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Marriage Market Equilibrium with Matching on Latent Ability: Identification using a Compulsory Schooling Expansion*

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Abstract

We use the 1972 UK Raising of the School-Leaving Age (RoSLA) to identify and estimate an equilibrium marriage market model with sorting on academic qualifications and latent ability. Our identification hinges on a RoSLA-induced discontinuity in the distribution of qualifications. We disentangle the contributions of qualification and ability to marital surplus; we find that they are complements. Ability increases the probability of ever marrying; a basic qualification does not. The observed marriage gap between basic qualified and unqualified individuals is entirely due to selection on ability. The RoSLA worsened marital prospects of low ability individuals, through general equilibrium effects.

Keywords: Marriage, Assortative mating, Return to education, Latent ability
JEL Classification: D10, D13, I26, J12

1. Introduction

Estimating the returns to education remains a central question in economics. As David Card's influential survey (Card, 2001) notes, accounting for unobserved heterogeneity is critical to answering this question, since individuals with higher educational attainment also have unobserved traits, including ability, that make them distinctly different from those with lower educational attainment. Much research in the past three decades has

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focused on quasi-experimental methods or on finding valid instrumental variables, so that the effects of education and unobserved ability on *individual* pecuniary and non-pecuniary outcomes (Oreopoulos and Salvanes, 2011) can be disentangled.

One potential avenue for a return to education that has recently received increased attention is via the marriage market. In most developed countries, a substantial majority of college graduates are now women. Chiappori, Iyigun, and Weiss (2009) and Chiappori, Salanié, and Weiss (2017) have argued that this is attributable to the secular increase in the marital return to education for women.[1] Since marriage formation is an *equilibrium* phenomenon, this literature has relied on structural models of the marriage market, as pioneered by Choo and Siow (2006), to estimate the payoffs in marriage to the two genders by their level of educational attainment. Hence, matching is on traits that are observable to an econometrician, with no role for ability or other latent variables.

This paper takes a first step towards bridging the two approaches by using an education reform to estimate an equilibrium model of the marriage market where individuals differ in academic qualification and in latent ability that is correlated with academic qualification. The reform allows us to separate the causal effect of holding a basic academic qualification versus the causal effect of academic ability on the probability of ever marrying. Our substantive finding is that the causal effect of a basic qualification versus no qualification on the probability of ever marrying is zero (negative for men) while the causal effect of ability (medium versus low) is positive and substantial for both genders.

The 1972 Raising of the School-Leaving Age (RoSLA) order raised the school leaving age in the UK from 15 to 16 for individuals born from September 1957 onwards. The RoSLA sharply increased the proportion of school leavers who left with the most basic UK academic qualification from (roughly) 35 to 45 percent, likely due to a large reduction in the opportunity cost of sitting the exam for this basic qualification.[2] However, the pecuniary returns to the additional schooling and qualification attainment induced by the RoSLA were small, see Grenet (2013).[3] With the exception of reduced criminality, there is also no evidence of substantial nonpecuniary returns to schooling or qualification

[1] Zhang (2021) provides an alternative explanation based on differential fecundity.

[2] By compelling individuals to stay in school up until the point where they could sit the exam for the most basic UK qualification, the RoSLA substantially reduced the labour earnings that a young individual would have to forego to acquire a basic qualification.

[3] Looking beyond the RoSLA, evidence from Europe on the pecuniary returns to schooling identified from compulsory schooling laws—see Pischke and von Wachter (2008) for Germany, Devereux and Hart (2010) for an evalution of an earlier British compulsory schooling law, and Grenet (2013) who also consider a French reform—show much lower returns than comparable evidence from North America—see Angrist and Krueger (1991) and Oreopoulos (2006).

attainment at the RoSLA margins.[4] Existing empirical evidence on the RoSLA thus indicate that the observed associations between qualification and earnings and other outcomes were largely driven by selection on ability, the distribution of which was plausibly unaffected by the RoSLA.[5] Indeed, using the UK National Child Development Study, which contains measures of ability, we show that the RoSLA strengthened the ability and qualification attainment correlation.

Guided by these observations, we develop a marriage market model with sorting on qualification, ability and age and estimate it using UK Labour Force Survey data coupled with UK Census data and Birth and Mortality data from the UK Office of National Statistics. Ability is correlated with qualification attainment and is a latent trait, i.e. observed by marriage market participants, but not by the analyst. We use the model to compute the causal effects of qualification and ability on marital outcomes and to evaluate wider marriage market implications of the RoSLA.

We make four contributions. First, we establish a set of novel empirical facts about the marriage market response to the RoSLA using cohorts born close to the reform threshold. The proportion never married (by age 45) increased among unqualified men and women born after the reform threshold. Qualification homogamy among the unqualified increased after the reform, while overall qualification homogamy remained largely unchanged. Marriages, of course, frequently occur across cohorts resulting in a husband-wife age gap. Across all years, the husband-wife age gap distribution is skewed towards positive gaps, where the husband is older than the wife, with a mode at one year. We document a temporary shift in the age gap distribution: members of the first RoSLA-exposed cohort are more likely to inter-marry than earlier and later cohorts.

Second, we generalize the influential marriage market model of Choo and Siow (2006) extended to accommodate latent ability. Under the empirically validated assumption that the RoSLA strengthened the correlation between ability and qualification attainment, the reform identifies our extended model. Accounting for latent ability markedly improves the model's ability to reproduce the observed marriage market response to the RoSLA. Both ability and qualification matter for marital surplus, and own and spousal ability, and own and spousal qualification, are complementary in generating surplus.

[4] Clark and Royer (2013) use the RoSLA and an earlier change to British compulsory schooling age to estimate zero returns to education on a number of health outcomes and Silles (2011) find compulsory schooling laws including the RoSLA delay childbearing, but does not alter overall fertility. Machin, Marie, and Vujić (2011) show that the RoSLA significantly reduced criminality.

[5] Ability forms in early life, has a distribution that changes slowly and is not directly under the control of policy (Cunha, Heckman, and Schennach, 2010).

Third, we compute causal effects of an academic qualification and of ability on the probability of ever marrying. For both men and women with medium ability, the causal effect of holding basic versus no qualification on the ever-marrying rate is negligible. In contrast, the causal effect of possessing medium versus low ability on the ever-marrying rate is substantial for individuals without a qualification. For unqualified men (women), we find that having medium versus low ability increases the ever-marrying rate by up to 10 (5) percentage points. Hence, the entire observed gap in ever-married rates between individuals with basic and no qualifications is accounted for by selection on latent ability: unqualified individuals marry less frequently than those with a basic qualification because they tend to have low ability, not because they lack qualifications per se.[6]

Fourth, we simulate a counterfactual marriage market without the RoSLA and show that the reform had general equilibrium effects on the marriage outcomes of individuals whose minimum school leaving age was not affected by the RoSLA. The typically positive husband-wife age gap meant that the reform was felt by men in the pre-RoSLA cohorts. Overall, the reform increased the marital mixing between medium and high ability individuals, but left low ability individuals isolated in the marriage market.

Choo and Siow (2006, henceforth CS) provided the seminal empirical implementation of the Becker-Shapley-Shubik transferable utility marriage market model (Shapley and Shubik, 1971; Becker, 1973). The CS approach groups individuals into a finite number of observable types, with a systematic marital surplus function that depends on a couple's type-profile, and with additively separable individual i.i.d. preferences over partner type. The CS framework has been extended in various directions and applied in a variety of contexts.[7] The literature has focused on marital sorting on observable traits, with only one notable exception: similar to us, Chiappori, Costa Dias, and Meghir (2018) allow for latent ability in the CS framework. They develop a dynamic model of investment in human capital, marriage and household labor supply, where matching takes place on the basis of a one-dimensional variable—human capital—which depends on latent ability and acquired education. Using longitudinal data with information on household labor supply and long-term earnings, they infer the joint distribution of education and ability,

[6] Conditional on marrying and on own ability, own qualification predicts spousal qualification. However, as spousal traits is defined conditional on marriage, this effect is not strictly causal.

[7] Recent papers that follow Choo and Siow (2006) include Dupuy and Galichon (2014), Galichon and Salanié (2021), Choo (2015), Brandt, Siow, and Vogel (2016), Mourifié and Siow (2021), Chiappori, Salanié, and Weiss (2017), and Chiappori, Costa Dias, and Meghir (2018). Following Dagsvik (2000), Arcidiacono, Beauchamp, and McElroy (2016) set up and estimate a matching model, where individuals can also choose the terms of the relationship, which they use to analyze high-school relationships.

and therefore, human capital. Their identification strategy rests on a fully dynamic model. We focus on short-run marriage market adjustments in a static model where identification derives from a large reform-induced change in the mapping from ability to qualification attainment. In this respect, we provide a prototypical example of how the CS framework can be extended to include a correlated latent type-dimension without sacrificing tractability, and be identified through a discontinuity in the environment and the associated changes in the observable marriage outcomes.

Central to our approach is that we study outcomes for cohorts born sufficiently close that it can be plausibly assumed that preferences are stable. This provides an interesting contrast to Chiappori, Dias, and Meghir (2020) who use the CS approach to decompose changes in marriage patterns over time into supply and preference changes. Noting that assortative matching occurs when the marital surplus—reflecting preferences—exhibits supermodularity, they argue, using data on educational attainments and marital outcomes in US cohorts born over a long timeframe (1930s through to the 1970s), that assortative matching has increased, and particularly so at the top of the education distribution.

Our extended model retains the standard CS assumptions, most notably the existence of a set of finite types where all market participants observe each other's type, including their latent ability. There are three qualifications levels—none, basic and advanced—and three ability levels—low, medium and high. Identification of the marital surplus matrix hinges on three restrictions. First, we assume that the RoSLA discontinuously shifted the distribution of academic qualifications, but not the distribution of latent ability. Second, we interpret the RoSLA as having reduced the opportunity cost of obtaining a basic qualification, which tightened the selection on ability into holding a qualification, and increased the ability-qualification correlation. Those who responded to the reform by obtaining a basic qualification were medium ability individuals who, in the absence of the reform, would have remained unqualified. Third, the husband-wife cohort-profile (determining their age-gap) is assumed to enter additively in the marital surplus. This restriction is tested and not rejected. We also need that some marriages occur between individuals born pre- and post-reform respectively. This is trivially confirmed in the data.

Identification of the roles of qualifications and ability for marital matching reflects the stylized facts referenced above. If ability did not matter for marital surplus—only qualifications did—then, as the RoSLA made unqualified individuals scarce, unqualified individuals should obtain a larger share of any marital surplus and marry more frequently. As this is opposite to what we observe, the data decisively indicates that the reform induced a marriage-surplus-relevant compositional change among the unqualified. Conversely, if only ability—not qualifications—mattered for marital surplus, there is no reason for the husband-wife age gap distribution to respond to the reform.

2. Data Sources

We use data for England and Wales where the academic year runs from September 1st to August 31st in the following calendar year. Individuals born September 1957 through August 1958 thus belong to the 1957 academic cohort, the first exposed to the RoSLA. We focus on a set of academic cohorts $\mathcal{C} = \{1953, ..., 1960\}$ born around the RoSLA and work with three ordered qualification levels, $z \in \mathcal{Z} = \{z^0, z^1, z^2\}$, representing no academic qualifications, a basic academic qualification, and an advanced academic qualification. A basic qualification refers to an Ordinary Level (O-Level) or a Certificate of Secondary Education (CSE) qualification, which is the very first tier of accredited examinations in England and Wales. An advanced qualification refers to an Advanced Level (A-Level) qualification, which is a prerequisite for entry into higher education.

2.1. Labour Force Survey

The UK Labour Force Survey (LFS) is representative of the UK population and contains information on year and month of birth and qualifications held for each household member and on relationships between household members. We pool all individuals observed in the 1984 - 2014 LFS, born in the UK and resident in England and Wales, and who are from some academic cohort $c \in \mathcal{C}$.[8] We use the LFS data to estimate the impact of the RoSLA on academic qualification rates and to characterize the marriage patterns in terms of couples' cohort and qualification profiles.[9] Table 1 provides descriptive statistics for the LFS sample by gender and marital status.

2.2. ONS Population Statistics and Census Data

We use birth statistics from the ONS to calculate academic cohort size by gender for England and Wales.[10] As a general characterization, the cohorts that we are studying

[8] The LFS is annual during 1983-1991, but became a quarterly rotating panel in 1992 where we use first interviews. We focus on England and Wales as other data are available only for these countries.

[9] The LFS provides information about the respondent's current marriage. Our analysis assumes that the observed current marriages are representative of first marriages in terms of spousal characteristics.

[10] We apply gender-cohort mortality rates to calculate academic cohort size at age 25. The gender-specific mortality rates by age were obtained from the ONS's principal projection of historic and projected

Table 1: Pooled LFS Sample of Individuals from Academic Cohorts 1953-1960

	Males			Females		
	All	Single	Married	All	Single	Married
Age in Years	38.86	38.05	39.25	38.99	39.44	38.80
	[9.11]	[9.56]	[8.86]	[9.12]	[9.41]	[8.98]
Academic cohort	1956.60	1956.93	1956.44	1956.60	1956.86	1956.49
	[2.29]	[2.28]	[2.28]	[2.30]	[2.30]	[2.29]
No Qualification z^0	0.35	0.38	0.34	0.32	0.35	0.31
Basic qualification z^1	0.38	0.36	0.39	0.43	0.40	0.45
Advanced qualification z^2	0.27	0.26	0.27	0.24	0.25	0.24
Observations	147,878	47,832	100,046	156,549	47,059	109,490

Notes: The sample pools all individuals observed in the 1984-2014 Labour Force Surveys from academic cohorts 1953-1960 with non-missing information on age, qualification and marital status. Standard deviations in square brackets. Basic qualification refers to CSE/O-Level qualifications, and advanced qualifications refer to A-Level or higher qualifications. See main text for details.

were steadily increasing in size by on average 3 percent per year, from around a cohort size of 650,000 towards the mid-1950s to close to 800,000 by 1960.

We commissioned tabulated data from the ONS based on the 2011 Census in order to characterize never-married rates by gender, academic cohort and qualification. We adjust the data to account for first marriages occurring past the age of 45, leaving us with the proportion never-married by age 45 by gender, academic cohort and qualification.[11]

2.3. National Child Development Study

The National Child Development Study (NCDS) sample individuals born in England, Scotland and Wales in a particular week of March, 1958.[12] The NCDS follows the sampled individuals via a set of "data sweeps" that combines questionnaires and administrative information from e.g. schools. We make use of the 1974 (at age 16) and 1991 (at age 33) data sweeps which contain information on the cohort members' academic ability, and their preferred and realized school leaving age, and their qualification attainment.

The NCDS data does not contain information on spouses and is therefore not suitable for marriage market analysis per se; instead, we use the NCDS data to inform the specification of our main extended CS model. To be consistent with the LFS data, we

mortality rates from the 2010 UK Life Tables. Migration is ignored in the population supply calculations.

[11] First marriages past the age of 45 are rare. We use ONS Cohabitation and Cohort tables on the proportions of never-married individuals by cohort. We assume that the rate of entry into first marriage beyond age 45 is homogenous across qualification groups.

[12] The initial survey, the "Perinatal Mortality Study," established a sample of 17,415 cohort members.

restrict the NCDS sample to individuals born in England and Wales.

3. The 1972 Raising of the School Leaving Age

3.1. The Reform

In the UK, individuals become eligible to leave school at the end of the academic year in which they reach the minimum age requirement, rather than on the day they reach the specified compulsory school leaving age. The UK Government introduced Statutory Act 444, known as the Raising of School Leaving Age (RoSLA) Order, in March, 1972. The RoSLA came into operation on September 1st, 1972, raising the minimum school leaving age requirement by one year to age 16, affecting individuals born from September 1st, 1957. In England and Wales, the RoSLA prompted a dramatic 25 percentage points increase in the proportion of individuals leaving education at age 16, rather than at age 15. The effect was limited to the lower end of the education distribution, with evaluations routinely concluding that the reform had no effect on the probability of leaving at ages 17 or above (see e.g. Chevalier, Harmon, Walker, and Zhu, 2004; Clark and Royer, 2013).

There are two levels of national accredited exams sat during school in England and Wales. The first tier, which we label a basic qualification, led to O-Level or CSE qualifications.[13] First tier examinations are available at the end of the academic year in which an individual turns 16. If an individual remains in school beyond that point, then at the end of the academic year in which they turn 18, a second tier of academic examinations can be taken, leading to A-Level qualification, which we label an advanced qualification.

3.2. The Impact of the RoSLA on Qualifications

As exposure to the RoSLA was determined by a threshold date of birth, we estimate the reform-induced shifts in the qualification rates using a regression discontinuity design (RDD), see e.g Hahn, Todd, and der Klaauw (2001) and Imbens and Lemieux (2008).

Let w be an individual's date of birth, the running variable. There is a deterministic mapping from date of birth w to academic cohort $c \in \mathcal{C}$ and we normalize w such that $\mathbb{1}(w \geq 0)$ indicates RoSLA exposure. Let $z \in \mathcal{Z}$ denote an individual's (highest) academic qualification level, and let y^z be an indicator for attaining level z. Cast in the potential outcomes framework, $y^z = y_0^z\,\mathbb{1}(w < 0) + y_1^z\,\mathbb{1}(w \geq 0)$, where y_1^z and y_0^z are the

[13] Since 1987, the first tier qualification is known as a General Certificate of Secondary Education (GCSE).

potential outcomes with and without RoSLA exposure, respectively.

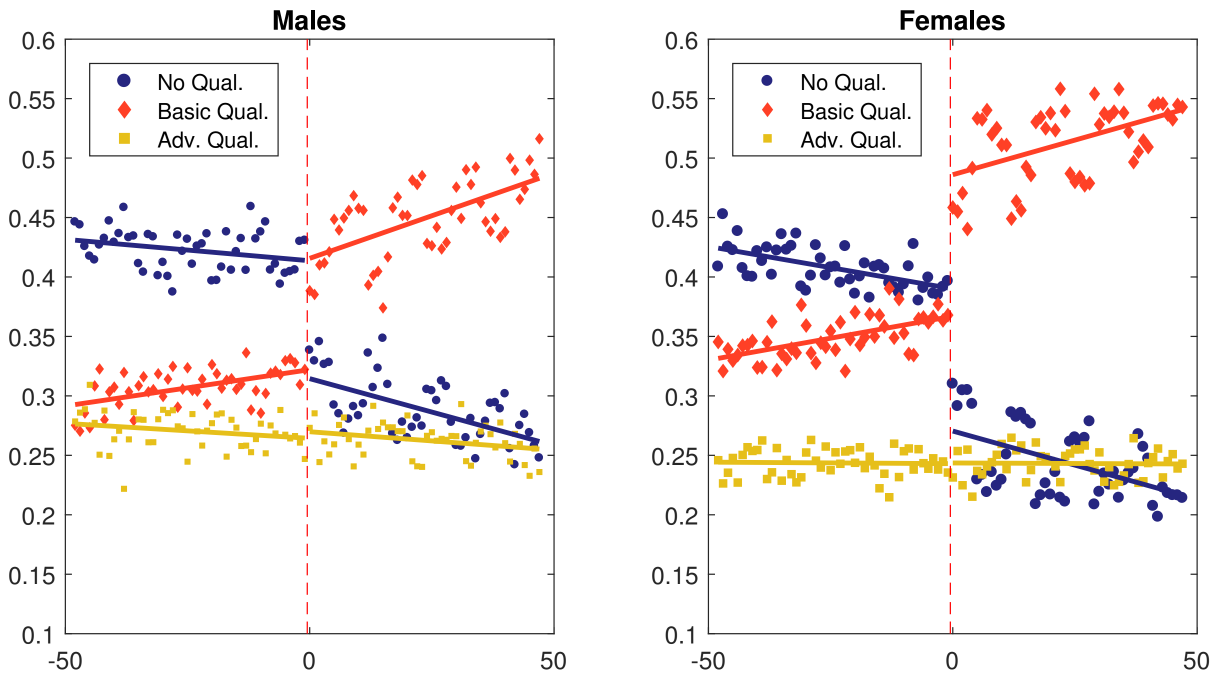
The RDD regression of interest is the linear probability model

$$y^z = \alpha_0 + t_0(w) + t_1(w)\mathbb{1}\,(w \geq 0) + \varphi\,\mathbb{1}\,(w \geq 0) + \epsilon, \tag{1}$$

where $t_0(w)$ and $t_0(w) + t_1(w)$ are the pre- and post-RoSLA trends, respectively, with $t_0(0) = t_1(0) = 0$. If the potential outcome regression functions $E[y_0^z|w]$ and $E[y_1^z|w]$ are continuous functions of w, the OLS estimator of φ in (1) consistently estimates $E\left[y_1^z - y_0^z|w = 0\right]$, the causal effect of the RoSLA on the level-z qualification rate at the reform threshold $w = 0$.

We estimate (1) by gender and qualification levels $z \in \mathcal{Z}$ using the LFS data described above (see Table 1). We include linear trends in the running variable w on either side of the threshold $w = 0$, as advocated by Gelman and Imbens (2019), and employ the Lee and Card (2008) procedure for correcting standard errors for specification errors arising from the LFS recording date of birth by month, an inherently discrete variable.

Figure 1: Distribution of Academic Qualifications by Month of Birth



Notes: The horizontal axes show month of birth normalized to 0 at the RoSLA threshold. The vertical axes show qualification rates.

Figure 1 is a graphical rendition of the RDD. There is a sharp drop in the rate of holding no qualification for each gender at the RoSLA threshold, with a corresponding discontinuous increase in the proportion holding a basic qualification. The RoSLA did not have any effect on the rate of holding an advanced qualification.

Table 2: Regression Discontinuity Estimates of the RoSLA-Effect on Qualification Rates

	Males		Females	
	(i)	(ii)	(iii)	(iv)
No Qualification	-0.099^{***} (0.008)	-0.106^{***} (0.006)	-0.120^{***} (0.009)	-0.128^{***} (0.007)
Basic qualification	0.094^{***} (0.008)	0.106^{***} (0.005)	0.119^{***} (0.010)	0.131^{***} (0.007)
Advanced qualification	0.006 (0.005)	-0.000 (0.005)	0.001 (0.005)	-0.002 (0.004)
Controls	No	Yes	No	Yes
Observations	147,878	147,878	156,549	156,549

Notes: The sample used in each regression is described in Table 1. We report the estimated coefficient on a RoSLA dummy for being born September, 1957 or later from separate regressions with the dependent variable being a dummy for having a particular level of qualification attainment. Distance of date of birth from the September, 1957 threshold measured in months is used as the running variable and is included in linear form and interacted with the RoSLA dummy. The demographic controls include a third degree polynomial in age, month of birth dummies, and year of interview dummies. *, **, and *** indicates statistical significance at the 10, 5, and 1 percent levels, respectively.

Table 2 reports estimates of φ in (1) by gender and qualification level $z \in \mathcal{Z}$, with and without the inclusion of demographic controls. The RoSLA reduced the fraction holding no qualification by about 10 percentage points for men and by about 12 percentage points for women, effect sizes that are very precisely estimated and in line with previous studies evaluating the RoSLA-effect on qualification rates.

3.3. RoSLA Effects by Ability: Evidence from the NCDS

All born in March, 1958, the NCDS cohort members were in the first RoSLA-treated academic cohort. The 1974 NCDS data sweep was conducted in the Spring of that year, as the NCDS cohort members were turning 16, and a few months before they were due to sit the O-level/CSE exams that would give them their first academic qualification.

3.3.1. School-Leaving Age and Qualifications. The 1974 data sweep asked NCDS cohort members two questions about preferred school-leaving age. First, they were asked "At what age do you think you are most likely to leave school?", with the lowest option being 16, consistent with this being the minimum school-leaving age for their particular cohort. Second, after being reminded that they were the first cohort required to stay in school for an additional year, they were asked "In your case, do you wish that you could have left when you were 15?". From these two questions, we define an individual's preferred school-leaving age with options 15, 16 and 17+. The 1991 data sweep, completed at age 33, collected information on realized school-leaving age and qualification attainment.

Using this information, we classify the NCDS cohort members as:[14]

- "Never-takers": Individuals who would have preferred to leave school at age 15, and who, having been required to stay until age 16, left school without a qualification
- "Compliers": Individuals who preferred to leave school at age 15, but who, having been required to stay until age 16, left school with a basic qualification
- "Always-takers": Individuals who preferred to stay until age 16 even if leaving at age 15 had been an option, and who left school with a basic qualification

Additionally we define as a separate class,

- "Stayers": Individuals who stayed on past age 16 and gained advanced qualification,

and document how individuals in these four subpopulations differ in academic ability.

3.3.2. Ability and selective RoSLA responses. The NCDS contains measures of cognitive and academic ability at age 16, including one reading comprehension test and one mathematics test, as well as teacher assessments in English, mathematics and science. We treat the five measures as noisy indicators of latent academic ability and use a measurement model to estimate a standardized ability measure (see Appendix A).

Figure 2 plots the density and the cumulative distribution of the NCDS ability for "Never-takers", "Compliers", "Always-takers", and "Stayers". The ability distributions of "Compliers" and "Always-takers" are strikingly similar.[15] That is, individuals pushed by the RoSLA to obtain a basic qualification that they would otherwise not have acquired ("Compliers"), are of similiar ability as individuals who, even in the absence of the RoSLA, would have left school with a basic qualification ("Always-takers").

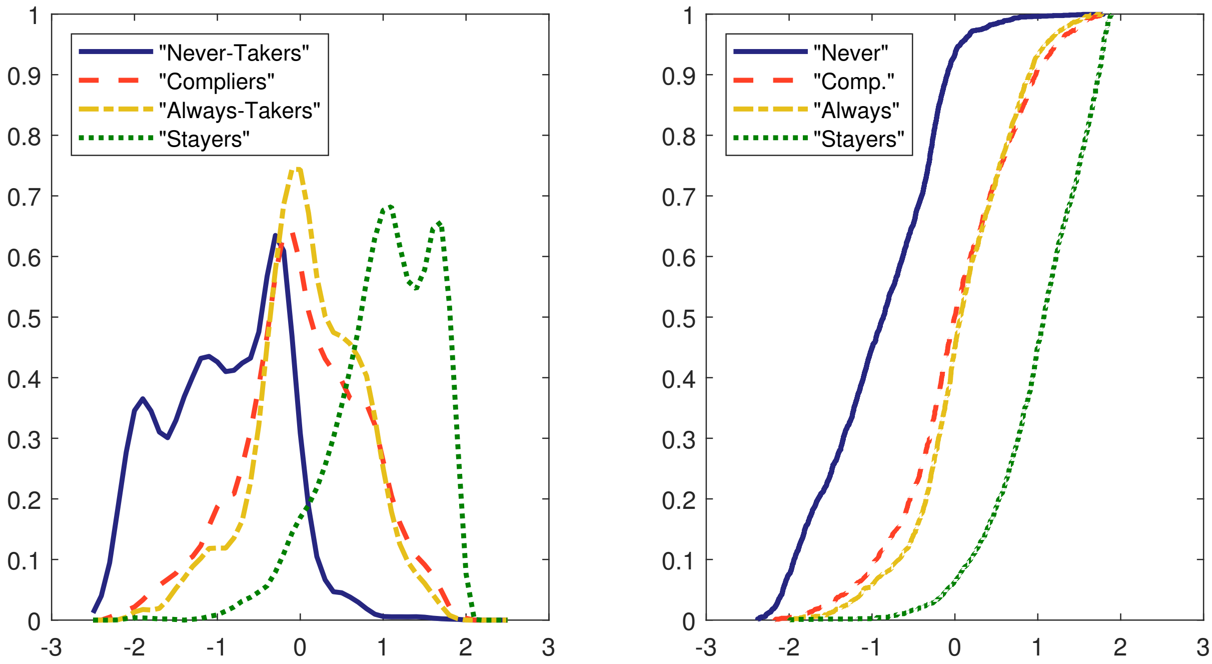
The ability distribution of "Stayers" stochastically dominates those of "Compliers" and "Always-takers", which in turn very dominate that of "Never-takers". That is, the

[14]We verify in Appendix A that (i) NCDS preferred school-leaving ages align closely with the pre-RoSLA LFS qualification distribution, (ii) preferred school-leaving age aligns well with realized school-leaving age under the constraint that leaving at age 15 is not an option, and (iii) NCDS qualifications closely resemble those observed in the LFS for the first RoSLA-affected cohort.

[15]These figures pool across men and women. In Appendix A we provide further details of mean estimated ability by gender and classification. Geruso and Royer (2018) also use information on preferred and actual school-leaving age in the NCDS, but do not relate this information to ability measures.

RoSLA primarily affected qualification attainment among individuals who were (i) more academically able than the least able, (ii) not as academically able as the most able, and (iii) of similar ability to those who absent the reform would attain basic qualification.

Figure 2: Ability Distributions by Individual Classification in the NCDS



Notes: The figure shows distributions of (estimated) academic ability by RoSLA Never-takers, Compliers, Always-takers, and Stayers in the National Child Development Study. The left panel shows kernel density plots (Epanechnikov kernel, bandwidth 0.1). The right panel shows the cumulative distribution of ability. The overall sample size in each panel is 6,365, with 2,054, 1,329, 1,280, and 1,702 individuals respectively in the four classes.

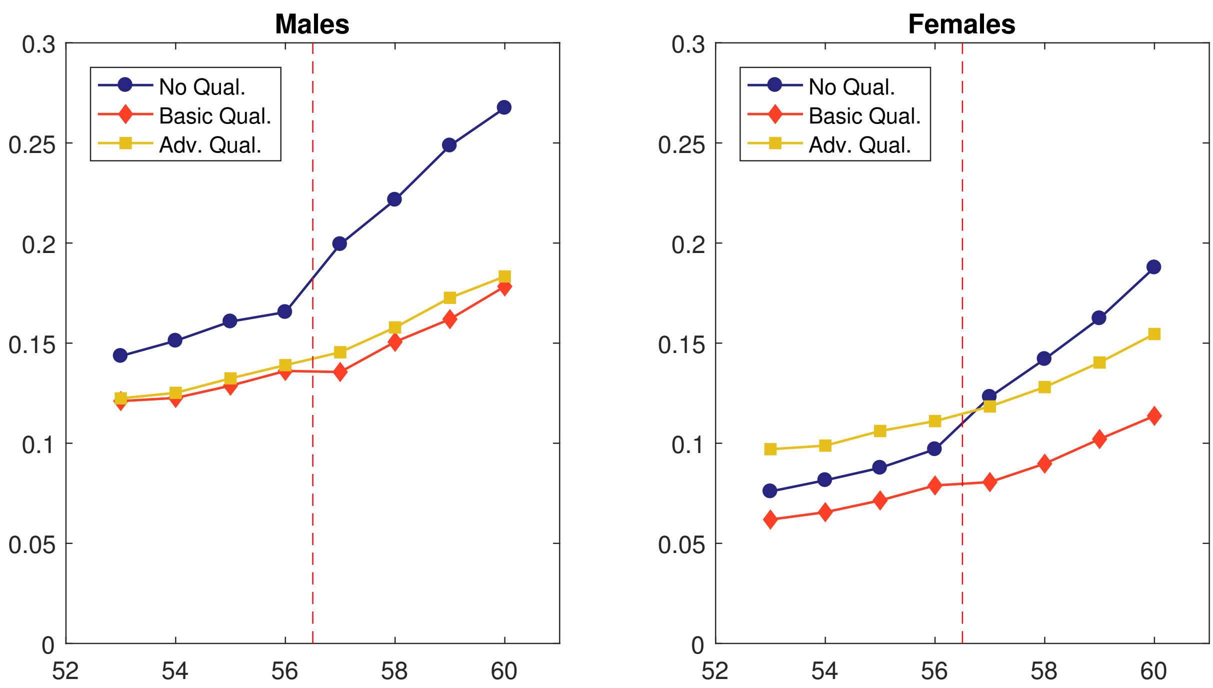
4. The RoSLA and the Marriage Market

4.1. Never-Married Rates

Figure 3 shows the never-married rate by age 45 by gender, cohort, and level of qualification. The never-married rates exhibit an increasing trend for all qualification levels. The never-married rate of men is above that of women for each cohort and qualification level.

The most striking feature of Figure 3 is the increase in the never-married rate for unqualified individuals at the RoSLA threshold. Indeed, for women the first affected academic cohort marks a key turning point. Whereas traditionally, the most qualified women would have been the least likely to marry in their lives, the first RoSLA affected cohort is also the first for which unqualified women were the least likely to ever marry. Among men, the unqualified were already least likely to marry, but at the reform threshold, the gap in the never-married rates for unqualified and qualified rose distinctly.

Figure 3: Never-Married (by Age 45) Rates by Cohort, Gender, and Qualification



Notes: Academic cohorts on horizontal axes. Never-married (by age 45) rates on vertical axes.

4.2. Qualification Homogamy

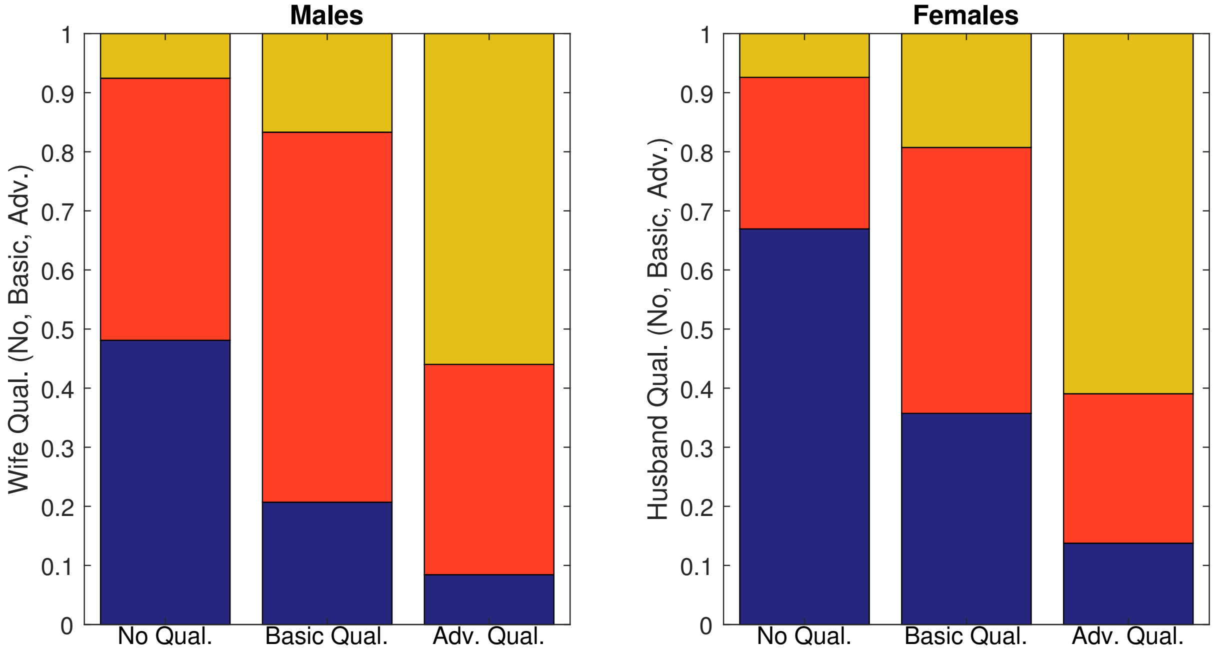
The left panel of Figure 4 shows the qualification distribution of the wives of all married men born between 1953 and 1960 by the husband's own qualification level. The right panel provides the corresponding distribution of husbands' qualifications by the wife's own qualification for the sample of married women. There is clear evidence of qualification homogamy: For each gender and qualification level, the qualification most frequently held by the spouse is the same as that held by the respondent.

Did the RoSLA alter the degree of qualification homogamy? We consider this question using a qualification homogamy index also used by Eika, Mogstad, and Zafar (2019). Let $g \in \{m, f\}$ index gender, where m stands for "male" and f for "female", and use prime to indicate own variables, and double-prime for the spouse. Then, consider

$$S^g(z,c) \equiv \frac{\Pr^g(z' = z, z'' = z | c' = c)}{\Pr^g(z' = z | c' = c) \Pr^g(z'' = z | c' = c)}, \quad g = m, f. \tag{2}$$

The homogamy index $S^g(z,c)$, for qualification z, is defined for the population of mar-

Figure 4: Qualification Homogamy by Gender



Notes: Each panel shows the spousal qualification distribution by own qualification level.

ried individuals of gender g and cohort c. The numerator is the probability that, for a randomly drawn individual in this subpopulation, both the individual and their spouse have qualification z. The denominator is the product of the marginals: the probability of the individual having qualification z and the probability of the spouse having that same qualification. Under random matching, $S^g(z,c)$ is unity and rises above unity if both partners holding qualification z is more common than under random matching.[16]

We compute $S^g(z,c)$ by qualification, gender and cohort using the LFS sample of married individuals, and an aggregate index where each $S^g(z,c)$ is weighted by the frequency of qualification z among gender g, cohort c individuals. The cohort profiles of the homogamy indices are shown in Figure 5 for married men (left panel) and for married women (right panel). The aggregate homogamy index profile is flat for both genders, a conclusion that is robust to other homogamy measures, for instance rank-correlation.[17]

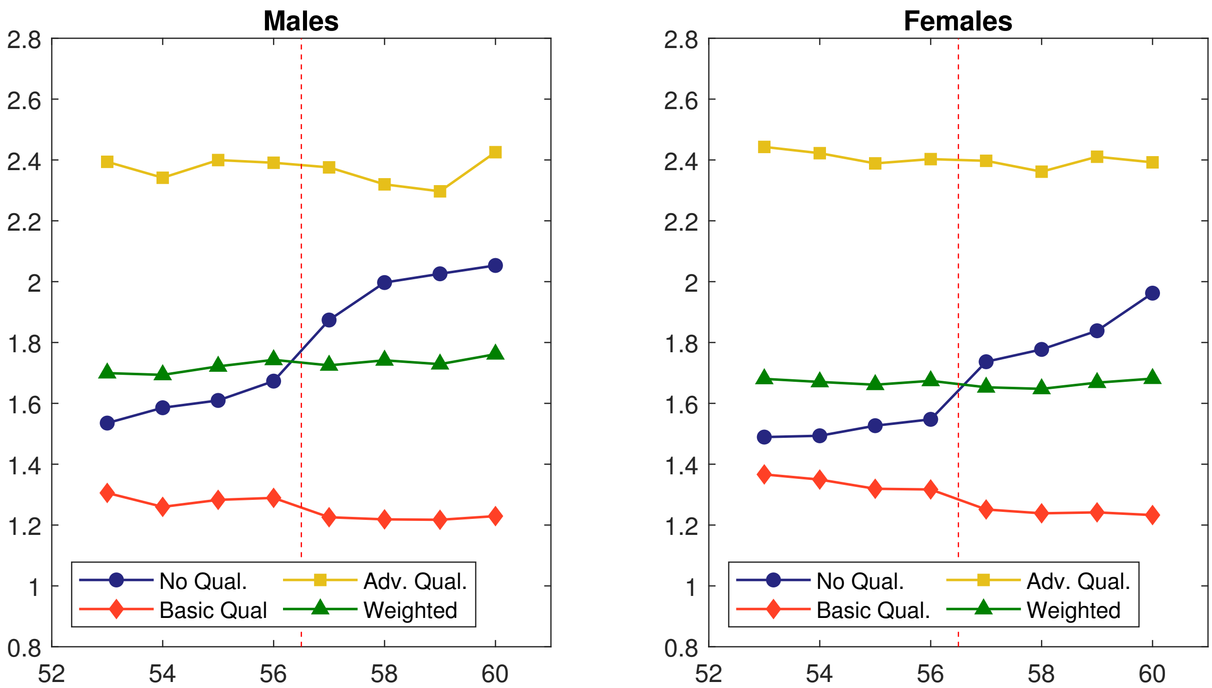
The aggregate index, however, masks considerable heterogeneity. First, the advanced

[16]A high $S^g(z,c)$-value may reflect small population shares, high single rates, or it may reflect that particular subgroups are likely to inter-marry, which increases the numerator in (2). The homogamy index does not disentangle these mechanisms, and we only deploy it as a descriptive device to pinpoint changes in marriage market outcomes around the RoSLA.

[17]Computing the Goodman-Kruskal gamma measure of the rank correlation among males (females), we get 0.628 (0.638) among the "before" cohorts 1953-56 and 0.633 (0.637) among "after" cohorts 1957-60, with no statistically significant before-after differences.

qualified always has the highest index value, and the basic qualified always has the lowest index value. Since the three qualifications groups are roughly equally frequent in the married population (see Figures 1 and 3) the clear homogamy index ranking likely reflect different tendencies for inter-marrying. Second, there is a clearly visible and permanent increase in the qualification homogamy index after the RoSLA for unqualified men and women. In part, this increase is mechanical as the unqualified become a smaller share of the married population. However, an opposite mechanical effect would apply to the population holding a basic qualification as their proportion increased after the RoSLA. Yet, for this group we see, at most, a modest decrease in the homogamy index. This suggests that the post-RoSLA increase in unqualified homogamy may reflect, at least in part, an increase in the tendency of unqualified individuals to inter-marry.

Figure 5: Qualification Homogamy by Cohort, Gender, and Qualification

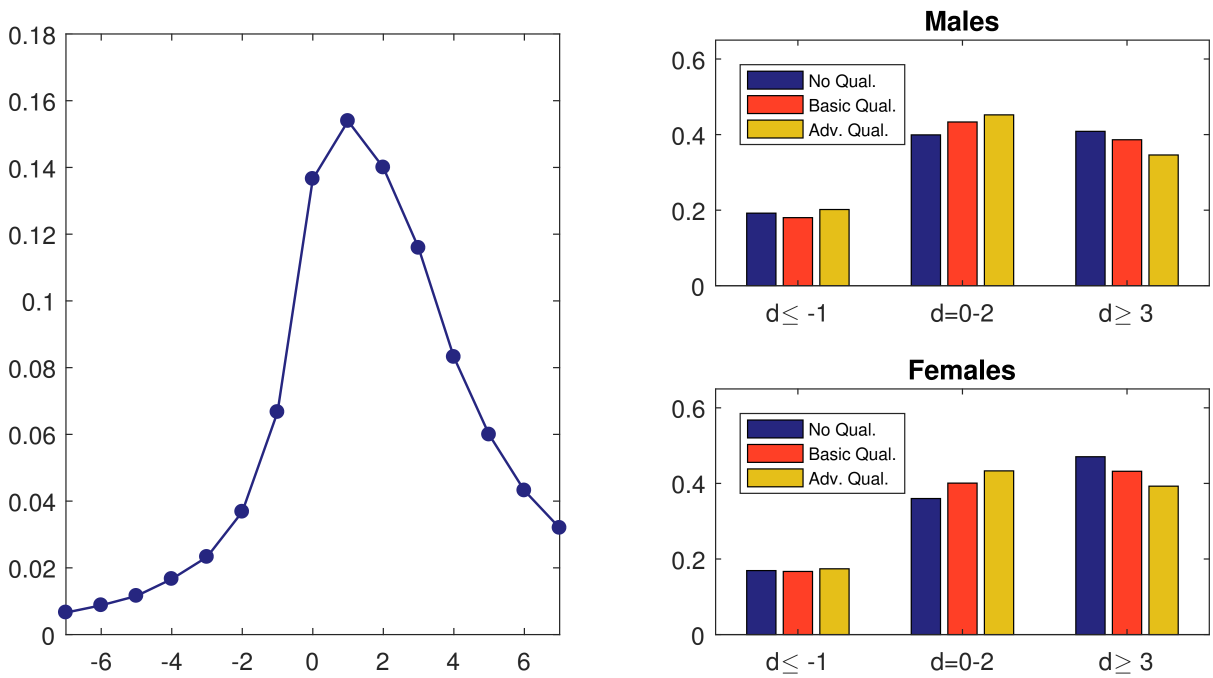


Notes: Academic cohorts on the horizontal axes. The homogamy index (2) on the vertical axes.

4.3. Age Gaps

We define the husband-wife age gap d as the difference in their academic cohorts: $d \equiv c' - c$, where c and c' are cohort of the husband and the wife, respectively. The left panel of Figure 6 shows the husband-wife age gap distribution in the LFS sample of married individuals. Age gaps of 0, 1 and 2 are the most frequent. There is a sharp drop in frequency when moving to negative age gaps, but a fat right tail for positive age gaps.

Figure 6: The Husband-Wife Age Gap Distribution



Notes: The age gap d is defined as $d \equiv c' - c$, where c and c' are cohort of the husband and the wife, respectively. The left panel shows the aggregate husband-wife age gap distribution. The right panels show the age gap distribution, by gender and qualification.

In the right panels of Figure 6, we show the age gap distribution, by gender and qualification. The distribution of husband-wife age gaps for married men born in some $c \in \mathcal{C}$ is displayed in the upper panel, while the lower panel does the same for married women. The right panels of Figure 6 suggests that there is no particular qualification pattern among individuals who choose to marry with a negative age gap. Among those marrying with non-negative age gaps, larger positive age gaps are slightly more common among less qualified individuals, consistent with Mansour and McKinnish (2014).

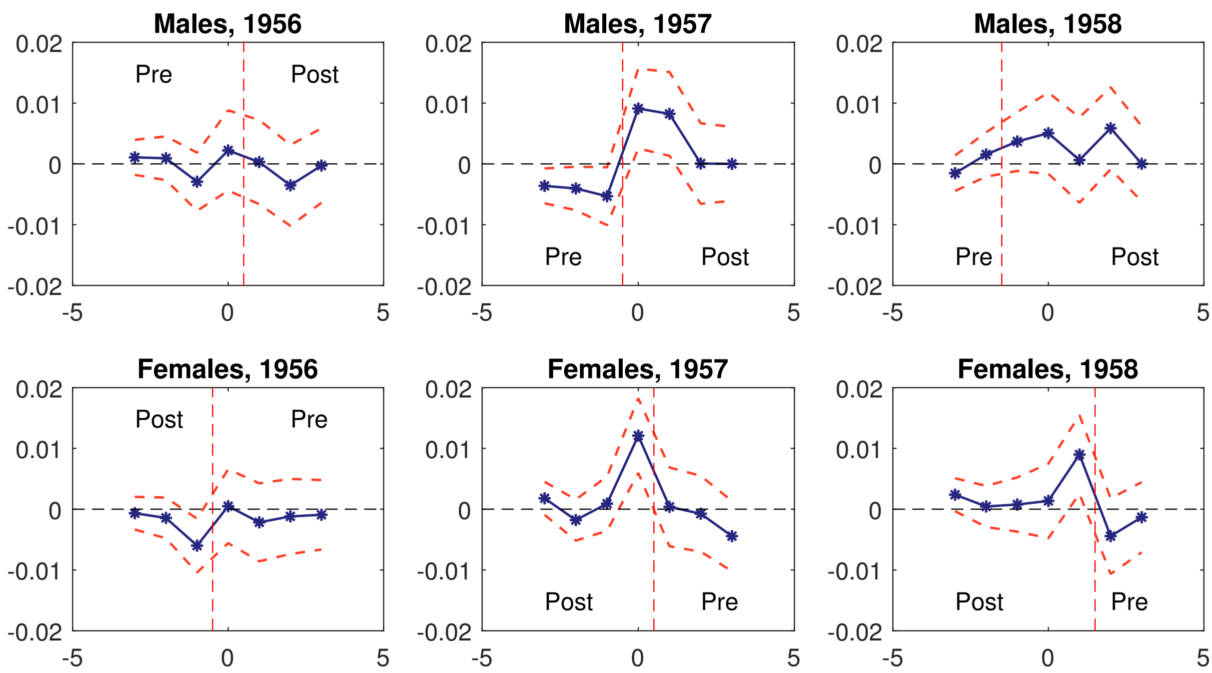
To explore whether the age gap distribution was affected by the RoSLA, we compare the cohort-specific distributions to the aggregate distribution around the reform threshold. For each age gap $\delta \in \{-3, -2, ..., 3\}$ and cohort $c \in \mathcal{C}$ we regress $\mathbb{1}(d = \delta)$ on a cohort-c dummy to determine whether cohort c individuals had a different likelihood of being married with age gap δ compared to individuals from other cohorts.

The estimated coefficients on the cohort-dummy are plotted in Figure 7. The panels in the top row consider men in each cohort 1956 to 1958. In each panel, a vertical line delineates whether the wife is from a pre- or post-RoSLA cohort. For men, the first

RoSLA affected cohort, the 1957 cohort, is the only cohort with statistically significantly different age gap frequencies, being about one percentage point more likely to be married with an age gap 0 or +1, but less likely to marry with a negative age gap.

The bottom row of Figure 7 shows the corresponding results for women. The vertical lines now delineate whether the husband is drawn from a pre- versus post-RoSLA cohort. Consistent with the findings for men, the most notable deviations are for early post-reform women—born in the 1957 and 1958 academic cohorts—who were about one percentage point more likely to marry with an age gap of 0 and +1 respectively (thus both marrying 1957 cohort men). Our evidence show that the RoSLA temporarily shifted the age gap distribution, with the early RoSLA-affected cohorts inter-marrying more frequently.[18]

Figure 7: Deviations from the Aggregate Age Gap Distribution by Cohort and Gender



Notes: The horizontal axes show age gap $\delta \in \{-3, -2, ..., 3\}$. The vertical axes show regression coefficients from a regression of $\mathbb{1}(d = \delta)$ on a cohort-dummy for being from cohort c. The vertical dashed lines delineate when a partner is drawn from a pre- versus post-RoSLA cohort.

[18] Our findings are largely consistent with those of Geruso and Royer (2018).

5. Model

5.1. The Choo-Siow Framework

Our theoretical analysis builds on Choo and Siow (2006). Assume continuum sets of men and women, each of finite Lebesgue measure. Each individual belongs to one of a finite set of systematic types $\mathcal{X}$, and their systematic type is publicly observed by all potential partners. Each individual must choose a type of partner in $\mathcal{X}_+ = \mathcal{X} \cup \{0\}$, where choosing 0 corresponds to remaining single. A match between a type-x man and a type-y woman results in a systematic match surplus Σ_{xy}. If an individual remains single, the systematic payoff that they obtain is normalized to zero. Man i is also subject to a vector of preference shocks, $(\varepsilon_i(y))_{y \in \mathcal{X}_+}$, where $\varepsilon_i(y)$ is an idiosyncratic incremental payoff (to man i) from matching with *any* woman of type $y \in \mathcal{X}$ (or remaining single if $y = 0$). Woman j is subject to a vector of shocks $(\varepsilon_j(x))_{x \in \mathcal{X}_+}$ over male systematic types. The surplus of a match between man i of type x and woman j of type y is

$$\Sigma_{xy} + \varepsilon_i(y) + \varepsilon_j(x). \tag{3}$$

The preference heterogeneity components $\varepsilon_i(y)$ and $\varepsilon_j(x)$ are separable, entering (3) additively. They depend on the partner's type, not their identity. The surplus can be divided in any way the couple chooses.

Under the assumption that the systematic type of every individual is observed by all market participants, existence and essential uniqueness of a stable matching is guaranteed (Decker, Lieb, McCann, and Stephens, 2012).[19] Chiappori, Salanié, and Weiss (2017) show that, under separability, a stable matching is characterized by a pair of vectors $(U_{xy}, V_{xy})_{x,y \in \mathcal{X}}$ such that for each $x, y \in \mathcal{X}$, $U_{xy} + V_{xy} = \Sigma_{xy}$. U_{xy} specifies the systematic component of the payoff to a type-x man when he matches with a type-y woman while V_{xy} specifies the corresponding payoff to the woman. The systematic payoff from remaining single, denoted by U_{x0} and V_{0y}, is zero. Each man i of type x maximizes his overall payoff $U_{xy} + \varepsilon_i(y)$ by his choice of $y \in \mathcal{X}_+$, and each women j of type y maximizes $V_{xy} + \varepsilon_j(x)$ by her choice of $x \in \mathcal{X}_+$. As a consequence of these choices, marriage markets clear: for each pair (x, y), the measure of type x men who choose to marry type y women equals the measure of type y women who choose to marry type x men.

[19]Note that existence and essential uniqueness applies equally to our generalized model with a latent ability, since we shall assume throughout that market participants observe the types of all potential partners.

Let $\mu^m_{y|x}$ denote the equilibrium probability that a man of type x chooses $y \in \mathcal{X}_+$, and similarly, let $\mu^f_{x|y}$ denote the equilibrium probability that a woman of type y chooses $x \in \mathcal{X}_+$. The preference shocks $\varepsilon_j(x)$ and $\varepsilon_i(y)$ are assumed to be i.i.d. Type I Extreme Value distributed,[20] such that

$$\log\left(\frac{\mu^m_{y|x}}{\mu^m_{0|x}}\right) = U_{xy}, \text{ and } \log\left(\frac{\mu^f_{x|y}}{\mu^f_{0|y}}\right) = V_{xy}. \tag{4}$$

Decker, Lieb, McCann, and Stephens (2012) show that the marriage market equilibrium exhibits natural comparative statics.

In large marriage markets, where the Law of Large Numbers hold, the population frequencies in (4) can be replace by their sample counterparts. Hence, if types are observable to the econometrician, U_{xy} and V_{xy}, and consequently also Σ_{xy}, are identified. The identification argument in the standard CS framework depends on the systematic types of the marriage market participants being observable to the econometrician, and thus restricts attention to marital sorting on observables. This is unfortunate, not least because the literature typically considers only low-dimensional systematic type-spaces.[21]

The focus on low-dimensional observable type-space also yield stark comparable static predictions for marriage market equilibrium responses to changes in the population distribution resulting from a large education reform as the RoSLA. Consider for instance a decrease in the supply of males of observable type x, say, men with no academic qualifications. The CS framework stipulates that men of this type will obtain a larger share of the marital surplus from a marriage to any type of woman. As a result, type x men are predicted to marry at a higher rate, i.e. the never-married rate $\mu^m_{0|x}$ is predicted to fall. Of course, the never-married rate of the relatively scarce post-RoSLA unqualified men markedly increased at the reform threshold, cf. Figure 3.[22]

5.2. A Model with Latent Ability

In our empirical setting, an individual's type has three dimensions. First, an individual belongs to an academic cohort $c \in \mathcal{C}$. Second, they are endowed with ability $a \in \mathcal{A}$. Finally, they hold an academic qualification, $z \in \mathcal{Z} = \{z^0, z^1, z^2\}$. Hence, an individual's

[20] The Extreme Value distribution assumption is standard although Galichon and Salanié (2021) show that the Choo-Siow framework remains tractable with minimum distributional assumptions.

[21] Chiappori, Oreffice, and Quintana-Domeque (2012) and Dupuy and Galichon (2014) who use rich datasets to analyze sorting with high-dimensional systematic type-spaces are notable exceptions.

[22] Admittedly, the RoSLA shifts population distributions of both genders, but we confirm that the intuition is useful for interpreting the marriage market responses to the RoSLA.

type is a triple $(c, a, z) \in \mathcal{C} \times \mathcal{A} \times \mathcal{Z}$. Informed by the NCDS evidence, we consider a parsimonious specification with three ability levels, $\mathcal{A} = \{a^0, a^1, a^2\}$, which we refer to as low, medium, and high ability, respectively. The academic cohorts in $\mathcal{C}$ are split into the pre- and post-RoSLA cohorts, $\mathcal{C}_0 = \{1953, ..., 1956\}$ and $\mathcal{C}_1 = \{1957, ..., 1960\}$.

An individual's systematic type is observed by prospective partners in the marriage market, but ability is unobserved by the econometrician. Hence, the identification arguments referenced above no longer apply. Identification will instead derive from a RoSLA-induced discontinuity in qualifications between cohorts, but not in ability.

Recall that w is date of birth, and let $\Pr^g(a|w)$ be the proportion of individuals of gender g, born at time w with ability a. We make the following assumption:

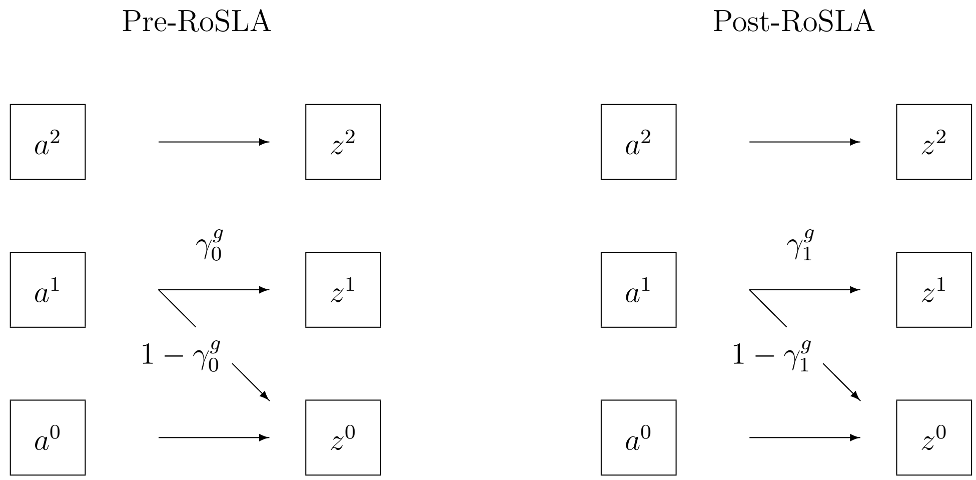
Assumption 1. $\Pr^g(a|w)$ is continuous in birth date w for $a \in \mathcal{A}$, and gender $g \in \{m, f\}$.

As the RoSLA sharply increased the proportion holding a basic qualification rather than no qualification, we focus on modeling a shift in the population proportions with $z = z^0$ and $z = z^1$. The NCDS evidence in Figure 2 suggest that this shift was driven by medium ability individuals. Appealing to these observations, Assumption 2 provides an empirically relevant, yet parsimonious, representation of the qualification process:

Assumption 2. Any individual of low ability, $a = a^0$, is always unqualified, $z = z^0$, and any individual with high ability, $a = a^2$, always attains an advanced qualification, $z = z^2$. A gender g and cohort $c \in \mathcal{C}_k$ individual of medium ability, $a = a^1$ attains a basic qualification with probability γ_k^g and remains unqualified with complementary probability $1 - \gamma_k^g$, for $k = 0, 1$, indicating pre- and post-RoSLA respectively, where $\gamma_1^g > \gamma_0^g$.

Figure 8 is a graphical representation of Assumption 2. Having low ability $a = a^0$ precludes the attainment of even a basic qualification. Individuals with high ability, $a = a^2$, are assumed to always find it worthwhile to attain an advanced qualification, $z = z^2$. The RoSLA changes the expected qualification level of individuals with medium ability $a = a^1$ for whom a basic qualification $z = z^1$ is assumed attainable. Pre-RoSLA, a share γ_0^g of the gender-g a^1-individuals attained a basic qualification. Post-RoSLA, a share γ_1^g of the gender-g a^1-individuals attained a basic qualification. Hence, there are four possible ability-qualification profiles: (a^0, z^0), (a^1, z^0), (a^1, z^1) and (a^2, z^2). Within this set, there is variation in ability (low versus medium) among the unqualified, and there is variation in qualifications (unqualified versus basic) among medium ability individuals. Let $\mathcal{X} \subset \mathcal{C} \times \mathcal{A} \times \mathcal{Z}$ be the set of full types that can arise and note that $|\mathcal{X}| = 32$.

Figure 8: Assumed Relation between Ability and Qualification by Education Regime



Assumption 2 implicitly stipulates that a medium ability individual's basic qualification attainment is determined by some further unobserved heterogeneity unrelated to marital surplus. We argue that the opportunity costs of attending school is an important source of such heterogeneity. To obtain a basic qualification, $z = z^1$, an individual must attend school up to and through the academic year in which they turn 16, and pass the exams held at the end of that year. While passing the exams generally depends upon ability, attending school entails an opportunity cost, an important component of which is foregone labor earnings. Pre-RoSLA, an individual would forego labor income if they attended school beyond age 15, but paid employment ceased to be an option for a 15-year old in the post-RoSLA regime.[23] Hence, the reform reduced the opportunity cost of acquiring a basic qualification, $z = z^1$, without altering the ability required to so. In the assumed setup, consistent with the NCDS evidence in Figure 2, the RoSLA impacted the qualification rate of a^1-individuals who would be weighing the costs and benefits of sitting the exams for the basic qualification level.[24]

As the reform eliminated the foregone earnings cost of acquiring a basic qualification there is a strong *ex ante* reason to believe that, after the RoSLA, those who had the

[23]The school leaving age and the minimum age for employment are statutorily linked. The 1933 Children and Young Persons Act for England and Wales sets out conditions for young people work. It essentially prohibits full time worker whilst in school, and was in force at the time of the RoSLA. In addition, the 1946 and 1965 National Insurance Acts stipulate that a person can work full time if they are "being over school leaving age". The 1965 National Insurance Act was in force at the time of the RoSLA reform and 1974 and 1980 amendments did not change the wording of who is an insured person.

[24]Bell, Costa, and Machin (2022) argue that compulsory schooling reduce crime due to dynamic "self-incapacitation" rather than improved educational outcomes. This is consistent with our interpretation that schooling entails foregone opportunities (in our case employment, in their case criminal activities.)

ability to gain a qualification would do so. This imply $\gamma_1^g = 1$ and we show that this hypothesis is not rejected. The significance of this finding will be clear just below where we use a simple 2 cohorts $\times$ 2 ability-types $\times$ 2 qualification-types specification to argue that, when $\gamma_1^g = 1$, $g = m, f$, the marital surplus matrix Σ_{xy} is identified.

For this we need, however, to impose one further separability assumption on the the systematic component of the marital surplus matrix Σ_{xy}. Assumption 3 restricts Σ_{xy} to be additively separable in ability-qualification and cohort profile.

Assumption 3. The systematic surplus function Σ_{xy} is additively separable,

$$\Sigma_{(c,a,z),(c',a',z')} = \zeta\left(a, z, a', z'\right) + \lambda\left(c, c'\right).$$

5.3. Identification in the $2 \times 2 \times 2$ *Case*

Consider the simple $2 \times 2 \times 2$ case in which there are only two cohorts, $\{c^0, c^1\}$—one pre-RoSLA cohort c^0 and one post-RoSLA cohort c^1—two ability types $\{a^0, a^1\}$ and two qualification types $\{z^0, z^1\}$ with the ability-qualification mapping as in Figure 8, but restricted to $\gamma_1^g = 1$ and ignoring the (observable) advanced-qualified high-ability type. There would, in this case, be 5 feasible full types for each gender, and thus 25 couple type-profiles, plus 10 singles rates. However, 20 of these 35 matching- and single rates are not directly observable. Appendix B tabulates the observable and unobservable rates.

Our main result in this section is the following Proposition:

Proposition 1. *Suppose that (i) there are two cohorts* $\{c^0, c^1\}$*, one pre- and one post-RoSLA, and (ii) there are two ability levels* $\{a^0, a^1\}$ *and two qualifications* $\{z^0, z^1\}$*. Under Assumption 1 with* $\Pr^g(a|c) = \Pr^g(a)$*, Assumption 2 with* $\gamma_1^m = \gamma_1^f = 1$*, and Assumption 3, the complete matching pattern can be inferred and* Σ_{xy}*,* U_{xy} *and* V_{xy} *are identified.*

Proof. See Appendix B. □

There are five types in the $2 \times 2 \times 2$ model of which three are distinguishable. The two indistinguishable types are those without qualifications in the pre-RoSLA cohort, who may be of low or medium ability. The proof of Proposition 1 utilizes that, from the matches between distinguishable types, we can invoke Assumption 3 to identify $\lambda\left(c, c'\right)$, $c, c' \in \{c^0, c^1\}$. These parameters in turn provide us with a means of relating matching patterns of the unqualified individuals in the post-RoSLA cohort, who are of low ability and therefore distinguishable, to the matching patterns of the unqualified low-ability individuals in the pre-RoSLA cohort. We show that the unobservable matches satisfy a system of non-linear equations in the observables. This system has a unique solution and yields formulas for the unobservable matching rates. Given the matching matrix, Σ_{xy}, U_{xy}, and V_{xy} are identified as in Choo and Siow (2006).[25]

5.4. Empirical Specification

Our empirical specification enriches the $2 \times 2 \times 2$ model by (i) including the high ability, advanced qualified type, (a^2, z^2), (ii) extending the observation window to eight cohorts, (iii) allowing for trends in the ability distributions, and (iv) allowing $\gamma_1^m \leq 1$ and $\gamma_1^f \leq 1$.

Including the (a^2, z^2)-type is empirically important as they are a sizeable subpopulation who occasionally marry partners with basic or no qualification, but raises no identification issues as the (a^2, z^2)-type is, per Assumption 2, an observable type.

Including additional cohorts raises two issues. First, our RDD identifies the increase in the basic qualification rate only at the reform threshold. Cohort variation in γ_k^g, within regime $\mathcal{C}_k$, $k = 0, 1$, is not distinguishable from variation in the frequency of ability levels a^1 and a^0. Assumption 2 makes clear that γ_k^g, $g = m, f$ are regime-specific time-invariant parameters. Second, there are evident trends in never-married rates. Ignoring such trends risk mischaracterizing discontinuities at the RoSLA threshold. Furthermore, with $|\mathcal{C}|^2 = 64$ possible cohort-profiles, it is natural to restrict how marital surplus depends on the husband-wife cohort profile (c, c'). We postulate the following surplus structure,

$$\Sigma_{(c,a,z),(c',a',z')} = \zeta\left(a, z, a', z'\right) + \lambda\left(c' - c\right) + \tau^m\left(c, a\right) + \tau^f\left(c', a'\right), \tag{5}$$

where, with a slight abuse of notation, (5) redefines $\lambda(\cdot)$ as a function of the husband-wife age gap $c' - c$ only, and includes gender- and ability-specific trends, $\tau^g(c, a)$. We specify $\lambda(\cdot)$ as fully non-parametric at age-gaps around zero, impose linear effects of age gap outside the range $\{-3, -2, ..., 3\}$, and normalize $\lambda(0) = 0$. Marital surplus trends are piecewise linear functions of c with a single knot at the RoSLA threshold.[26]

Finally, allowing for $\gamma_1^m \leq 1$ or $\gamma_1^f \leq 1$ is empirically prudent, but as we shall see, the case $\gamma_1^m = \gamma_1^f = 1$ covered in Proposition 1 in fact offers the best fit to the data.

[25] We note that it is empirically sensible and, in fact, essential to the identification result in Proposition 1 that individuals from the pre- and post-RoSLA regimes operate in a single marriage market.

[26] Ability-specific trends formally violates the additive structure in Assumption 3, but they are identified from observable trends by qualification and gender, and crucially, they facilitate the identification of the RoSLA threshold discontinuities. Details of $\lambda(\cdot)$ and $\tau^g(\cdot, a)$ are given in Appendix E.

6. Estimation

The ζ-matrix contains 16 parameters. The age-gap and trend terms add 22 parameters. We stack these 38 systematic surplus parameters in $\boldsymbol{\theta}$. We must also deal with $\boldsymbol{\gamma} \equiv (\gamma_0^m, \gamma_1^m, \gamma_0^f, \gamma_1^f)$, the share of a^1-men and -women with $z = z^1$ pre- and post-RoSLA.

6.1. The Likelihood Function

Our model has $|\mathcal{X}| = 32$ full types making choices from the set $\mathcal{X}_+$.[27] Let $\mu^m_{y|x}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the probability that a type-$x \in \mathcal{X}$ man marry a type-$y \in \mathcal{X}_+$ woman and let $\mu^f_{x|y}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the probability that a type-y woman marry a type-$x \in \mathcal{X}_+$ man (see Appendix C).

The equilibrium in full types $x, y \in \mathcal{X}$ is aggregated to yield choice probabilities over observable types. Let $\widetilde{x}, \widetilde{y} \in \widetilde{\mathcal{X}}$ denote observable types where $\widetilde{\mathcal{X}} \equiv \mathcal{C} \times \mathcal{Z}$. Observable choices are in the set $\widetilde{\mathcal{X}}_+ \equiv \widetilde{\mathcal{X}} \cup \{0\}$. Let $\widetilde{\mu}^m_{\widetilde{y}|\widetilde{x}}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ denote the probability that a male of observable type $\widetilde{x} \in \widetilde{\mathcal{X}}$ is matched to a female of observable type $\widetilde{y} \in \widetilde{\mathcal{X}}_+$. Female observable choice probabilities are similarly denoted $\widetilde{\mu}^f_{\widetilde{x}|\widetilde{y}}(\boldsymbol{\theta}, \boldsymbol{\gamma})$. The following equations describe the aggregation,

$$\widetilde{\mu}^m_{c',z'|c,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a \in \mathcal{A}} \sum_{a' \in \mathcal{A}} \mu^m_{c',a',z'|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^m(a|c,z;\boldsymbol{\gamma}), \tag{6}$$

$$\widetilde{\mu}^f_{c,z|c',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a' \in \mathcal{A}} \sum_{a \in \mathcal{A}} \mu^f_{c,a,z|c',a',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^f(a'|c',z';\boldsymbol{\gamma}), \tag{7}$$

where $\Pr^g(a|c,z;\boldsymbol{\gamma})$ is the population proportion of gender-g individuals of cohort c and with qualification z who are of ability a. These proportions depend on $\boldsymbol{\gamma}$ and are consistent with the empirical qualification distribution, see Assumption 2 and Figure 8. Probabilities for observable types for choosing singlehood are obtained in analogous fashions.

Our data is a pair of gender-specific matrices of marriage frequencies. A generic entry in the male data matrix is $M^m_{\widetilde{x}\widetilde{y}}$, the number of males in our data who are of observable type $\widetilde{x} \in \widetilde{\mathcal{X}}$ and who have made the observable marriage choice $\widetilde{y} \in \widetilde{\mathcal{X}}_+$. Similarly, a generic entry in the female data matrix is $M^f_{\widetilde{x}\widetilde{y}}$, the number of females who are of observable type $\widetilde{y} \in \widetilde{\mathcal{X}}$ and who have made the observable marriage choice $\widetilde{x} \in \widetilde{\mathcal{X}}_+$. The

[27] To account for marriages involving partners that are not in $\mathcal{C}$, we extend the full type space slightly to $\mathcal{X}_+ \equiv \mathcal{X} \cup \{0, \text{pre}, \text{post}\}$, where "pre" and "post" indicate marriages to partners born prior to 1953 and after 1960, respectively. We approximate pre- and post-spouse marriage probabilities using the relative weight put on out-of-sample marriages by the age gap function $\lambda(\cdot)$. See Appendix C for details.

log-likelihood function is:

$$\log \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}_+} M^m_{\widetilde{x}\widetilde{y}} \log \widetilde{\mu}^m_{\widetilde{y}|\widetilde{x}}(\boldsymbol{\theta}, \boldsymbol{\gamma}) + \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}_+} M^f_{\widetilde{x}\widetilde{y}} \log \widetilde{\mu}^f_{\widetilde{x}|\widetilde{y}}(\boldsymbol{\theta}, \boldsymbol{\gamma}). \tag{8}$$

Appendix C provides further details on the likelihood function.

6.2. A Three-Step Estimation Procedure

Estimation is in three steps.

Step 1: Assumptions 1 and 2 imply that the observed discontinous increase in the basic qualification rate at the RoSLA threshold is driven by a proportionately equal increase in the basic qualification rate of medium-ability individuals. That is,

$$\frac{\gamma_1^g}{\gamma_0^g} = \frac{\lim_{w \downarrow 0} E^g[y^{z^1}|w]}{\lim_{w \uparrow 0} E^g[y^{z^1}|w]}, \text{ for } g = m, f, \tag{9}$$

where y^{z^1} is an indicator for attaining qualification $z = z^1$ and w is date of birth relative to the RoSLA threshold date. The RDD estimator of (1) for qualification z^1 allows us to obtain precise estimates of the right hand side of (9), and we therefore treat the (reciprocal) ratio γ_0^g/γ_1^g as known and equal to 0.755 (0.011) for men and 0.738 (0.008) for women where the numbers in parenthesis are boostrapped standard errors.[28]

The post-RoSLA z^1-qualification rate is the product of γ_1^g and the proportion of individuals who have ability level a^1, where the latter cannot exceed the complement of the proportion holding qualification z^2 (as these individuals have ability level a^2). This places a lower bound on γ_1^g, denoted $\underline{\gamma}_1^g$, which we find to be 0.69 for both genders.[29] Altogether, we obtain that the empirically feasible set $\mathcal{G}$ for $\boldsymbol{\gamma}$ is:

$$\mathcal{G} = \left\{ \boldsymbol{\gamma} : \gamma_1^g \in [0.69, 1] \text{ for } g = m, g, \text{and } \frac{\gamma_0^m}{\gamma_1^m} = 0.755 \text{ and } \frac{\gamma_0^f}{\gamma_1^f} = 0.738 \right\}.$$

The ratio restrictions on $\boldsymbol{\gamma} \in \mathcal{G}$ imply that there are only two free parameters in $\boldsymbol{\gamma}$.

Interestingly, when $\gamma_1^g = \underline{\gamma}_1^g = 0.69$ for $g = m, f$, all unqualified individuals have medium ability and no one has low ability. In this limit, everyone is distinguished by

[28] To see this, note that $\gamma_0^g/\gamma_1^g = 1 - \varphi_{z^1}^g / \lim_{w \downarrow 0} E^g \left[y^{z^1}|w\right]$ where the estimated values of $\varphi_{z^1}^g$ from (1) are 0.106 (0.005) for men and 0.131 (0.007) for women (see Table 2), and estimates of the values of $\lim_{w \downarrow 0} E^g \left[y^{z^1}|w\right]$ can simply be obtained as the empirical rate of holding qualification z^1 among individuals in the first RoSLA-affected cohort, 0.433 (0.004) for men and 0.499 (0.004) for women.

[29] The lower bound is defined as $\underline{\gamma}_1^g \equiv \max_{c \in \mathcal{C}_1} \left\{ \Pr^g\left(z = z^1 | c \in \mathcal{C}_1\right) / \left[1 - \Pr^g\left(z = z^2 | c \in \mathcal{C}_1\right)\right] \right\}$.

qualification, there is no latent ability, and our model collapses to a standard CS model.

Step 2: We estimate $\boldsymbol{\theta}$ conditional on $\boldsymbol{\gamma} \in \mathcal{G}$. For each $\boldsymbol{\gamma}$-value on a fine grid on $\mathcal{G}$, we obtain $\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}) \in \arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ and $\mathcal{L}(\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}), \boldsymbol{\gamma})$. While this estimation step is intermediate, it yields a number of insights which we detail in Appendix D. First, we provide a numerical counter-example to generic identification of our latent ability marriage market model in that we identify a set of $\boldsymbol{\gamma}$-values for which $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ is not a singleton. Second, reassuringly, our numerical analysis illustrates that non-identification arises only under knife edge conditions. Third, we confirm that the CS model is a limiting case of our latent ability model and (unsurprisingly) that the standard CS model is identified.

Step 3: Even though $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ may not be singletons for all feasible $\boldsymbol{\gamma}$-values, the conditional likelihood values $\mathcal{L}(\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}), \boldsymbol{\gamma})$ can be used to find a $(\boldsymbol{\theta}, \boldsymbol{\gamma})$ that provides a best fit to the data. We show in Appendix D that the CS model obtained at $\gamma_1 = \underline{\gamma}_1 = 0.69$ provides a particularly poor fit. We also show that, across all feasible $\boldsymbol{\gamma} \in \mathcal{G}$, $\gamma_1^m = \gamma_1^f = 1$ provide the best and far superior fit to the data, which implies $\gamma_0^m = 0.755$ and $\gamma_0^f = 0.738$.[30] That is, our estimate of $\boldsymbol{\gamma}$ is $\widehat{\boldsymbol{\gamma}} \equiv (\widehat{\gamma}_0^m, \widehat{\gamma}_1^m, \widehat{\gamma}_0^f, \widehat{\gamma}_1^f) = (0.755, 1, 0.738, 1)$.

With $\widehat{\gamma}_1^m = \widehat{\gamma}_1^f = 1$, *all* individuals with medium ability obtain a basic qualification in the post-RoSLA regime. This is consistent with the RoSLA dramatically reducing the opportunity cost of acquiring a basic qualification and imply that the compositional shift at the RoSLA threshold is at its extreme: prior to the reform, the unqualified comprised a mix of low- and medium ability individuals, after the reform only low ability types remain. It is also empirically convenient: with two cohorts, two ability-types, and two qualification levels, Proposition 1 states that Assumptions 1, 2, and 3 with $\gamma_1^m = \gamma_1^f = 1$, ensures that the marital surplus matrix is identified from observed marriage- and single-rates. Our analysis confirms that this insight carries over to our empirical specification with high-ability, advanced qualified individuals, eight cohorts, age gap preferences and trends. Indeed, at $\gamma = \widehat{\boldsymbol{\gamma}}$, $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \widehat{\boldsymbol{\gamma}})$ is a singleton and $\boldsymbol{\theta}$ is identified.

[30] As robustness we have conducted our empirical analysis for values of each γ_0^g between 0.715 and 0.775. This affects the point estimates of the elements of the marital surplus matrix, but does not qualitatively affect the conclusions of our analysis. Details are available on request from the authors.

7. Results, Model Fit, and Specification Tests

7.1. Ability-Qualification Profile Contributions to Marital Surplus

The top panel of Table 3 gives the estimates of the systematic surplus function $\zeta(a, z, a', z')$ defined over ability-qualification profiles.[31] The upper left 2×2 sub-matrix shows the estimated surpluses from marriages where both spouses are unqualified, but with low or medium ability. This sub-matrix also trivially exhibits increasing differences. Among the unqualified there is strong complementarity with respect to ability. Similarly, the centre 2×2 sub-matrix gives the estimated surpluses from marriages where both spouses have medium ability, but with or without a basic qualification. This sub-matrix too exhibits increasing differences, indicating strong complementarity with respect to holding a qualification. If we then disregard the medium ability, but unqualified (second column and second row), the remaining 3×3 matrix gives the estimated marital surpluses associated type-profiles where each spouse has an ability and a qualification level that are perfectly aligned. It too exhibits increasing differences, indicating complementarity with respect to aligned ability-qualification combinations.

From the top panel of Table 3 we can compute the contribution of ability of unqualified men and women to marital surplus and the contribution of a basic qualification for men and women of medium ability. These contributions are reported in the lower panel of Table 3. The ability and qualification contributions exhibit similar patterns for men and women. First, from the columns labeled "Basic vs. no qual.", a basic qualification always increases marital surplus when the spouse has at least a basic qualification (third and fourth row), but does not necessarily do so when the spouse is unqualified (first and second row). Second, from the columns labeled "Medium vs low ability", medium ability in itself does not increase marital surplus when the spouse is academically qualified (third and fourth row); in contrast, when the spouse is unqualified, complementarity in ability means medium ability increases surplus when the spouse also has medium ability, but reduces surplus when the spouse has low ability (first and second row), although the positive contribution when the spouse has medium ability is not statistically significant.

7.2. Model Fit

7.2.1. Never-Married Rates Figure 9 plots empirical and model predicted never-married rates by cohort, gender and qualification level. The estimated model replicates the key

[31] The estimated parameters of the age gap and trend functions are presented in Appendix E.

Table 3: The Marital Surplus Matrix

Marital surplus by ability-qualification profile				
	Wife type			
	(a^0, z^0)	(a^1, z^0)	(a^1, z^1)	(a^2, z^2)
Husband type (a^0, z^0)	-0.580^{***} (0.222)	-3.061^{***} (0.544)	-2.030^{***} (0.139)	-5.042^{***} (0.159)
Husband type (a^1, z^0)	-2.697^{***} (0.559)	-1.472^{**} (0.669)	-2.234^{***} (0.407)	-4.921^{***} (0.443)
Husband type (a^1, z^1)	-2.500^{***} (0.197)	-2.501^{***} (0.338)	-1.133^{***} (0.083)	-3.064^{***} (0.090)
Husband type (a^2, z^2)	-4.656^{***} (0.208)	-4.271^{***} (0.355)	-2.310^{***} (0.089)	-0.498^{***} (0.090)

Contribution of ability and qualification to marital surplus				
	Own gender			
	Male		Female	
	Medium vs. low ability	Basic vs. no qual.	Medium vs. low ability	Basic vs. no qual.
Spouse type (a^0, z^0)	-2.117^{***} (0.633)	0.197 (0.522)	-2.481^{***} (0.681)	1.031^{*} (0.529)
Spouse type (a^1, z^0)	1.589^{*} (0.943)	-1.029^{*} (0.597)	1.225 (0.821)	-0.762 (0.545)
Spouse type (a^1, z^1)	-0.204 (0.514)	1.101^{***} (0.397)	-0.001 (0.511)	1.368^{***} (0.327)
Spouse type (a^2, z^2)	0.122 (0.565)	1.857^{***} (0.435)	0.385 (0.532)	1.961^{***} (0.344)

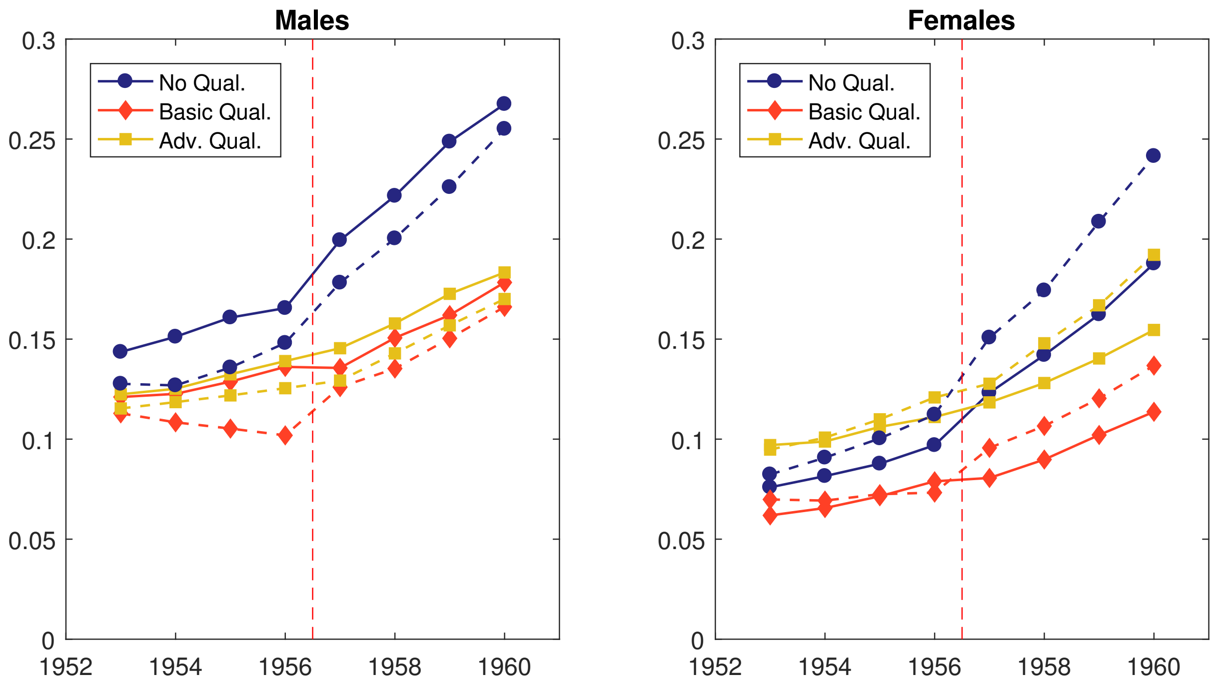
Notes: Asymptotic standard errors in parentheses. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. In the bottom panel, the "Medium vs. low ability"-column assumes own qualification $z = z^0$. The "Basic vs. no qual."-column assumes own ability $a = a^1$.

qualitative patterns in the never-married rates across cohorts and qualifications. Specifically, the model predicts increasing never-married rates for both unqualified men and women at the RoSLA reform threshold. The estimated model also fits the never-married rates for individuals with basic and advanced qualifications, possibly with the exception of men with a basic qualification before the reform. Here, the model predicts an increase in the never-married rate at the RoSLA reform threshold of individuals holding a basic qualification due to their increased supply. However, there is little evidence of such an effect in the data.

7.2.2. Qualification Homogamy Appendix E shows that the model reproduces the empirical distribution of spousal qualification by own qualification in Figure 4 very precisely.

Figure 10 shows the predicted homogamy indices $S^g(z, c)$ by gender and cohort as

Figure 9: Predicted and Empirical Never-Married Rates by Cohort, Gender, Qualification



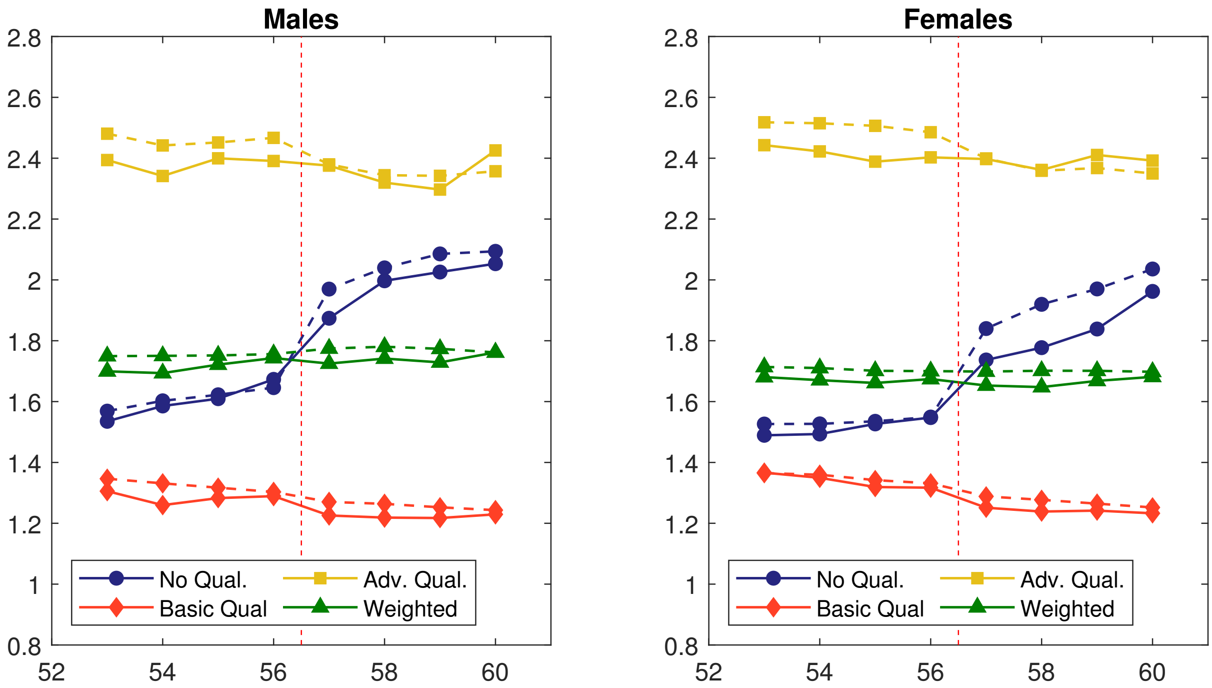
Notes: The horizontal axes show academic cohorts. The vertical axes show never-married rates. Solid lines renders the data (see Figure 3). Dashed lines renders model predictions.

dashed lines, with solid lines representing the data. The model replicates the stability of the aggregate homogamy index across cohorts. It also replicates the markedly higher homogamy indices for advanced qualified individuals and the observed increases in the homogamy indices for individuals with no qualifications at the RoSLA threshold.

7.2.3. Age Gaps The estimated model reproduces the observed age distribution (Figure 6), very accurately (see Appendix E for details, in particular Figure E.2). Our descriptive analysis highlighted a small temporary shift in the age gap distribution among the cohorts born just after the RoSLA threshold (Figure 7). For instance, individuals from the 1957 cohort were found to be about one percentage point more likely than individuals from other cohorts to have married with a zero age gap, suggesting that qualifications matter for marital surplus. The model captures only a small fraction of this temporary shift. Hence, if anything, the model may be overstating the strength of age preferences.[32]

[32]Details of the models fit to the overall age gap distribution and the fit to the distribution by cohort and gender are available on request.

Figure 10: Predicted and Empirical Qualification Homogamy by Cohort, Gender, Qualification



Notes: The horizontal axes show academic cohorts. The vertical axes show the homogamy index, see (2). Solid lines renders the data. Dashed lines renders model predictions.

7.3. Specification Tests

7.3.1. Latent Ability At $\gamma_1^g = \underline{\gamma}^g$ for $g = m, f$, our model coincides with a standard CS model without latent ability: Everybody with no or a basic qualification have medium ability both pre- and post-reform. Our estimation procedure confirms that this nested specification yields a lower likelihood value than the specification with $\gamma_1^g = 1$ for $g = m, f$. The lower bound limiting case, however, imposes an additional subtle restriction because individuals with no or basic qualification share a common medium ability-specific trend. Alternatively, we can impose that ability does not matter for the $\zeta(a, z, a', z')$-component of marital surplus, but retain the estimated ability distribution and three ability specific trends. This involves seven restrictions which are rejected ($LR = 215.6 \sim \chi^2(7)$). Incidentally, these nested restricted models yield virtually identical likelihood values.

Arguably the most natural CS-counterpart to our latent ability model is a "qualification-only" model without latent ability but with three qualification level-specific trends. Appendix F presents estimates of such a model which is not nested within our latent ability model, but yields a likelihood value that is very close to those of the nested restricted models described above (see the “CS”-label in Figure D.1 in Appendix D). The non-nested nature of the qualification-only model complicates testing against our model with latent ability, but it is informative to check how the qualification-only model fares in terms of replicating the empirical marriage market responses to the RoSLA. Figure F.1 in Appendix F shows that the qualification-only model predicts never-married rates of unqualified individuals to fall at the RoSLA-threshold, when in fact they increased. This patently counterfactual prediction reflects that the qualification-only model does not allow for any compositional change among the unqualified at the RoSLA-threshold, and is easy to understand based on comparative statics in the CS framework: When a type becomes relatively scarce (as the unqualified individuals post-RoSLA), they obtain a larger share of any marital surplus and therefore become more—not less—prone to marry.

7.3.2. Additively Separable Cohort Preferences and Linear Trends Appendix F shows that the model, given the empirically verified restriction $\gamma_1^m = \gamma_1^f = 1$, admits a simple specification test of the assumption of additively separable cohort preferences and linear trend terms. The test fails to reject our specification with additive cohort (or age gap) preferences and gender- and ability-specific piecewise linear trends.

8. Qualifications, Ability and Marriage Market Outcomes

Identification of the causal effects of qualification z and ability a on marriage market outcomes requires variation in z given a and variation in a given z. Viewed through the lens of the model, the RoSLA delivers such variation at two margins: Variation in ability, low and medium, conditional on no qualification, and variation in qualification, no and basic, conditional on medium ability. We focus on the effects of own qualification and ability on the probability of ever marrying at these two margins. We also consider whether own qualification and ability predict spousal qualification and ability. As spousal traits are conditional on marriage, the latter effects do not have a strict causal interpretation.

8.1. The Causal Effects of Qualifications and Ability on the Ever-Married Rates

The gender-g ever-married rate is $\Pr(\text{Ever married}|c, a, z) = 1 - \mu^g_{0|c,a,z}$. Let $\Delta^g_a(c)$ be the causal effect of possessing medium versus low ability, i.e. $a = a^1$ versus $a = a^0$, on the ever-married rate of individuals with no qualification, $z = z^0$. Let $\Delta^g_z(c)$ be the causal effect of basic qualification attainment versus no qualification, i.e. $z = z^1$ versus $z = z^0$, on the ever-married rate of medium ability individuals, $a = a^1$. Clearly,

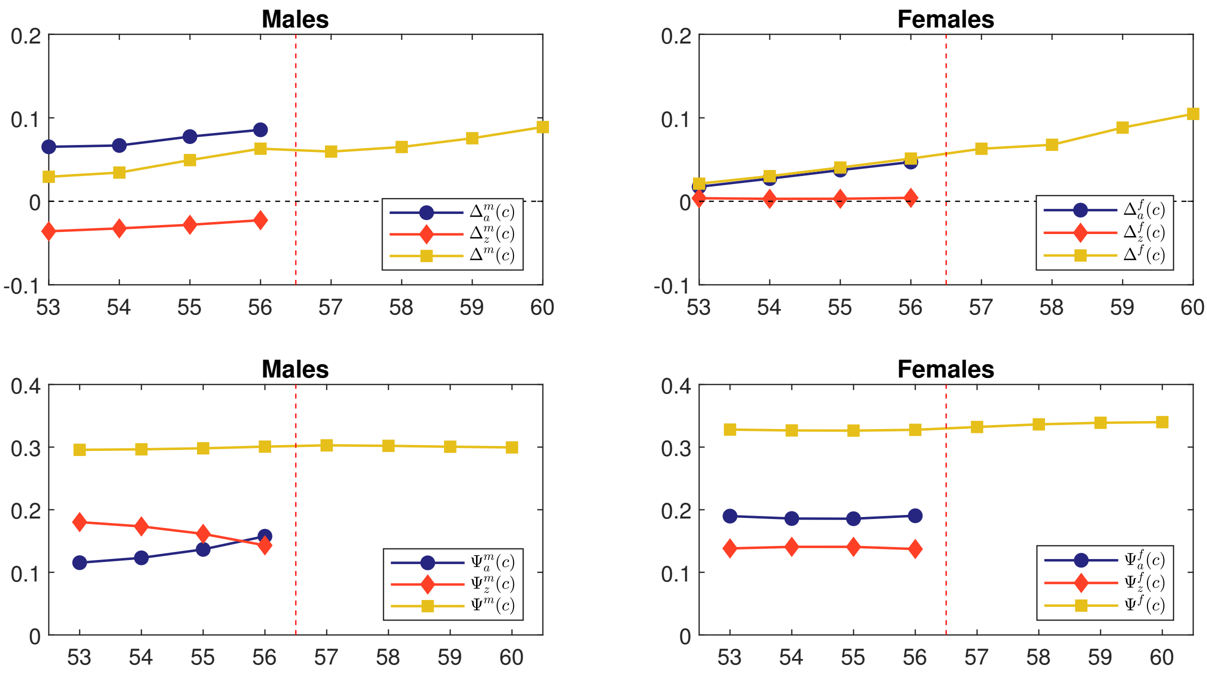
$$\Delta_a^g(c) \equiv \mu_{0|c,a^0,z^0}^g - \mu_{0|c,a^1,z^0}^g, \quad \text{and} \quad \Delta_z^g(c) \equiv \mu_{0|c,a^1,z^0}^g - \mu_{0|c,a^1,z^1}^g. \tag{10}$$

Let $\Delta^g(c)$ be the effect on $\Pr(\text{Ever married}|c,a,z)$ of having medium ability *and* a basic qualification compared to having low ability *and* being unqualified. Clearly,

$$\Delta^g(c) \equiv \Delta_a^g(c) + \Delta_z^g(c). \tag{11}$$

We identify $\Delta_a^g(c)$ and $\Delta_z^g(c)$ only for the pre-RoSLA cohorts. In contrast, $\Delta^g(c)$ is identified for all sample cohorts, but only directly observable for the post-RoSLA cohorts.

Figure 11: The Causal Effects of Ability and Qualification on Marital Outcomes



Notes: The horizontal axes show academic cohorts. The vertical axes show the effect of own ability and basic qualification attainment on the rate of (i) ever marrying (top row) and (ii) the spouse holding at least a basic academic qualification (bottom row).

The top panels of Figure 11 shows $\Delta_a^g(c)$, $\Delta_z^g(c)$, and $\Delta^g(c)$ for men and women, respectively. $\Delta^g(c)$ grew substantially over the sample cohorts for both men and women, from two to ten percentage points. For women, the causal effect of basic qualification, $\Delta_z^f(c)$, is effectively zero. For men, $\Delta_z^m(c)$, is negative, but small. In contrast, the causal effects of medium ability, $\Delta_a^g(c)$, are positive for both men and women. As a result, the total gap in marriage probability $\Delta^g(c)$ is exclusively driven by the positive causal effect of ability. Put differently, the observed gap in ever-married rates between individuals with basic and no qualifications is accounted for by selection on latent ability: unqualified individuals marry less frequently than those with a basic qualification because they tend to have low ability, not because they lack qualifications per se.

The absence of substantial marriage market returns to qualification once ability is controlled for is consistent with imprecise estimated effects in Lefgren and McIntyre (2006) and Anderberg and Zhu (2014) who use instrumental variables that are credibly consistent with equilibrium formation in the marriage market.[33]

The causal effects of qualification and ability on the ever-married probability connects to the literature on "marital premia" which uses that, in the CS framework, differences in marriage rates across types reflect differences in expected marital utility. As noted by Chiappori, Salanié, and Weiss (2017), the negative of the log never-married rate for a given gender-type measures their average marital utility, whereby log differences in never-married rates across types serve as a measure of a "marriage premium". Indeed,

$$-\log\left(\frac{\mu^g_{0|c,a^1,z^0}}{\mu^g_{0|c,a^0,z^0}}\right) \approx \frac{\Delta^g_a(c)}{\mu^g_{0|c,a^0,z^0}}, \quad \text{and} \quad -\log\left(\frac{\mu^g_{0|c,a^1,z^1}}{\mu^g_{0|c,a^1,z^0}}\right) \approx \frac{\Delta^g_z(c)}{\mu^g_{0|c,a^1,z^0}}. \tag{12}$$

Our model thus shows positive (medium) ability marriage premia for both men and women, but no (for men, even negative) basic qualification marriage premia.

8.2. Ability, Qualifications and the Spousal Qualification Gap

Define $\Psi^g_a(c)$ as the difference in the probability of the spouse holding at least a basic qualification between those with medium a^1 and low ability a^0, conditional on being unqualified z^0 and married, for gender $g = m, f$ and cohort c. Similarly, define $\Psi^g_z(c)$ as the difference in spouse qualification rate between those with qualification z^1 and those unqualified z^0, conditional on medium ability a^1 and married, for gender $g = m, f$. Finally, define $\Psi^g(c) = \Psi^g_a(c) + \Psi^g_z(c)$ as the total gap in spouse qualification rate between those of ability-qualification type (a^1, z^1) and those of type (a^0, z^0), and being married. $\Psi^g_a(c)$ and $\Psi^g_z(c)$ are identified only for pre-RoSLA cohorts, whereas $\Psi^g(c)$ is directly observable and identified for all sample cohorts. The spousal qualification gap is defined conditional on marriage so $\Psi^g_z(c)$ and $\Psi^g_a(c)$ do not have strict causal interpretations.

The lower panels of Figure 11 shows that the probability of being married to an academically qualified spouse increases with own ability and with own (basic) qualification. For both men and women, ability and an own qualification have similar positive effects

[33] These studies lack statistical power to draw conclusive inference which justifies our alternative approach of modeling a marriage market equilibrium with selection into qualification based on ability.

on the qualification rate of the spouse. The total effect of both ability and a qualification is about 30 percent for both men and women, which corresponds to the differences seen in Figure 4. That is, conditional on marrying, own qualification attainment and own ability are both important predictors of spousal traits.

9. General Equilibrium Marriage Market Effects of the RoSLA

The RoSLA affected marital outcomes of a wide set of people, including some whose educational outcomes were not affected by the reform. We demonstrate these general equilibrium effects by contrasting marriage market outcomes simulated from our estimated model to those obtained from a counterfactual simulation without the RoSLA.

In the counterfactual scenario we assume that the pre-reform qualification attainment process in Figure 8 continued to apply across all the sample cohorts $c \in \mathcal{C}$, providing us with counterfactual qualification distributions and marriage market equilibrium. We focus on differences in outcomes by ability type as ability was unaffected by the RoSLA.

9.1. Never-Married Rates and the RoSLA

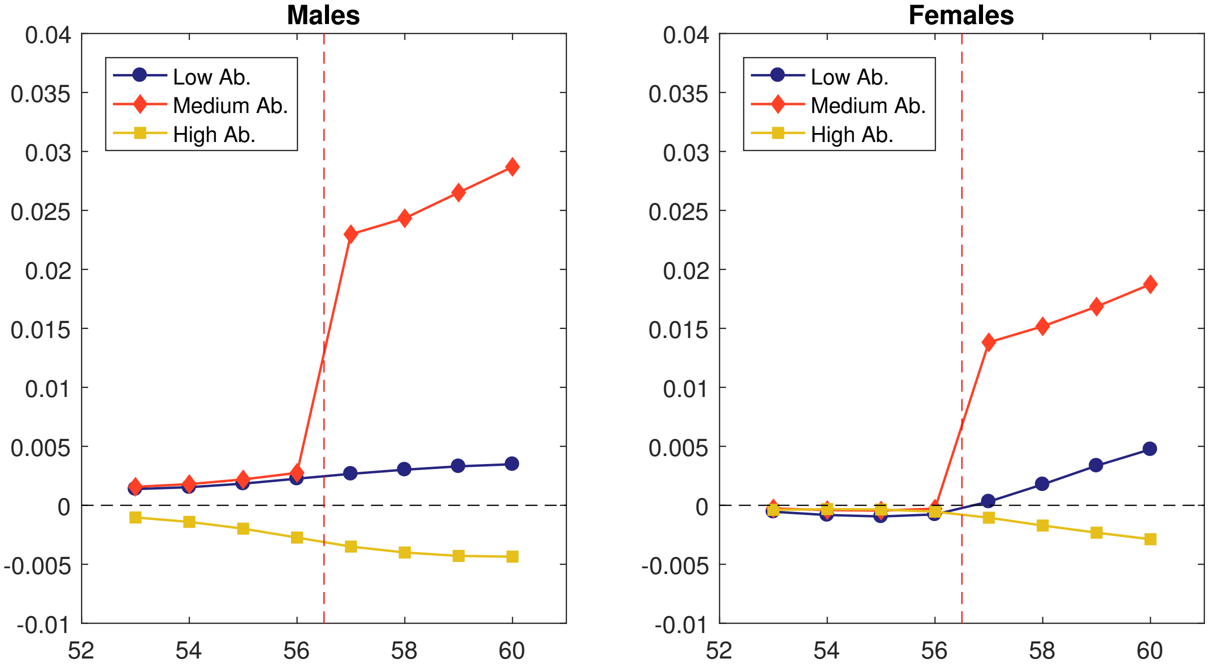
Figure 12 plots the difference in never-married rates with and without the RoSLA induced population-shifts. A positive number for a particular ability level, gender and cohort in Figure 12 means that the RoSLA increased never-married rate for that type.

Medium ability individuals were the only ones directly affected by the reform in terms of their qualifications, and this is also the only type for which the impact of the reform was discontinuous at the threshold: the reform increased the never-married rates for medium ability individuals of both genders. This reflects that the reform created a positive supply shock of basic qualified individuals, and, for men, that a basic qualification given medium ability is associated with a reduced marriage rate for men (see Figure 11).

The other two ability types were only indirectly affected by the RoSLA in terms of their marital outcomes. Pre-RoSLA, unqualified low ability men and women, would typically marry unqualified spouses. When the RoSLA reduced the supply of unqualified partners their never-married rate increased. The typically positive husband-wife age gap meant that the reform increased the never-married rate for low ability males born before the threshold. For women the effect was concentrated among the post-reform cohorts.

For high ability individuals, the unqualified medium-ability type was never an attractive spouse. However, when more individuals gained basic qualifications as a result of

Figure 12: The RoSLA Effects on the Never-Married Rates by Ability, Cohort, Gender



Notes: The horizontal axes show academic cohorts. The vertical axes show the difference in never-married rates with and without the RoSLA.

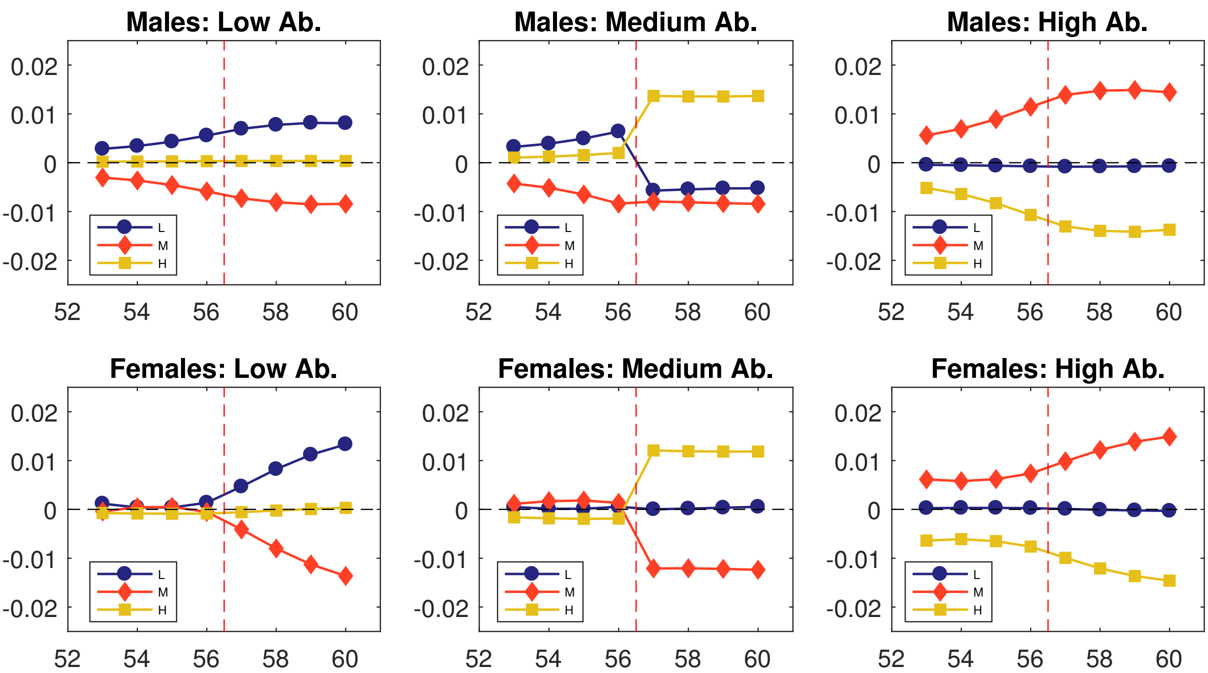
the reform, high ability individuals benefited from the increased supply of academically qualified potential partners, leading them to marry more frequently. While the effect of the reform, due to the marital age gaps, affected earlier cohorts of men than women, within a couple of years, both low and high ability types of both genders where affected in terms of their probability of ever-marrying at a rate of close to half a percentage point, negatively for the low ability type and positively for the high ability type.

9.2. Marital Sorting and the RoSLA

Figure 13 displays the impact of the reform on the distribution of spouse ability by own ability, cohort and gender, conditional on marriage. The top left panel shows that low ability males, as a consequence of the RoSLA, married low ability women more frequently and medium ability women less frequently. A similar effect is seen for low ability women in the bottom left panel. Hence, the reform unambiguously worsened the marital prospects for the low ability types, reducing their chances of ever marrying and making them more prone to marry among themselves rather than marrying up in terms of ability.

For the high ability types—who always attain an advanced qualification—the probability of ever marrying increased as a consequence of the reform, and moreover, they married less frequently among themselves and married more frequently medium ability types, reflecting that the reform increased the qualification rate of the latter ability type.

Figure 13: The Effect of the RoSLA on the Distribution of Spouse Ability



Notes: The horizontal axes show academic cohorts. The vertical axes show the difference in spousal ability rates with and without the RoSLA.

This is also reflected in the two middle panels which shows the effect of the RoSLA on the ability distribution of spouses of medium ability individuals. Here discontinuities naturally occur as the reform directly affected the qualifications held by the medium ability type. For instance, for medium ability males from the pre-reform cohorts—whose qualification rate was still low—the reform increased the probability of marrying low ability women, but decreased the probability of marrying medium ability women. This reflects that age gap preferences dictates that their wives would often have been from the post-reform cohorts where the medium ability women now had a basic qualification. For medium ability males from the post-reform cohorts—whose own qualification rate was increased—the reform generated a switch away from low ability spouses towards high ability spouses. For the medium ability women, the reform induced more mixing with high ability men and relatively less marriages to medium ability men.

As a broad characterization, the RoSLA (i) increased the never-married rates of low and medium ability individuals, while decreasing it for high ability individuals, (ii) increased assortative mating among low ability individuals, and (iii) increased marital mixing between high and medium ability types. In effect, the RoSLA left low ability individuals isolated in the marriage market. The effects are similar across genders, but different cohorts of men and women are impacted differently due age gap preferences.

10. Conclusion

We utilize a well known UK compulsory schooling expansion—the Raising of the School Leaving Age (RoSLA)—to identify and estimate a Choo and Siow (2006) model of the marriage market where men and women match on qualifications, ability and age (gap). Ability is correlated with qualification attainment and is a latent trait that is unobserved by the econometrician. Ability is a key model ingredient: Removing it yields predictions that are sharply at odds with observed marriage patterns around the RoSLA reform.

Own and spousal ability, and own and spousal qualification, are complementary in marital surplus. The causal effect of ability on the ever-married rate of the unqualified is large and positive for both genders, while the causal effect of qualification attainment of medium ability individuals is negligible. Marriage market adjustments made the RoSLA felt by men and women whose qualification outcomes were not impacted by the reform. The RoSLA left low ability men and women isolated in the marriage market.

Identification comes from a RoSLA-induced reduction in the opportunity cost of acquiring a qualification. The literature on the returns to schooling has utilized other factors that change the opportunity cost of education (Card, 2001), including distance to nearest college. By using richer data sets and some ingenuity, one may be able to similarly allow for latent ability and estimate marriage market models in these contexts.

Finally, we have emphasized latent ability as a simple way to reconcile the Choo and Siow (2006) framework with observed marriage market responses to the RoSLA, while retaining analytical and empirical tractability. Still, alternative model formulations based on e.g. imperfect information or search in the marriage market may also fit the data well.

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Appendices For Online Publication

A. The NCDS Data

As described in the main text, the National Child Development Study (NCDS) follows the lives of a set of cohort members, initially 17,415 individuals, born in England, Scotland and Wales in a single week of 1958. To be consistent with the our main data and analysis, we restrict our sample to individuals born in England and Wales.

We use the responses to two questions from a data sweep completed in the Spring of 1974, as the NCDS cohort members were turning 16, to measure preferred school-leaving age. The first asked for their expected age of leaving school in $\{16, 17, 18+\}$. The second question asks whether they wish they could have left at age 15 with binary responses $\{0, 1\}$. We combine the answers to these two questions into a *preferred school leaving age* in $\{15, 16, 17+\}$.

Using information on which year the cohort members left school, collected in a data sweep completed in 1991 when the NCDS cohort members were aged 33, we characterize their *realized school leaving age* in the binary indicator $\{16, 17+\}$ where leaving at age 16 meant leaving at the minimum school-leaving age and 17+ meant staying on beyond this age. Also using the information collected in the 1991 sweep, we characterize the cohort members in terms of qualification attainment, z, using the same classification as used for the LFS, that is $z \in \{z^0, z^1, z^2\}$, where z^0 represents no academic qualifications, z^1 represents a basic (i.e. O-level/CSE) qualification, and z^2 refers to an advanced academic qualification, which here is an A-level or further qualification.[34]

A.1. Comparison to the LFS Panel A of Table A.1 shows the distribution of preferred school-leaving age. This shows that the proportion stating that they would have preferred to leave at 15 (i.e. before first examination, implying that they would leave without qualification) is close to the proportion leaving without qualifications in the final pre-RoSLA cohorts as observed in the LFS (see Figure 1). Moreover, the proportion stating that they expect to stay in school beyond age 16 is only slightly above the proportion observed in the LFS to have a high academic qualification rate. Panel B compares the stated preferred school-leaving age with the individual's actual school-leaving age. As information on the latter comes from the later 1991 data sweep we have fewer observations. However, when both pieces of information are available, the individual's actual leaving age is consistent with their stated preferred leaving age for over 90 percent of the cohort members. Panel C shows the qualification distribution in the NCDS cohort. This aligns well with that observed in the LFS for the first post-RoSLA cohort (see Figure 1). Not shown here, the NCDS distribution also exhibits the gender-pattern that males more frequently had no qualification than did the women while women more frequently held a basic qualification, with the gender-gaps being similar to that observed in the LFS.

A.2. Measuring Academic Ability We use five indicators from the NCDS to construct a measure of an individual's latent academic ability: a mathematics test, a reading comprehension test,

[34]A small number of individuals record a qualification level below what would be achievable at their stated preferred school-leaving age. Specifically, about five percent of the cohort members stated a preferred school-leaving age of 16 and yet gained no academic qualification. Similarly, about seven percent stated a preference for staying past the minimum school-leaving age but gained no advanced qualification. Inspection of these two groups suggest that their "under-performance" was due to having low ability. The mean ability in the first group was -0.75, while the mean ability in the second group was 0.28, respectively.

Table A.1: School-Leaving Age and Qualifications in the NCDS

Panel A: Preferred School-Leaving Age			
	Age 15	Age 16	Age 17+
Proportion of respondents	0.381 (0.005)	0.322 (0.005)	0.297 (0.004)
Number of observations	10,637		
Panel B: Preferred and Actual School-Leaving Age			
	Preferred		
	Age 15	Age 16	Age 17+
Actual Age = 16	0.350 (0.005)	0.285 (0.005)	0.044 (0.002)
Actual Age = 17+	0.014 (0.001)	0.029 (0.003)	0.278 (0.005)
Number of observations	8,627		
Panel C: Qualification Distribution			
	Qualification		
	None	Basic	Adv.
Proportion of respondents	0.364 (0.005)	0.401 (0.005)	0.235 (0.004)
Number of observations	10,309		

Notes: The sample contains all NCDS cohort members born in England or Wales. Basic qualification refers to CSE/O-Level qualifications, and advanced qualifications refer to A-Level or higher qualifications.

both completed as part of the 1974 (age 16) NCDS data sweep, and teacher-reported ability ratings in mathematics, English, and science.[35] The mathematics and reading test scores are raw scores on a scale of 0-31 and 0-35 respectively. Teacher ratings were given on a five-point scale (ranging from "little ability" to "sufficient ability to complete an A-level or higher"). We treat each of the five indicators as a noisy measurement of a single latent factor, which we interpret as academic ability, and use a standard measurement model to filter the noise and obtain an estimate of individual ability (see e.g. Bollen, 1989). The estimated factor loadings from the latent variables model and the associated signals are presented in Table A.2; here, the signal is the share of the variance of each measure that is explained by the latent ability measure. We use the predicted value of the latent factor as our estimate of individual academic ability. For ease of interpretation, we further standardize the estimated ability. Table A.3 shows the mean estimated ability by gender and individual classification as defined in Section 3.1.

B. *Proof of Proposition 1*

Recall that an individual's type is a triplet: cohort, c; ability $a \in \{a^0, a^1\}$; qualification, $z \in \{z^0, z^1\}$. We will establish identification when there is a single cohort prior to the reform, and a single cohort after, so $c \in \{c^0, c^1\}$. Furthermore, given Assumption 2 with $\gamma_1^m = \gamma_1^f = 1$, every medium-ability individual acquires a qualification post-reform, and only five types exist. That

[35] Ability tests were also conducted at the ages of 7 and 11, see Shepherd (2012) for further details. Our results are robust to the inclusion of these test (results are available from the authors on request).

Table A.2: Factor Loadings and Signal Ratios for Ability Measurement Model

	Factor Loading	Signal
Mathematics Test	1	0.679
Reading Comprehension Test	0.869*** (0.012)	0.589
Teacher Assessment Math	0.183*** (0.002)	0.816
Teacher Assessment English	0.167*** (0.002)	0.745
Teacher Assessment Science	0.182*** (0.002)	0.755
Number of observations	6,365	

Notes: The table presents estimated factor loadings and signal values for five measurements, at age 16 in the NCDS, reflecting a single latent ability factor. The first factor loading of unity reflects a normalization.

Table A.3: Mean Estimated Ability by Gender and Classification

	"Never-takers"	"Compliers"	"Always-takers"	"Stayers"
Men	−0.897 [−0.939,−0.855] $n = 1,167$	0.042 [−0.020,0.104] $n = 628$	0.123 [0.071,0.174] $n = 601$	1.075 [1.034,1.115] $n = 875$
Women	−0.941 [−0.987,−0.896] $n = 887$	0.013 [−0.038,0.065] $n = 701$	0.073 [0.025,0.120] $n = 679$	0.947 [0.907,0.986] $n = 827$
All	−0.916 [−0.947,−0.885] $n = 2,054$	0.027 [−0.013,0.067] $n = 1,329$	0.096 [0.061,0.130] $n = 1,280$	1.012 [0.984,1.041] $n = 1,702$

Notes: The table presents the mean estimated ability by gender and NCDS classification. 95 percent confidence intervals in square brackets, observation numbers below.

is, for each gender $g \in \{m, f\}$:

$$\mathcal{X} \equiv \left\{1 \coloneqq \left(c^0, a^0, z^0\right), 2 \coloneqq \left(c^0, a^1, z^0\right), 3 \coloneqq \left(c^0, a^1, z^1\right), \tilde{1} \coloneqq \left(c^1, a^0, z^0\right), \tilde{3} \coloneqq \left(c^1, a^1, z^1\right)\right\}. \tag{B.1}$$

where we have denoted the types by $1, 2, 3, \tilde{1}$ and $\tilde{3}$. Types 1 and $\tilde{1}$ correspond to (a^0, z^0), i.e. low-ability and unqualified, in cohorts 0 and 1 respectively. Types 3 and $\tilde{3}$ correspond to (a^1, z^1), i.e. medium-ability and qualified, in cohorts 0 and 1 respectively. Type 2 corresponds to (a^1, z^0, c^0)—i.e. medium-ability and unqualified in cohort 0, for whom there is no counterpart in cohort 1.

Gender is observable and we shall refer to male types as $x \in \mathcal{X}$ and female types as $y \in \mathcal{X}$. As analysts we further observe an individual's cohort and qualifications, but not their ability. This means that we cannot directly distinguish between individuals of the first two types: 1 and 2 make up the set of *indistinguishable types*, $\mathcal{X}^I$. In contrast, the last three types, i.e. 3, $\tilde{1}$ and $\tilde{3}$, make up the set of *distinguishable types*, $\mathcal{X}^D$. Consequently, we can directly observe the total number of matches between any two distinguishable types, e.g. the number of matches between type 3 males and type $\tilde{1}$ females, denoted $N_{3\tilde{1}}$. We can also observe the number of singles of any distinguishable type, which we denote by N^m_{x0} for males, and N^f_{0y} for females. However, we cannot observe the number of matches involving at least one indistinguishable type, nor can we observe the number of singles of any indistinguishable type.[36]

These observations are summarized in Table B.1, where the rows indicate male types and the columns indicate female types. Each row/column is augmented with a 0-type to indicate the unmatched singles. The cell entries denote the number of matches between the corresponding types. Question marks indicate those matches whose numbers cannot be observed.

Table B.1: Observed and unobserved marriage and singlehood frequencies

Women

Men	1 (a^0, z^0, c^0)	2 (a^1, z^0, c^0)	3 (a^1, z^1, c^0)	$\tilde{1}$ (a^0, z^0, c^1)	$\tilde{3}$ (a^1, z^1, c^1)	0 ·
1	?	?	?	?	?	?
2	?	?	?	?	?	?
3	?	?	N_{33}	$N_{3\tilde{1}}$	$N_{3\tilde{3}}$	N_{30}
$\tilde{1}$	?	?	$N_{\tilde{1}3}$	$N_{\tilde{1}\tilde{1}}$	$N_{\tilde{1},\tilde{3}}$	$N_{\tilde{1}0}$
$\tilde{3}$	?	?	$N_{\tilde{3}3}$	$N_{\tilde{3}\tilde{1}}$	$N_{\tilde{3}\tilde{3}}$	$N_{\tilde{3}0}$
0	?	?	N_{03}	$N_{0\tilde{1}}$	$N_{0\tilde{3}}$	

In addition, we observe the total number of matches between any distinguishable type and the set of indistinguishable types, $\mathcal{X}^I = \{1, 2\}$, which we index by I. That is we observe N_{Iy} and N_{xI} for any $x, y \in \mathcal{X}^D$. We also observe the number of matches where both types are indistinguishable, N_{II}, and we also observe the number of singles who are indistinguishable, N^m_{I0} and N^f_{0I}.

We will now show that we can use the separability assumption (Assumption 3 in the main text) to fill in the question marks in Table B.1. For the reader's convenience, we restate Assumption 3 as it pertains to the $2 \times 2 \times 2$ model specification as Assumption B.3:

Assumption B.3. Let $x = (c, a, z)$ denote the type of the man and let $y = (c', a', z')$ denote the type of a woman. The systematic surplus function Σ_{xy} is additively separable:

$$\Sigma_{xy} = \zeta\left(a, z, a', z'\right) + \lambda_{cc'}.$$

Since there are two cohorts, we have four parameters capturing the cohort-profile aspect of preferences: λ_{00}, λ_{01}, λ_{10}, λ_{11}. Further, observe that the matrix $\left(\Sigma_{xy}\right)_{x,y\in\mathcal{X}}$ is invariant to transformations that add a constant k to each ζ term and subtract the same k from each λ value. We may therefore, without loss of generality, normalize λ_{00} to zero.

Lemma B.1. *The cohort preferences, $\Lambda := (\lambda_{01}, \lambda_{10}, \lambda_{11})$ is overidentified under Assumption B.3.*

[36] Since our focus is on identification, we assume that the laws of large numbers apply, and thus the observed values have no sampling variation.

Proof. Observe first that if $x, y \in \mathcal{X}^D$, then Σ_{xy}, is identified. This follows from Choo and Siow (2006), who show that

$$\exp(\Sigma_{xy}) = \frac{(N_{xy})^2}{N^m_{x0} N^f_{0y}}. \tag{B.2}$$

Let i and j denote generic elements of the set of types $\{1, 2, 3\} \subset \mathcal{X}$, all belonging to cohort 0 (index i will refer to males, index j to females). We will use $\tilde{i}$ (resp. $\tilde{j}$) to denote the type from cohort 1 who has the same ability and qualifications as i (resp. j). Under Assumption B.3,

$$\Sigma_{\tilde{i}j} - \Sigma_{ij} = \lambda_{10} - \lambda_{00} = \lambda_{10},$$

independent of the values of i and j. Similarly, $\Sigma_{i\tilde{j}} - \Sigma_{ij} = \lambda_{01}$ and $\Sigma_{\tilde{i}\tilde{j}} - \Sigma_{ij} = \lambda_{11}$, independent of the ability-qualification profiles of i or j.

Consider the set of types $\{3, \tilde{3}\} \subset \mathcal{X}^D$, for both men and for women—i.e. qualified with medium-ability. Since both types are distinguishable, we observe the number of matches, N_{xy}, for any x, y belonging to $\{3, \tilde{3}\}$. Furthermore, we observe the number of single men N^m_{x0} and single women N^f_{0x}, for each type x in this set. Consequently, using B.2 we can infer Σ_{33}, $\Sigma_{\tilde{3}3}$, $\Sigma_{\tilde{3}\tilde{3}}$, and $\Sigma_{3\tilde{3}}$. Thus, the vector of parameters Λ is identified.

Furthermore, since $\tilde{1}$ is also in $\mathcal{X}^D$ we can infer $\Sigma_{\tilde{1}3}$ and $\Sigma_{\tilde{1}\tilde{3}}$, and their difference is an independent measure of $\lambda_{10} - \lambda_{11}$. Similarly, as we can infer $\Sigma_{3\tilde{1}}$ and $\Sigma_{\tilde{3}\tilde{1}}$, we have an independent measure of $\lambda_{01} - \lambda_{11}$. This yields two over-identification restrictions. □

We now proceed to the main part of the argument: the demonstration that we can use the parameters in Λ in order to infer the entire matching pattern for all types, observable and unobservable, for both genders. In essence, the vector Λ and the observable matches imply a system of non-linear equations in the unobservable matches that has a unique solution. Indeed, we obtain an explicit formula for each of the unobservable matches, in terms of the observable matches and Λ.

Inferring the Number of Single Low-Ability Males in Cohort 0 The key step lies in showing that we can infer the number of single males of the *indistinguishable types*, i.e. types 1 and 2.[37] Recall that these types are the unqualified in cohort 0, with type 1 having low-ability and type 2 having medium-ability. Since we observe the total number of unqualified single males in this cohort, it suffices to identify N^m_{10}, the number of single unqualified low-ability males in cohort 0, which we now proceed to.

Re-state (B.2) for the pairs (i, j) and $(\tilde{i}, j)$:

$$\exp(\Sigma_{ij}) = \frac{(N_{ij})^2}{N^m_{i0} N^f_{0j}}, \tag{B.3}$$

and

$$\exp(\Sigma_{\tilde{i}j}) = \frac{\left(N_{\tilde{i}j}\right)^2}{N^m_{\tilde{i}0} N^f_{0j}}. \tag{B.4}$$

If we divide (B.3) by (B.4), the left-hand side equals $\exp(-\lambda_{10})$, and on re-arranging, we get

$$N_{ij} = N_{\tilde{i}j} \sqrt{N^m_{i0}} \frac{\exp(-\lambda_{10}/2)}{\sqrt{N^m_{\tilde{i}0}}}. \tag{B.5}$$

[37] The same argument applies for females.

We may now replace i with 1 and $\tilde{i}$ with $\tilde{1}$ in the above to get:

$$N_{1j} = N_{\tilde{1}j}\sqrt{N_{10}^m}\frac{\exp(-\lambda_{10}/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.6}$$

This is an expression for the unobserved N_{1j} but contains the unobservable N_{10}^m. Critically, the expression is linear in $N_{\tilde{1}j}$, with a coefficient that is independent of j, a property that is important for the aggregation that is to follow. We rewrite this equation for each possible value of j: first for $j = 1, 2$,

$$N_{11} = N_{\tilde{1}1}\sqrt{N_{10}^m}\frac{\exp(-\lambda_{10}/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.7}$$

$$N_{12} = N_{\tilde{1}2}\sqrt{N_{10}^m}\frac{\exp(-\lambda_{10}/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.8}$$

Consequently,

$$N_{11} + N_{12} = (N_{\tilde{1}1} + N_{\tilde{1}2})\sqrt{N_{10}^m}\frac{\exp(-\lambda_{10}/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.9}$$

Although we observe neither $N_{\tilde{1}1}$ nor $N_{\tilde{1}2}$, we do observe their sum, which we denote by $N_{\tilde{1}I}$, since this is the total number of matches between unqualified males of cohort 1 and unqualified females of cohort 0. Similarly, for $j = 3$,

$$N_{13} = N_{\tilde{1}3}\sqrt{N_{10}^m}\frac{\exp(-\lambda_{10}/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.10}$$

Similarly, one can write down the expressions for $\exp(\Sigma_{1\tilde{j}})$ and $\exp(\Sigma_{\tilde{1}\tilde{j}})$. Since the ratio of the first to the second equals $\exp(\lambda_{01} - \lambda_{11})$, we get

$$N_{1\tilde{j}} = N_{\tilde{1}\tilde{j}}\sqrt{N_{10}^m}\frac{\exp((\lambda_{01} - \lambda_{11})/2)}{\sqrt{N_{\tilde{1}0}^m}}. \tag{B.11}$$

Setting $\tilde{j} = \tilde{1}$ and $\tilde{3}$ in turn, we get the expressions for $N_{1\tilde{1}}$ and $N_{1\tilde{3}}$.

Let T_1^m denote the total population of type 1 males, i.e. the number of males in cohort 0 who are of low ability. Note that we observe the total number of low ability males in cohort 1, since they correspond to the number who do not get a qualification. At this point, we invoke that the proportion of low ability males in cohorts 0 and 1 are equal (a condition in Proposition 1). This implies that we observe T_1^m, since this equals the size of cohort 0 multiplied by the observed proportion of low-ability males in cohort 1. Now,

$$T_1^m = \left(N_{11} + N_{12} + N_{1\tilde{1}} + N_{13} + N_{1\tilde{3}}\right) + N_{10}^m. \tag{B.12}$$

While none of the terms on the right-hand side above are directly observed, our derivations imply that they can be written in terms of observables and a single unobservable, as follows:

$$T_1^m = \left[(N_{\tilde{1}I} + N_{\tilde{1}3})\exp\left(-\frac{\lambda_{10}}{2}\right) + (N_{\tilde{1}\tilde{1}} + N_{\tilde{1}\tilde{3}})\exp\left(\frac{\lambda_{01} - \lambda_{11}}{2}\right)\right]\frac{\sqrt{N_{10}^m}}{\sqrt{N_{\tilde{1}0}^m}} + N_{10}^m. \tag{B.13}$$

Thus we have a quadratic equation in a single unknown, $\sqrt{N_{10}^m}$, since all the coefficients are observed, $N_{\tilde{1}I}$ is observed, as are the other values, $N_{\tilde{1}\tilde{1}}, N_{\tilde{1}\tilde{3}}$ and $N_{\tilde{1}3}$. $N_{\tilde{1}0}^m$ is the number of singles of type $\tilde{1}$ and is also observed.

Since the right-hand side is increasing in $\sqrt{N_{10}^m}$ when $\sqrt{N_{10}^m} > 0$, and is strictly less than the left-hand side when $\sqrt{N_{10}^m} = 0$, and strictly greater when $\sqrt{N_{10}^m} = \sqrt{T_1^m}$, there is a unique solution in the interval $(0, \sqrt{T_1^m})$, that is given by the familiar quadratic formula. Furthermore, since we observe the sum $N_{10}^m + N_{20}^m$, i.e. the total number of unqualified men in cohort 0, we also infer N_{20}^m. We therefore are able to observe directly or infer, the number of singles for every type of man. Since the argument for women is symmetric, we also observe or infer the number of singles for every type of women.

Inferring the Matching Matrix We now show that we can infer all the elements of the matching matrix. We directly observe N_{ij} and infer Σ_{ij} when both i and j belong to the distinguishable set $\mathcal{X}^D = \{3, \tilde{1}, \tilde{3}\}$.

Consider then $i = 1$ and $j \in \mathcal{X}^D$. Since we infer $\Sigma_{\tilde{1}j}$ (as $\tilde{1}, j \in \mathcal{X}^D$), and we infer the elements of Λ we can infer Σ_{1j}. For example, $\Sigma_{1\tilde{1}} = \Sigma_{\tilde{1}\tilde{1}} + \lambda_{01} - \lambda_{11}$. We can therefore use equation (B.3) to infer N_{1j}, for $j \in \mathcal{X}^D$. But since we observe the sum $N_{1j} + N_{2j}$, we can also infer N_{2j}, for $j \in \mathcal{X}^D$.

The final step is to show that we can infer N_{ij} when both $i \in \mathcal{X}^I$ and $j \in \mathcal{X}^I$. Since we infer $\Sigma_{1\tilde{1}}$ and also λ_{01}, we can infer Σ_{11}. Equation (B.3) then allows us to infer N_{11} since we also know the number of singles. But, invoking the assumption that the ability distribution is stable (Assumption 1), gives us the total number of type 1 men, T_1^m, allows us to infer N_{12}, as a residual. Hence we have inferred the number of matches N_{1j} for all j. Similarly, we can infer N_{21}, and finally, N_{22}.

Having inferred all elements of the matching matrix, and the number of singles of each type, all entries Σ_{ij} in the surplus matrix can be inferred from (B.3). Furthermore, for each possible type profile we also identify U_{xy} and V_{xy}, the systematic component of match payoffs for men and women respectively, since these are the dual variables corresponding to the surplus maximization program, as shown by Shapley and Shubik (1971) and Choo and Siow (2006).

This completes the proof of the Proposition.

Remark 1. Although cohort preferences Λ are overidentified, we have exact identification (rather than overidentification) of the surplus matrix conditional on Λ.

Remark 2. It is critical for identification that we have inter-marriage between pre-reform and post-reform cohorts. If cohorts were separate markets—an assumption that is sometimes made in the literature—identification, and disentangling the roles of ability and qualifications, would be impossible. To see this, let us suppose that there are no matches between cohorts 0 and 1. This would correspond to $\lambda_{01} = \lambda_{10} = -\infty$. Thus, a critical step in the proof, the derivation of equation (B.5), would not be possible. Indeed, even if we had access to independent information on Λ, we would be unable to use this. The proof uses matches between type $\tilde{1}$—the unqualified individuals in cohort 1, who are necessarily low ability—to infer the matches involving type 1, the low ability individuals in cohort 0.[38]

C. The Maximum Likelihood Estimator

An individual is either male (superscript m) or female (superscript f). The model focuses on as set of cohorts $c \in \mathcal{C} = \{1953, ..., 1960\}$, that are split halfway into a pre-RoSLA regime

[38] In the industrial organization context, identification is often possible when there are separate markets. This may be due to the fact that supply is uniform across markets, while demand varies. In our marriage market context, both sides of the market are affected by the reform, and vary across cohorts.

$\mathcal{C}_0$ and a post-RoSLA regime $\mathcal{C}_1$. The marriage market participants are endowed with ability $a \in \mathcal{A} = \{a^0, a^1, a^2\}$, where a^0 indicates low ability, a^1 indicates medium ability, and a^2 indicates high ability. Each marriage market participant is further characterized by a qualification-level $z \in \mathcal{Z} = \{z^0, z^1, z^2\}$, with z^0 denoting no qualification, z^1 denoting a basic qualification level, and z^2 denoting an advanced qualification level.

The marital surplus function is indexed by a parameter $\boldsymbol{\theta}$, i.e. $\Sigma_{x,y} = \Sigma_{x,y}(\boldsymbol{\theta})$ for $x, y \in \mathcal{X}$. The $\boldsymbol{\theta}$-parameter is the parameter of interest. The qualification attainment process is indexed by a parameter $\boldsymbol{\gamma} = (\gamma_0^m, \gamma_1^m, \gamma_0^f, \gamma_1^f)$. Given $\boldsymbol{\gamma}$, it is straightforward to recover the population measures over the full type-space, which we denote $h^m(x; \boldsymbol{\gamma})$ and $h^f(y; \boldsymbol{\gamma})$ for males and females, respectively ($x, y \in \mathcal{X}$).

Assumption 2 lays out the regime-specific qualification attainment process. With $\gamma_1^g < 1$ for $g = m, f$, $\mathcal{X} \subset \mathcal{C} \times \mathcal{A} \times \mathcal{Z}$ features $N = 4 \times |\mathcal{C}_0| + 4 \times |\mathcal{C}_1| = 32$ types. In the case where $\gamma_1^g = 1$ for $g = m, f$, which turns out to be the empirically supported case, Assumption 2 implies that four (a, z)-types exist in $\mathcal{C}_0$ but only three of these exist in $\mathcal{C}_1$. Hence, when $\gamma_1^g = 1$ for $g = m, f$, $\mathcal{X} \subset \mathcal{C} \times \mathcal{A} \times \mathcal{Z}$ features $N = 4 \times |\mathcal{C}_0| + 3 \times |\mathcal{C}_1| = 28$ types. Accounting for out-of-sample marriages adds 2 types of marriage partners (pre- and post-sample).

C.1. Computing Equilibrium Choice Probabilities

Out-of-Sample Marriages. Out-of-sample marriages occur relatively frequently for males towards the end of $\mathcal{C}$ and for females in the beginning of $\mathcal{C}$, but will—as large age gaps are quite rare—be quite infrequent for individuals born close to the reform threshold. In order to account for marriages to non-sample-cohort spouses we make use of the age gap preferences.

Let $pre_c^m(\boldsymbol{\theta})$ be the share of cohort-c males' marriages that involve pre-sample females ($c' < 1953$), and let $post_c^m(\boldsymbol{\theta})$ be the share of cohort-c males' marriages that involve post-sample females ($c' > 1960$). Recall that $d = c' - c$ is the husband-wife age gap. Then, $pre_c^m(\boldsymbol{\theta})$ is the share of cohort-c males' marriages that involves age gaps $d \leq \min\{\mathcal{C}\} - 1 - c$, and $post_c^m(\boldsymbol{\theta})$ is the share of cohort-c males' marriages that involve age gaps $d \geq \max\{\mathcal{C}\} + 1 - c$.

We approximate $pre_c^m(\boldsymbol{\theta})$ by the relative weight put on age gaps $d \leq \min\{\mathcal{C}\} - 1 - c$ by the age gap component of the marital surplus, conditional on $d \in \{1 - |\mathcal{C}|, ..., |\mathcal{C}| - 1\}$, and $post_c^m(\boldsymbol{\theta})$ by the relative weight put on age gaps $d \geq \max\{\mathcal{C}\} + 1 - c$ by the age gap component of the marital surplus. Formally,

$$pre_c^m(\boldsymbol{\theta}) = \frac{\sum_{d=1-|\mathcal{C}|}^{\min\{\mathcal{C}\}-1-c} \exp(\lambda(d; \boldsymbol{\theta})/2)}{\sum_{d=1-|\mathcal{C}|}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)} \quad \text{and} \quad post_c^m(\boldsymbol{\theta}) = \frac{\sum_{d=\max\{\mathcal{C}\}+1-c}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)}{\sum_{d=1-|\mathcal{C}|}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)}. \tag{C.1}$$

The female out-of-sample marriage shares are denoted by $pre_{c'}^f(\boldsymbol{\theta})$ and $post_{c'}^f(\boldsymbol{\theta})$. A woman from cohort c' is married to a pre-sample male if $d \geq c' - \min\{\mathcal{C}\} + 1$, and she is married to a post-sample male if $d \leq c' - \max\{\mathcal{C}\} - 1$. Hence, we define

$$pre_{c'}^f(\boldsymbol{\theta}) = \frac{\sum_{d=c'-\min\{\mathcal{C}\}+1}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)}{\sum_{d=1-|\mathcal{C}|}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)} \quad \text{and} \quad post_{c'}^f(\boldsymbol{\theta}) = \frac{\sum_{d=1-|\mathcal{C}|}^{c'-\max\{\mathcal{C}\}-1} \exp(\lambda(d; \boldsymbol{\theta})/2)}{\sum_{d=1-|\mathcal{C}|}^{|\mathcal{C}|-1} \exp(\lambda(d; \boldsymbol{\theta})/2)}. \tag{C.2}$$

Equilibrium Algorithm. The equilibrium outcome of interest is a set of never-married rates and marriage rates by gender and type. For given values of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$, we compute these using the following algorithm.

0. Initiate the algorithm with guesses on the N-vector of type-specific single rates for each gender, denoted $\widehat{\boldsymbol{\mu}}_0^m = (\widehat{\mu}_{0|x}^m)_{x\in\mathcal{X}}$ and $\widehat{\boldsymbol{\mu}}_0^f = (\widehat{\mu}_{0|y}^f)_{y\in\mathcal{X}}$ for males and females, respectively. Go to step 1.

1. Using $pre_c^m(\boldsymbol{\theta})$, $post_c^m(\boldsymbol{\theta})$, $pre_{c'}^f(\boldsymbol{\theta})$, and $post_{c'}^f(\boldsymbol{\theta})$ from (C.1) and (C.2), predict the gender- and type-specific out-of-sample marriage rates as $\widehat{\mu}_{pre|x}^m(\boldsymbol{\theta}) = (1-\widehat{\mu}_{0|x}^m)pre_c^m(\boldsymbol{\theta})$, $\widehat{\mu}_{post|x}^m(\boldsymbol{\theta}) = (1-\widehat{\mu}_{0|x}^m)post_c^m(\boldsymbol{\theta})$, $\widehat{\mu}_{pre|y}^f(\boldsymbol{\theta}) = (1-\widehat{\mu}_{0|y}^f)pre_{c'}^f(\boldsymbol{\theta})$, and $\widehat{\mu}_{post|y}^f(\boldsymbol{\theta}) = (1-\widehat{\mu}_{0|y}^f)post_{c'}^f(\boldsymbol{\theta})$. There are $2N$ out-of-sample marriage rates for each gender. Go to step 2.

2. Given $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$, the candidate vectors of single rates, and $h^m(x;\boldsymbol{\gamma})$ and $h^f(y;\boldsymbol{\gamma})$, the population measures of men and women of types x and y, respectively, compute the gender-specific candidate marriage rates

$$\widehat{\mu}_{y|x}^m(\boldsymbol{\theta},\boldsymbol{\gamma}) = \left(\widehat{\mu}_{0|x}^m\widehat{\mu}_{0|y}^f\frac{h^f(y;\boldsymbol{\gamma})}{h^m(x;\boldsymbol{\gamma})}\right)^{1/2}\exp\left(\frac{\Sigma_{xy}(\boldsymbol{\theta})}{2}\right), \tag{C.3}$$

and

$$\widehat{\mu}_{x|y}^f(\boldsymbol{\theta},\boldsymbol{\gamma}) = \left(\widehat{\mu}_{0|x}^m\widehat{\mu}_{0|y}^f\frac{h^m(x;\boldsymbol{\gamma})}{h^f(y;\boldsymbol{\gamma})}\right)^{1/2}\exp\left(\frac{\Sigma_{xy}(\boldsymbol{\theta})}{2}\right), \tag{C.4}$$

as implied by the marriage market equilibrium. There are N^2 marriage rates for each gender. Stack the type-specific never-married and (in- and out-of-sample) marriage rates in vectors $\widehat{\boldsymbol{\mu}}^m(\boldsymbol{\theta},\boldsymbol{\gamma})$ for males and $\widehat{\boldsymbol{\mu}}^f(\boldsymbol{\theta},\boldsymbol{\gamma})$ for females. The vectors $\widehat{\boldsymbol{\mu}}^m$ and $\widehat{\boldsymbol{\mu}}^m$ each contain $N+2N+N^2$ rates. Go to step 3.

3. Given $\widehat{\boldsymbol{\mu}}^m(\boldsymbol{\theta},\boldsymbol{\gamma})$ and $\widehat{\boldsymbol{\mu}}^f(\boldsymbol{\theta},\boldsymbol{\gamma})$, compute the implied gender and type-specific excess supplies, denoted $\widehat{\Delta}_x^m(\boldsymbol{\theta},\boldsymbol{\gamma})$ and $\widehat{\Delta}_y^f(\boldsymbol{\theta},\boldsymbol{\gamma})$, and defined as

$$\widehat{\Delta}_x^m(\boldsymbol{\theta},\boldsymbol{\gamma}) \equiv \widehat{\mu}_{0|x}^m + \widehat{\mu}_{pre|x}^m(\boldsymbol{\theta}) + \widehat{\mu}_{post|x}^m(\boldsymbol{\theta}) + \sum_{y\in\mathcal{X}}\widehat{\mu}_{y|x}^m(\boldsymbol{\theta},\boldsymbol{\gamma}) - 1, \tag{C.5}$$

and

$$\widehat{\Delta}_y^f(\boldsymbol{\theta},\boldsymbol{\gamma}) \equiv \widehat{\mu}_{0|y}^f + \widehat{\mu}_{pre|y}^f(\boldsymbol{\theta}) + \widehat{\mu}_{post|y}^f(\boldsymbol{\theta}) + \sum_{x\in\mathcal{X}}\widehat{\mu}_{x|y}^f(\boldsymbol{\theta},\boldsymbol{\gamma}) - 1. \tag{C.6}$$

Stack the gender- and type-specific excess supplies in the $2N$-vector $\widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta},\boldsymbol{\gamma})$. In equilibrium, excess supply is zero for each gender and all types. Let $||\cdot||_\infty$ be the uniform norm. If the candidate equilibrium marriage rates leaves no excess supply, i.e. if $||\widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta},\boldsymbol{\gamma})||_\infty \leq \epsilon$, where we take $\epsilon = 10^{-5}$, terminate the algorithm and take $\boldsymbol{\mu}^m(\boldsymbol{\theta},\boldsymbol{\gamma}) = \widehat{\boldsymbol{\mu}}^m(\boldsymbol{\theta},\boldsymbol{\gamma})$ and $\boldsymbol{\mu}^f(\boldsymbol{\theta},\boldsymbol{\gamma}) = \widehat{\boldsymbol{\mu}}^f(\boldsymbol{\theta},\boldsymbol{\gamma})$ as the equilibrium marriage (and never-married) rates. If $||\widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta},\boldsymbol{\gamma})||_\infty > \epsilon$, go to step 4.

4. Update the candidate equilibrium never-married rates with a simplified (and dampened) Newton-step. Let $\widehat{\mathbf{J}}$ be the $2N\times 2N$-matrix with partial derivatives of the excess supply vector $\widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta},\boldsymbol{\gamma})$ with respect to the log single rate of own (gender and) type on the diagonal, and zeros on the off-diagonals. Hence, $\widehat{\mathbf{J}}$ is the Jacobian of $\widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta},\boldsymbol{\gamma})$, taken with respect to the log single rates, but with the off-diagonal elements set to zero. For example, the diagonal entry in $\widehat{\mathbf{J}}$ corresponding to a male type-x_i individual therefore contains

$$\frac{\partial\widehat{\Delta}_x^m(\boldsymbol{\theta},\boldsymbol{\gamma})}{\partial\log\widehat{\mu}_{0|x}^m} = \left\{1 - pre_x^m(\boldsymbol{\theta}) - post_x^m(\boldsymbol{\theta}) + \frac{1}{2}\left(\frac{\widehat{\mu}_{0|y}^f}{\widehat{\mu}_{0|x}^m}\cdot\frac{h^f(y;\boldsymbol{\gamma})}{h^m(x;\boldsymbol{\gamma})}\right)^{1/2}\exp\left(\frac{\Sigma_{xy}(\boldsymbol{\theta})}{2}\right)\right\}\widehat{\mu}_{0|x}^m. \tag{C.7}$$

Stack the gender-specific vector of candidate never-married rates $\widehat{\boldsymbol{\mu}}_0^m$ and $\widehat{\boldsymbol{\mu}}_0^f$ in $\widehat{\boldsymbol{\mu}}_0$, and Newton-update $\log \widehat{\boldsymbol{\mu}}_0$ according to

$$\log \boldsymbol{\mu}_0' = \log \widehat{\boldsymbol{\mu}}_0 + K \cdot \widehat{\mathbf{J}}^{-1} \widehat{\boldsymbol{\Delta}}(\boldsymbol{\theta}, \boldsymbol{\gamma}), \tag{C.8}$$

where $K < 1$ is a scalar dampening factor. We take $K = 2/3$. Update $\widehat{\boldsymbol{\mu}}_0 = \boldsymbol{\mu}_0'$. Go to step 1 with the updated never-married rate candidates $\widehat{\boldsymbol{\mu}}_0 = (\widehat{\boldsymbol{\mu}}_0^m, \widehat{\boldsymbol{\mu}}_0^f)$.[39]

C.2. The Likelihood Function There are three observable types (qualification-levels) for each cohort. Let $\widetilde{\mathcal{X}} = \mathcal{C} \times \mathcal{Z}$ be the observable type-space, with generic element $\widetilde{x}$. Let $\widetilde{\mathcal{X}}_+ = \widetilde{\mathcal{X}} \cup \{0, pre, post\}$ be the observable spouse type-space which is the same as the own type-space but extended to non-marriage, and marriage to an out-of-sample spouse. We have $|\widetilde{\mathcal{X}}| = 24$ and $|\widetilde{\mathcal{X}}_+| = 27$.

Our data can be represented by a matrix of male marriage frequencies, $\mathbf{M}^m = (M^m_{\widetilde{x}\widetilde{y}})$ for $\widetilde{x} \in \widetilde{\mathcal{X}}$ and $\widetilde{y} \in \widetilde{\mathcal{X}}_+$, and a matrix of female marriage frequencies, $\mathbf{M}^f = (M^f_{\widetilde{x}\widetilde{y}})$ for $\widetilde{x} \in \widetilde{\mathcal{X}}_+$ and $\widetilde{y} \in \widetilde{\mathcal{X}}$. $M^m_{\widetilde{x}\widetilde{y}}$ is the number of type-$\widetilde{x}$ males in our data making marriage choice $\widetilde{y}$. Similarly, $M^f_{\widetilde{x}\widetilde{y}}$ is the number of type-$\widetilde{y}$ females in our data making marriage choice $\widetilde{x}$.

Let $\mu^m_{0|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the equilibrium probability that a male of full type-(c, a, z) remains single, and likewise, let $\mu^f_{0|c',a',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the equilibrium probability that a female of full type-(c', a', z') remains single. The implied never-married rate for the observable male type (c, z) is

$$\widetilde{\mu}^m_{0|c,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a \in \mathcal{A}} \mu^m_{0|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^m(a|c, z; \boldsymbol{\gamma}), \tag{C.9}$$

with an analogous expression for the observable female never-married rates $\widetilde{\mu}^f_{0|c',z'}(\boldsymbol{\theta})$. There are $|\mathcal{C}| \times |\mathcal{Z}| = 24$ unconditional (on ability) never-married rates for each gender.

The equilibrium marriage rates are aggregated across the unobserved ability-levels in a similar fashion. Consider first the out-of-sample marriage rates. Let $\mu^m_{pre|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma})$, $\mu^m_{post|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma})$, $\mu^f_{pre|c',a',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ and $\mu^f_{post|c',a',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the equilibrium male and female, full-type-specific pre- and post-sample marriage rates. Aggregating across the unobserved ability levels yields out-of-sample marriage rates with observable counter-parts. For males, we have

$$\widetilde{\mu}^m_{pre|c,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a \in \mathcal{A}} \mu^m_{pre|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^m(a|c, z; \boldsymbol{\gamma}), \tag{C.10}$$

and

$$\widetilde{\mu}^m_{post|c,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a \in \mathcal{A}} \mu^m_{post|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^m(a|c, z; \boldsymbol{\gamma}), \tag{C.11}$$

where female rates are analogously defined. There are $|\mathcal{C}| \times |\mathcal{Z}| = 24$ observable pre-sample rates and $|\mathcal{C}| \times |\mathcal{Z}| = 24$ observable post-sample rates for each gender.

Finally, let $\mu^m_{c',a',z'|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the equilibrium probability that male of full type-(c, a, z) marries a woman of full type-(c', a', z'), and let $\mu^f_{c,a,z|c',a',z'}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ be the equilibrium probability that a woman of full type (c', a', z') marries male of full type (c, a, z) male. In terms of observable types, aggregating over both the own and the spouse ability we have that

$$\widetilde{\mu}^m_{c',z'|c,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{a \in \mathcal{A}} \sum_{a' \in \mathcal{A}} \mu^m_{c',a',z'|c,a,z}(\boldsymbol{\theta}, \boldsymbol{\gamma}) \Pr{}^m(a|z, c; \boldsymbol{\gamma}), \tag{C.12}$$

[39] Our Newton-step update only uses the diagonal elements of the Jacobian, but nonetheless converges almost instantaneously.

with an analogous expression for the female rates. There are $(|\mathcal{C}| \times |\mathcal{Z}|)^2 = 576$ observable marriage rates for each gender.

Having characterized the model implied choice probabilities that a male or female of a given type marries a spouse of a given type, marries out-of-sample, or never marries, as the case might be, the likelihood that the model delivers the observed marriage frequencies $\mathbf{M}^m$ and $\mathbf{M}^f$ is easily obtained. Indeed, the log-likelihood of observing $\mathbf{M}^m$ and $\mathbf{M}^f$ is

$$\log \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma}) = \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}_+} M^m_{\widetilde{x}\widetilde{y}} \log \widetilde{\mu}^m_{\widetilde{y}|\widetilde{x}}(\boldsymbol{\theta}, \boldsymbol{\gamma}) + \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}_+} M^f_{\widetilde{x}\widetilde{y}} \log \widetilde{\mu}^f_{\widetilde{x}|\widetilde{y}}(\boldsymbol{\theta}, \boldsymbol{\gamma}), \tag{C.13}$$

where $\widetilde{\mu}^g_{\widetilde{y}|\widetilde{x}}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ is given by (C.9), (C.10), (C.11), or (C.12), or their female analogs.

The Asymptotic Sampling Distribution. The parameter of interest, $\boldsymbol{\theta}$, as well as $\boldsymbol{\gamma}$, can be estimated by Maximum Likelihood in a three-step procedure. This procedure yields $\widehat{\boldsymbol{\gamma}} = (\widehat{\gamma}^m_0, \widehat{\gamma}^m_1, \widehat{\gamma}^f_0, \widehat{\gamma}^f_1) = (0.755, 1, 0.738, 1)$. Let $\boldsymbol{\theta}_0$ represent the true value of $\boldsymbol{\theta}$, and let $\widehat{\boldsymbol{\theta}}$ be the maximum likelihood estimator of $\boldsymbol{\theta}_0$. Regularity conditions and standard arguments implies that $\operatorname{plim} \widehat{\boldsymbol{\theta}} = \boldsymbol{\theta}_0$ and that $\sqrt{M}(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) \xrightarrow{d} \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega})$, where $\boldsymbol{\Omega} = \mathrm{E}[-\mathbf{H}(\mathbf{M}^m, \mathbf{M}^f; \boldsymbol{\theta}_0)]^{-1}$, $\mathbf{H}(\mathbf{M}^m, \mathbf{M}^f; \boldsymbol{\theta}) = \nabla^2_{\boldsymbol{\theta}} \log \mathcal{L}_p(\boldsymbol{\theta})$ is the Hessian matrix of the log-likelihood function (C.13), the expectation is taken with respect to the distribution of $(\mathbf{M}^m, \mathbf{M}^f)$, and $M = M^m + M^f$ where $M^m = \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}_+} M^m_{\widetilde{x}\widetilde{y}}$ is the number of observations on males and $M^f = \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}_+} M^f_{\widetilde{x}\widetilde{y}}$ is the number of observations on females. In the empirical implementation, $\boldsymbol{\Omega}$ is estimated by

$$\widehat{\boldsymbol{\Omega}} = \left[-M^{-1} \left\{ \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}_+} M^m_{\widetilde{x}\widetilde{y}} \nabla^2_{\boldsymbol{\theta}} \log \mu^m_{\widetilde{y}|\widetilde{x}}(\widehat{\boldsymbol{\theta}}, \widehat{\gamma}) + \sum_{\widetilde{y} \in \widetilde{\mathcal{X}}} \sum_{\widetilde{x} \in \widetilde{\mathcal{X}}_+} M^f_{\widetilde{x}\widetilde{y}} \nabla^2_{\boldsymbol{\theta}} \log \mu^f_{\widetilde{x}|\widetilde{y}}(\widehat{\boldsymbol{\theta}}, \widehat{\gamma}) \right\} \right]^{-1}. \tag{C.14}$$

We report standard errors and draw inference based on $\widehat{\mathrm{Avar}}(\widehat{\boldsymbol{\theta}}) = M^{-1}\widehat{\boldsymbol{\Omega}}$. $\widehat{\mathrm{Avar}}(\widehat{\boldsymbol{\theta}})$ does not account for the estimation errors embedded in $\widehat{\boldsymbol{\gamma}}$.

D. Details on the Three-Step Estimation Procedure

Recall that, with four (a, z) combinations, $\zeta(a, z, a', z')$ is a 4×4 matrix of 16 parameters, that the parameterized age-gap preferences and trends add 22 parameters, and that we stack these 38 systematic surplus parameters in $\boldsymbol{\theta}$. $\boldsymbol{\theta}$ is the parameter of interest. Additionally, we must deal with $\boldsymbol{\gamma} \equiv (\gamma^m_0, \gamma^m_1, \gamma^f_0, \gamma^f_1)$, the four proportions of medium ability men and women who gain a basic qualification pre- and post-RoSLA. We estimate the parameters by Maximum Likelihood and approach the estimation problem in a three-step procedure briefly described in the main text. Although there is overlap with the description in the main text, this appendix provides additional details on the procedure, especially on step 2 and 3.

Step 1: Assumptions 1 and 2 imply that the observed discontinous increase in the basic qualification rate at the RoSLA threshold is driven by a proportionately equal increase in the basic qualification rate of medium-ability individuals. That is,

$$\frac{\gamma^g_1}{\gamma^g_0} = \frac{\lim_{w \downarrow 0} E^g[y^{z^1}|w]}{\lim_{w \uparrow 0} E^g[y^{z^1}|w]}, \text{ for } g = m, f, \tag{D.1}$$

where y^{z^1} is an indicator for attaining qualification $z = z^1$ and w is date of birth relative to the RoSLA threshold date. The RDD estimator of (1) for qualification z^1 allows us to obtain precise estimates of the right hand side of (D.1), and we therefore treat the (reciprocal) ratio

γ_0^g/γ_1^g as known and equal to 0.755 (0.011) for men and 0.738 (0.008) for women where the numbers in parenthesis are boostrapped standard errors.[40]

Trivially, each element of $\boldsymbol{\gamma}$ is in the unit interval. However, the observed qualification distribution actually imposes a tighter lower bound on γ_1^g. To see this, note that the observed rate of holding qualification z^1 post-RoSLA is the product of γ_1^g and the proportion of individuals who have ability level a^1, where the latter cannot exceed the complement of the proportion holding qualification z^2 (as these individuals, per Assumption 2, have ability level a^2). This places a lower bound on γ_1^g, denoted $\underline{\gamma}_1^g$, which we find to be 0.69 for both genders.[41] Altogether, we thus obtain that the empirically feasible set $\mathcal{G}$ is:

$$\mathcal{G} = \left\{ \boldsymbol{\gamma} : \gamma_1^g \in [0.69, 1] \text{ for } g = m, g, \text{and } \frac{\gamma_0^m}{\gamma_1^m} = 0.755 \text{ and } \frac{\gamma_0^f}{\gamma_1^f} = 0.738 \right\}.$$

The ratio restrictions on $\boldsymbol{\gamma} \in \mathcal{G}$ imply that there are only two free parameters in $\boldsymbol{\gamma}$.

Interestingly, in the lower limit where $\gamma_1^g = \underline{\gamma}_1^g = 0.69$ for $g = m, f$, all unqualified individuals—both pre- and post-RoSLA—have medium ability and no one has low ability. This means that, in this limit, everyone is distinguished by their observable qualification level, implying that there is no latent ability. In other words, when γ_1^g approaches the lower limit $\underline{\gamma}_1^g = 0.69$ for $g = m, f$, our latent ability model collapses to the standard CS model.

Step 2: We compute maximum likelihood estimates conditional on $\boldsymbol{\gamma} \in \mathcal{G}$ by estimating the model on a fine grid of alternative $\boldsymbol{\gamma} \in \mathcal{G}$. Specifically, for each $\boldsymbol{\gamma}$-value on the grid, we obtain $\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}) \in \arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ and the likelihood value $\mathcal{L}(\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}), \boldsymbol{\gamma})$. Note that $\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma})$ may not be unique.

The upper panel of Figure D.1 plots conditional maximum likelihood values for the special case where we additionally restrict $\gamma_1^m = \gamma_1^f = \gamma_1$, leaving γ_1 as the only free element in $\boldsymbol{\gamma}$. The top panel of Figure D.1 yields a number of insights. First, the conditional maximum likelihood value is naturally a continuous function of γ_1, but exhibits a kink (at $\gamma_1 = 0.81$). At this point (and only at this point) $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ is not a singleton, implying a failure of identification: at this specific $\boldsymbol{\gamma}$-value, there are two very different $\boldsymbol{\theta}$-vectors fit the data equally well. Note, however, that non-identification come about only under knife edge conditions.[42] Second, noting that $\gamma_1 = \underline{\gamma}_1 = 0.69$ corresponds to the CS model without latent ability, we also estimate this model separately (see Appendix F for details) and indicate the maximum likelihood value with the label "CS". This provides numerical confirmation that the CS model is in fact a limiting case of our latent ability model and that the standard CS model is identified.

The lower panel of Figure D.1 plots maximum likelihood values conditional on γ_1^m and γ_1^f, in the general case where these are allowed to differ. Generalizing from the kink-point in the upper panel, the lower panel highlights paths of kink-points at which $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\gamma})$ is not a singleton.

Step 3: Using the step-2 conditional likelihood values, $\mathcal{L}(\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}), \boldsymbol{\gamma})$, we find the $\boldsymbol{\gamma}$-value where the likelihood function attains its overall maximum. That is, if $\widehat{\boldsymbol{\gamma}} \in \arg\max_{\boldsymbol{\gamma} \in \mathcal{G}} \mathcal{L}(\widehat{\boldsymbol{\theta}}(\boldsymbol{\gamma}), \boldsymbol{\gamma})$, then

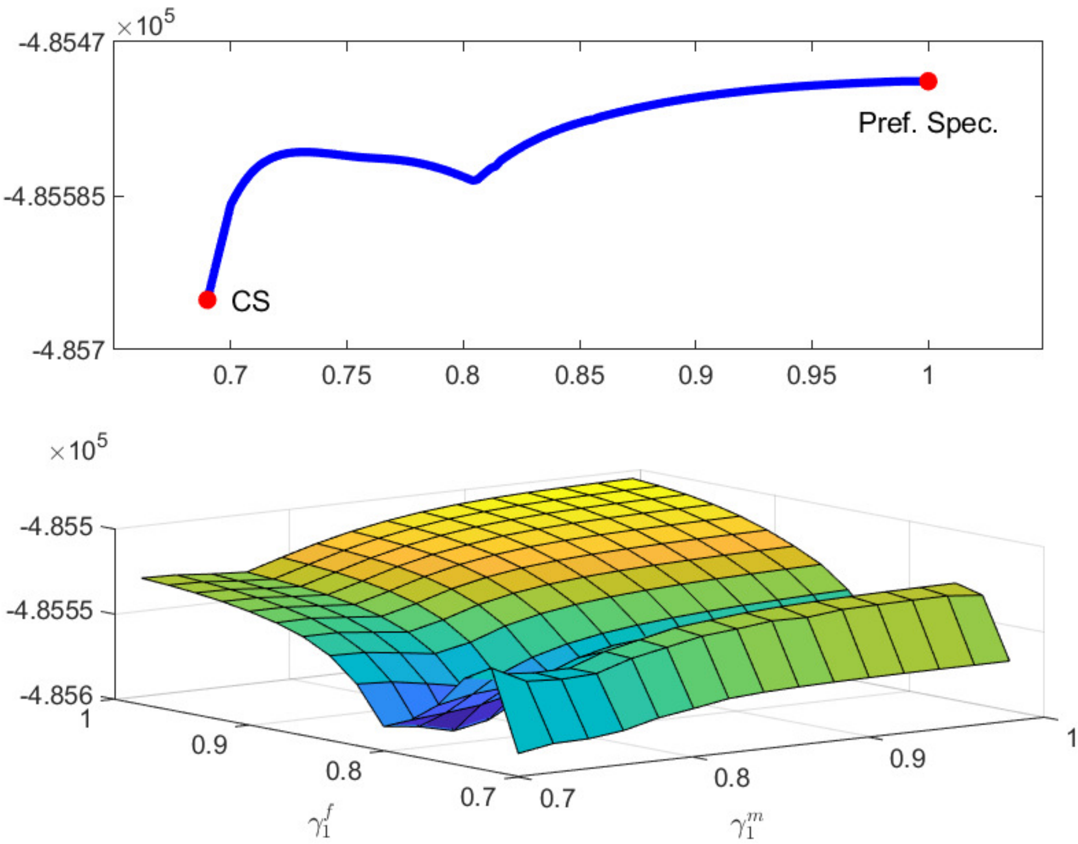
[40] To see this, note that $\gamma_0^g/\gamma_1^g = 1 - \varphi_{z^1}^g / \lim_{w \downarrow 0} E^g \left[y^{z^1} | w \right]$ where the estimated values of $\varphi_{z^1}^g$ from (1) are 0.106 (0.005) for men and 0.131 (0.007) for women (see Table 2), and estimates of the values of $\lim_{w \downarrow 0} E^g \left[y^{z^1} | w \right]$ can simply be obtained as the empirical rate of holding qualification z^1 among individuals in the first RoSLA-affected cohort, 0.433 (0.004) for men and 0.499 (0.004) for women.

[41] Specifically, the lower bound $\underline{\gamma}_1^g$ is defined as $\underline{\gamma}_1^g \equiv \max_{c \in \mathcal{C}_1} \left\{ \Pr^g \left(z = z^1 | c \in \mathcal{C}_1 \right) / \left[1 - \Pr^g \left(z = z^2 | c \in \mathcal{C}_1 \right) \right] \right\}$.

[42] The kink in the likelihood value at $\gamma_1 = 0.81$ arises as the intersection between the paths of two local maximizers, $\hat{\boldsymbol{\theta}}^1(\gamma_1)$ and $\hat{\boldsymbol{\theta}}^2(\gamma_1)$. For $\gamma_1 < 0.81$, $\hat{\theta}^1(\gamma_1)$ is the the global maximum, while $\gamma_1 > 0.81$ yields $\hat{\theta}^2(\gamma_1)$ as the global maximum. Exactly at $\gamma_1 = 0.81$, $\arg\max_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}, 0.81) = \{\hat{\boldsymbol{\theta}}^1(0.81), \hat{\boldsymbol{\theta}}^2(0.81)\}$.

$\widehat{\boldsymbol{\theta}}(\widehat{\boldsymbol{\gamma}})$ is a maximum likelihood estimate of the parameters of interest $\boldsymbol{\theta}$. With reference to (the top panel of) Figure D.1, we first note that the CS model obtained at $\gamma_1 = \underline{\gamma}_1 = 0.69$ provides a particularly poor fit to the data. Re-iterating arguments already laid out and previewing specification tests to come, the poor fit of CS model without latent ability stems from patently counterfactual predictions of the RoSLA response of the single rates of unqualified individuals (see Figure F.1 in Appendix F). More importantly, the plots in the upper and lower panels of Figure D.1 confirm that, across all feasible $\boldsymbol{\gamma} \in \mathcal{G}$, $\gamma_1^m = \gamma_1^f = 1$ provide the best fit to the data, a point we label "Pref. Spec." in the upper panel. Of course, $\gamma_1^m = \gamma_1^f = 1$ implies $\gamma_0^m = 0.755$ and $\gamma_0^f = 0.738$. That is, our estimate of $\boldsymbol{\gamma}$ is $\widehat{\boldsymbol{\gamma}} \equiv (\widehat{\gamma}_0^m, \widehat{\gamma}_1^m, \widehat{\gamma}_0^f, \widehat{\gamma}_1^f) = (0.755, 1, 0.738, 1)$. It is reassuring that the γ-values that offer the best and far superior fit are well removed from the kinkpoints in the empirical likelihood.

Figure D.1: Maximum Likelihood Values Conditional on $\boldsymbol{\gamma} \in \mathcal{G}$



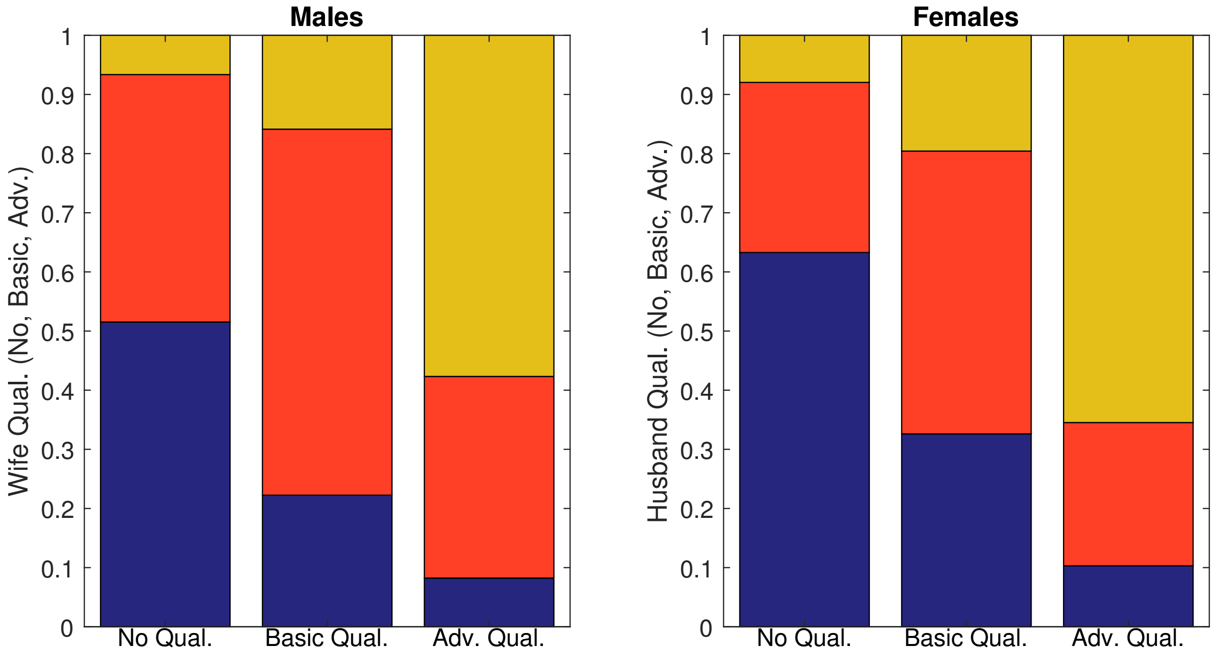
Notes: The figure plots the maximum likelihood value associated with alternative values of $\gamma_1^g \in \mathcal{G}$. In the upper panel we restrict attention to the case where $\gamma_1^m = \gamma_1^h$. The "CS" marker indicates the maximum likelihood value associated with the CS model without latent ability and "Pref. Spec"-marker indicates the overall maximum likelihood value. The lower panel plots the maximum likelihood value for all feasible values of $\boldsymbol{\gamma} \in \mathcal{G}$.

E. Additional Analysis of Model Fit

E.1. Qualification Homogamy Figure E.1 shows the model-predicted version of the empirical distributions of spousal qualifications by own qualification level in Figure 4. Comparing Figures

4 and E.1, the estimated model replicates the overall assortative mating on qualifications well.

Figure E.1: Predicted Assortative Matching on Qualifications



Notes: Each panel shows the predicted spousal qualification distribution by own qualification level.

E.2. Estimated Age Gap and Trend Functions Recall that $d = c' - c$ is the husband-wife age gap. The age gap function $\lambda(d)$ is parameterized as follows:

$$\lambda(d) = \sum_{\delta=-3}^{3} \beta^{\delta} \mathbb{1}(d = \delta) + \left(\beta_0^- + \beta_1^- d\right) \mathbb{1}(d \leq -4) + \left(\beta_0^+ + \beta_1^+ d\right) \mathbb{1}(d \geq 4), \tag{E.1}$$

which is fully non-parametric at age-gaps around zero, but, for simplicity, imposes linear terms at age gaps outside the range $\{-3, -2, ..., 3\}$. We normalize $\beta^0 = 0$, implying that $\lambda(0) = 0$; hence, (E.1) introduces 10 parameters.

With only a small number of cohorts on either side of the threshold, we model marital surplus trends $\tau^g(c, a)$ for $g = m, f$ as piecewise linear functions:

$$\tau^g(c, a) = \beta_a^g (c - 1953) + \beta_{a,\mathcal{C}_1}^g (c - 1956)\, \mathbb{1}(c \in \mathcal{C}_1), \quad g = m, f, \tag{E.2}$$

thus adding a total of 12 additional parameters.

The ten parameters of the age gap function $\lambda(d)$ are stacked in

$$\boldsymbol{\theta}_\lambda = \left(\beta^{-3}, \beta^{-2}, \beta^{-1}, \beta^{1}, \beta^{2}, \beta^{3}, \beta_0^-, \beta_1^-, \beta_0^+, \beta_1^+\right),$$

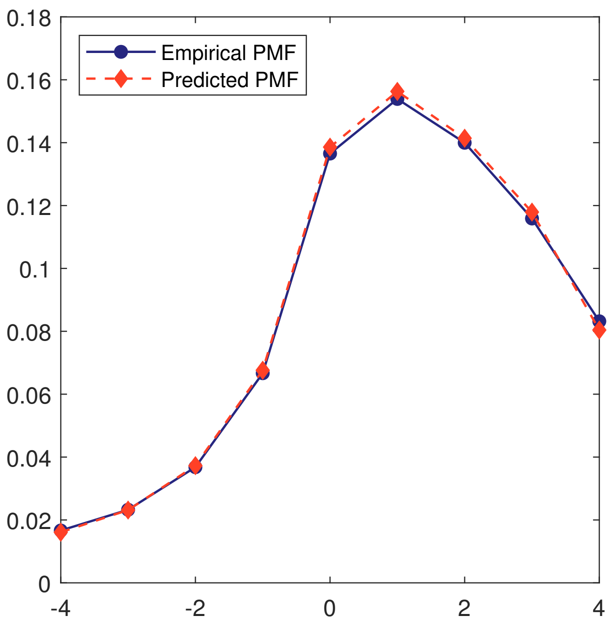
and the estimate of $\boldsymbol{\theta}_\lambda$ is

$$\widehat{\boldsymbol{\theta}}_\lambda = \Big(\underset{(0.042)}{-3.579}, \underset{(0.032)}{-2.628}, \underset{(0.024)}{-1.435}, \underset{(0.019)}{0.249}, \underset{(0.002)}{0.055}, \underset{(0.022)}{-0.300}, \underset{(0.163)}{-3.147}, \underset{(0.030)}{0.286}, \underset{(0.074)}{0.088}, \underset{(0.013)}{-0.284}\Big),$$

where asymptotic standard errors are reported in parentheses. With the exception of $\widehat{\beta}_0^+$, all the elements in $\widehat{\boldsymbol{\theta}}^\lambda$ are statistically significant at the 1 percent level.

Figure E.2, which plots the predicted age gap distribution alongside the empirical one for the central values of -4 to $+4$, shows that the estimated $\lambda(d)$ yields a close fit to the empirical age gap distribution.

Figure E.2: Predicted and Empirical Age Gap Distributions



Notes: The age gap d is defined as $d \equiv c' - c$, where c and c' are cohort of the husband and the wife, respectively. Solid lines renders the data (see left panel of Figure 6). Dashed lines renders model predictions.

The trend functions $\tau^m(c,a)$ and $\tau^f(c,a)$ each has 6 parameters, see (E.2), which we stack in the two vectors $\boldsymbol{\theta}_\tau^g = \left(\beta^g_{a^0}, \beta^g_{a^0,\mathcal{C}_1}, \beta^g_{a^1}, \beta^g_{a^1,\mathcal{C}_1}, \beta^g_{a^2}, \beta^g_{a^2,\mathcal{C}_1}\right)$ for $g = m, f$. We obtain

$$\widehat{\boldsymbol{\theta}}_\tau^m = \Big(\underset{(0.023)}{-0.076}, \underset{(0.032)}{-0.109}, \underset{(0.015)}{0.066}, \underset{(0.028)}{-0.136}, \underset{(0.017)}{-0.039}, \underset{(0.036)}{-0.065}\Big),$$

$$\widehat{\boldsymbol{\theta}}_\tau^f = \Big(\underset{(0.036)}{-0.187}, \underset{(0.044)}{-0.054}, \underset{(0.017)}{0.014}, \underset{(0.031)}{-0.136}, \underset{(0.019)}{-0.085}, \underset{(0.039)}{-0.087}\Big),$$

where, as above, asymptotic standard errors are reported in parentheses. Most estimated trend parameters in $\widehat{\boldsymbol{\theta}}_\tau^m$ and $\widehat{\boldsymbol{\theta}}_\tau^f$ are statistically significant and negative, which is consistent with never-married rates increasing across cohorts.

F. Specification Tests

F.1. The "Qualification-Only" CS Model An individual's type is defined as $x \in \mathcal{C} \times \mathcal{Z}$ with all combinations possible. We impose the same separability assumption on marital surplus as in (5). We also impose the same age-gap preference structure and the same trend structure except that trends are qualification-specific, and not ability-specific. That is, the "qualification-only" CS model has the following marital surplus function:

$$\Sigma_{(c,z),(c',z')} = \zeta\left(z, z'\right) + \lambda\left(c' - c\right) + \tau^m\left(c, z\right) + \tau^f\left(c', z'\right), \tag{F.1}$$

with $\lambda(d)$ representing the age gap preferences as in the main text ($d = c' - c$ is the husband-wife age gap), and where $\tau^g(c, z)$ are piecewise linear trends that allow for a break at the RoSLA threshold. The estimated qualification surplus matrix is shown in Table F.1.[43]

Table F.1: The Marital Surplus Matrix in the Constrained Model

	Wife type		
	z^0	z^1	z^2
Husband type z^0	0.244^{***} (0.076)	-1.413^{***} (0.079)	-4.350^{***} (0.091)
Husband type z^1	-1.701^{***} (0.083)	-1.088^{***} (0.083)	-3.029^{***} (0.090)
Husband type z^2	-3.762^{***} (0.095)	-2.285^{***} (0.089)	-0.482^{***} (0.090)

Notes: Asymptotic standard errors in parentheses. *, **, and *** indicates statistical significance at the 10, 5, and 1 percent levels, respectively

The loss in the maximized log likelihood value relative to our main model in this case is 163.7 (and larger than the corresponding loss of 107.8 for the restricted model where trends were defined on ability). There is no visible difference in the fit to the observed aggregate assortative mating on qualifications compared with our full model and the same applies to the aggregate age gap distribution.[44]

The central difference between our model with latent ability and the one estimated here without latent ability is in terms of predicted never-married rates. Figure F.1 presents the fit to the empirical never-married rates of the model without latent ability. The restricted model without latent ability severely misrepresents how the never-married rate of unqualified men and women changed at the reform threshold, predicting a sharp reduction in response to the reduced supply brought about by the RoSLA.

F.2. Testing Additive Separability with Linear Trends Consider a man from cohort $c \in \mathcal{C}_1$ with qualification z and a woman from cohort $c' \in \mathcal{C}_1$ woman with qualification z'. As both are from the post-RoSLA cohorts, by Assumption 2 and using that $\gamma_1^g = 1$ for $g = m, f$, the qualifications imply aligned ability levels, a and a'. If the gender- and ability-specific trend terms are linear as in our main specification, then the marital surplus function (5) implies a zero double-difference in cohorts,

$$\left[\Sigma_{(c,a,z),(c',a',z')} - \Sigma_{(c-1,a,z),(c'-1,a',z')}\right] - \left[\Sigma_{(c-1,a,z),(c'-1,a',z')} - \Sigma_{(c-2,a,z),(c'-2,a',z')}\right] = 0. \quad \text{(F.2)}$$

In post-reform cohorts, this double-difference is observable: using that the terms in (4) sum up to the systematic surplus, we have that

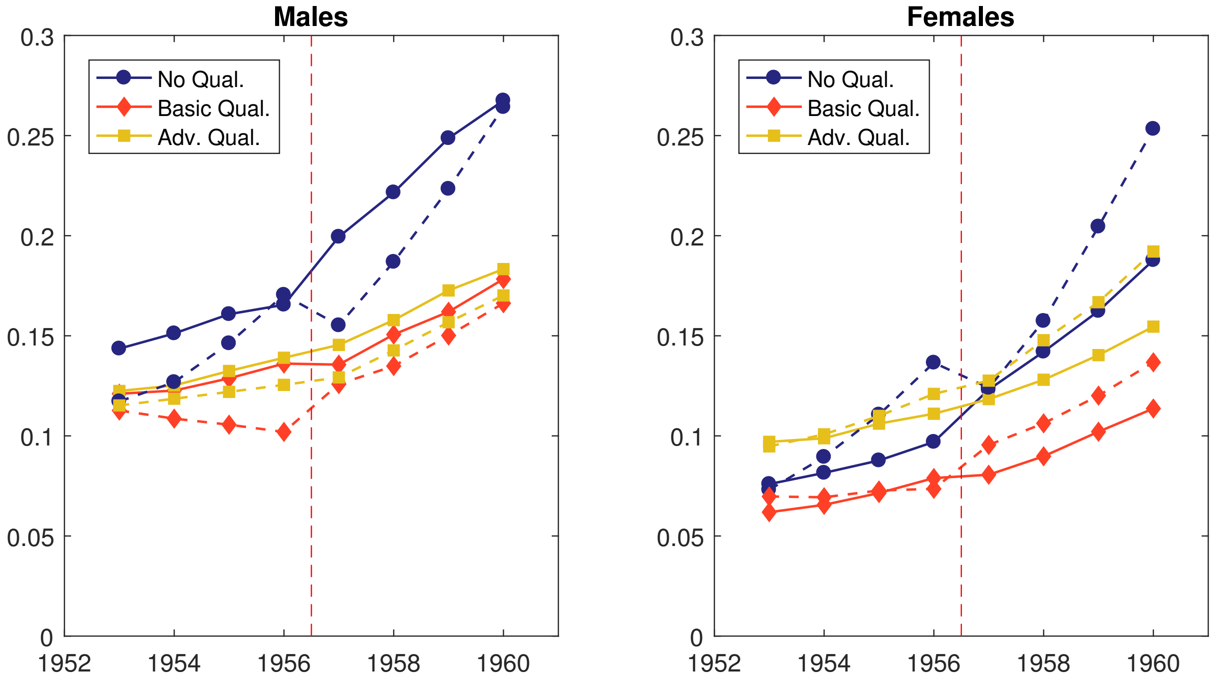
$$\log\left(\frac{\mu^m_{c',a',z'|c,a,z}}{\mu^m_{0|c,a,z}}\right) + \log\left(\frac{\mu^f_{c,a,z|c',a',z'}}{\mu^f_{0|c',a',z'}}\right) = \Sigma_{(c,a,z),(c',a',z')}, \quad \text{(F.3)}$$

where the marriage and never-married rates on the left-hand side are observed for $c, c' \in \mathcal{C}_1$. Hence, the double-differenced marital surplus can be computed by double-differencing the cor-

[43] The estimated parameters in the age gap and trend functions, $\lambda(d)$, $\tau^m(c, z)$ and $\tau^f(c, z)$, are not reported by are available on request.

[44] Details of these model predictions are available from authors on request.

Figure F.1: Predicted (Constrained Model) and Empirical Never-Married Rates by Cohort, Gender, and Qualification

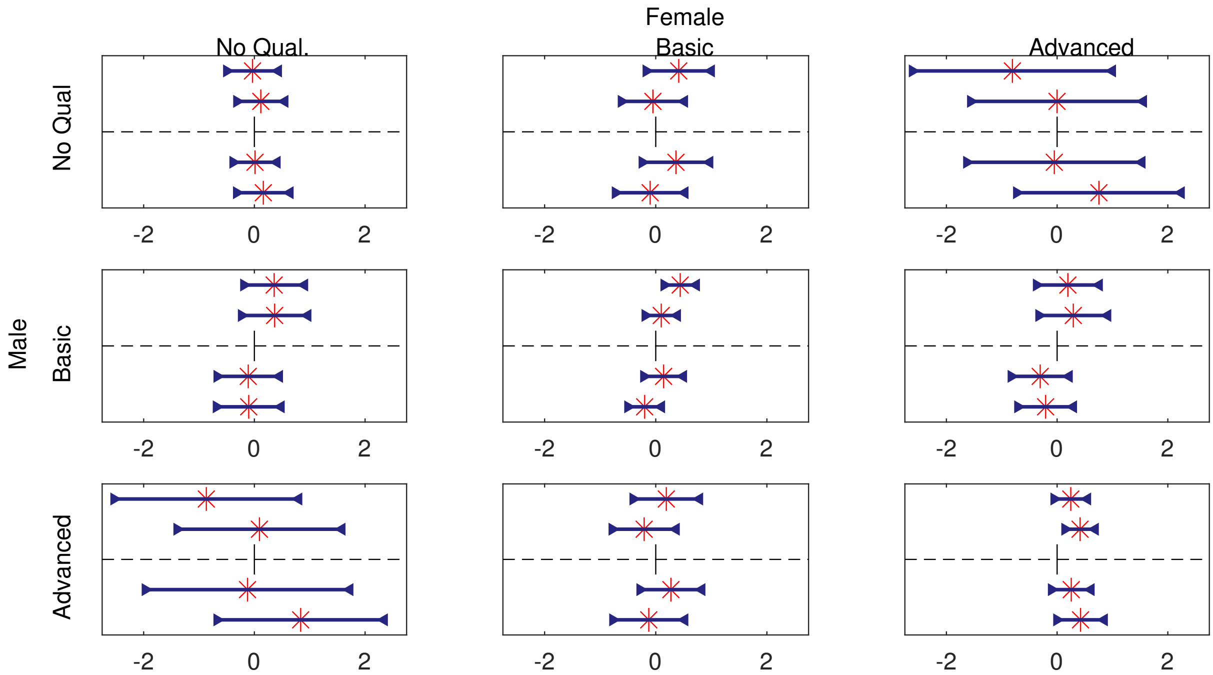


Notes: The horizontal axes show academic cohorts. The vertical axes show never-married rates. Solid lines renders the data. Dashed lines renders model predictions.

responding empirical sum of log-ratios, thus rendering the restriction (F.2), implied by (5), testable.

As all cohorts included in the double-difference have to be in $\mathcal{C}_1$, the possible base years are 1960 and 1959. This leaves four possible male-female base year combinations, and as there are nine possible husband-wife qualification profiles, a total of 36 post-reform double differences can be computed. All 36 estimates are plotted in Figure F.2 along with 95 percent confidence intervals. Despite fairly high precisions in some categories, the hypothesis of a zero double-difference in marital surplus is rejected in only two cases and with no particular pattern emerging. We conclude that the marriage data from the post-reform cohorts does not reject a specification with additive age-gap-based preferences and linear trends.

Figure F.2: Specification Tests Based on Marital Surplus Double Differencing



Notes: The horizontal axes show double-differenced marital surplus, see (F.2) and (F.3). Point estimates are indicated by a red asterisks. The blue bars indicate 95% confidence intervals. The double differences are computed only on the post-RoSLA cohorts where ability and qualifications are aligned, such that there are 3 types for each gender. Within each subfigure, the husband-wife base year combinations, reading from top to bottom, are (1960, 1960), (1960, 1959), (1959, 1960), and (1959, 1959).