γ corresponds to higher persistence in socio-economic status across generations, or equivalently lower social mobility. Importantly, γ is both affected by the parent-child correlation, but also the relative variance in their outcomes (Gihleb and Lang, 2016; Eika et. al., 2019). To adjust for the fact that the distribution of occupational scores evolves over time, we also present intergenerational correlation estimates, in which *logOccscore* and *logParentOccScore* in equation (2) are normalized to have a mean of 0 and a standard deviation of 1 within cohort groups.

We supplement these log-log estimates using a rank-rank approach (Chetty et al., 2014). For these analyses, we rank father's occupational score relative to all the fathers of the U.S.-born women in cohort *j* from the most recent census when they were under age 10. For instance, we use the national distribution of fathers' occupational income scores for women born between 1901 and 1910 from the 1910 Census, when most girls were co-residing with their fathers. We rank husbands by occupational score for a woman in birth cohort j observed in census year t. We then estimate equation (2) replacing *logOccscore* with occupational rankings. A higher rank-rank coefficient suggests stronger marital sorting on occupation and lower intergenerational mobility for women. All regressions are weighted by the inverse propensity score weights and standard errors are clustered at the birth cohort level (Moulton 1986).

Both the rank-rank coefficients and intergenerational elasticities measure relative mobility, without much information on upward or downward mobility. Following Chetty et al. (2017), our third measure is absolute mobility: (1) the mean husband's occupational rank for a woman born to a father ranked below the median in the fathers' occupational score distribution, and (2) the mean husband's occupational rank for a woman born to a father ranked above the median. The former measures absolute upward mobility, whereas the latter measures absolute downward mobility. See Deutscher and Mazumder (2023) for an in-depth comparison of these measures.

5. Results: Marital Matching in the Late 19*th* and Early 20*th* Centuries

We begin with an analysis of age homogamy. Figure 1B compares the age-adjusted and unadjusted (raw) series of husband-wife age differences for cohorts born from 1790 to 1920 (married from around 1810 to 1940). The unadjusted series is based on the simple averages by cohort in the combined censuses. The age-adjustment has a significant effect on the antebellum national trends, correcting the sharp upward rise in husband-wife age differences for the fact that women born earlier in the century are older when they are observed in the 1850 Census. The age-adjusted series increases from 4.7 years for the 1790 cohort to 5.3 years for the 1840 cohort, whereas the unadjusted series increases from 3.2 years to 5.3 years for the same cohorts. After peaking for cohorts born from 1830 to 1840 at 5.3, husband-wife age differences decrease to around 5 years for the 1880 birth cohort—the women getting married around the turn of the century. In short, age homogamy in marriage changed much more modestly over the 19*th* century than previously believed—much less than implied by the series unadjusted for age-selection (cf. Ferrie and Rolf 2008).[12] The big picture is that relative stability in age homogamy during the 19*th* century makes the transition to smaller within-couple age gaps beginning in the 20*th* century appear more exceptional, rather than a return to antebellum U.S. marriage patterns.

[12] Appendix Figure B.1, Panels A and B, shows a similar trend in the absolute age difference and the probability of marrying a husband at least three years older.

We also compare changes in age homogamy for the weighted LIFE-M sample to two references: (1) the age-adjusted population for Ohio-born women for the same cohorts from the Census and (2) the age-adjusted population for all U.S.-born women. Figure 2A plots these results for women born between 1865 and 1920 and married between roughly 1885 and 1940. Importantly, both the levels and trends in the LIFE-M data track those for the population of Ohio-born women in the Census. This finding underscores the ability of high-quality links and inverse-propensity score reweighting to recover population parameters even when linked samples are not representative. This finding increases our confidence in the results for occupational sorting that are only based on linked samples when census estimates are unavailable.

Another key finding is that, while trends in age homogamy among Ohio-born women appear similar to changes in the U.S. after 1880, the average husband-wife age difference was around half a year smaller in Ohio—a difference likely due to Ohio's considerable industrialization and economic development relative to the national average. Indeed, Figure 2B makes clear the pattern in age differences by level of economic development, with the most developed census region (Northeast) having smaller husband-wife age differences than the least developed census region (South). The Ohio sample from LIFE-M exhibits a smaller age gap on average but follows patterns identical to the Midwest.

We next extend our analysis of marital homogamy to nativity. Figure 3 plots the age-adjusted estimates of the likelihood of same-nativity marriages based on birth country groups of a woman's father and father-in-law. The age-adjusted trend shows a continuous decline in same-nativity marriages between the 1820 and 1890 cohorts, roughly married between 1840 and 1930. The probability of a woman marrying a husband from the same nativity group decreased, from 92 percent for the 1820 cohort to around 75 percent for the 1890 cohort. After that, the age-adjusted probability of a same-nativity marriage remained fairly stable between the 1890 and 1910 cohorts (marriages roughly occurring between 1910 and 1940), whereas the unadjusted trend shows significantly increasing same-nativity marriages for this period. The differences between the unadjusted trend and the age-adjusted trend can also be explained by selection into marriage for more recent cohorts. As Appendix Figure C.1 shows, women marrying at younger ages (which are the ones we observe for these younger cohorts) tended to marry husbands in the same nativity group, and the age adjustment helps adjust for this tendency.[13]

Figure 3B presents the probability of a same-nativity marriage for Ohio-born women in both the LIFE-M sample and analogous census population data. Similar to the estimates for husband-wife age differences, the age-adjusted LIFE-M estimates and census estimates for Ohio-born women are almost identical (so much so that the dashed line for the census is barely visible in the figure once the LIFE-M data appear for women born after 1865). This similarity again lends credibility to the linked LIFE-M sample's findings and underscores the power of using inverse-propensity reweighting to achieve balance. A second finding, however, is the divergence in the trend for Ohio-born women from U.S.-born women. Among Ohio-born women, nativity homogamy *increased* from around 0.75 to 0.82 between 1885 and 1940 (cohorts born between 1865 and 1910), signaling an increase in marital sorting by father's country group of origin in the rapidly industrializing economies of the Midwest. Examining regional trends for all U.S.-born women in Figure 3C shows only slight increases in nativity homogamy in the broader Midwest census region and West in the early 20*th* century (cohorts marrying between 1910 and 1930), suggesting that the patterns in Ohio were more the exception than the norm in this period.

Next, we consider changes in marital matching on education, as measured by the association of husbands' and wives' education in the 1940 Census using equation (2). Although these trends are not well estimated for cohorts born before 1880, these comparisons are available for all U.S.-born individuals as well as for Ohio-born individuals in the 1940 Census and LIFE-M samples.[14] Figure 4 shows the cohort-specific slope coefficients (panel A) and correlations (panel B) using equation (2). Notably, the reweighted LIFE-M data again track the census estimates for Ohio-born individuals very closely, which lends credibility to results using the LIFE-M sample when it cannot be benchmarked in the

[13] Appendix Figure C.2 shows a similar national trend when defining same-nativity marriages as a woman's father and husband being born in the same group of countries. Similar to the series in Figure 3A, we find a significant decline in same-nativity marriage between the 1820 and 1870 cohort, and after that, the probability of a same-nativity marriage remained steady between 1870 and 1910.

[14] The 1940 Census is the first to ask this question and the education-mortality gradient makes older cohorts more selected and less representative.

intergenerational analyses. The results show that the association of husbands' and wives' slope coefficients remained stable for thirty years, for women born between 1880 and 1910 (married between 1900 and 1930), decreasing very slightly for the youngest cohorts (born between 1905-1910). Similarly, correlation coefficients increased by only a few points over the period, suggesting very slight increases in assortative matching on education after accounting for the decreasing variance in women's educational attainment relative to men's across cohorts.

In addition, differences between the estimates for the entire U.S. versus Ohio-born residents suggest that Ohio had less assortative matching on education, which is important to keep in mind when considering the external validity of the estimates from the LIFE-M sample. Figure 5 shows the correlation coefficients by census region, which indicates that women in the Northeast, Midwest and West were less assortatively matched on education than women in the South, which raises the estimates for the nation. Like the national trends, however, the regional trends are very stable over time.

In contrast, Figure 6 shows that women's intergenerational mobility, as measured by father's and husband's occupational standing, was stable in the 19*th* century and increased meaningfully in the early 20*th* century. Importantly, these comparisons are not available for all U.S.-born women, so this figure only uses the LIFE-M sample for women born in Ohio from 1865 to 1920. Panel A plots the cohort-specific rank-rank coefficients, the intergenerational elasticities (IGE, or log-log coefficients), and correlations based on the regressions specified in equation (3). For the 1865 to 1890 cohorts (marriages from 1890 to 1910), we find little change in either the rank-rank or IGE estimates. Assortative matching in terms of husbands' and fathers' occupational standing was fairly stable in the 19*th* century.

However, intergenerational persistence declined, and mobility increased, rapidly for the cohorts born between 1890 and 1920–marriages taking place between 1910-1940. Both the IGE and rank-rank coefficients decrease, from 0.32 for the 1890 cohort to 0.15 for the 1920 cohort, which correspond to marriages occurring between 1910 and 1940. Panel B plots changes in absolute mobility, which follows similar patterns. For all cohorts, the average occupational rank of husbands was significantly higher for daughters of above-median occupational rank fathers than for daughters of below-median occupational rank fathers. This is strong evidence for assortative marital matching by socio-economic status. These patterns remained fairly stable for cohorts born between 1865 and 1890 (marriages from 1885 to 1910), but both upward and downward mobility increased sharply for cohorts born between 1890 and 1920 (marriages from 1910 to 1940).

Although we cannot compute estimates for other census regions, Figure 7 compares our estimates to those from other studies. Our estimates of Ohio-born women are slightly lower in level but compare favorably to Olivetti and Passerman (2015), especially for their Midwest sample. The fact that names are stickier than occupations, which can be upgraded over one's lifetime, may explain why occupational homogamy appears lower and economic mobility appears higher using occupational measures. Differences from levels in Jacome et al. (2021) likely reflect the fact that retrospective reports of fathers' occupations may reflect his most persistent occupation rather than his work at only one point in time, as measured in the census.[15] Said another way, our measures of occupation from the census may mismeasure socio-economic standing for much of childhood relative to retrospective reports due to transitory factors or life-cycle biases (Solon 1992, Mazumder 2005).

It is harder to interpret the differences in levels for Craig et al. (2019) who also use occupational measures, but lower match rates (10 to 13 percent) and higher linking error rates (9 to 13 percent) than in the LIFE-M data could make their data less representative or attenuate intergenerational elasticities. In addition, intergenerational occupational mobility may differ between Massachusetts and Ohio, as suggested by our age, nativity, and education results.

The largest differences in levels and trends emerge between our estimates and those of Buckles et al. (2023) who use the CensusTree data, a different occupational-income score definition, and an instrumental variables approach to account for measurement error in occupational status. These differences in outcomes remain open questions for the literature to resolve.

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[15] See Ward (2021) for an in depth discussion of this source of measurement error in occupations in historical census data and Haider and Solon (2006) for a discussion of lifecycle bias more generally.

As a complement to these findings, we also examine marital sorting by occupational standing of a woman's father and father-in-law, instead of the husband. The level of marital sorting by parents' socioeconomic outcomes can reflect the relative strength of ascribed and acquired traits in the marriage market (Charles et al., 2013). We measure the sorting by fathers' occupations by estimating equation (3), but we replace the husband's occupational standing with that of his own father (Appendix Figure D.1 plots the results). We find a similar trend between the 1870 and 1890 cohort, and the rank-rank coefficients decreased significantly from 0.35 for the 1890 cohort to around 0.25 for the 1910 cohort. The decline is smaller than that of rank-rank coefficients between father and husband (in Figure 6, panel A), suggesting that the increase in intergenerational mobility of women was caused by both decreasing marital sorting on parents' socioeconomic status and increasing intergenerational mobility of husbands.

Overall, the trends in Figure 7 reinforce the idea that occupational homogamy changed little in the late 19*th* century for marriages starting between 1880 and 1900 (cohorts born between 1860-1880). However, intergenerational persistence was decreasing and economic mobility was increasing for women born in the early 20*th* century.

6. Conclusion

This paper characterizes the evolution of marital matching during the late 19*th* and early 20*th* century, the eras of mass immigration, rapid industrialization and economic growth, urbanization, and the Great Depression. We find that age homogamy changed very little during the 19*th* century, which makes the rapid transition to smaller within-couple age gaps in the 20*th* century appear exceptional rather than a return to antebellum U.S. marriage patterns. As mass immigration to the U.S. transformed the nation, the likelihood that a woman was married to a man whose father was born in the same group of countries as her father declined rapidly—a decrease in nativity homogamy suggesting inter-marriage helped stir the U.S. melting pot. From 1900 to 1940, women's intergenerational mobility in terms of her husband's occupational standing relative to her father's increased, whereas the association of husbands' and wives' educational attainment changed little. As the High School Movement transformed America's public school landscape, we conclude that women's own educational attainment remained a powerful force in shaping their socioeconomic status in adulthood. Understanding how these trends shaped—and were themselves shaped—by the Demographic Transition, rapid industrialization, and the transformation of women's paid work remains for future research.

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Table 1. Summary of LIFE-M Linked Data and Analysis Samples

	1850 Census	1860 Census	1870 Census	1880 Census	1900 Census	1910 Census	1920 Census	1930 Census	1940 Census	All Censuses
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Ever-married woman born in the U.S. and ages 20-60 in the census										
All	2,402,578	3,074,331	4,372,836	7,116,727	11,263,010	14,301,494	17,509,586	22,037,814	26,552,781	108,631,120
Born in Ohio, 1865-1920					371,560	671,904	977,037		1,301,988	3,322,489
LIFE-M links					79,122	179,210	293,196		391,643	943,171
% population linked					***21.3%***	***26.7%***	***30.0%***		***30.1%***	***28.4%***
B. Age Sample: Panel A & co-resident with husband										
All	2,402,578	3,074,331	4,372,798	5,992,634	9,502,522	12,132,365	14,902,751	18,616,633	22,275,760	93,272,372
Born in Ohio, 1865-1920					342,633	609,060	862,236		1,123,879	2,937,808
LIFE-M links					78,078	176,882	290,337		373,728	919,025
% population linked					***22.8%***	***29.0%***	***33.7%***		***33.3%***	***31.3%***
C. Nativity Sample: Panel B & non-missing birthplace of father and father-in-law										
All				5,992,634	9,502,522	12,132,365	14,902,749	18,616,633		61,146,903
Born in Ohio, 1865-1920					342,633	609,060	862,236			1,813,929
LIFE-M links					78,091	176,885	290,331		164,969	710,276
% population linked					***22.8%***	***29.0%***	***33.7%***			
D. Education sample: Panel B & non-missing education of couple										
All									21,807,116	
Born in Ohio, 1865-1920									1,110,811	
LIFE-M links									368,720	
% population linked									***33.2%***	
E. Occupational intergenerational mobility: Panel B & non-missing occupations of father and husband										
LIFE-M links					9,669	28,223	68,524		156,842	263,258

Notes: The table reports the number of women that satisfy various criteria for different samples. We first report the U.S.-born female population and then the Ohio-born female population satisfying the sample conditions. Then we report the number of women in the LIFE-M who are linked to each census and satisfy the same conditions. Finally, we calculate the percentage of the female population linked through LIFE-M (bold). In Panel C, the population in the 1940 Census is missing because father's birthplace is only reported for sample-line respondents but not all individuals. Panel E excludes the census population and the link rate because it is unknown how many fathers and husbands have non-missing information outside the LIFE-M sample. The occupation of the father is only available in the LIFE-M sample, which contains the occupation of the father from his own link to any census between 1880 and 1940.

Table 2. Sample Means in the Ohio-Born Population and LIFE-M Data

	Panel A. Age and Nativity Sample								
	Ohio-born sample Table 1, Panel B	Age Sample				Nativity Sample			
	1900-40 Censuses	LIFE-M unweighted	Diff (2)-(1)	LIFE-M weighted	Diff (4)-(1)	LIFE-M unweighted	Diff (6)-(1)	LIFE-M weighted	Diff (8)-(1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Woman's birth year	1888	1889	1.157*** (0.016)	1888	0.00 (0.030)	1885	-3.019*** (0.0154)	1888	0.00 (0.048)
Woman's age	35.52	35.63	0.107*** (0.012)	35.52	0.00 (0.018)	35.25	-0.270*** (0.013)	35.52	0.00 (0.023)
Husband's age	39.53	39.37	-0.160*** (0.013)	39.48	-0.052** (0.020)	39.07	-0.468*** (0.014)	1884	0.089*** (0.025)
Urban residence	0.576	0.513	-0.062*** (0.0006)	0.576	0.0004 (0.001)	0.481	-0.094*** (0.0007)	0.575	-0.0004 (0.0011)
Farm residence	0.218	0.272	0.054*** (0.0005)	0.218	0.0001 (0.001)	0.300	0.082*** (0.0006)	0.219	0.0007 (0.0008)
Migration out of birth state	0.242	0.058	-0.184*** (0.0003)	0.241	-0.001 (0.001)	0.052	-0.190*** (0.0004)	0.238	-0.004** (0.0015)
Coresidence with father	0.031	0.027	-0.004*** (0.0002)	0.031	-0.0004 (0.0003)	0.026	-0.005*** (0.0002)	0.030	-0.0008* (0.0004)
Coresidence with child under 5	0.352	0.459	0.107*** (0.0006)	0.352	0.0004 (0.0008)	0.509	0.157*** (0.0007)	0.353	0.001 (0.001)
Foreign-born husband	0.058	0.047	-0.011*** (0.0003)	0.057	-0.0008 (0.0006)	0.045	-0.013*** (0.0003)	0.055	-0.003*** (0.0008)
Husband's occupational income score	24.81	24.31	-0.500*** (0.014)	24.81	0.007 (0.023)	23.62	-1.184*** (0.016)	24.82	0.013 (0.028)

Notes: This table presents means for the population of interest (columns 1, 10, 15), the unweighted LIFE-M samples (columns 2, 6, 11, and 16), the inverse propensity-score reweighted LIFE-M samples (columns 4, 8, 13, and 18). The mean differences between the unweighted linked samples and the target population are reported in columns 3, 7, 12, and 16. The differences between the reweighted linked samples and the target population are reported in columns 5, 9, 14, and 19. See text for more details. *** indicates statistically different from the population at the 1-percent level; ** at the 5-percent level; and * at the 10-percent level. Husbands' occupational income scores are based on the median total income (in hundreds of 1950 dollars) of all persons with that particular occupation in 1950. The occupational scores are provided by IPUMS (Ruggles et al., 2021).

Sources: 1880-1940 Full-Count Census Data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a).

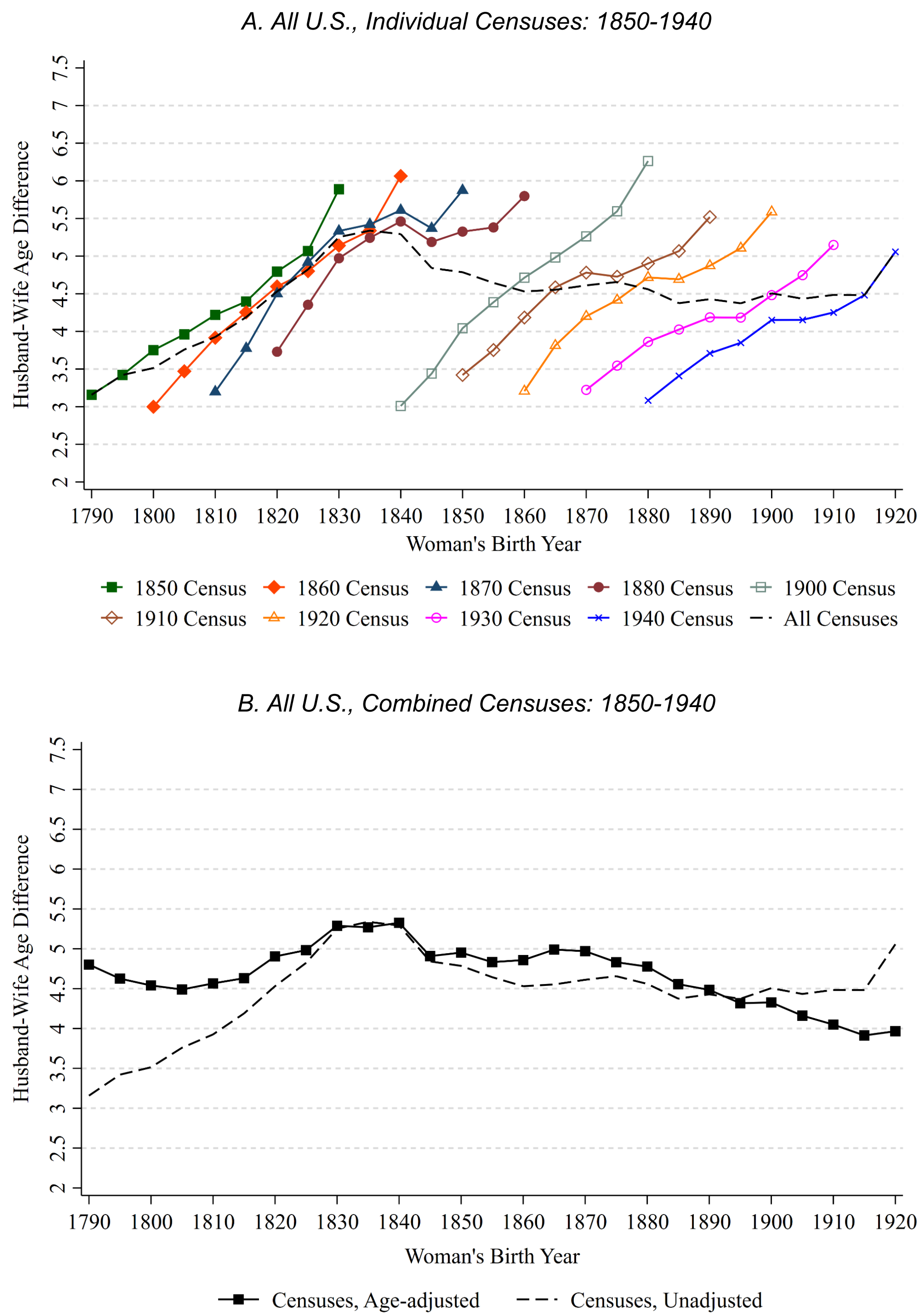
Table 2. Sample Means in the Ohio-Born Population and LIFE-M Data (Continued)

	Panel B. Education and Occupation Sample									
	Ohio-born Sample Table 1, Panel D	Education Sample				Ohio-born Sample Table 1, Panel E	Occupation Sample			
	1940 Census	LIFE-M unweighted	Diff (11)-(10)	LIFE-M weighted	Diff (13)-(10)	1900-40 Censuses	LIFE-M unweighted	Diff (16)-(15)	LIFE-M weighted	Diff (18)-(15)
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Woman's birth year	1897	1897	-0.169*** (.0173)	1897	0.000 (0.023)	1888	1896	7.927*** (0.027)	1888	0.000 (0.111)
Woman's age	43.17	43.34	0.169*** (0.0173)	43.17	0.000 (0.023)	35.37	34.03	-1.342*** (0.019)	35.37	0.000 (0.060)
Husband's age	46.53	46.66	0.132*** (0.0193)	46.51	0.02 (0.025)	39.28	37.52	-1.765*** (0.020)	39.12	-0.160** (0.064)
Urban residence	0.6348	0.584	-0.051*** (0.0010)	0.6350	0.0002 (0.001)	0.572	0.515	-0.057*** (0.001)	0.577	0.005 (0.003)
Farm residence	0.1778	0.222	0.044*** (0.0009)	0.1780	0.0002 (0.0009)	0.225	0.269	0.044*** (0.001)	0.224	-0.001 (0.003)
Migration out of birth state	0.2246	0.080	-0.145*** (0.0007)	0.2247	0.0001 (0.0013)	0.238	0.055	-0.183*** (0.0005)	0.231	-0.007 (0.005)
Coresidence with father	0.0251	0.023	-0.002*** (0.0003)	0.0250	-0.0002 (0.0004)	0.031	0.067	0.036*** (0.0005)	0.032	0.001 (0.001)
Coresidence with child under 5	0.1563	0.163	0.007*** (0.0008)	0.1562	-0.0001 (0.0009)	0.356	0.456	0.100*** (0.001)	0.351	- 0.005* (0.003)
Foreign-born husband	0.0546	0.046	-0.009*** (0.0004)	0.0542	-0.0004 (0.0006)	0.057	0.034	-0.024*** (0.0004)	0.054	-0.003 (0.002)
Husband's occupational income score	26.65	26.21	-0.442*** (.0246)	26.67	0.015 (0.029)	26.11	25.52	-0.586*** (0.022)	26.08	-0.023 (0.076)

Notes: Same as above.

Sources: 1880-1940 Full-Count Census Data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a).

Figure 1. Husband-Wife Age Differences, by Wife's Birth Cohort

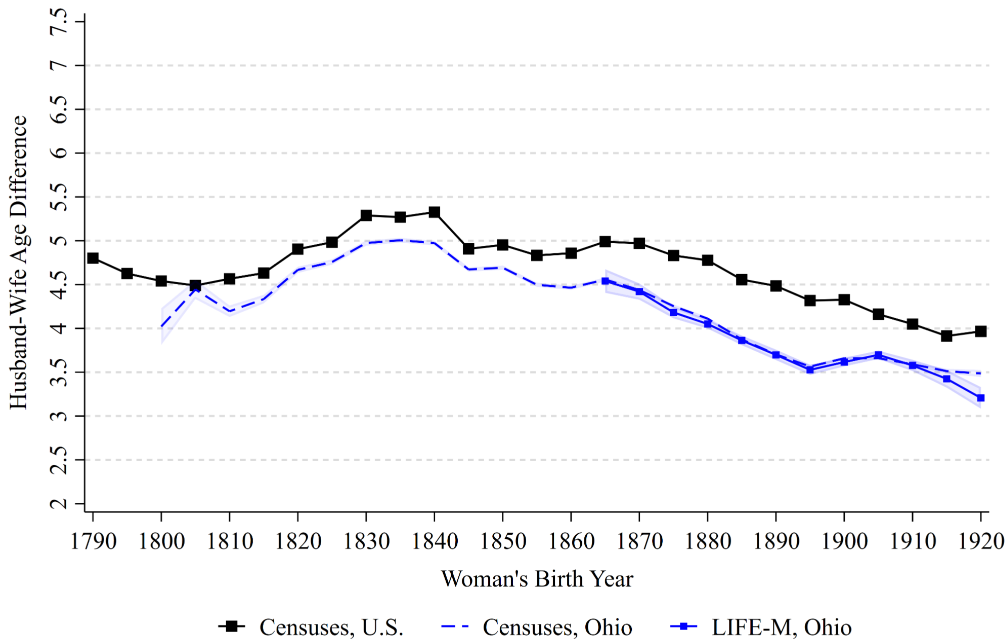


Notes: The figures depict the mean husband-wife age difference (husband's minus wife's age) by woman's birth year. Due to the age-heaping in the Census and sample sizes in LIFE-M, we group women into five-year birth cohorts and plot the estimates for the midpoint of each five-year birth-year group. Panel A presents the mean age differences by census for the sample in Table 1A and also the birth cohort average (dashed line). Panel B presents the cohort-specific mean, unadjusted and age-adjusted as described in the text.

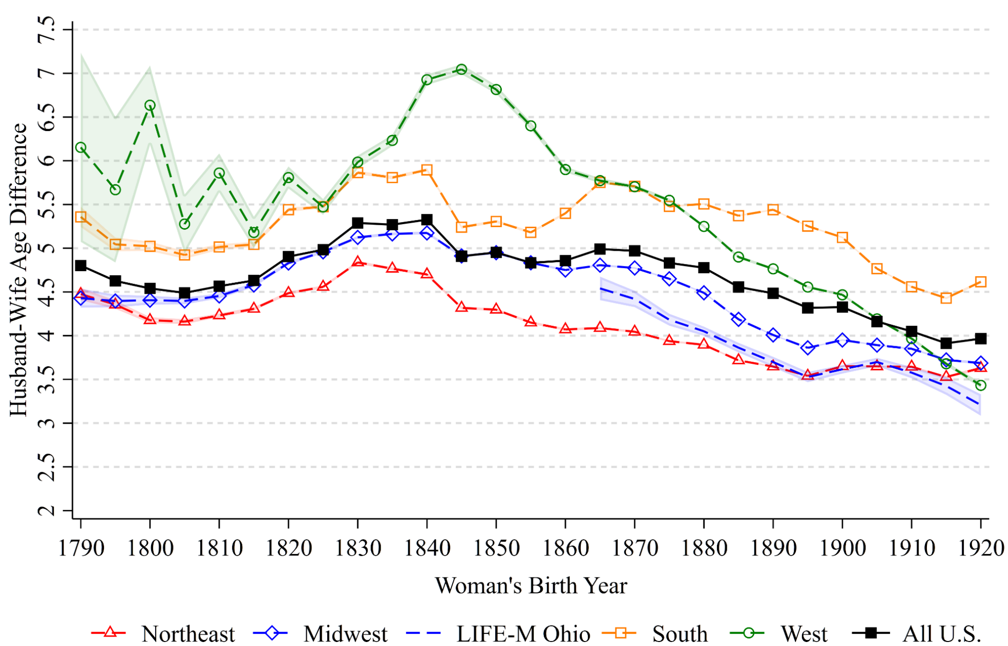
Sources: 1850-1940 Full-Count Census Data (Ruggles et al., 2021).

Figure 2. Husband-Wife Age Differences, by Wife's Birth Cohort

A. U.S.-Born Women vs. Ohio-Born Women



B. U.S.-Born Women, by Census Region

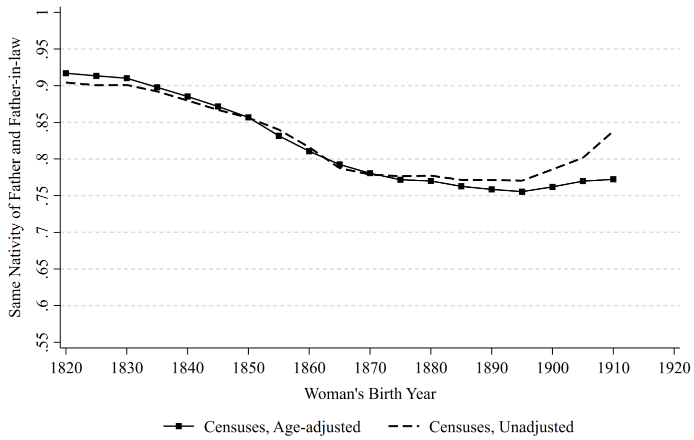


Notes: The figures depict the mean husband-wife age difference by women's year of birth. Panel A presents the age-adjusted cohort-specific mean for U.S.-born women in the censuses, Ohio-born women in the censuses, and weighted LIFE-M sample of women. The LIFE-M data are weighted using inverse propensity scores as described in the text. Panel B presents the age-adjusted cohort-specific mean for U.S.-born women by their census region of residence along with the LIFE-M data.. Due to age-heaping in the Census, we group women into five-year birth cohorts and plot the estimates for the midpoint of each five-year birth-year group. 95-percent confidence intervals are shown as the shaded area.

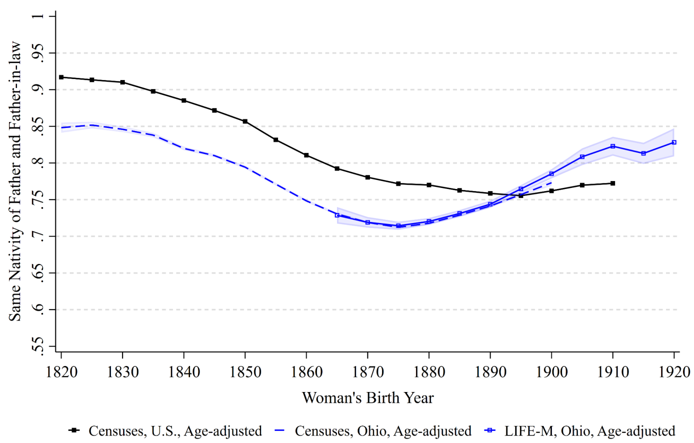
Sources: 1850-1940 Full-Count Census Data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a).

Figure 3. Nativity Homogamy by Father and Father-in-Law's Country Group of Origin, by Wife's Birth Cohort

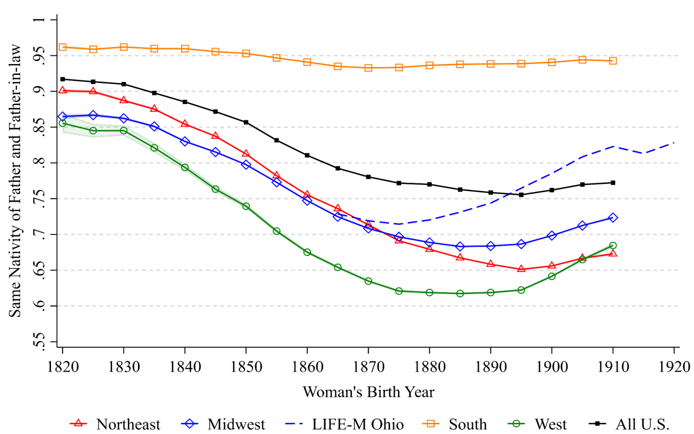
A. All U.S.-Born Women, Census Data



B. Ohio-Born Women vs. U.S.-Born Women, Census and LIFE-M Data



C. U.S.-Born Women by Region of Residence, Census Data

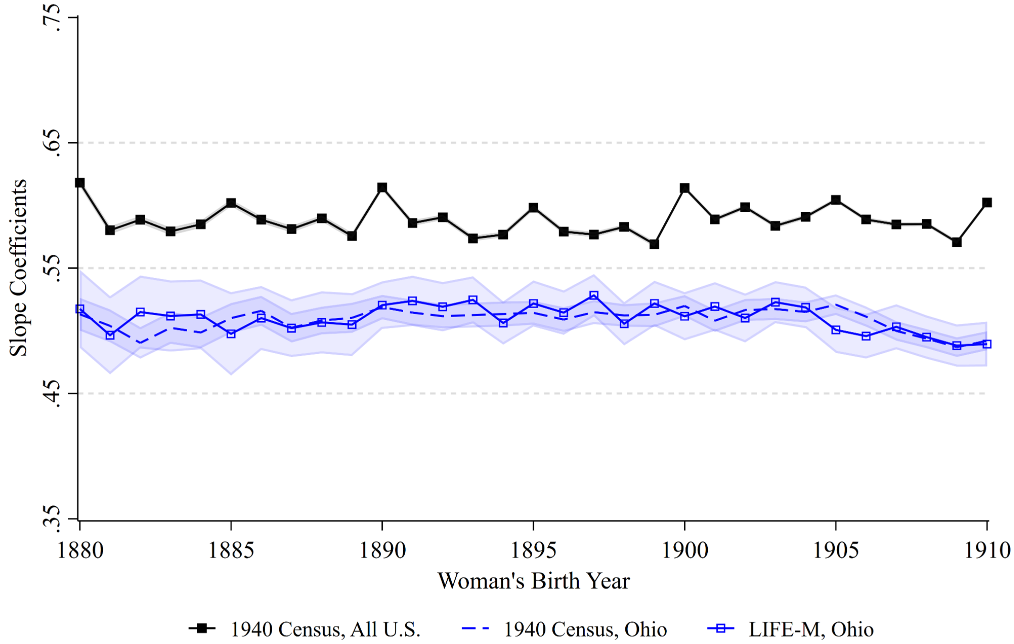


Notes: Series show nativity homogamy, defined as a woman's father and her father-in-law being born in the same group of countries. Panel A plots the age-adjusted nativity homogamy by the woman's birth year. (See corresponding series by census and not adjusted by age in Appendix Figure C.1.) Panel B plots the age-adjusted nativity homogamy by the woman's birth year for all U.S.-born women and Ohio-born women in the weighted LIFE-M and census data. The LIFE-M data are weighted using inverse propensity score weights as described in the text. Panel C plots age-adjusted nativity homogamy in census samples by women's census region of residence. Due to age-heaping in the Census, we group women into five-year birth cohorts and plot the estimates at the midpoint of the group. 95-percent confidence intervals are shown as the shaded area.

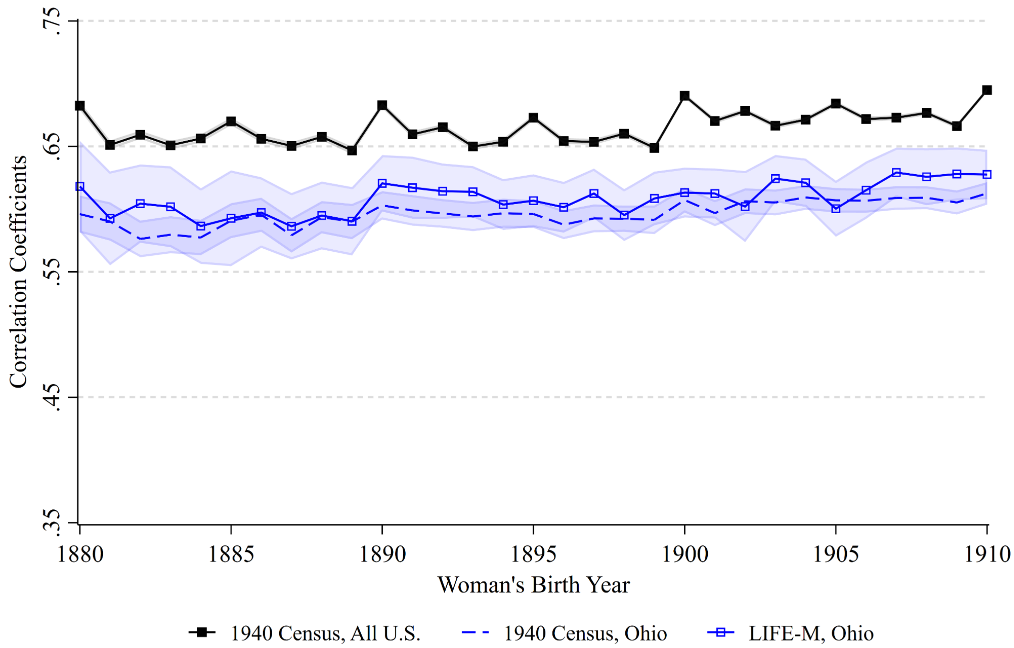
Sources: 1880-1930 Census data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a).

Figure 4. Assortative Matching by Educational Attainment, by Wife's Birth Cohort

A. Slope Coefficients



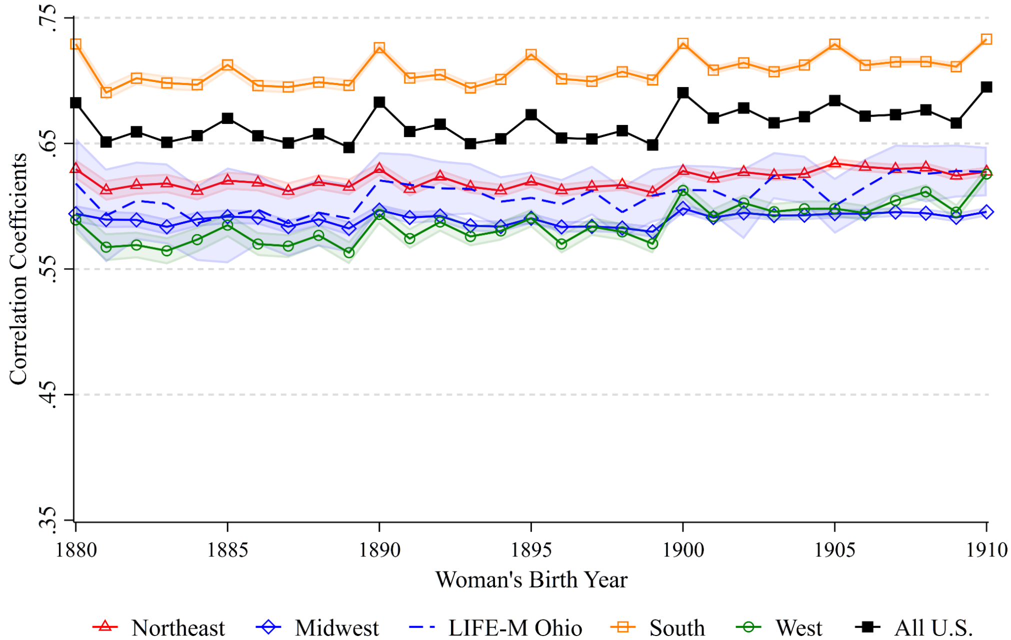
B. Correlation Coefficients



Notes: Panel A depicts education homogamy as captured by regressing a wife's educational attainment on her husband's educational attainment. Educational attainment measures the highest grade completed as reported in the 1940 Census. Panel B presents the correlation coefficients. The LIFE-M data are weighted using inverse propensity score weights as described in the text, and 95-percent confidence intervals are shown as the shaded area.

Sources: 1880-1940 Full-Count Census Data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a).

Figure 5. Assortative Matching by Educational Attainment, by Wife's Birth Cohort and Census Region

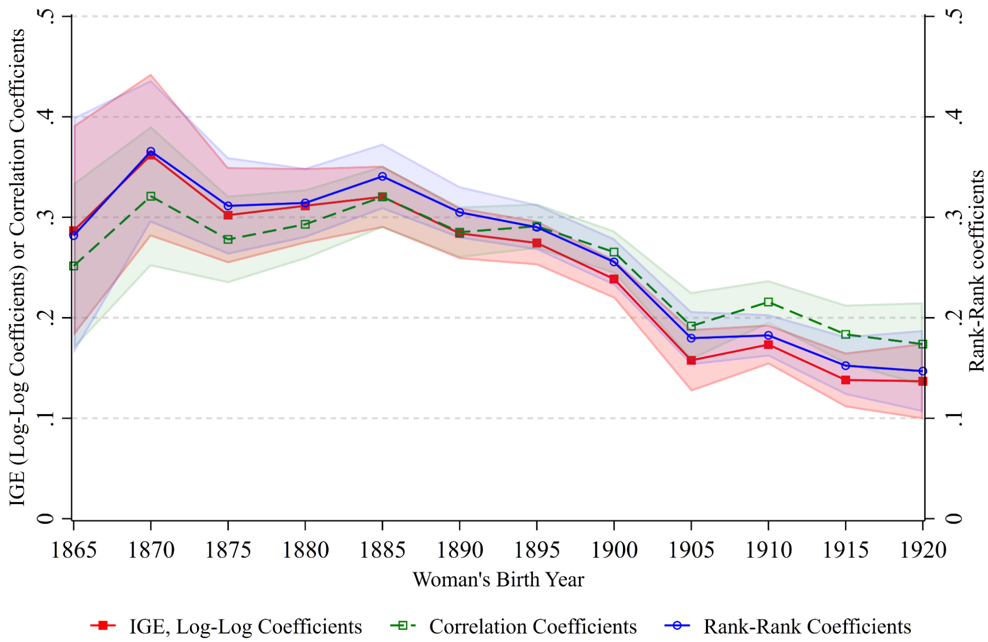


Notes: The series plots the correlation coefficients in educational attainment by wife's birth cohort using the 1940 Census. For region-specific coefficients, we group women into 5-year cohorts centering on years ending with 5 or 10. For the earliest cohorts, we group the 1880-1882 cohorts and plot them as the 1880 cohort. For the latest cohorts, we group the 1908-1910 cohort and plot their estimates as the 1910 cohort. The shaded area shows the 95-percent confidence intervals. See also Figure 6 notes.

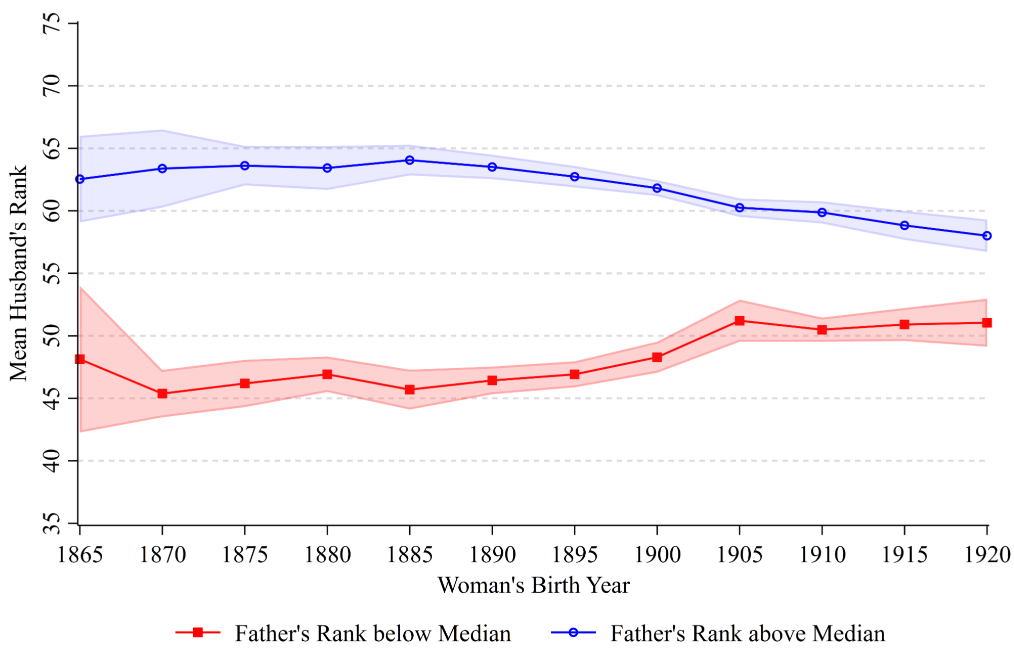
Sources: 1880-1940 Full-Count Census Data (Ruggles et al., 2021).

Figure 6. Intergenerational Mobility by Husband's and Father's Occupation Score, by Wife's Birth Cohort

A. Relative Intergenerational Mobility



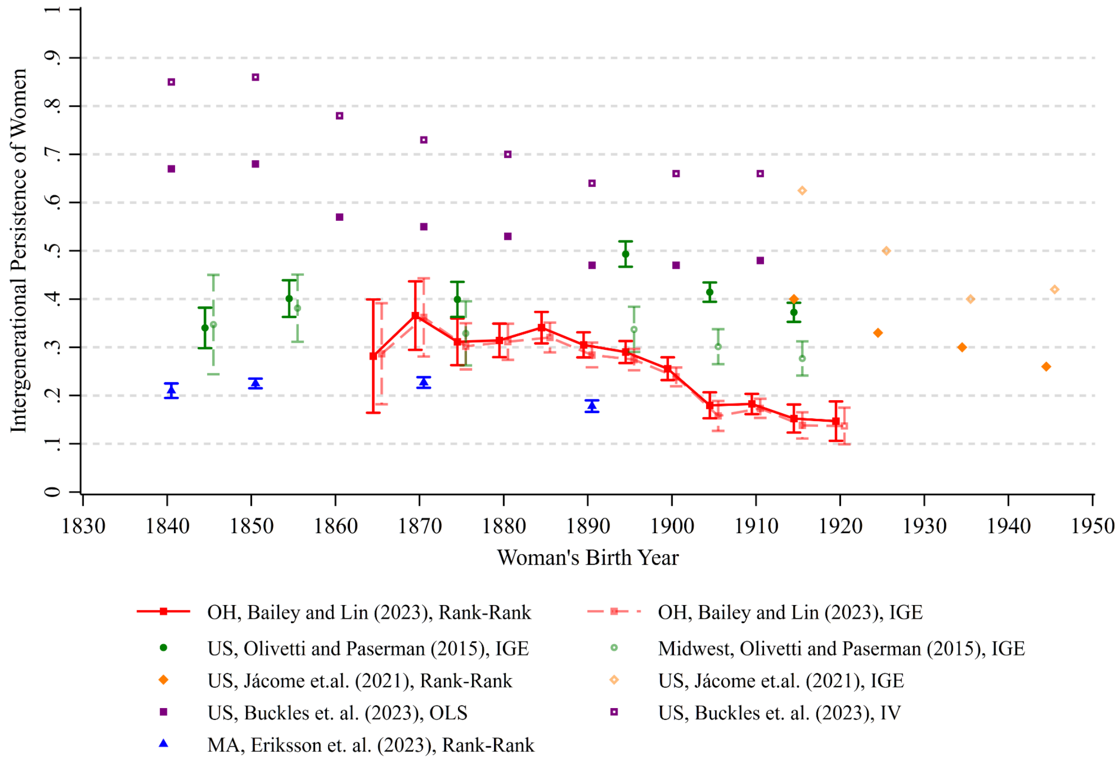
B. Absolute Intergenerational Mobility



Notes: The figures depict changes in occupational homogamy by women's year of birth according to the relationship between her father's and husband's occupational income scores, which are based on the 1950 Census occupational scores. Panel A characterizes relative mobility in terms of log-log and rank-rank coefficients derived from regressing the log/rank of father's occupational score on the log/rank of husband's occupational score. Panel B plots absolute upward and downward mobility by plotting the husband's occupational rank for women whose fathers fall below or above the national median. We group women into five-year birth cohorts and plot the estimates for the midpoint of each five-year birth-year group. The LIFE-M data are weighted using inverse propensity score weights as described in the text. 95-percent confidence intervals are shown as the shaded area.

Sources: LIFE-M samples (Bailey et al., 2022a).

Figure 7. Estimates from Different Studies of Intergenerational Mobility, by Wife's Birth Cohort



Notes: The figure depicts estimates of intergenerational persistence of women in this paper (the red points), as well as the other three related works. The purple points refer to the estimates by Buckles et. al. (2023). The green points refer to the estimates by Olivetti and Paserman (2015). Their estimates are based on a child's first name and pseudo-linking between a father's occupational income score and a husband's occupational income scores, as defined by median total income (in hundreds of 1950 dollars) of all persons with that particular occupation in 1950 (Ruggles et al., 2021). Their estimates are calculated by census years, and we realign them on the woman's birth cohort by subtracting 25 from the census years. The orange points refer to the estimates by Jácome et. al. (2021), which uses surveys reporting fathers' occupations to create occupational-income scores and daughters' family incomes. Their estimates are calculated by the woman's birth cohort and are plotted accordingly. The blue points are estimates from Eriksson et. al. (2023), which are based on links between Massachusetts marriage certificates from 1850 to 1915 to the 1850, 1860, 1870, 1880, 1900, 1910, and 1920 Censuses. We plot their estimates based on 1950 occupational income scores for best comparison with our estimates. They do not report confidence intervals so these are not reported here. We translate their estimates for the marriage cohorts 1850-1870, 1860-1880, 1880-1900, and 1900-1920 to the birth cohorts of the 1840s, 1850s, 1870s, and 1890s.

Sources: LIFE-M samples (Bailey et al., 2022a).

Online Appendix

Marital Matching and Women's Intergenerational Mobility in the Late-19*th* and Early-20*th*-Century U.S.

By Martha J. Bailey[1,2] and Peter Z. Lin[3]

June 14, 2024

A. Inverse Propensity Score Weighting for Linked Sample

We generate an inverse propensity score weight for each observation in the LIFE-M sample using the method proposed by Bailey et al. (2020). We first group women in the LIFE-M sample by their birth year and the census year when they and their husbands are observed. The women in each group are then weighted to be a representative sample of the women born in the same year in the relevant census population. For example, we weight the Ohio-born women who were born in the 1910 birth cohort and linked to the 1940 Census to make them a representative sample of all married Ohio-born women born in the 1910 cohort in the 1940 Census. Considering that the analytic samples for different dimensions of homogamy vary significantly, we customize the weights for each sample.

We take the following steps to weight the linked women in each group:

Step 1. We extract Ohio-born women in the birth cohort j from the full-count decennial census t. We apply the same restrictions including (1) age 20-60 in the census; (2) married and co-resided with her husband in the same household.

Step 2. We combine the extracted women from the full-count census with the linked women in the LIFE-M sample.

Step 3. We estimate the following probit model using the pooled LIFE-M census dataset,

$$Pr\left(sample_{ijt} = 1|X_{ijt}\right) = \Phi\left(X_{ijt}\beta\right)$$

where $sample_{ijt}$ is a dummy variable equal to 1 if the observation comes from the linked sample, and equal to 0 if it comes from the census; $\Phi(.)$ is the cumulative distribution function for the standard normal distribution; X_{ict} is a vector of covariates, including an indicator for specific race (1=White, 0=Non-white), urban residence, farm residence, migration away from birth state, having an occupation associated with positive income score, living with father, living with mother, living with children under age 5, father's nativity (only for the women in the 1900, 1910, and 1920 Census), husband's nativity, husband's occupational income score, and women's name characteristics (length of first name, last name, commonality score of these names). We also include two-way interactions between these covariates.

Step 4. We predict the propensity score of being linked and calculate the inverse propensity score weight as follows:

$$wgt = \left(\frac{1-p}{p}\right) \times \left(\frac{q}{1-q}\right)$$

where p is the predicted propensity score of linkage, and q is the ratio of observations in the LIFE-M sample to the observations in the referenced women population.

Step 5. We repeat this procedure for all other combinations of women's birth cohorts and census years. We also conduct the procedures repeatedly for different marriage homogamy outcomes.

Step 6. As the last step, we augment the weights for sample women in each group to make the weights sum to the referenced women population in the birth cohort and census year. We use this augmented weight to derive descriptive statistics of the overall sample.

We find that the LIFE-M sample is not a representative sample of the analogous population (see table 2, panel A, columns 3, 7 and panel B, columns 3, 8). We find that the LIFE-M samples are over-represented by women who are white, living on farms, and living with children under age 5. Meanwhile, the LIFE-M samples are under-represented by women living in urban areas, born to a foreign-born father, and reporting an occupation associated with a positive occupational income score.

We also verify that the weighted LIFE-M sample is balanced in terms of the observable covariates by woman's birth cohort. To demonstrate this, we estimate the following model with the LIFE-M sample (weighted and unweighted), as well as the referenced population in censuses:

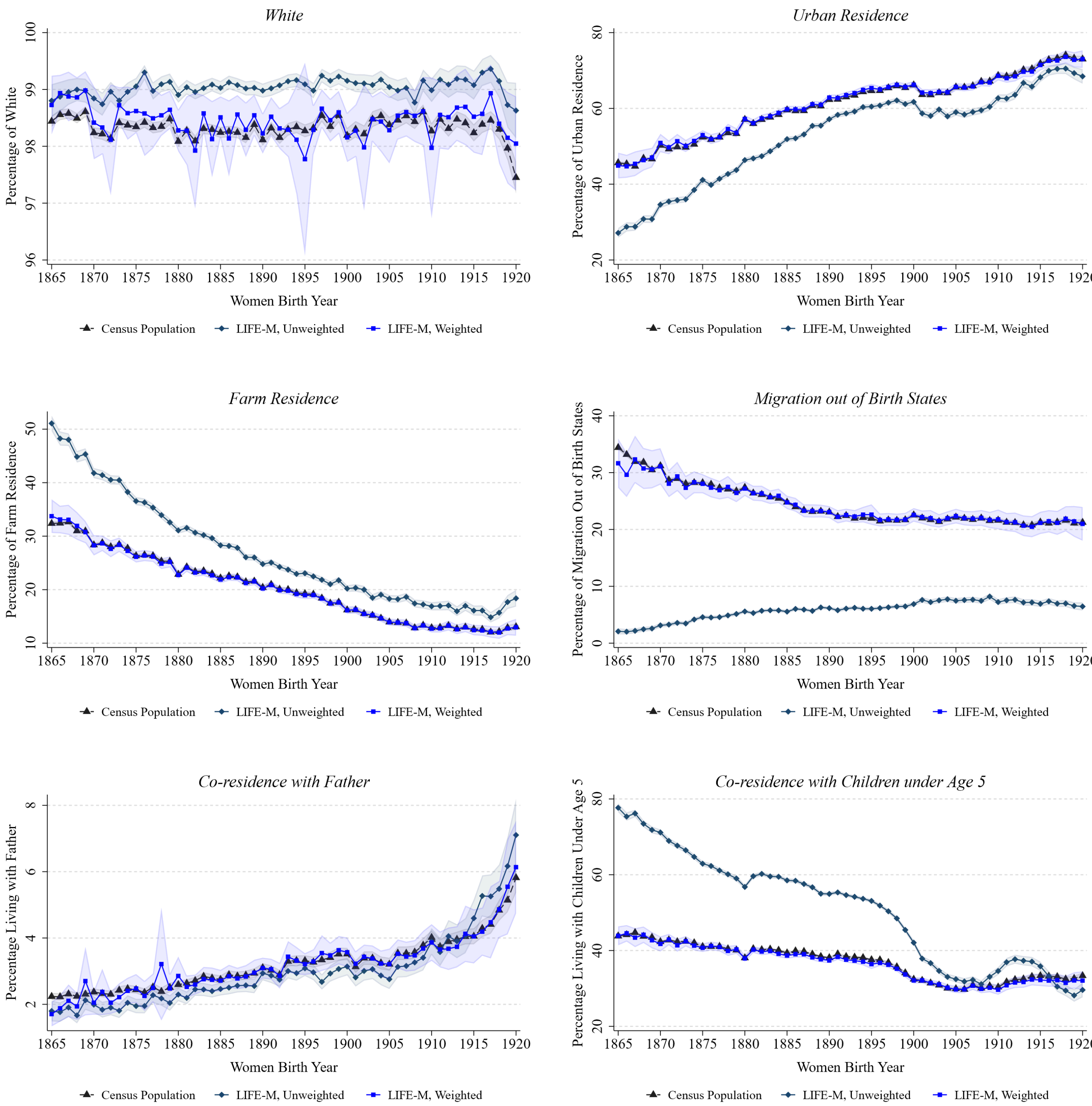
$$Y_{it} = \sum_{j} \beta_j Cohort_j + q(age_{it}) + \varepsilon_{it}$$

where Y_{it} is the covariate of interest, $Cohort_j$ is a dummy variable for women in cohort j, and $q(age_{it})$ is a quartic function of woman's age in the observed census. After estimating this model, we predict the mean covariate for each cohort at the age of 35. Figures A.1-A.4 plot the predicted mean covariates by woman's birth cohort for women in the LIFE-M samples for age, nativity, and occupation homogamy. For the education homogamy sample, we estimate cohort-specific mean covariates by the following model:

$$Y_{it} = \sum_{j} \beta_j Cohort_j + \varepsilon_{it}$$

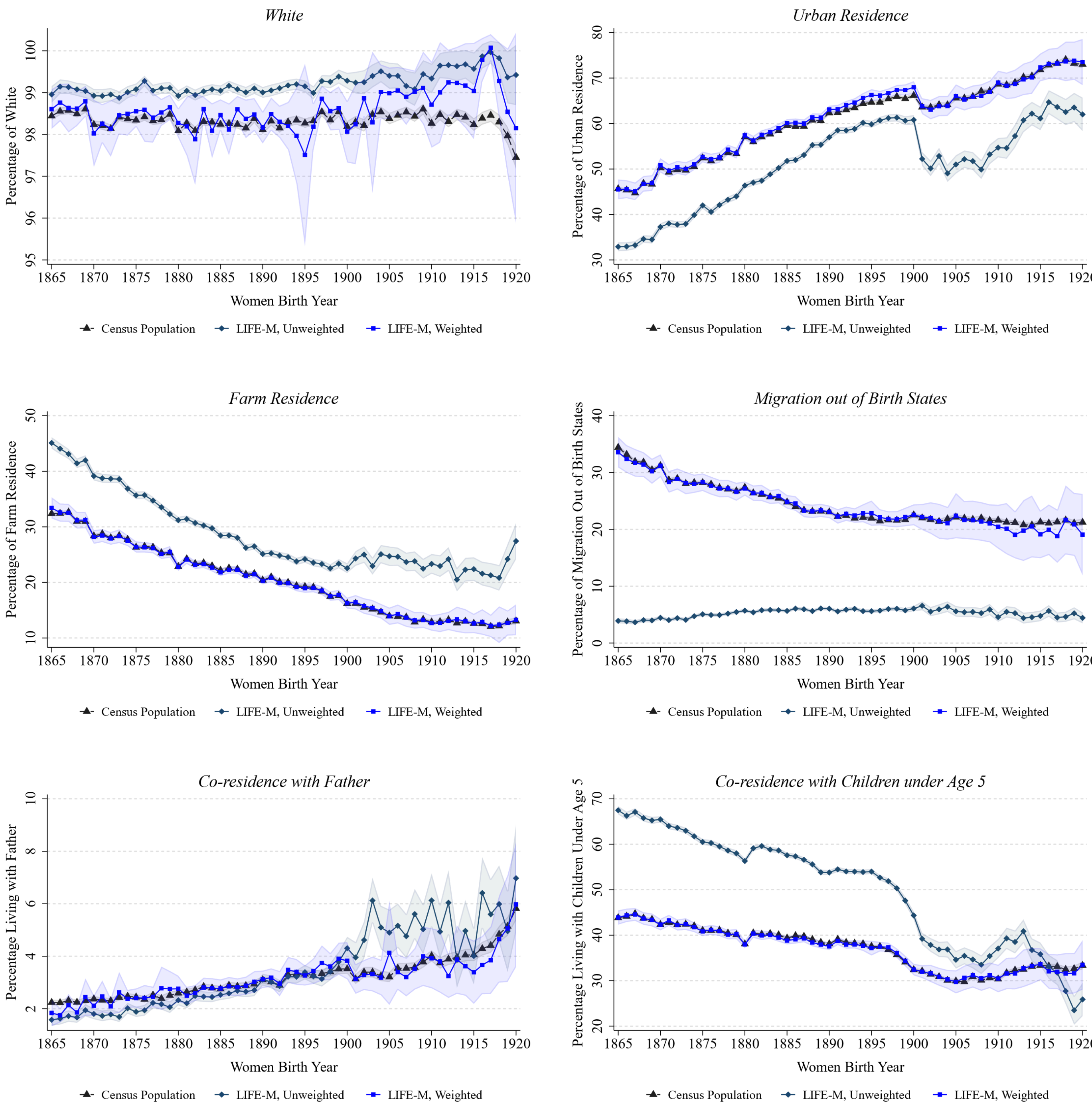
We cannot control for women's age for the education sample because women in this sample were only observed in the 1940 Census, and no additional age variation is available in a single census. For almost all covariates, the LIFE-M samples are not balanced without weighting. Instead, we make the LIFE-M samples indifferent or at least insignificantly different from the referenced population by inverse propensity weights.

Figure A.1. Balance, Age Sample



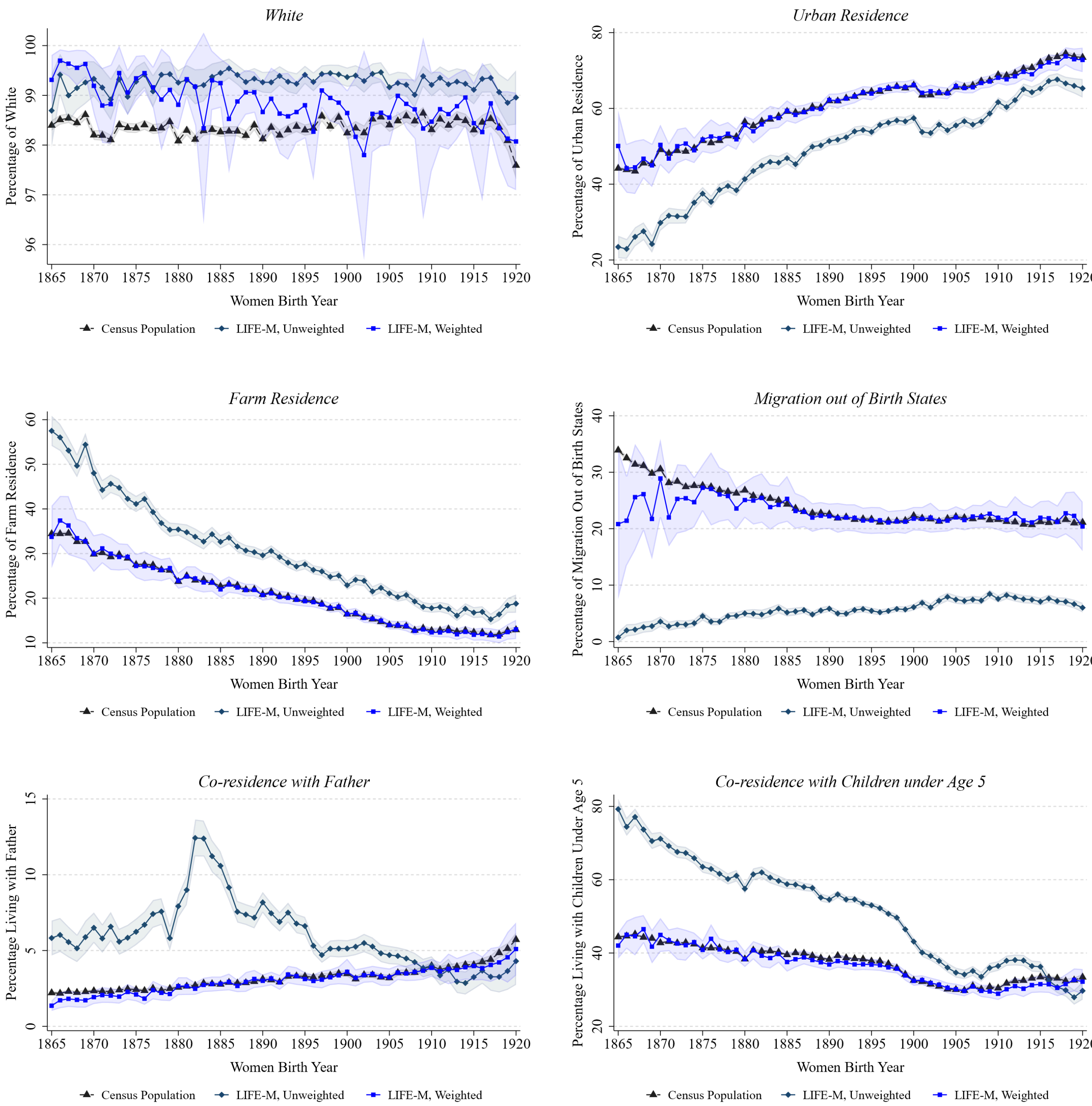
Notes: The figures depict the estimated mean of six covariates indicated in the panel header by wife's birth cohort. These series are age adjusted and projected at age 35 using equation (1). The black curve plots the estimates from corresponding target population in the census, the navy curve plots the unweighted LIFE-M estimates, and the blue curve plots the inverse-propensity score reweighted LIFE-M estimates.

Figure A.2. Balance, Nativity Sample



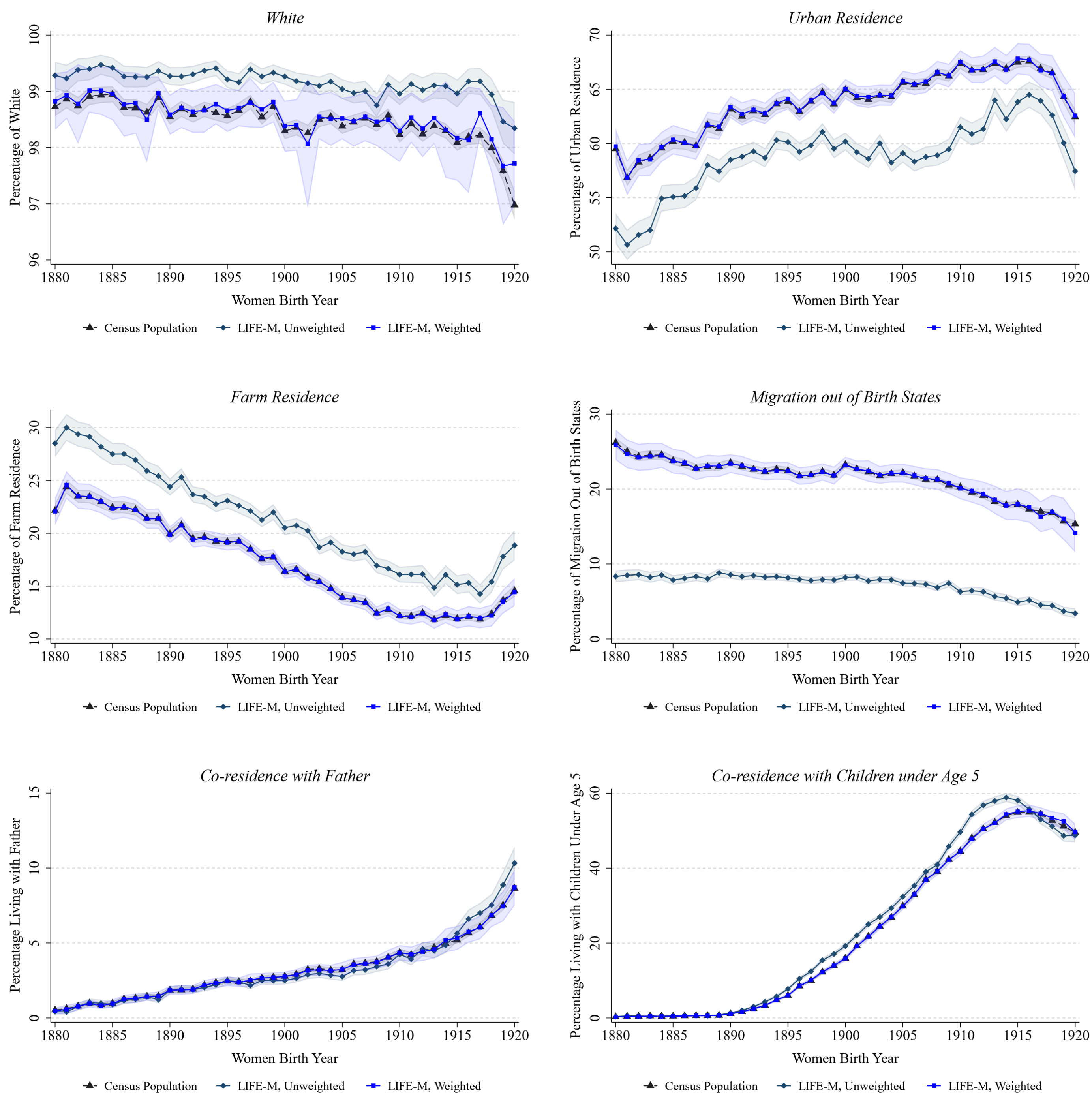
Notes: See Figure A.1 notes

Figure A.3. Balance, Occupational Sample



Notes: See Figure A.1 notes

Figure A.4. Balance, Education Sample

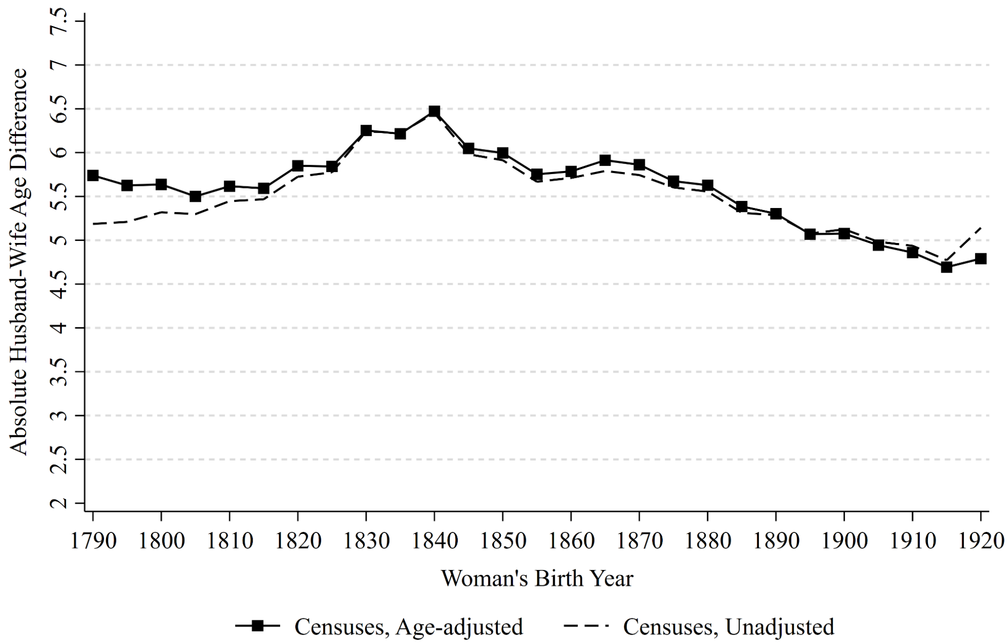


Notes: The figures depict the estimated mean of six covariates indicated in the panel header by wife's birth cohort for the education sample. The black curve plots the estimates from corresponding target population in the census, the navy curve plots the unweighted LIFE-M estimates, and the blue curve plots the inverse-propensity score reweighted LIFE-M estimates.

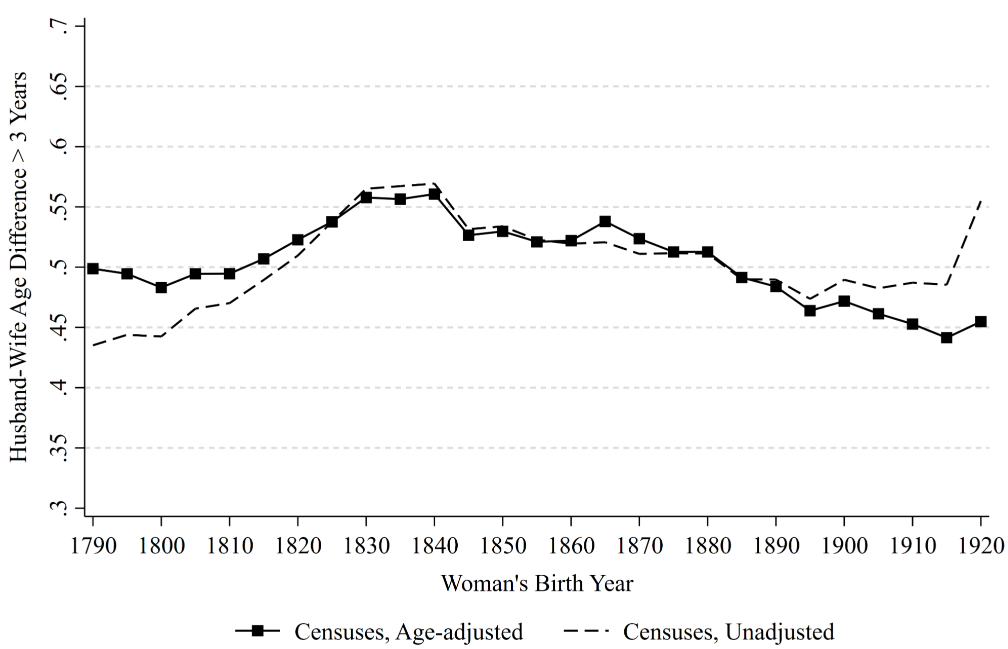
B. Alternative Measure of Age Homogamy and Heterogenous Trends

Figure B.1. Age Homogamy (Alternative Measures) by Wife's Birth Cohort

A. Absolute Husband-Wife Age Difference



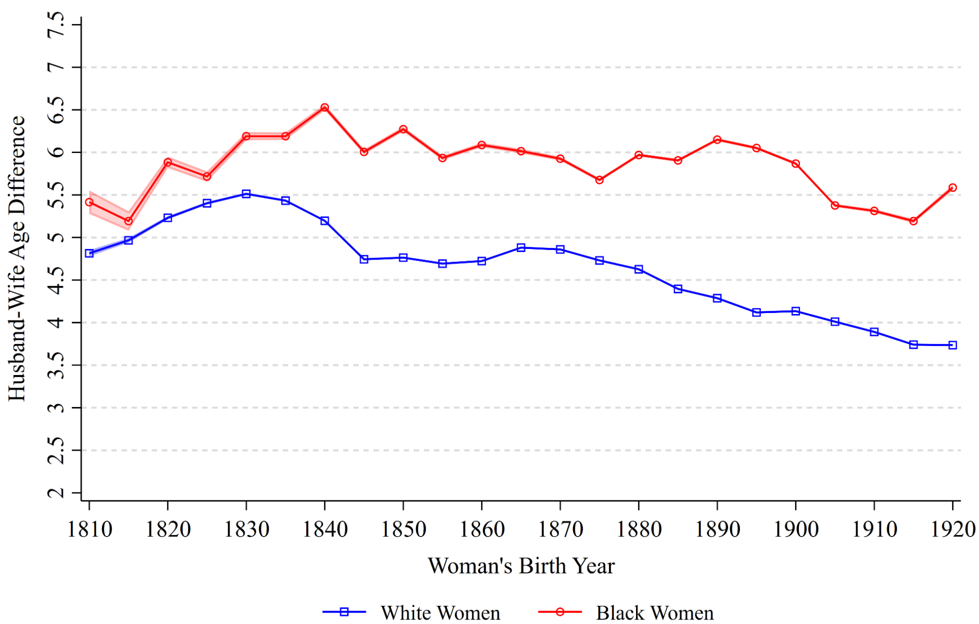
B. Prob(Husband-Wife Age Difference>3 Years)



Notes: The figures depict alternative measures of age homogamy by a woman's birth cohort: (1) the absolute differences between a husband's and wife's ages; (2) the likelihood that a husband is more than 3 years older than his wife.

Sources: 1850-1940 Censuses (Ruggles et al., 2021).

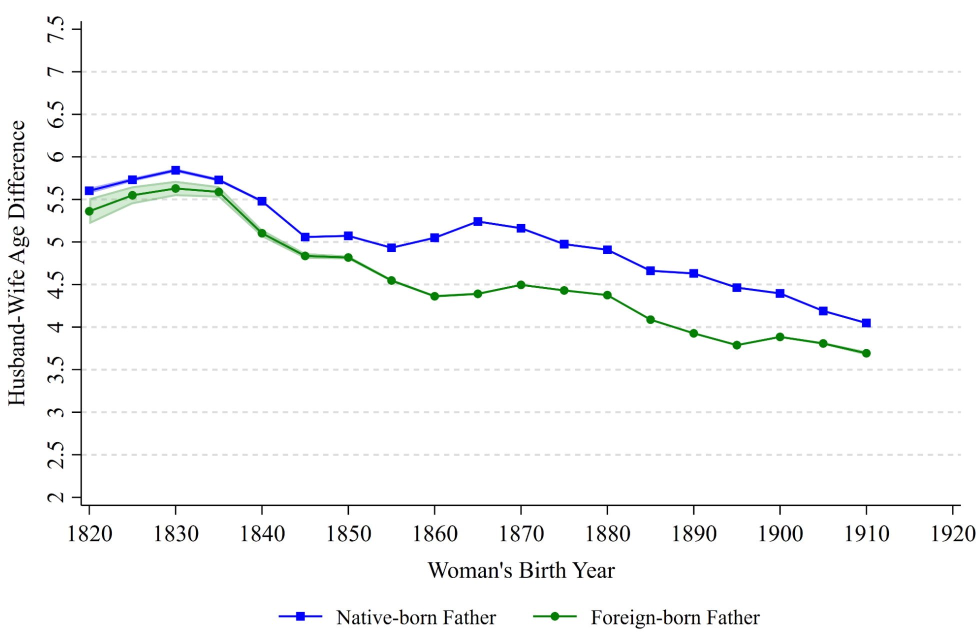
Figure B.2. Age Homogamy (Alternative Measures) by Wife's Birth Cohort and Race



Notes: This figure depicts differential trends of age homogamy by woman's race. We focus on women born after 1810 because Black women were first enumerated in the 1870 Census following the Civil War. We estimate the mean age difference separately for white women (blue line) and Black women (red line).

Sources: 1870-1940 Censuses (Ruggles et al., 2021)

Figure B.3. Age Homogamy (Alternative Measures) by Wife's Birth Cohort and Father's Nativity



Notes: This figure depicts differential trends of age homogamy by a woman's father's nativity (native-born vs. foreign-born). We use the 1880-1930 Censuses (for women born between 1820 and 1910) because they required reporting father's birthplace.

Sources: 1880-1930 Censuses (Ruggles et al., 2021)

C. Measure of Nativity Homogamy and Heterogenous Trends

Our primary measure of nativity homogamy for a couple is based on the birth country of the wife's father and her husband's father. Considering the frequent border changes in the early twentieth century (especially for Central and Eastern Europe), we categorize the birth countries (coded by IPUMS) closely connected in terms of geography and culture into multiple groups. Specifically, the groups are:

(1) All states in the U.S

(2) U.S. outlying areas: American Samoa, Guam, Puerto Rico, and U.S. Virgin Islands.

(3) Canada and other North America: St. Pierre and Miquelon and Atlantic Islands.

(4) Central America: Mexico, Central America, Cuba, and West Indies.

(5) South America: all South American countries

(6) North Europe: Denmark, Finland, Iceland, Norway, Sweden.

(7) Ireland and the United Kingdom: England, Scotland, Wales.

(8) West Europe: Belgium, France, Liechtenstein, Monaco, Netherlands, Switzerland.

(9) South Europe: Albania, Andorra, Gibraltar, Greece, Italy, Malta, Portugal, San Marino, Spain, Vatican City.

(10) Central and Eastern Europe: Austria, Bulgaria, Czechoslovakia, Germany, Hungary, Poland, Romania, Yugoslavia.

(11) Russian Empire: Estonia, Latvia, Lithuania, and other USSR/Russia territories.

(12) China

(13) Japan

(14) Korea

(15) Southeast Asia: Cambodia (Kampuchea), Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand, Vietnam.

(16) Southwest Asia: Afghanistan, India, Iran, Maldives, Nepal.

(17) Middle East Asia: Bahrain, Cyprus, Iraq, Saudi Arabia, Israel/Palestine, Jordan, Kuwait, Lebanon, Oman, Qatar, Syria, Turkey, and other non-specified Middle East countries.

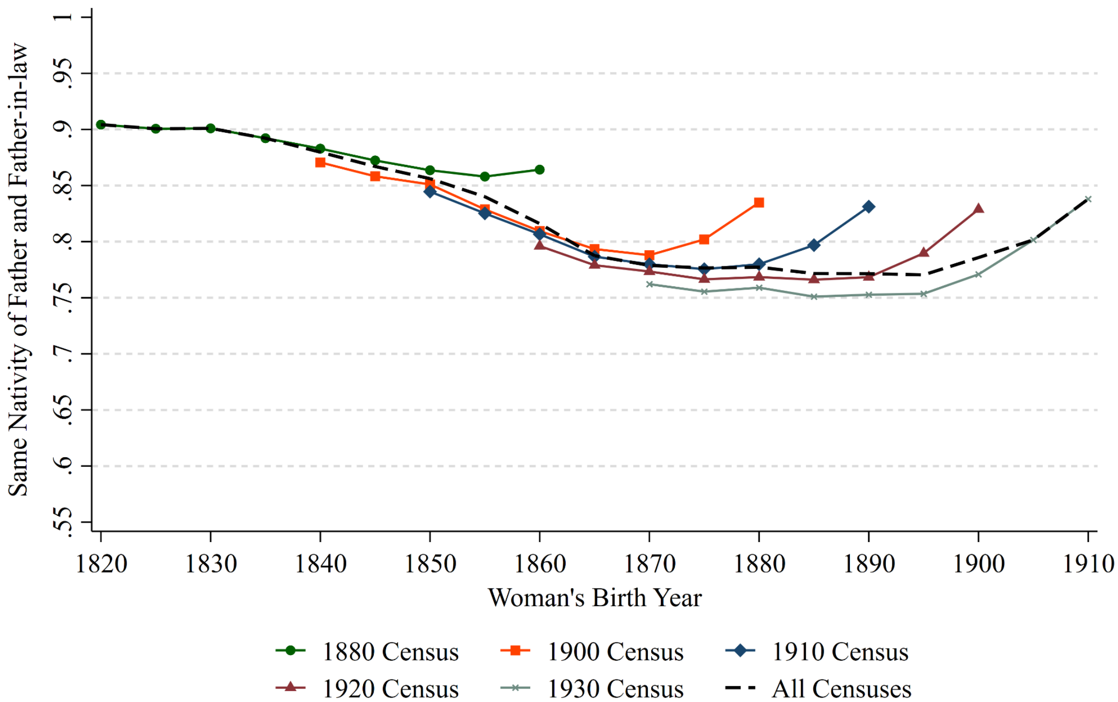
(18) Africa

(19) Oceania: Australia, New Zealand, Pacific Islands.

A woman's father and father-in-law are considered "same nativity" if their birth countries are both included in the same country group as defined above. We treat the father and father-in-law as the same nativity if one (either the father/father-in-law) reports a non-specified European/Asian country and the other reports a specific European/Asian country.

As an alternative measure of nativity homogamy, we also estimate the probability of a couple for which the husband's (rather than father-in-law's) nativity is the same as that of the woman's father. Figure C.2 plots this alternative measure.

Figure C.1. Probability of Same-Nativity of Father and Father-in-Law, by Wife's Birth Cohort and Census

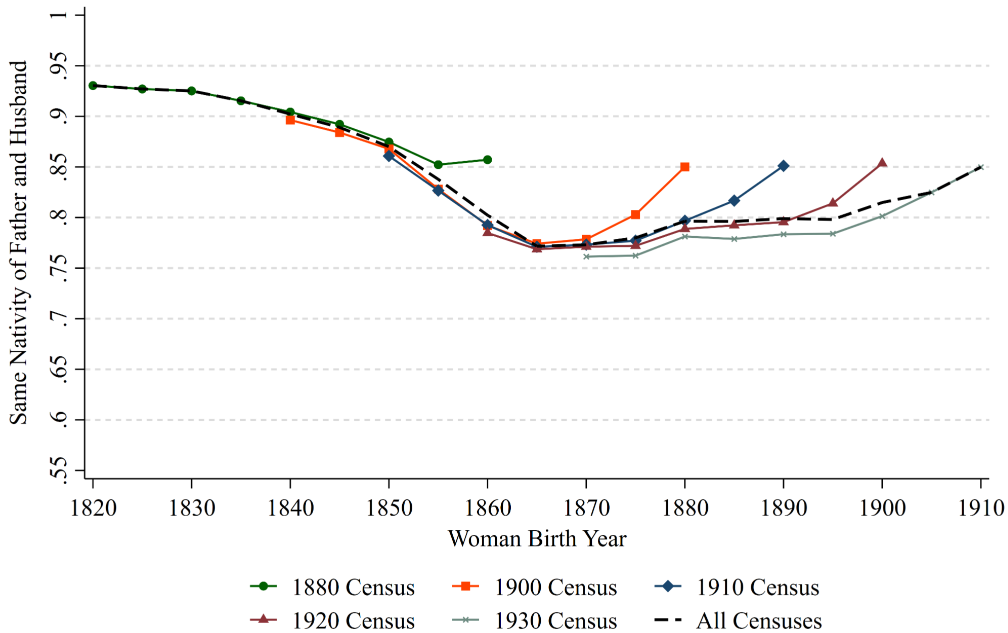


Notes: This figure depicts the likelihood of same-nativity for father and father-in-law by woman's birth cohort in individual censuses between 1880 and 1930.

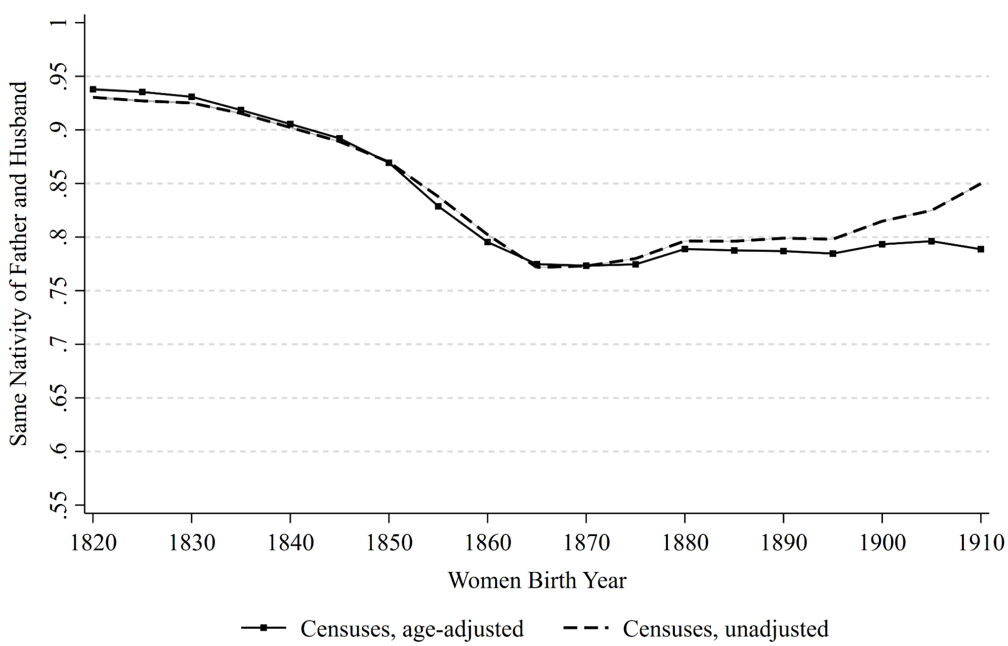
Sources: 1880-1930 Censuses (Ruggles et al., 2021)

Figure C.2. Probability of Same-Nativity of Father and Husband, by Wife's Birth Cohort and Census

A. All U.S. Individual Censuses: 1880-1930



B. All U.S. Combined Censuses: 1880-1930

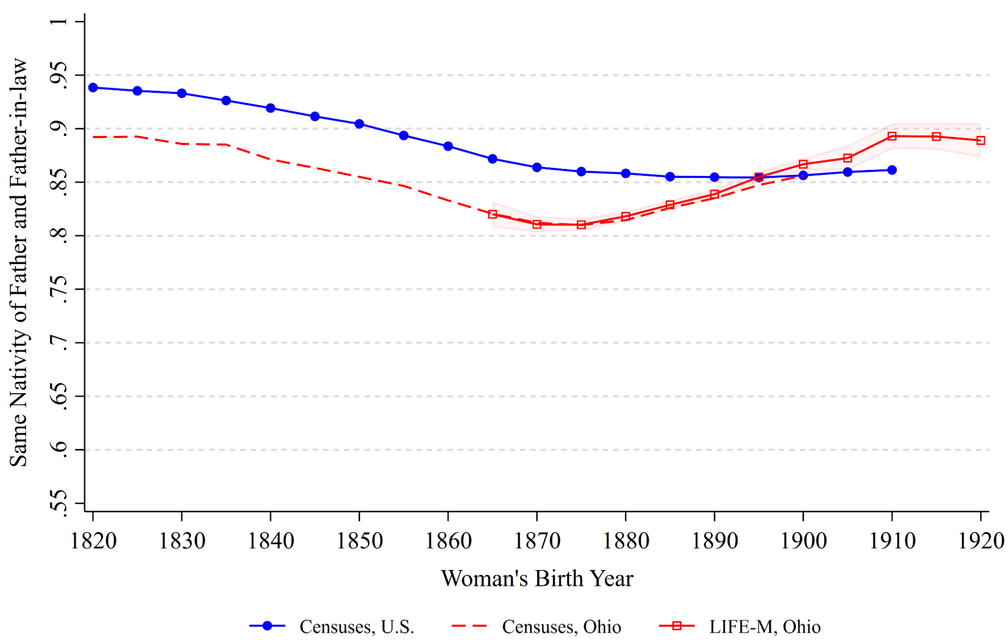


Notes: The figures depict an alternative measure of nativity homogamy: the likelihood of same nativity of a woman's father and her husband. In panel A, we plot the estimated probability by woman's birth cohort in each individual census. In panel B, we plot the estimated probability by the combined census data, with and without age adjustment.

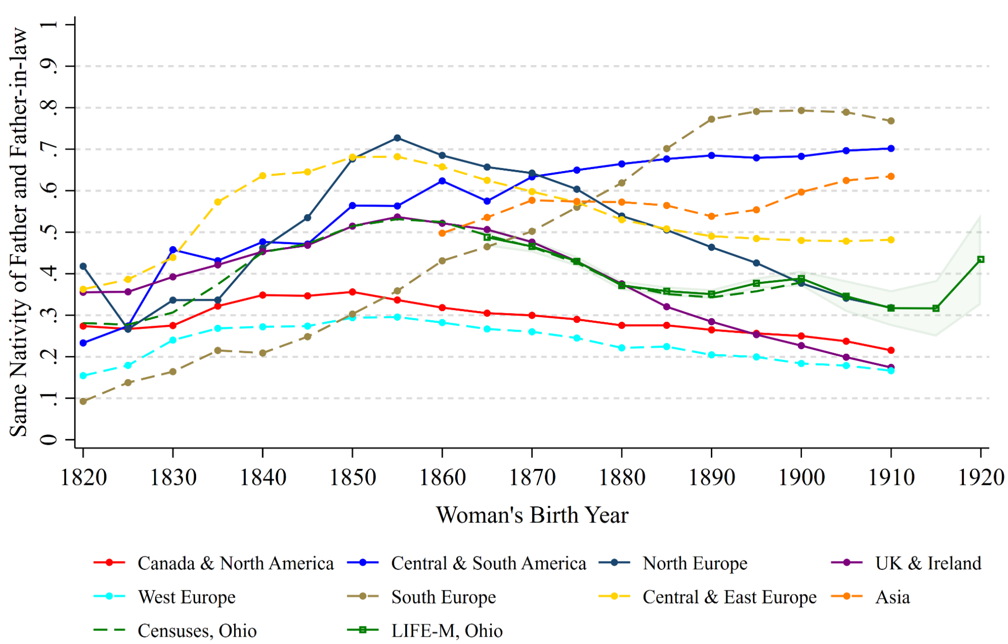
Sources: 1880-1930 Censuses (Ruggles et al., 2021)

Figure C.3. Probability of Same-Nativity of Father and Husband, by Wife's Birth Cohort and Father's Country of Origin

A. Native-born Father



B. Foreign-born Father

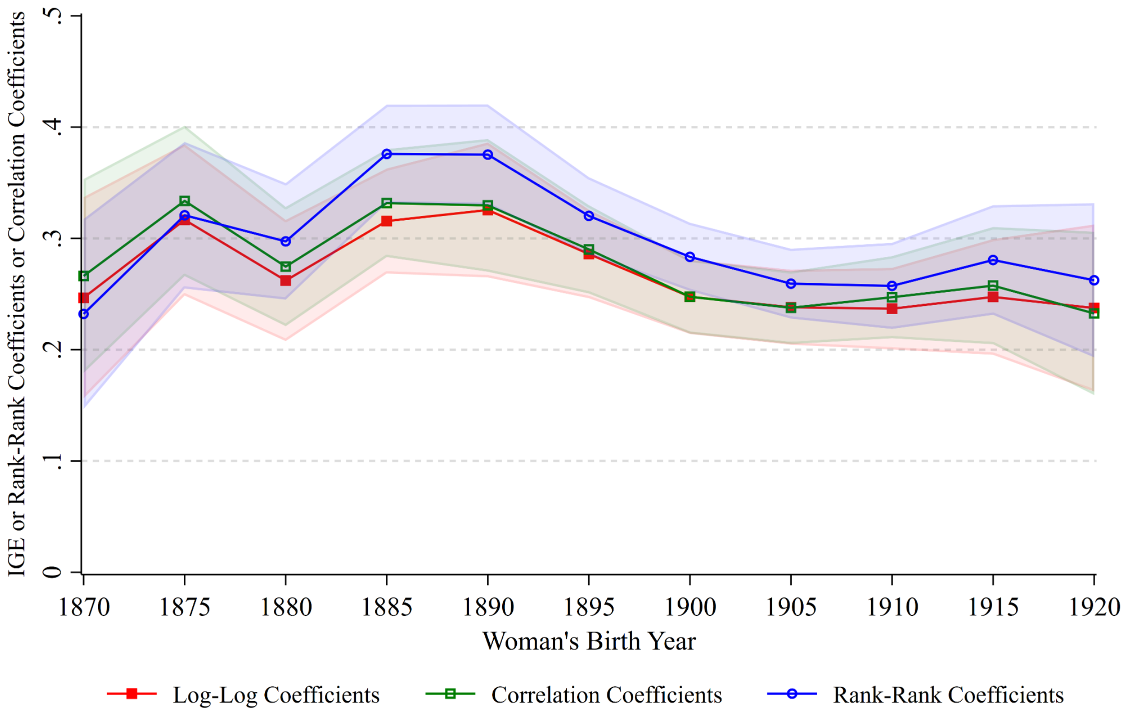


Notes: The figures depict differential trends of nativity homogamy by a woman's father's nativity. Panel A plots the trends for women whose fathers are U.S-born; Panel B plots the trends for women whose fathers are foreign-born. In Panel B we separate daughters of foreign-born fathers into eight groups depending on fathers' country of origin. We also plot the Ohio-born women whose fathers were foreign-born in the LIFE-M sample and Censuses.

Sources: 1880-1930 Census data (Ruggles et al., 2021) and LIFE-M samples (Bailey et al., 2022a)

D. Alternative Measures of Occupational Homogamy and Heterogenous Trends

Figure D.1. Assortative Matching by Father's and Father-in-Law's Occupational Score, by Wife's Birth Cohort



Notes: The figures depict changes in occupational homogamy by women's year of birth according to the relationship between her father's and father-in-law's occupational income scores, which are based on the 1950 Census occupational scores. We characterize the level of assortative matching by the log-log and rank-rank coefficients derived from regressing the log/rank of father's occupational score on the log/rank of husband's occupational score. We also plot the correlation coefficients derived from regressing the standardized log of father's occupational score on the standardized log of husband's occupational score. We group women into five-year birth cohorts for a more accurate and smoother trend. Estimates are weighted by inverse propensity scores weights and 95-percent confidence intervals are shown as the shaded area.

Sources: LIFE-M samples (Bailey et al., 2022a)