

Degrees Are Forever: Marriage, Educational Investment, and Lifecycle Labor Decisions of Men and Women*

Mary Ann Bronson[†]

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Abstract

Women attend college today at higher rates than men, but continue to select disproportionately into low-paying majors. This paper aims to explain these gender gaps in college attendance and choice of major. I provide reduced-form evidence that, first, degrees may provide insurance against very low income for women, especially in case of divorce; and second, majors differ substantially in the degree of “work-family flexibility” they offer, such as the size of wage penalties for temporary reductions in labor supply. Based on this evidence, I construct and estimate a dynamic structural model of marriage, educational choices, and lifetime labor supply. I use the model to quantify the relative importance of rising skill premiums and changes in the marriage market for the observed changes in the college gender gaps between 1960 and 2010. I then use the model to test the effects of educational and work-family flexibility policies on educational choices. Differential tuition policies that charge less for technical majors, as proposed in some U.S. states, can substantially increase the share of women choosing such majors, but only subsidize men who would have chosen technical majors regardless of the policy. Among interventions intended to improve work-family flexibility, subsidized child care and part-time work entitlements increase the share of women in science and business, while extended maternity leaves have the opposite effect.

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[†]Georgetown University, Dept. of Economics, Washington, DC. Email: mary.ann.bronson@gmail.com.

Why do women today invest in a college education at much higher rates than men, but continue to choose lower-paying majors? The main objective of this paper is to answer these two questions, and to explain the dynamics in the two college gender gaps from 1960 to 2010. Historically, men made up the majority of college students in the U.S., and earned more than 90% of all high-paying degrees in science and business. While women reversed the gender gap in graduation rates by the mid-1980s and now make up 58% of graduating college students, gender convergence in choice of major almost ceased after the mid-1980s. For example, in 1985 women were awarded more than 75% of degrees in education and health support fields, but fewer than 30% of hard science and engineering degrees. The same is still true today.¹

Women's high rate of graduation, with on average lower-paying majors, has implications not only for individual labor market outcomes. Women's persistently low participation in majors like science and engineering contributes to potentially low supply of science-related skills in the U.S. Additionally, women's higher graduation rate despite lower lifetime labor supply runs counter to the predictions of a standard human capital investment model (Becker (1962), Ben-Porath (1967), Mincer and Polachek (1974)), raising important questions about the determinants of returns to different educational choices for men and women.

In the first part of the paper, I document what might potentially explain the above-mentioned gender gaps between 1960 and 2010. I show that changes in the wage premium over time and differences in major-specific premiums across men and women do not explain the observed patterns. I then provide quasi-experimental evidence using divorce law reforms that changes in the marriage market starting in the 1970s, such as rising divorce rates, changed the relative returns to a college education for men and women. The intuition is simple: women with high school education or less draw from a substantially lower wage distribution than men, and are also more likely to have custody of and financial responsibility for children. A college degree allows women access to higher paid jobs, providing insurance against very low income for women outside a two-earner household.

Next, I present evidence that majors are characterized not only by different wage premiums, but also by different levels of "work-family flexibility." By flexibility I mean that some majors are associated with occupations that provide easier access to part-time or part-year work and have lower wage penalties for a temporary absence from the workforce. I show that college women reduce their labor supply substantially during their childbearing years, and that these patterns differ across majors and occupations. The data patterns that I document indicate that women are more likely than men both to take advantage of flexibility associated with some majors, as well as to choose more flexible majors.

The documented empirical patterns indicate that insurance and flexibility are important drivers of the gender gaps, but it is difficult to quantify the impact of these factors on the college gender gaps using the reduced-form analysis alone. The main reason for this is that

¹National Center for Education Statistics, Digest of Education Statistics (2012), Tables 343-365.

other variables, like returns to skill, also changed over this time period, and will also affect decisions about education, marriage and divorce, and labor supply. To address this, I develop and estimate a dynamic structural lifetime model of individual decisions about education, marriage, and labor supply. The model is constructed based on the documented data patterns. The model follows individuals starting at age 18 over three phases of life: education, work, and retirement.

In the first phase, individuals decide whether to go to college. If they go to college, they choose between two majors. One major is associated with occupations that have a high return, but also a high rate of skill depreciation, meaning that individuals incur large wage penalties for any reductions in labor supply. The second major is associated with occupations that have a lower return, but also a lower rate of skill depreciation. These differences between the majors match those observed in the data. Individuals make decisions based on their expected lifetime utility from each educational choice and their effort cost of completing each major.

In the second, working phase of life individuals make decisions about time allocated to market and home production, marriage and divorce, occupational choice, and savings. If an individual is single, each period he or she is matched with a potential partner and decides whether to marry. Having a college education increases one's probability of meeting a college-educated partner. If married, the partners make household decisions jointly, but there is no commitment, meaning that if in some period the partners are not both better off in the marriage than they would be if they were single, they renegotiate their bargaining power in the household or divorce (Marcet and Marimon (1992)). There are shocks to marital match quality, wages, and fertility. After a fertility shock, the presence of a young child in the household increases the productivity of hours dedicated to child care and home production. In the final, retirement stage of life, individuals only make decisions about consumption, home production, and savings. For different cohorts, decisions over the lifetime and therefore expected returns to education are affected by changes in the wage structure, such as rising skill premiums, and by changes in the marriage market after the reform in divorce laws.

The model is estimated using the Simulated Method of Moments. The estimated model matches well the marriage and labor supply patterns of men and women over the lifecycle, and educational choices of cohorts over time. It generates a reversal in the gender gap in graduation rates, and the persistence in the gender gap in majors. In the model, the current differences in educational choices are generated through the interaction between the gender wage gap and marriage over the lifecycle. On the one hand, the "insurance" value of the degree drives up the return to college for women in case of divorce, regardless of the major they choose. As a result, they graduate at higher rates. On the other hand, conditional on being married, women are more likely to be the lower wage-earners and therefore more likely to specialize in home production and child care. Because of this, women are more likely than men to incur wage penalties for reductions in labor supply, and thus to select majors

that offer flexibility. Apart from matching the main education and labor supply features in the data, the model also correctly matches several non-obvious data patterns, including the fact that college-educated women allocate more time to child care than non-college women (Guryan et al. (2008)) and have lower divorce rates (Stevenson and Wolfers (2007)).

Using model counterfactuals, I estimate that equalizing wage penalties across occupations increases the share of college women choosing a high-return major from 34% to 45%, implying that flexibility is an important factor. Nevertheless, this is far less than 66%, the share of men choosing such majors. The reason for this is that women reduce their hours worked when flexibility is available. As a result, the difference in lifetime financial returns to different majors is still smaller for women than for men, making them more likely to choose a major based on taste or effort cost. I also estimate that around half of the convergence in the gender gap in graduation in the 1970s and early 1980s was generated by the increase in the value of “insurance” that the college degree provides for women in case of divorce. This insurance value is equal to around 31% of the return to college for women.

Lastly, I analyze the impact of different policies on educational choices. Women’s persistently lower representation in high-return, low-flexibility fields suggests that there may be scope for welfare-improving “family-friendly” policies, like paid maternity leave or part-time work entitlements. Such policies have been enacted in various countries to encourage gender equality in the labor force. However, as Blau and Kahn (2012) point out, “family-friendly” policies have theoretically ambiguous effects on women’s labor supply, occupational, and educational choice, even absent any potential discriminatory response from employers. I use the model to analyze the effects on occupational and educational choices. My results show that some policies, like part-time work entitlements or subsidized child care, have the potential to increase the share of women in science and business majors, while policies that markedly reduce women’s accumulated experience over the lifecycle, such as extended paid maternity leaves, amplify *both* current gender gaps in education.

I also evaluate a differential tuition policy that lowers the cost of technical majors, as proposed in Florida (Alvarez (2012)) and several other states. I find that the policy induces a substantial share of women to switch to technical degrees, but only subsidizes men who would have chosen technical majors regardless of the policy. The main explanation for this is that because women work less over the lifetime and are more likely to incur wage penalties for taking time out of the labor force, the additional financial return to the technical major over a non-technical one is lower for them. As a result, women are far more likely to be on the margin between choosing the two majors than men, and to switch their major in response to the tuition policy.

This paper extends the literature in several important ways. It builds on the literature that models and estimates the dynamic, intertemporal aspects of household decisions using

a collective household model.² Household decisions about the degree of specialization, marriage, and divorce directly affect anticipated and actual returns to college attendance and choice of major.³ To understand how different policies may affect educational choices, it is therefore important to know how they will affect these other lifecycle decisions. The paper also contributes to the literature examining the “flexibility” of different professions and the relationship with human capital investments. Recent work includes Goldin and Katz (2011), Goldin and Katz (2012), and Bertrand, Goldin, and Katz (2010). Unlike these papers, however, the present study focuses on choices of college major. Additionally, unlike previous work the present paper estimates a dynamic model that permits the analysis of different policy interventions intended to address the low representation of women in high-paying fields.

Finally, the paper contributes to the literature on the gender gap in educational choices. Two main explanations exist for the gender gap in choice of majors, as summarized by Zafar (2009). One possible explanation, largely rejected by empirical work, is that men and women may have innately different abilities and thus choose different fields (Kimura, 1999).⁴ A second explanation for the gender gap in the choice of major is that men and women have systematically different preferences for different majors. For example, Wiswall and Zafar (2013) estimate a model of choice of college major. They find that earnings are a significant determinant of major choice, but residual factors, interpreted as tastes, are dominant, with women more likely to have a taste for the arts and humanities. This finding is similar to that of Zafar (2007), Beffy et al. (2011) and Gemici and Wiswall (2011), who similarly attribute the gender gap in majors primarily to differences in tastes. However, these studies do not account for non-financial characteristics of majors, like flexibility, which differentially affect lifetime expected returns for women and men. As a result, the differences in choices about majors that may be explained by such characteristics are instead attributed to tastes.⁵

The rest of the paper is organized as follows. Section 1 presents the reduced-form results. In Section 2, I describe the model. Section 3 provides details about the estimation. Section 4 summarizes the results. In Section 5, I present the outcomes of policy experiments. Section 6 concludes.

²See, for example, Mazzocco et al. (2009), Lundberg et al. (2003), Van der Klaaw and Wolpin (2004), Voena (2012) Gemici and Laufer (2011), Lise and Yamada (2014).

³See early work by Becker (1973), Mincer and Polachek (1974), and Polachek (1978, 1981). For evidence about college students’ expectations about career, family, and within-household specialization, see Fetterold (2011), Brown and Diekmann (2010), and Stone and McKee (2000). Survey evidence shows that even at elite colleges women expect to significantly reduce their labor supply after having children. A 2004 survey of Yale women found that roughly 60% of respondents planned to cut back on work or stop working entirely after having children. About half of these women said they planned to work part time, and half wanted to stop work “for at least a few years” (Story, 2005). See also Sennett (2006).

⁴Turner and Bowen (1999), Xie and Shauman (2003) show that gender differences in mathematical achievement cannot explain men’s higher propensity to major in sciences and engineering. Moreover, the gender gap in mathematics preparation and performance is small and decreasing over time (Goldin et al. (2006)).

⁵This paper also contributes to the substantial literature on the gender gap in college attendance. See, for example, Goldin, Katz, and Kuziemko (2006), Chiappori, Iyigun, and Weiss (2009), Charles and Luoh (2003), Averett and Burton (1996), Rios-Rull and Sanchez-Marcos (2002).

1 Stylized Facts and Reduced-Form Evidence

Figures 1 and 2 show, respectively, college graduation rates by gender, 1960 to 2010, and the share of undergraduate degrees in each major awarded to women. Four main facts stand out from these figures. First, graduation rates increased substantially for both men and women over this period (Figure 1), in line with rising skill premiums. Second, a considerable difference between men and women is that in the early 1970s men’s college attainment stalled and even fell, while women continued to increase their college graduation rates over almost the entire time period, reversing the “college gender gap” that historically favored men.

Third, similar to graduation rates, starting around 1970 a significant convergence occurred in choices of major between men and women (Figure 2). Most dramatically, the share of business degrees earned by women increased from less than 10% in 1970 to more than 40% by 1985. Finally, men and women converged only partly in their choices of majors. Remarkably, gender convergence in choice of majors almost completely ceased after the early 1980s.⁶

In the remainder of the section, I provide evidence on the potential drivers of these patterns. I focus first on the change in men’s and women’s graduation rates over time. I then examine changes in choice of college majors over the 1970s. Finally, I consider the persistence in the gender gap in majors since the mid-1980s.

Changes in Graduation Rates

In Figure 3, Panel A replicates graduation rates by gender, while Panel B graphs the college wage premium for men and women from 1960 to 2010. In a standard human capital investment model (Ben-Porath (1967), Becker (1962)), the college wage premium is an important driver of educational choices. Differences in the wage premium for men and women over time may therefore help explain changes in their educational investments. However, Figure 3 shows that premiums evolved similarly for men and women between 1960 and 2010, and cannot explain the gender differences in graduation rates over time.⁷ In fact, women’s college wage premiums grew more slowly than men’s between the mid-1970s and 2010, while their graduation rates increased more rapidly. Interestingly, Figure 3 shows that for men educational choices are in line with the predictions of a standard human capital investment model. The wage premium doubled from around 30 log points in 1960 to more than 60 log points in 2012, in keeping with the large increase in college attendance rates. As the premium declined in the 1970s, fewer men invested in a college education. However, for women one does

⁶Note that Figure 2 does not account for the change in the popularity of different majors over time. In Appendix A.2 I document that, after taking account of the change in relative popularity of different majors, the time series patterns demonstrate the exact same characteristics, i.e. convergence in the 1970s and persistence in the gender gap in majors after the 1980s.

⁷Changes in choice of major over time affects the evolution of the wage premium in Figure 3. Women selected into higher-paying majors in the 1970s, driving up women’s observed wage premium. If one were to hold constant the share of individuals choosing each type of major at the 1970 level, the wage premium for women after this year would be lower than the one recorded in Figure 3. It would therefore make it even more difficult to explain why women increased their college attendance rates relative to men after the 1970s.

not observe such a relationship between the wage premium and college graduation. Despite falling wage premiums, women continued to increase their college enrollment substantially in the 1970s, and thus rapidly converged with men.

Why did women continue to increase their graduation rates despite falling wage premiums? The timing in the gender convergence starting in the 1970s suggests that changes in the marriage market may provide one possible explanation. In particular, 1970 marked the beginning of so-called no-fault, unilateral divorce law reforms across the U.S., which made divorce significantly easier in most states.⁸ As has been widely documented, the reforms were followed by a rapid, immediate increase in the number of divorces (Friedberg (1998), Wolfers (2003)).

Figure 4 maps the share of individuals divorced since 1960, as well as the ratio of women to men enrolled in four-year-universities, with the dotted line marking the start of divorce law reforms. The similar evolution in divorce rates and the gender gap, especially the rapid increase in both series in the 1970s, suggest a possible association between these factors.⁹ The intuition behind why women’s return to college may increase when divorce rates rise is that a college degree can provide an important form of “insurance” against low household income for women in case of divorce. While the focus of the discussion in this section is on divorce, the same economic intuition can also apply to unmarried women, or the risk that a woman who wishes to marry does not find a suitable mate. Low-skill wages for women are substantially lower than those for men. In 2000, women ages 18 to 50 with less than a college degree had average full-time earnings of \$27,156, compared with \$36,751 for men (IPUMS USA, 2000). Moreover, women on average bear a majority of the child care costs following separation or divorce (Grail (2002)). As a result, securing the college wage premium may become more valuable to women as they anticipate spending more of their lifetime in a single-earner household, something not captured by trends in the skill premium.

Friedberg (1998) documents that divorce law reforms were introduced in different years across states. This quasi-experimental variation in timing has been used to test a number of hypotheses about the effects of divorce law reforms on various economic outcomes.¹⁰ The variation in timing also provides a test for the explanation that expected returns to a college education increase for young women when they anticipate a higher probability of divorce. The premise of the test is that if this is true, then one should observe women increasing their relative graduation rates in those states that already passed legislation that increases the probability of divorce.

Appendix A.1 provides full details of the test below. The estimating equation of interest

⁸The reforms eliminated the need to demonstrate “fault,” such as abuse, adultery, or negligence in court, and allowed each spouse to obtain divorce without the consent of the other.

⁹Note that women’s rising wage premiums relative to men in the 1960s can help account for the limited gender convergence in the female-male enrollment ratio prior to 1970, but not for its rapid increase afterwards.

¹⁰Outcomes include divorce rates (Friedberg (1998), Wolfers (2007)), domestic violence (Stevenson and Wolfers (2007)), labor supply (Gray (1998), Stevenson (2008)), and savings decisions (Voena (2014)).

is:

$$Gap_{s,c} = \alpha + \sum_{a,s,c} \beta_{s,c}^a Ageatlaw_{s,c}^a + \sum_s \gamma_s + \sum_c \lambda_c + \varepsilon_{s,c} \quad (1)$$

where the outcome variable “gap” is the share of women graduating from college minus the share of men graduating from college in state s and birth cohort c . The independent variables of interest are a set of age-at-law indicators that are set equal to one if cohort c in state s was of a particular age a at the time of unilateral divorce law adoption. If higher anticipated divorce rates increase the share of women graduating from college relative to men, then the coefficients for the age-at-law indicator will be positive for cohorts who were young enough to still make a decision about their educational investment at the time of the passage of the divorce law legislation in their state. This includes those 18 or younger at the time of the reform, and potentially those up to three or four years older, who can still decide whether or not to complete their degree.

Figure 5 graphs the coefficients from this regression, with age at law on the x-axis ordered from old to young. The coefficients $\beta_{s,c}^a$ on the age-at-law indicators are small and insignificant for ages above 21. They start to become significant at the 10 percent level at age 20, which suggests that the response to reforms was immediate. The coefficients remain positive and significant or marginally significant at younger ages, i.e. for those who made a decision about whether or not to go to college after divorce law reforms occurred. The test therefore provides evidence in favor of the hypothesis that women’s educational returns increased relative to men’s following divorce law reforms.

Changes in Choice of Major in the 1970s

Another pattern documented in the paper is that the gender gap in choice of college major narrowed in the 1970s. Switching to a higher-paying major like business or sciences constitutes an additional potential source of insurance for women in case of divorce. To test whether changes in divorce laws also contributed to the increase in the relative number of women in these fields, I conduct a test similar to the previous one. Details of the test and data used (1965-1985 Higher Education General Information Survey) are provided in Appendix A.1. For this purpose, I first classify majors into two groups – “sciences/business,” and “humanities/all others.” I record the outcome variable $Gap_{s,y}$ as the share of graduating men and women who choose a science or business major in a given year y and state s minus the share of college men who graduate with such majors.¹¹ Conducting a similar test as before, I estimate the following equation:

$$Gap_{s,y} = \alpha + \sum_{n,s,y} \beta_{s,y}^n Yearssincelaw_{s,y}^n + \sum_s \gamma_s + \sum_y \lambda_y + \varepsilon_{s,y} \quad (2)$$

¹¹Grouping major choices into these two broadly defined categories allows me to construct a single variable, the share of individuals choosing a science and business major, which simplifies the reduced form analysis.

“Years-since-law” is a set of indicators corresponding to the number of years since the divorce law reform was passed in state s .¹²

Table 1 reports the coefficients on the years-since-law indicators. The results are in line with those in the previous section. As expected, the coefficient corresponding to the years prior to the divorce law reforms is statistically zero. Unlike the results obtained for the gender gap in college graduation, in which the effect of divorce law reforms was immediate, the effect on the gender gap in majors becomes statistically significant only after four years. The difference between the two results is likely explained by the fact that it is difficult to switch majors after already completing one or more years of study. As a result, one would not observe a response in choice of major until at least four years after the divorce law reform.

The results obtained using cross-state variation in the timing of divorce law reforms provide evidence that both “gender gaps” narrowed following divorce law reforms, suggesting that both the returns to getting a college education as well as to getting a higher-paying major increased for women relative to men after the reforms. How large are these effects? The size of the regression coefficients from the reduced-form analysis suggest that divorce law reforms explain around 13% of the convergence between men and women in graduation rates observed in the 1970s. The effects of the gender gap on majors are somewhat smaller. However, it is possible that the size of the coefficients understates the real effect. Firstly, individuals’ mobility across states after graduation introduces substantial measurement error in the analysis. Secondly, contamination effects may play a role. For example, as more states implement reforms with time, individuals in states under the old divorce law regime may nevertheless respond to the nationwide changes, e.g. by anticipating similar reforms in their own state. Both factors would bias the coefficients downward. In Section 4, I estimate using the structural model an alternative measure of the effect of divorce laws on college attendance and compare it to the reduced-form estimates.

Persistent Differences in Choice of Major Since the Mid-1980s

The persistent difference in the choice of undergraduate major documented in Figure 2 raises the question why, given their high college attendance rates, women did not converge with men along this second margin, or similarly overtake them. To analyze whether persistent differences in choice of major are driven by gender differences in wage premiums by field, Table 2 compares the premiums for men and women for different undergraduate majors over time, relative to an undergraduate major in the arts and humanities, the omitted category.¹³

Table 2 documents that men’s and women’s returns to different college majors exhibit similar patterns. The lowest-paying major for men and women is education, which pays

¹²Because of the small number of observations, I group the years n for the years-since-law indicator in the following way: -2 to 0, 1 to 3, 4 to 6, 7 to 9, and 10 or more. The first of these indicators allows me to test for a pre-trend, similarly as in the previous analysis using ages.

¹³See note in Table 2. Specifically, the coefficient is interpreted to be the “additional” income in log points that individuals in a given major receive, relative to those in the baseline humanities major.

at least 7% less than a humanities degree in all years. For both men and women, a social sciences degree provides a very similar return to a humanities degree. Among non-science and non-business majors, degrees in health support fields stand out for their high return, with similar premiums for men and women that range from 14 to 19 log points (13-17%) in 1993 and 2003, and with even higher returns in 2010.¹⁴

The second finding documented in Table 2 is that full-time workers with science, engineering and business majors have high premiums relative to those with humanities, education, or social science degrees. Business and math/science majors are associated with an additional return of between 16 and 26 log points (15-23%) for men, and 14 to 20 log points (13-18%) for women. Degrees in engineering and technology are the highest-paying degrees. The additional premium for men is 31-36 log points (27-30%), and for women it is even higher, 38-45 log points (32-37%).

To summarize, these patterns together imply that with the notable exception of nursing/health support, a field that represents about 11% of degrees for women, women are substantially more likely than men to select majors that have on average low expected returns.

Majors and Flexibility

If women frequently choose lower-paying majors, some other characteristic of these majors should compensate them for the lower return. The popularity of degrees like education and nursing among women suggests that one such possible characteristic is the degree of “flexibility” offered in occupations associated with different majors. I define “flexibility” by high availability of part-time or part-year work and by low wage penalties in case of a temporary absence from the workforce or reduction of weekly hours worked. If women value such flexibility more than men, this may help explain observed differences in choice of major.

Before analyzing how majors differ along this margin, I provide evidence first for why college-educated women today may value such flexibility. Figure 6 graphs the share employed among college-educated men and women ages 22 to 50, and the share working full-time in 2000.¹⁵ Figure 6 shows that immediately after college graduation, men and women exhibit similar rates of employment and full-time work. However, college women begin to drop their employment rates and their hours worked in their late twenties, and continue to do so through their child-bearing years. At age 35, 60% of college-educated women work full-time, compared to more than 90% of college-educated men. After their mid-30s, women gradually increase their labor supply again. As Panel B shows, these large reductions in labor supply

¹⁴“Health” majors include nursing and health support programs. Bio-med and pre-med majors, which prepare students for medical research or practice, are classified under “sciences.” See Appendix A.4.

¹⁵I observe nearly identical age profiles using the 1990 Census and 2009-2011 ACS as when using the 2000 Census data. This confirms that the U-shaped employment profile captures systematic differences by age over the life-cycle for women, and is not driven by any cohort effects.

over the lifetime are primarily driven by women with young children under the age of 6 in the household.

In the rest of the section, I examine whether labor supply patterns differ substantially by the type of major chosen and its associated occupations. I analyze the following measures of flexibility: part-time work, employment rates, annual hours worked, and wage penalties by major and occupation group for reductions in labor supply.

In Table 3, I document NSCG data on employment rates and rates of part-time work (less than 35 hours per week) by major in 2000, separately for college-educated women with and without children under age 6. Table 4 documents the same measures for men.

Table 3 shows, first, that across all majors, women without young children in the household work at high rates and their part-time work rates are fairly low, although women in humanities and health are somewhat more likely to work part-time. Secondly, across all majors, college-educated women with children under 6 reduce their labor supply substantially. As expected, Table 4 shows that this is not true for men. Finally, Table 3 shows that there is systematic variation across majors in the degree to which women with young children reduce their labor supply. This variation is most apparent for the recorded rates of part-time work. By a large margin, the highest rates of part-time work for women with children under 6 are observed in health and in the humanities, 43% and 31% respectively. Education majors stand out for their low part-time work rates (20%) among non-science, non-business majors; however, the part-time work measure does not capture the part-year nature of work in teaching professions.¹⁶

While rates of part-time work for science/business majors are low compared to other majors, at 21-23% they are not insignificant. To understand which women in science/business fields are most likely to work-part time, in Figure 7 I divide women not only by major, but also by the occupation they work in: science/business vs. all other occupations. Panel A of Figure 7 shows that among women with science/business majors who also work in a science/business occupation, the part-time work rate is only around 5%. By contrast, science majors in non-science, non-business occupations work part-time at much higher rates, with up to 16% working part-time in their mid-30s. Panel B shows that a similar pattern holds for humanities/other majors. The women who work part-time work primarily in a non-science, non-business occupation.¹⁷

Differences in employment rates across majors for women with young children are somewhat less clearcut than part-time rates, but suggest that women in science and engineering

¹⁶NSCG data shows that education majors with children under 6 work about the same annual hours as health majors, who have high part-time rates: 1,237 and 1,253, respectively. The difference is not statistically significant.

¹⁷The share of science/business majors who work in a science/business occupation is substantially lower among women than men. In 2000, 81% of men who were science/business majors worked in their related occupation. By contrast, this was true for only 57% of women with a science/business degree (Table 5).

have fairly high employment rates, relative to most other majors (Table 3).¹⁸ As with part-time rates, employment rates may vary systematically not just with major but also with occupation. Moreover, many women switch occupations after a leave from the labor force. I examine this in detail in Appendix A.3. I find that among female science and business majors with children under age six, those who ultimately return to a science/business occupation take much less time out of the workforce and work on average more than 1,800 hours annually, or 35 hours per week. By contrast, the average hours worked for those who switch out of a science/business occupation following childbirth is only 961 hours annually (Figure B.2). This is in line with the previous evidence for part-time work that reductions in labor supply are concentrated in non-science, non-business occupations.

A final measure of flexibility is the size of the wage penalty associated with part-time work and/or time taken off from the labor force. To measure how such penalties differ by major, I use NLSY79 panel data to run the following individual fixed-effects regression separately for science/business and humanities/other majors:

$$\ln w_{i,t} = \alpha_i + \beta_1 \text{exp}_{i,t} + \beta_2 \text{exp}_{i,t}^2 + \beta_3 \mathbb{I}[\text{Part-Time}]_{i,t} + \beta_4 \mathbb{I}[\text{Time Off}]_{i,t} + \varepsilon_{i,t}, \quad (3)$$

The independent variables include a polynomial in experience, an indicator variable for whether or not the individual worked part-time in the current or the previous year, and another indicator variable set equal to one if the individual left the work force for more than 9 months in the last two years. Table 6 reports the coefficients on this regression by field in columns 1 and 2. In line with the previous evidence, the coefficients corresponding to part-time work and time taken off are somewhat larger for science and business majors. In the remaining four columns of Table 6, I record results from fixed effects regressions that additionally allow the specifications to vary with the starting occupational status, based on an individual's primary occupation between ages 26 to 30. This captures the penalties incurred for individuals who began their careers in a particular occupation.¹⁹

The results show that for women whose initial occupation was science and business (columns 3 and 4), the penalties for working part-time or taking time out of the labor force are substantially higher than for women in all other occupations (columns 5 and 6). In science and business occupations, the penalties for reductions in labor supply are around 16% for humanities/other majors, and between 18 and 21% for science/business majors. In non-science, non-business occupations, penalties are smaller. Penalties for part-time work are between 8 and 11%, and penalties for time taken off are around 3%. Note that the penalties estimated in column 1 are much lower than those in column 3 because a significant portion of women

¹⁸Interestingly, health majors have even higher employment rates than engineers with young children; however, this appears to be driven by the high availability of part-time work in the health field.

¹⁹The age 26 to 30 was chosen based on the age profile for occupational transitions, which indicate that the majority of occupational transitions into science/business occupations occur by age 30. Analysis is based on data in NLSY79. I provide evidence on this age profile pattern in Section 4. See also Figure 11.

with science-business majors ultimately select into a non-science, non-business occupation.

To conclude, the various measures of “flexibility” documented in this section show that majors and their associated occupations differ significantly in the degree to which they facilitate temporary reductions in labor supply, and that women incur high wage penalties in science/business occupations for time taken out of the labor force or for working part-time. The documented patterns suggest that these differences in flexibility may be a key factor explaining why, among women with science/business majors, in 2000 only slightly over half worked in a high-paying field related to their major. Finally, the results in this section show that women are more than 1.5 times as likely to select majors that are associated with occupations with low wage penalties for reductions in labor supply, and higher availability of flexible work arrangements, like part-time work.

2 Model

In this section, I develop and estimate a lifetime model of individual decisions that aims to capture the empirical features around education, labor supply, and marriage and divorce described in the previous section. There are several reasons why such a model is useful. Firstly, with a model it is possible to account explicitly for the fact that marriage, labor supply, and education decisions are jointly made: a change in the optimal choice about one of these factors affects the optimal decision about all the others. Most importantly, this permits analysis of cumulative processes and interactions, such as changes in divorce or labor supply, which can be both results of as well as drivers of educational investment decisions. The second advantage of the model is that it is possible to analyze the relative importance of changes in the wage structure and changes in the marriage market in generating the observed dynamics in educational choices. Finally, using the model it is possible to perform simulation exercises to analyze the potential effects of policies that seek to increase the share of science-technology majors in general, and among women in particular. Because the model in this paper explicitly considers household labor supply, marriage, and household specialization, it is well-suited for analyzing the channels through which such policies may affect educational choices.

In this section, I first provide an overview of the main features of the model and the set of dynamics that the model can capture. I then provide details about each component of the model, and finally about the decisions of individuals in each period.

2.1 Overview of the Model

The model is a dynamic individual lifetime model, where individuals live for T periods, starting at age 18. I first outline the main idea of the model and its four most important features.

There are three phases of life: education, working life, and retirement. The first two phases, education and working life, are the main focus of the model.

In the first phase, young individuals decide whether to make an educational investment. If they do not go to college, they begin the working phase of their life. Education choices cannot be changed once the working life phase begins. If an individual decides to go to college, he or she chooses between two majors. One major is associated with a high-return, high skill depreciation occupation. In this occupation, there is a high wage penalty for temporary absences from the workforce and for part-time work. The other major is associated with a lower-return, lower skill depreciation occupation. These differences in characteristics between the majors are designed to correspond to differences between science/business majors vs. humanities/other majors documented in the empirical section. This is the first key feature of the model.

In the second, working life phase individuals make decisions about marriage and divorce. If single, an individual meets a potential partner with some probability and decides whether or not to marry; if married, he or she decides whether to remain married or to divorce. Couples cooperate when making decisions but cannot commit to future allocations of resources. Divorce occurs when no reallocation of resources within the household can make both individuals better off married than single. This lack of full commitment allows for divorces to occur in the model as they do in the data and it is the second important feature of the model.

In every period of the second phase individuals also make decisions about labor supply, which is allocated to market, home production, and leisure. During the working life phase, there are three sources of uncertainty—wage shocks, marital match quality shocks, and fertility shocks. Fertility is modeled as an exogenous process, conditional on marital status and age. After a fertility shock, the presence of children has the effect of increasing the productivity of labor in home production, which allows the model to capture the large increase in hours allocated to home production and child care observed in the data after childbirth. This aspect of the model also enables me to capture potential gains to partial or full specialization in market and home production for married couples. This is the the third important feature of the model.

Finally, the model not only follows individuals from a given cohort over the lifecycle, but also simulates different cohorts over time. There are two main sources of variation across cohorts, assumed to be exogenous. One is the distribution of entry wages, conditional on sex and education. The other is the cost of divorce. In particular, there is a one-time drop in the cost of divorce in 1970 corresponding to the beginning of divorce law reforms. This captures that divorce became substantially easier after the reforms, the final important feature in the model. Young individuals in each cohort take into account the change in divorce laws when they form expectations about their own future probability of divorce.

The four outlined features make up the structure that generates the key dynamics of the

model, over the lifetime as well as across cohorts. In each cohort, individuals face competing considerations. In some periods, especially when there are young children in the household, married individuals may find it optimal to specialize by having one of the spouses commit substantial time to home production, by partly or fully reducing the labor supplied to the market. It will often, but not always, be optimal for the woman to be the one to reduce her labor supply, since she draws on average from a lower wage distribution. On the other hand, working in the labor market increases human capital, and thus future wages. The spouse that reduces labor supply reduces his or her future labor market prospects. Moreover, depending on current occupation, the spouse who reduces labor supply may incur a high additional wage penalty, in addition to the wage losses from foregone experience. Individuals' decisions about labor supply and education will reflect these competing considerations. Changes in the wage structure and in marriage and divorce patterns over time will in turn affect those considerations.

With this overall idea of the model in mind, we now turn to the specific modeling choices. I first provide details about each component of the model, and then characterize the decisions of individuals in each period.

2.2 Preferences

Individuals derive utility from consumption c , leisure l and a household-produced good Q . Q is a privately consumed good (Q^i) if individual i is single, and it is consumed as a shared public good (Q) if the individual is married. Couples additionally derive utility from match quality θ . Preferences are separable across time and across states of the world. In each period, the utility function is assumed to be separable in (c_t^i, l_t^i) and Q_t to simplify the estimation, and to take the following form:

$$u_{single}^i = u(c_t^i, l_t^i) + A \log Q_t^i \qquad u_{married}^i = u(c_t^i, l_t^i) + A \log Q_t + \theta_t.$$

Following empirical evidence from Attanasio and Weber (1995) and Meghir and Weber (1996) that individual preferences are not separable in consumption and leisure, I assume the following functional form for the subutility $u(c_t^i, l_t^i)$:

$$u(c_t^i, l_t^i) = \frac{(c_t^{i a} l_t^{1-a})^{1-\sigma}}{1-\sigma}, \quad \sigma > 0, \quad 0 < a < 1$$

The last component of utility is match quality. Match quality is assumed to follow a random walk stochastic process, where

$$\theta_t = \theta_{t-1} + z_t, \quad z_t \sim N(0, \sigma_z).$$

2.3 Household Technology

The good Q_t is produced within the household using market good m_t , labor input d_t , and number of children n_t . To keep the computation simple, I assume a form for the household good production function that is log linear in the inputs:

$$\log(Q_t) = \alpha_{1,t} \log d_t + \alpha_2 \log m_t + \alpha_3 \log(1 + n_t), \quad (4)$$

where $d_t = d_t^i$ if the individual is single, and $d_t = d_t^i + d_t^j$, i.e. the sum of the husband's and the wife's labor allocated to home good production, if the individual is married. Note that this is equivalent to assuming that the husband's and wife's labor inputs are perfectly substitutable. Children increase the production of the household good directly, to capture that one of the additional potential returns to marriage is having a family with children.

To introduce heterogeneity in the productivity of labor in home production, $\alpha_{1,t}$ is allowed to differ over time and across households. Specifically, the parameter $\alpha_{1,t}$ can take one of five values, which will be estimated using time use data on hours allocated to home production and child care: a value for households without children; two values for households with young children, one for each of two educational levels (high school or college); and two values for households with older children, one for each educational level (high school or college). Labor productivity in home production does not depend on major.²⁰

By allowing $\alpha_{1,t}$ to vary with the age and presence of children, it is possible to capture the large difference in labor allocated to home production between households without children, households with children under the age of six, and households with children over the age of six. The reason the parameter is allowed to vary additionally with education in households with children is that it allows the model to capture the systematic differences in time allocated to child care by educational attainment. For example, Guryan, Hurst, and Kearney (2008) document that college-educated women allocate more hours both to the labor market and to child care than high-school educated women.

2.4 Fertility Process

Children are born according to an exogenous fertility process that depends on marital status, age, and the current number of children. A fertility shock can occur if an individual is married and of childbearing age, which in the model is set to 38. The fertility hazard rates are estimated externally.

²⁰In married households, I have to choose which spouse's education will be used to determine the household's $\alpha_{1,t}$ parameter. I assume the education of the woman determines the productivity parameter. I assign productivity based on the wife's education because women tend to supply the majority of labor in home production in the data (ATUS, 2003). This is not a restrictive assumption since spouses have the same educational attainment in the majority of couples in the data.

2.5 Wage Process and Human Capital

Wages in the model depend on education, current occupation, and accumulated experience. I provide information about each of these factors first, and at the end of the subsection I describe in detail how they enter into the wage process.

2.5.1 Education and Occupation

There are three educational choices: (1) high school only; (2) college with a major “ L ” that provides a premium in low-return, low skill-depreciation occupations; and (3) college with major “ H ” that provides a premium in high-return, high skill-depreciation occupations. I refer to the occupations described respectively as “ \mathcal{L} ”-type and “ \mathcal{H} ”-type. The two majors (L, H) capture the differences in the data documented in the previous section between science/business vs. humanities/other majors. College individuals then choose whether to work in a science/business occupation (\mathcal{H}) or all other occupations (\mathcal{L}).

I make a simplifying assumption that individuals with a high school education all work in the same \mathcal{L} -type occupation. In the NLSY79, the share of individuals without a college education who work in a \mathcal{H} -type (science/business) occupation is less than 8%.

2.5.2 Experience

Individuals who work the equivalent of at least 500 annual hours in a given period accumulate one additional period of experience. Experience in the model is occupation-specific. If an individual decides to switch occupations, he or she loses his or her accumulated experience, and must begin accumulating experience again from zero. Though it would be preferable to keep track of experience accumulated in each occupation, I make this assumption to keep the model tractable. In the NLSY79, I observe that most occupational switches occur before the age of 28, that is before individuals have had the opportunity to accumulate substantial experience, which suggests that the assumption is not highly restrictive. The share of men and women who switch between the two categories of occupations more than once after age 30 is around 12%.

2.5.3 Part-Time Work and Time Out of the Labor Force

Working a minimum number of hours in the model matters for accumulating experience. Additionally, the number of hours worked in a given period is important because it determines whether or not an individual will incur a wage penalty for working less than full-time, full-year. I do not model separately the decision to work part-time and the decision to take time out of the labor force. In the model, only the total number of hours worked in a given period is relevant. If the amount of labor supplied in the current period is equivalent to less than

35 hours per week, the individual incurs a wage penalty in the following period. The size of the wage penalty depends on whether the individual works in a \mathcal{L} - or \mathcal{H} -type occupation.

2.5.4 Wage process

Individuals draw from wage processes specific to their sex, occupation, and education. I will describe first the wage process for individuals with a high school education, and then describe the process for individuals with a college education.

Individuals with a high school education draw a wage every period for only one possible occupation. This means that there are a total of two wage processes to be estimated for high school individuals, one for women and one for men. An individual of gender k , experience exp_t , and number of hours h_{t-1} worked in the previous period draws a wage from the following process:

$$\ln w_t = \beta_0^{k,HS} + \beta_1^{k,HS} exp_t + \beta_2^{k,HS} exp_t^2 + \beta_3^{k,HS} \mathbb{I}(h_{t-1} < \bar{h}) + \varepsilon_t^{k,HS}, \quad (5)$$

$$\varepsilon_t^{k,HS} \sim N(0, \sigma_{\varepsilon^{k,HS}})$$

where \bar{h} is equivalent to the minimum hours worked for a full-time, full-year worker. The coefficient β_3 on the indicator function $\mathbb{I}(h_{t-1} < \bar{h})$ is the current-period wage penalty incurred for working less than full time in the previous period. If the wage drawn in a particular period falls below a value equivalent to the minimum wage, the effective wage is zero and the individual is not employed. Otherwise, the individual may work at hourly wage w_t .

The structure of the wage process for individuals with a college education is similar, except that college-educated individuals draw wages for up to two occupations, \mathcal{H} and \mathcal{L} . An individual who enters the period having last worked in a particular occupation will draw a wage from that occupation with probability one. Additionally, with probability η the individual draws a wage from the second occupation and can choose whether or not to switch occupations. Specifically, an individual of gender k with a given major M who enters the period having last worked in occupation q_{t-1} draws the following wage for occupation $q = q_{t-1}$:

$$\ln w_t = \beta_0^{k,M,q} + \beta_1^{k,M,q} exp_t + \beta_2^{k,M,q} exp_t^2 + \beta_3^{k,M,q} \mathbb{I}(h_{t-1} < \bar{h}) + \varepsilon_t^{k,M,q}, \quad (6)$$

$$\varepsilon_t^{k,M,q} \sim N(0, \sigma_{\varepsilon^{k,M,q}})$$

The coefficients are indexed by k and M because the wage processes are estimated separately by sex and major.

If the individual draws a second wage for the other occupation $r \neq q_{t-1}$, the wage is characterized by

$$\ln w_t = \beta_0^{k,M,r} + \beta_3^{k,M,r} \mathbb{I}(h_{t-1} < \bar{h}) + \varepsilon_t^{k,M,r}, \quad (7)$$

$$\varepsilon_t^{k,M,r} \sim N(0, \sigma_{\varepsilon^{k,M,r}})$$

since the individual loses his or her accumulated experience after switching. As before, the coefficient on $\mathbb{I}(h_{t-1} < \bar{h})$ is a penalty for working less than full-time. To reflect the data, this estimated penalty will be high in \mathcal{H} -type occupations, and lower in \mathcal{L} -type occupations.

Allowing for occupational choices in addition to educational choices in the model is important for two reasons. Firstly, it allows the model to capture the fact that only a small share of men but almost half of women with a science/business major work in non-science, non-business occupations, as documented in the previous section.²¹ This difference in occupational choices strongly affects the return to a science/business major for women relative to men, and the model should be able to capture this feature of the data. The second reason is that variation in wages across occupations is greater than the variation in wages within occupations in the data. This suggests that accounting for the actual occupational choice is important.

In the data individuals that have majors that correspond to their occupation on average earn more in that occupation than those in the occupation who have a different major. These differences observed in the data will be reflected in the estimated wage process parameters. Estimation of the wage process parameters will be discussed in detail in Section 3.

2.6 Educational Costs

Individuals who choose to go to college incur a tuition cost τ , which is deducted from their assets. Individuals also have major-specific utility costs C_L^i and C_H^i , interpreted to be the individual's ability or effort costs for completing a particular major. This is the only source of unobserved heterogeneity across individuals. Individuals draw C_L^i and C_H^i from normal distributions characterized by parameters (μ_L, σ_L) and (μ_H, σ_H) . Men and women have the same distributions of effort costs. Educational decisions can only be made in the first period.

2.7 Cost of Divorce

If a married couple wishes to divorce, each individual incurs a one-time utility cost K_t . The cost takes two possible values. K_0 corresponds to the cost of divorce before no-fault, unilateral divorce law reforms. K_1 corresponds to the cost of divorce after such reforms. The change from K_0 to K_1 occurs in 1970, corresponding to the timing of the start of divorce law reforms. I assume that cohorts did not anticipate the change. The change in K_t can be interpreted as a change in the amount of effort required to secure a divorce, in line with historical evidence. For example, prior to reforms individuals and/or couples resorted in many cases to perjury or providing exaggerated or false testimony to provide fault-based grounds (Herbert (1988)).

²¹Similarly, some men and women with humanities/other majors work science/business occupations.

2.8 Individual Decisions

With all the main components of the model laid out, I now describe households' decisions, starting with the working life stage. Afterwards, I describe the retirement stage, which is a simplified version of the household's problem during the working life stage. Finally, after the description of what happens over the lifecycle, I discuss the educational decision that takes place in the first period. It is best left for last to discuss this decision because it requires knowledge of the expected stream of lifetime utility from each educational choice.

During the working life phase, individuals enter every period t either single or married, and make a decision about their marital status that period. Shocks to wage, match quality and fertility are realized at the beginning of the period, before any decisions are made. An individual who has completed his or her education and enters the period as single meets a potential spouse j with probability one, and draws a match quality θ_t . This individual must now choose whether to stay single or to marry the potential partner, and to make this decision, he or she must compare the value of staying single with the value of marrying the potential partner. Similarly, an individual who enters as married makes a decision between staying married or getting divorced, and to do that he or she compares the values of those two options.

I will first describe the problem of an individual who enters the period as married. If the couple to whom the individual belongs decides to divorce, he or she will experience the value of being single, $V_t^{i,S}$, that can be computed as follows. The individual will choose the levels of own consumption c_t^i , labor supplied to the market h_t^i , labor supplied to home production d_t^i , leisure l_t^i , savings s_t^i , and the amount of the market good m_t^i devoted to home good production that maximizes his or her lifetime expected utility. If an individual receives a wage draw from more than one occupation, the individual additionally chooses which occupation to work in, q_t^i . The value of staying single for the individual is therefore equal to

$$\begin{aligned}
 V_t^{i,S} &= \max_{c_t^i, l_t^i, m_t^i, d_t^i, h_t^i, q_t^i, s_{t+1}^i} u^i(c_t^i, l_t^i, Q_t^i) + \beta E[V_{t+1}^i(\omega_{t+1}|\omega_t)] \\
 \text{s.t.} \quad c_t^i + m_t^i + p_k n_t^i &= w_t^i h_t^i + R s_t^i - s_{t+1}^i && \text{(Budget Constraint)} \\
 Q_t^i &= F^i(m_t^i, d_t^i, n_t^i) && \text{(HH Good)} \\
 w_t^{i,q=q_{t-1}} &= G^i(ed^i, exp_t^i, h_{t-1}^i, \varepsilon_t^i) && \text{(Wage I)} \\
 w_t^{i,r \neq q_{t-1}} &= G^i(ed^i, h_{t-1}^i, \varepsilon_t^i) && \text{(Wage II)} \\
 h_t^i + d_t^i + l_t^i &= \mathcal{T} && \text{(Time Constraint)}
 \end{aligned}$$

where ω_t is the set of state variables in period t , and $E[V_{t+1}^i(\omega_{t+1}|\omega_t)]$ is the expected value function of the individual when he or she enters period $t+1$ as single.

Now consider the value of staying married, $V_t^{i,M}$, for the same individual that enters the period as married. The value $V_t^{i,M}$ is determined by modeling the decisions of the married household as a Pareto problem with participation constraints. In determining $V_t^{i,M}$, I follow the literature on decisions with limited commitment (e.g. Marcet and Marimon (1992, 1998), Ligon et al. 2000), and in particular its application to models of intra-household allocation (Mazzocco (2007)). This literature shows that the Pareto problem with participation constraints can be solved in two steps. In the first step, the household solves the unconstrained problem. This means that in period t the married couple chooses the vector $z_t = \{c_t^i, c_t^j, l_t^i, l_t^j, d_t^i, d_t^j, h_t^i, h_t^j, q_t^i, q_t^j, m_t, s_{t+1}\}$ to solve the following Pareto problem, with weights μ_t and $(1 - \mu_t)$:

$$\max_{z_t} \mu_t [u^i(c_t^i, l_t^i, Q_t, \theta_t) + \beta E[V_{t+1}^i(\omega_{t+1}|\omega_t)]] + (1 - \mu_t) [u^j(c_t^j, l_t^j, Q_t, \theta_t) + \beta E[V_{t+1}^j(\omega_{t+1}|\omega_t)]]$$

$$\text{s.t.} \quad c_t^i + c_t^j + m_t + p_k n_t = w_t^i h_t^i + w_t^j h_t^j + R s_t - s_{t+1} \quad (\text{Budget Constraint})$$

$$Q_t = F^i(m_t, d_t^i, d_t^j, n_t) \quad (\text{HH Good})$$

$$w_t^{k,q=q_t-1} = G(ed^k, exp_t^k, h_{t-1}^k, \varepsilon_t), \quad k = i, j \quad (\text{Wage I})$$

$$w_t^{k,r \neq q_t-1} = G(ed^k, h_{t-1}^k, \varepsilon_t), \quad k = i, j \quad (\text{Wage II})$$

$$h_t^k + d_t^k + l_t^k = \mathcal{T}, \quad k = i, j \quad (\text{Time Constraint})$$

When the optimal solution z^* to the unconstrained problem is determined, one can calculate

$$V_t^{*k,M}(z^*) = u^i(c_t^{*i}, l_t^{*i}, Q_t^{*i}) + \beta E[V_{t+1}^{*i}(\omega_{t+1}|\omega_t)], \quad k = i, j$$

i.e. the value of being married for spouse k at the current Pareto weights μ_t and $(1 - \mu_t)$.

In the second step, one can then check that the solution satisfies both individuals' participation constraints. Recall that if the couple divorces, each partner incurs the one-time utility cost K_t . Hence, the constraints for individuals that entered the period married take the form

$$V_t^{*k,M} \geq V_t^{k,S} - K_t, \quad k = i, j$$

If the participation constraints for both partners are satisfied at $V_t^{*k,M}(z^*)$, the allocations determined in the first stage are the final allocations and the couple stays married. In that case,

$$V_t^{k,M} = V_t^{*k,M}(z^*), \quad V_t^k = V_t^{k,M}, \quad k = i, j.$$

If both constraints are violated, the marriage generates no surplus and the couple divorces. Finally, if only one of the constraints is satisfied for the married couple, there is potential for a renegotiation. I use the result from Ligon, Thomas, and Worrall (2002) that in the optimal

solution, the constrained individual's Pareto weight is increased so that the individual is exactly indifferent between staying in the marriage and leaving it. Suppose under this new weight corresponding to $\tilde{\mu}_t$, the solution to the household's maximization problem is \tilde{z}^* . If the other spouse's participation constraint is still satisfied under the solution \tilde{z}^* , then the couple stays married. If not, then there is no value of the Pareto weight that simultaneously satisfies the participation constraints of both partners, and the individuals divorce. In that case, V_t^k is the value of being divorced, $V_t^{k,S} - K_t$, for $k = i, j$. For married couples, μ_t constitutes an additional state variable.

Individuals who enter the period as single calculate the value of being single and the value of being married to a potential partner in almost the exact same fashion. However, there are no participation constraints for individuals who enter the period as single. They simply compare their value of being single and their value of being married. If the latter is higher for both individuals, they marry. The initial Pareto weights for a couple that marries are determined using symmetric Nash bargaining.

The problem of the household in retirement is a simpler version of the household's problem in the working life. The only decisions in retirement are about consumption, leisure, savings, and the amount of time and market good allocated to home production. In the final period, all resources are used and savings are equal to zero. Because retirement decisions are not the focus of the model, I simplify the problem by not allowing individuals to divorce or marry in retirement. As a result, individuals who enter retirement married simply solve the married household's unconstrained problem, with the Pareto weights fixed throughout retirement.

Now that I have described the decisions that occur over the lifetime, I can describe the educational decision that takes place in the first period. The decision takes into account expectations about marriage, divorce, occupational and labor supply choices over the lifetime, conditional on each educational choice. The expectations at the time of the educational decision about future lifetime utility from each educational choice is expressed as $E[V_1|ed]$. Additionally, the decision about education depends on the idiosyncratic utility costs associated with going to college and choosing major L or H . An individual will choose to go to college if either

$$\begin{aligned} E[V_1|ed=L] - C_L^i &\geq E[V_1|ed=HS], \quad \text{or} \\ E[V_1|ed=H] - C_H^i &\geq E[V_1|ed=HS]. \end{aligned}$$

If neither condition holds, the individual does not go to college and begins the working stage of his or her life. Otherwise, the individual chooses the major that gives him or her the higher return, $\max\{(E[V_1|ed=L] - C_L^i), (E[V_1|ed=H] - C_H^i)\}$. This individual does not make any decisions about labor supply or marriage for two periods, equivalent to four years in the model. After completing college, the individual begins the working life stage. It is not

possible to change one’s education after the initial educational decision is made.

3 Estimation

In this section I discuss the simulation and estimation of the model. I first provide additional details about matching in the marriage market and assumptions about divorce and children, which are needed to operationalize the model. I then discuss the estimation method.

3.1 Implementation Details for Model Simulation

To be able to simulate the model, I must make additional assumptions which were not discussed in Section 2 about how individuals meet in the marriage market, about the cost of children in the household, and about how couples split wealth and child custody after divorce. I describe these assumptions and the data patterns they are founded on below.

Individuals in the model draw potential partners from their own cohort. To capture that more than 80% of individuals marry someone with the same educational attainment (IPUMS USA, 2000), I introduce an assumption about how individuals meet in the marriage market.²² I assume that the probability each period that a single individual draws a potential partner with the same educational attainment (high school or college) is equal to p_m , which is estimated in the model. Conditional on drawing a college-educated partner, the probability that the partner has a particular major simply corresponds to the share of individuals of that sex who choose that major.

Spouses in the model pool their savings after marrying. If a married household has children, the household pays a cost per child p_k equivalent to \$6000 per year for the first child and \$4500 for subsequent children, as estimated from the Consumer Expenditure Survey.²³ If a couple divorces, the individuals split their total savings evenly, to reflect available data on asset allocations after divorce. Additionally, I must choose a rule that determines how couples split custody and financial responsibilities for children after divorce. According to the Census Bureau, women represent 85% of all custodial parents. About 45% of custodial mothers receive any kind of child support, and the average amount received for these women is \$3,800 (Grail (2002)). Given the cost of children p_k , the received child support payments cover about 14.3% of the child expenditures in a divorced household with two children. As a result, I assume that divorced women are responsible for the majority of financial costs for the children, 85%, while divorced men are responsible for the remainder.

²²In 2000, 80% of married individuals between ages 18 and 60 were married to a spouse with same educational attainment as their own, where the two categories of attainment are defined as “college” and “less than college.” Note that the share did not change substantially over time. In 1970, 1980, and 1990, the share of individuals with a spouse that has the same education were 87.7%, 84.2%, and 81.7%, respectively.

²³I use estimates of the expenditures per child from Mazzocco, Ruiz, and Yamaguchi (2009), based on data from the Consumer Expenditure Survey (CEX, 1980-1996). I adjust their estimates to be in year 2000 dollar values.

To simplify the simulation of the model, I assume that if a divorced woman with children remarries, the new household treats the children as its own. If a divorced father re-marries, he does not bring any children into the new household, and I cease keeping track of children from his previous marriage. When an individual with children from a previous marriage re-marries, both new marriage partners pay a re-marriage penalty P_{RM} , a one-time fixed utility cost, which is estimated. This assumption allows me to match the pattern that divorced individuals with children have lower re-marriage rates than those without children (NLSY79).

Since I do not keep track of the age of children, I need an assumption about when children leave the household. I assume that after age 46, a household with children transitions each period with a one-half probability to a state in which there are no more children in the household. At age 50, I assume that all individuals are without children in the household.

3.2 Estimation Method

In this subsection I discuss the estimation of the model's parameters. The parameters in the model fall into three categories, depending on whether they are estimated within the model, estimated externally, or calibrated using estimates from the literature. The first category consists of parameters that I estimate using the simulated method of moments. This category includes (1) all parameters of the home good technology production function; (2) parameters related to the marriage market, including those governing the match quality process and matching along educational lines, the cost of divorce, and the marriage market penalty for being divorced with children; (3) the probability for college-graduates of receiving a wage draw from more than one occupation; and (4), the distribution of utility costs of education by major. The second category consists of parameters that I estimate externally from the data and use in the model. This category includes all wage process parameters. Additionally, I set financial costs related to children and fertility hazards directly to those I estimate in the data. Finally, the third category consists of parameters that I calibrate using estimates from the literature. The parameters in the third category include the CRRA risk aversion parameter, the Cobb-Douglas parameter for consumption and leisure, and the discount factor.

Note that all of the parameters in the first category except one of the two cost of divorce parameters can feasibly be estimated based only on the lifetime decisions of one cohort. Estimating both cost of divorce parameters requires at least two cohorts, a cohort that made the majority of its marriage and divorce decisions before the reform, and a cohort that made the majority of its decisions after the reform. To make the estimation of the parameters in the model computationally feasible, I take advantage of this fact that most parameters estimated within the model are time-invariant and I conduct the estimation in two steps. In the first step, I estimate all the parameters of the model except K_0 using a single cohort that graduated after the introduction of divorce law reforms. In the second step, I run the model using the estimated parameters from the first step for the cohort that was exposed to the

pre-reform divorce regime, and estimate the remaining parameter K_0 .

The main estimation (step I) requires selecting a cohort. I choose the cohort that graduated college in 1980, for three reasons. First, it satisfies the requirement that the cohort made its decisions under the new divorce law regime. Secondly, it is possible to follow this cohort almost over the entirety of its working lifetime, which is not possible with the more recent cohorts graduating in 1990 or 2000. Finally, NLSY79 panel data is available for this cohort, which has detailed microdata about majors, occupations, and labor supply over the lifetime.

I estimate the main parameters of the model, i.e. those in the first category, using the Simulated Method of Moments (McFadden (1989)).²⁴ The moments used in the estimation are as follows. The first group of moments includes a set of labor supply moments that correspond to annual hours worked by sex, education, occupation (for college-educated individuals), and family structure (single, married without children, married with children under age 6, and married with children ages 6 to 16). Additionally, I estimate the share of individuals in “ \mathcal{H} ”-type occupations by sex and major. These sample moments are estimated using the 2009-2011 ACS and the NLSY79.

The second set of moments is constructed using the American Time Use Survey and describes the average annual hours spent on child care and housework for different groups. Because the American Time Use Survey does not provide information about the major chosen, I construct these moments by sex and family structure for three groups: high school, college in a “ \mathcal{L} ”-type occupation, and college in a “ \mathcal{H} ”-type occupation.

I construct a third set of moments related to the marriage market. I estimate the overall share married and divorced, the share of married individuals that have the same educational attainment as their spouse, and the share of individuals married by 30 for the 1980 graduating cohort. I use the CPS for these four moments rather than the NLSY because it is a larger sample and provides more precise estimates of these measures. The remaining two moments related directly to the marriage market, the difference in the hazard rate of divorce for individuals with and without children, and the hazard rate of re-marriage after divorce for individuals with children, require panel data and are constructed using the NLSY.

Finally, I use NCES data to construct the last set of moments corresponding to the share of men and women going to college, and the share of male and female college graduates choosing a science degree.

I will now discuss the intuition behind the identification of the parameters, starting with the marriage market. The share of married individuals with the same education as their partner allows me identify p_m , the probability that an individual is matched with a partner

²⁴I solve the model recursively following Keane and Wolpin (1997) and use it to generate an artificial dataset of choices about labor supply, marriage, etc. I then construct moments based on this simulated data. The estimation method chooses structural parameters that minimize a weighted average distance between a set of data moments and the corresponding moments simulated from the model.

who has the same educational attainment. The difference in the re-marriage hazard between divorced individuals with and without children identifies P_{RM} , the re-marriage penalty for divorced individuals with children. The remaining marriage market moments—the overall share married, the share ever married by 30, the share divorced, and the difference in the divorce hazard rate for couples with and without children—jointly identify the match quality process and the cost of divorce. They also contribute to the identification of the parameter determining the direct contribution of children to the home good, since the ability to have children induces single individuals in the model to marry more frequently early in life and less frequently later in life. The labor supply and home production moments are necessary to identify all the remaining parameters of the home good technology function, including the differences in the productivity of labor allocated to home production by educational attainment. The shares of men and women in “ \mathcal{H} ”-type occupations by major are necessary to identify the probability η of drawing a wage from a second occupation.

There are additional moments that could be used in the model estimation, such as marriage and divorce patterns that are specific to the educational groups, since these patterns differ for high school and college-educated individuals in the data. I leave these auxiliary moments as additional tests of the model.

The baseline wage process parameters are estimated using a fixed effect specification with an additional selection term (Wooldridge (2002)). The parameters are summarized in Table 7. Table 8 summarizes the values for the calibrated parameters. Note that some parameters, such as the discount factor β , are adjusted to take into account that each period in the model corresponds to two years.

4 Results

Tables 9-11 present the estimates of the main parameters, and Table 12 summarizes the main marriage, occupation, home production, and labor supply moments of interest in the data and those that are implied by the estimated model. Table 12 shows that the estimated model does a good job matching marriage patterns, as well as occupational choices and labor supply differences by gender and education. Since the allocation of hours to non-market work is of substantial interest in the model, Table 12 also details the hours supplied to child care and home production by individuals in different educational and occupational groups, focusing on married men and women without any children and with children under the age of 6.

Table 12 documents that households with children under 6 spend more than 70 hours in child care and home production in the data, and nearly as much in the model.²⁵ The model captures that in households with young children, women supply around twice as many hours to non-market work as men. It also captures that relative to other women, those in

²⁵Sample data for time spent in home production and child care comes from the American Time Use Survey (ATUS, 2003). I follow Guryan, Hurst, and Kearney (2008) in constructing this measure.

science/business (\mathcal{H} -type) occupations spend less time in child-care and home production, although the model somewhat underestimates their non-market work.

The estimates of the parameters of the home production technology in Table 9 provide insight about how the model matches these patterns in home production. There are two main observations in the table. The first is that after having children, estimated home labor productivity increases more for college-educated individuals than for high school-educated individuals. The reason for this is that in the data, college-educated women have both higher wages and higher wage penalties for labor supply reductions. Nevertheless, when there are young children in the household, they increase their hours worked in home production and child care more than high school women. As a result, the model implies a high home labor productivity for them. College women's higher productivity in child care is one way to rationalize the empirical findings from Guryan, Hurst, and Kearney (2008) that college-educated women spend more hours on child care than high school educated women, while at the same time also spending more time working in the labor market.

A second observation is that by assumption the parameters in Table 9 do not differ for men and women. Nevertheless, hours spent in home production do, especially in households with children. In the model, differences in wages between spouses and the resulting household specialization generate this pattern. Because men's wages are on average higher, it is optimal in most households for the woman to supply relatively more labor to home production. This dynamic is further strengthened in the model by the fact that the household wishes to avoid wage penalties for both partners. As a result, it is optimal for only one individual in the household to reduce working hours below the full-time threshold.

Finally, the other parameters with interesting economic intuition include those that govern the cost of divorce and the utility or effort costs of schooling. Table 10 shows that the estimated cost of divorce decreased after reforms, in line with the historical evidence that it became easier to secure a divorce after the reforms in 1970. Table 11 shows that effort costs in the model are higher on average for the high-return science/business (H) major than for the lower-return humanities/other (L) major. Note that if the opposite were true, men in the model, for whom the expected return to the science/business major is always higher, would almost never choose the lower-return humanities/other major.

4.1 Lifecycle Patterns

Figures 8 through 10 show the lifetime labor supply, home production, and marriage patterns implied by the model for the baseline cohort graduating in 1980, along with the same patterns in the data. These lifecycle patterns provide good tests for the model's ability to match the data, because they are not matched directly. To match lifetime labor supply patterns, the model has to correctly simulate the timing in marriage and divorce decisions, children, and household specialization; the same is true for home labor production over the lifecycle.

Figure 8 shows that the model can capture well the market labor supplied by men and women over the lifecycle, including the substantial decrease in college women’s working hours during their thirties. Both in the model and in the data, the decrease is accompanied by a significant increase in women’s home production hours over same period of the lifecycle. Figure 9 maps simulated home production hours against actual data on home production and child care from the American Time Use Survey. The model captures well the large and rapid increase in home production hours for high school women in their late twenties and a similar increase for college women in their thirties. The model estimates a slightly earlier reduction in hours worked in home production relative to the data. It also overestimates somewhat labor supply to the market at the end of the lifecycle for both men and women. Otherwise, it captures well the lifecycle dynamics in time allocated to market and to home production, as well as difference in these patterns across sex and educational groups.

Figure 10 graphs lifecycle marriage and divorce patterns. In the estimation, I do not construct separate marriage and divorce moments for high school and college-educated individuals. Matching these differences across educational groups therefore constitutes an additional test for the model. Figure 10 shows that the model captures that high school educated individuals marry earlier, although this result is mechanical, since individuals who choose to go to college in the model enter the marriage market only after they complete their education. However, the differences in divorce patterns provide a validity test for the model, and the model correctly predicts the higher share divorced among high school-educated individuals. The reason for this is that college-educated couples in the model have higher marital surplus, both because they have higher productivity of home labor, and also because they allocate more resources to the market good component of the public home good.

Finally, Figure 11 and Table 13 focus on occupational choices and choices of major for men and women. Figure 11 shows that the model captures well that women enter into science/business (\mathcal{H} -type) occupations at a significantly lower rate than men, regardless of major. This lifecycle pattern is driven partly by the fact that both in the model and in the data many women do not enter into the low-flexibility science/business occupation in the first place, even if they have the science/business major.

Table 13 shows how these patterns in labor supply and occupational choices generate the expected returns to different majors for women and men. The table records the share of individuals choosing each major in the 1980 cohort and, for expositional purposes, also the model’s implied expected return in terms of discounted lifetime utility for each major for women and for men. The purpose of showing the latter is to provide intuition for how the model generates the different shares of men and women going to college and choosing different majors, since individuals make their educational choices partly based on these expected overall returns in lifetime utility, and partly based on their own effort costs for each major.

Table 13 records the expected utility returns in two steps. First, it records the implied

return to the humanities/other (L) major relative to going to high school. This return is higher for women. Next, it records the *additional* return to a science/business (H) major relative to a humanities/other (L) major. This return is substantially higher for men than for women, although it is positive for both sexes.

The reason that the model implies a high expected return to the humanities/other major for women is that even though the premium for this type of major is relatively low, it increases women's consumption and therefore their utility substantially in periods when they are relying only on their own wages, which are low compared to men's. This implies that not just the size of the premium matters for the returns to college, but also its interaction with the level of wages. Because women have a high return to a major that has low effort costs, the model implies that a lot of women go to college.

Next, the model implies a much lower additional return to science/business majors for women than for men for two reasons. Firstly, women are more likely to incur the high associated wage penalties in science/business occupations than men, since they are more likely to reduce their labor supply over the lifecycle. Secondly, as captured in Figure 11, women are less likely to enter science/business occupations in the first place, even if they have a science/business major. Both factors reduce the additional benefits to a science/business major. As a result, the share of women choose such a major is low. On the other hand, men in the model do not incur wage penalties and select at high rates into the science/business occupation. As a result, the share of men choosing the science/business major is high.

4.2 Patterns Across Cohorts

In addition to labor supply and marriage dynamics over the lifecycle, the dynamics in educational choices over time are also of central interest in the paper. Recall that there are two changes over time in the model: changes in wages and the one-time change in the cost of divorce.

Figure 12 shows that the model captures the main dynamics in college attendance and choice of major across cohorts with only these two sources of variation. Firstly, the model captures that men's decisions about college attendance follow closely the changes in the wage premium (Panel A). This reflects that the premium is the main driver of men's college attendance decisions over time. Secondly, the model also successfully replicates the consistent increase in women's college graduation rates and the reversal in this gender gap, even though it predicts a slightly earlier reversal, around 1980. Finally, the model also correctly replicates the persistence in the gender gap in choice of majors (Panel B).²⁶ In the remainder of this section, I use counterfactuals to illustrate how changes in divorce laws affect these patterns.

²⁶Note that there is an observed peak in the data in the share of men choosing science/business majors in 1980. This is also generated in the model. The reason for this peak in the model is that the college wage premium was on average very low in 1980. As a result, the men choosing to invest in college in 1980 were predominantly those with a relatively low effort cost for the higher-paying science/business major.

Change in Cost of Divorce in 1970

In this subsection, I conduct a counterfactual in which I vary the cost of divorce (K_0, K_1) for the 1970 cohort. The analysis has two main objectives. The first objective is to understand how changes in divorce laws affected the decisions of cohorts when they were initially passed, in the early 1970s. The second objective is to compare the size of this effect with the effect implied by the reduced-form analysis in Section 1.

To conduct the counterfactual, I simulate the 1970 graduating cohort twice. In the first simulation, individuals in the cohort do not anticipate that there will be a change in the cost of divorce from K_0 to K_1 , as in the baseline results in Figure 12. In the second simulation there is a change in the law, and individuals correctly anticipate it when they make their educational choice. The difference in educational decisions in the two simulations gives me a measure of the net effect that divorce law reforms have on educational choices of cohorts in the early 1970s. This measure can then be compared with the quasi-experimental reduced-form estimate of the same effect from Section 1.

The reason I conduct this particular counterfactual is the following. Note that it is not possible to run a cross-state difference-in-difference regression as in Section 1 using simulated data from the model. The reason is that for computational reasons I only consider cohorts graduating in decennial years in the model, and only for the aggregate U.S. population. The 1970 cohort simulated under two different divorce laws, however, provides both a “control group,” which did not experience divorce law reforms, and a “treatment” group which did, similar to the quasi-experimental reduced-form design. I focus on the 1970 cohort because the majority of reforms across states occurred in the early 1970s, with around half of the U.S. population affected by reforms by 1974 (Friedberg (1998)). As a result, most of the identification in the cross-state experiment relies on changes in reforms that occurred in the early 1970s.

The results of this exercise imply that the change in the cost of divorce had the effect of increasing the share of women going to college in 1970 by 2.8 percentage points, from 18% to about 21%. This is a substantial increase that would have reduced the college gender gap observed in the data in 1970 by nearly one-half. The effect on graduation rates is larger than the one implied by the reduced-form coefficient, which is equal to 1.1 percentage points. This is in line with the discussion about measurement error and potential contamination effects in Section 1, which are likely to bias the reduced-form coefficient downwards. I discuss additional possible reasons for the difference in the measured effects in the next counterfactual, focused on a present-day change in the cost of divorce.

The model predicts that the additional return to a science/business major in 1970 is relatively small, increasing the share of women in science and business majors by about 8 percentage points. The increase in the share of women choosing this degree in 1980 is generated by the increase in women’s labor supply between 1970 and 1980. This is driven

in the model partly by changes in wages, and partly by their interaction with divorce law reforms, which lead women to work more to accumulate additional human capital in case of divorce. Given this higher rate of lifetime labor supply, it is optimal in the model for a larger share of women to choose science/business occupations, and as a result science/business majors. College women's labor supply does not further increase after the 1980 graduating cohort, both in the model and in the data. As a result, the model implies that the shares in science/business occupations and majors after this period also remains flat.

High Cost of Divorce in 2010

Next, I consider how a return to a regime with a high cost of divorce would influence men's and women's decisions about college today. I consider this counterfactual for two reasons. Firstly, it is interesting from a policy perspective to know how a more stringent divorce law regime might affect decisions of individuals today. I will show that such a policy would have a counterintuitive effect on educational choices. Secondly, it allows me to measure the difference in educational choices under the two regimes in exactly the same way as in the previous counterfactual exercise, and therefore to comment about how the reduced-form results would generalize to other periods.

The model implies that implementing a strict divorce law regime today would further increase the share of women graduating relative to men. The model implies that an additional 3% of women invest in a college education in 2010 under the strict divorce law regime. Figure 13 explains this counterintuitive result by graphing the counterfactual marriage and labor supply patterns in 2010 under a more stringent divorce law regime. First, Panel A shows that there is a negative effect on marriage rates. The model implies that under today's wages, individuals postpone marriage or do not marry at all, to avoid being trapped in a poor-quality marriage. Panel B shows that as a result, more women remain single and on average supply more labor in the early part of their lifecycle than they do under the more liberal divorce law regime. The economic intuition for why women go to college at higher rates is that the college wage premium is valuable to women because under the strict divorce law regime they marry less and spend an even larger share of their life outside of marriage.²⁷ The reason one does not observe this pattern in 1960 in the model despite the same high cost of divorce is driven mainly by women's low wages at the time, and thus by their low options outside of marriage.

Interestingly, the results of the exercise imply that the estimates obtained using cross-state quasi-experimental variation do not generalize to the present period. The findings suggest that when using divorce law reforms as a source of variation one should consider the effects of

²⁷Note that the model does not allow for alternative household structures. The rate of cohabitation would likely increase under the more rigid divorce law regime today. In as far as the literature has documented that household specialization is lower for cohabiting couples (Gemici and Laufer (2009)), many of the same labor supply patterns as in the counterfactual exercise may still be observed. This is an interesting area for further research.

interactions between wages and divorce laws over time in the analysis, as reforms may yield opposite effects on behaviors like labor supply or education, depending on the time period considered. Finally, the results also suggest another potential reason why the effect of divorce law reform on education around 1970 may be higher in the model than in the reduced-form analysis; namely, part of the identification for the reduced-form coefficient relies on divorce law reforms in later periods, when the net effect of the reforms was smaller or even reversed signs.

To conclude the analysis, I use a final counterfactual to quantify the effect that insurance has on educational choices. To isolate the value of insurance, separately from other returns to college over the lifecycle, I conduct the following exercise. I consider how the lifetime utility of a college-educated women is affected if she draws from a wage distribution of a high-school educated woman after divorce, all else equal. To assign a dollar value to this utility, I calculate the annual lifetime stream of payments that such a woman would have to receive in order to be indifferent between having the insurance in case of divorce and not having it. The exercise implies that the size of the annual payment is about \$8,200. Given that the average additional earnings of full-time college-educated women relative to high-school educated women are equal to \$26,670 in 2010 (IPUMS USA ACS, 2010), this is equivalent to about 31% of their earnings premium.

Finally, the results suggest that eliminating “insurance” in case of divorce from individuals’ returns would reduce the gap in graduation rates today between men and women by 36%. The model implies that the remainder of the gender gap is driven primarily by two factors. Both factors are directly related to the concept of insurance and women’s options outside of marriage. First, the college degree has a high return for never married women. Second, having “insurance,” or a high option outside of marriage, raises college women’s decision power within the marriage. The model implies that the average Pareto weight for married college-educated women is 0.49, compared to 0.42 for high school-educated women.

5 Policy Simulations

In this final section I consider policies that can potentially affect individuals’ choices about majors. Two policy-relevant issues related to undergraduate majors are frequently discussed in the popular and business media. One is the issue of potential skill shortages in science and engineering fields; the other is the low share of women in technical majors.²⁸ The two concerns are related, as women’s low participation in such majors contribute to potentially low skill supply in technical fields in the U.S. The structural model developed in this paper can analyze the effectiveness of policies that address these two issues. In this section, I consider two sets of policies: one in which differential tuition is charged for different majors;

²⁸See, for example Koebler (2011), Carnevale, Smith, and Melton (2011), and Pollack (2013). There are differing opinions as to whether or not a shortage of STEM skills exists in the U.S. See Freeman (2006).

and a second set in which I consider various “family-friendly” policies, which are geared at improving work-family flexibility.

5.1 Differential Tuition for Majors

Recently some states have proposed a policy to charge lower tuition for science, technology, engineering, and math majors at state universities, most famously in Florida.²⁹ The direct objective of the policy is to increase the share of individuals who choose those majors. To analyze the potential effects of this type of policy on educational choices, I conduct an experiment in which I reduce the tuition cost for Type H (science/business) majors in the model by one-third. This is roughly in line with Florida’s early policy suggestions.³⁰

Table 14 summarizes the changes in educational choices under this policy. The model predicts that substantially more women choose the less expensive H (science/business) major, and it predicts almost no effect of the policy on men. The reason for this potentially surprising result is that in the baseline model, many women are on the margin between choosing the two types of majors, but men are not. To see why, recall that in the baseline model the science/business major provides a slightly higher expected return in lifetime utility for women than the humanities/other major, but that many women nevertheless choose the latter because it has a substantially lower effort cost. By contrast, the return to the science/business major for men is sufficiently high in the baseline model that almost all men who have a reasonably low effort cost for the major will choose it over the humanities/other major. In the policy experiment, when tuition for the science/business major is reduced, many of the women who were previously on the margin between the two majors are now induced to switch to the lower-cost major. Meanwhile, the men in the baseline model who choose the humanities/other major are relative outliers, who have either a very high cost for science/business majors or extremely low cost for humanities/other majors. The change in tuition does little to induce them to switch majors.

These results suggest that a differential tuition policy could induce women to switch majors, but would mostly subsidize men who would have chosen the majors of interest even without the lower tuition.³¹ An additional concern is that about half of women with science/business majors do not choose to work in science/business occupations, which reduces the policy’s effectiveness at increasing the supply of science skills to the labor market.

²⁹Governor Rick Scott of Florida has been a high-profile advocate of a differential tuition system. See Alvarez (2012). Governors in several other states have praised the idea. Providing scholarships to individuals with science and technology majors is an alternative way to implement the policy and to extend it to non-state schools.

³⁰However, note that the H -major category also includes business, which is not targeted by the Florida policy.

³¹It is still possible that within the science/business (H) category, some men could be induced to switch majors using the policy, e.g., from business to engineering. However, given that the returns to engineering for men are significantly higher than those for business (see Table 2), it is likely that the same intuition applies even within the science/business category.

5.2 Family-Friendly Policies

One potential way to affect women’s educational choices is to address the issue of work-family flexibility directly, with policies that can make it easier for women to allocate labor between market and non-market work. In many OECD countries, “family-friendly” policies include paid parental leave, part-time work entitlements, and subsidized child care (OECD (2010)). By comparison, the U.S. has limited policies around work-family flexibility.³² In the remainder of this section, I analyze the potential effects of family-friendly policies on household labor supply and on the occupational and educational choices of women and men.

One concern with “family-friendly” policies is that employers may respond in the long run by discriminating against women, a general equilibrium response that this model cannot evaluate. However, another concern with family-friendly policies is that they have theoretically ambiguous effects on women’s labor supply, occupational, and educational choice, even without employer discrimination. For example, family-friendly policies may encourage more women to stay in the labor force or, in the case of a maternity leave policy, to return to their original positions after an absence from the work force. On the other hand, they may also have a negative impact on women’s accumulated experience and thus on their labor supply and occupational choices over the lifecycle.³³ To evaluate the direct effects of such policies on women’s labor supply, occupation, and education choices, a household model that incorporates specialization and optimal household responses to such policies is necessary.

In this set of experiments, I consider three policies: a paid maternity leave policy, a policy that entitles all workers to a part-time work opportunity with their employer, and a subsidized child care policy.

5.2.1 Paid Maternity Leave

In this first experiment, I consider a maternity leave policy that provides paid extended leave for women in the model for one period, i.e. up to two years, immediately after a positive fertility shock. The amount of paid leave provided is based on the woman’s earnings in the period prior to the leave. It is equivalent to her hourly pay times her hours worked that prior period, up to but no more than the full-time equivalent of 35 hours per week. Women who choose to take the paid leave may return to their previous position, meaning that in the model they do not suffer the “wage penalty” for having reduced their labor supply in the prior period. However, they will not accumulate experience for that period if they work less than the minimum number of hours required to gain experience.

³²Currently, the federal Family and Medical Leave Act of 1993 requires large employers in the U.S. with more than 50 employees to provide 12 weeks of unpaid family leave, at the end of which the worker may return to the previous position.

³³See, for example, Blau and Kahn (2012). Cross-country comparisons in that paper suggest that relative to countries with stronger work-family flexibility policies, women in the U.S. are less likely to work overall, but more likely to work as managers or professionals.

The series indicated by the blue line in Figure 14 records women's lifecycle labor supply response to such a policy. The series indicated by the red line records labor supply in the baseline model without the policy. Because the implied effects for L and H majors are very similar, I only graph the labor supply response for the latter.

The model implies that there are three main effects on women's labor supply. First, women predictably decrease their labor supply after childbirth. Since the maternity leave is paid, the policy essentially constitutes an indirect tax on the woman's earnings. As a result, women in the model choose to take some or all of the leave, and reduce their labor supply in their thirties substantially more than they do in the baseline model. The second effect of the policy is that women's labor supply early in life increases. The reason for this is that eligibility for maternity leave in any given period depends on employment and earnings in the prior period. This incentivizes women to increase their labor supply before they have children.

The third main effect on labor supply is that women allocate less time to market work after their thirties than they do in the baseline model, especially when there are still children in the household. Under the maternity leave policy women accumulate less experience by their mid- to late-thirties, and thus have lower wages later in life. From the household's perspective, it is not optimal for the woman to work the same high hours that she would have with the additional accumulated human capital. As a result, women on average work fewer hours and spend more time in home production and leisure. As children leave the household and as women accumulate human capital towards the end of the lifecycle, they increase their labor supply again.

The policy affects men's labor supply only marginally, as Figure 14B shows. Men in their thirties decrease their hours somewhat relative to the baseline model. The reason for this is that the household has more income under the paid leave policy, and men as a result supply less labor than they would in the baseline model.

Finally, the model predicts that the policy increases both college gender gaps. The reason that women decrease their participation in science/business majors under the policy is related to the observation above that women take more time off from the labor force and therefore accumulate less experience. Because returns to experience are high in the science/business occupation, this further reduces women's return to the science/business major. The model also implies that *more* women go to college overall. The reason women's return to college further increases is that women on leave are compensated according to their most recent earnings, and therefore can benefit from the college wage premium even in the periods after childbirth when they are not working.

5.2.2 Part-Time Work Entitlement

In the second experiment, I consider a non-discriminatory part-time work policy, in which employees are entitled to work part-time without any wage penalty, if they choose. Policies aimed to provide this kind of benefit to workers have been enacted in Belgium, France, and the Netherlands among other OECD countries (OECD (2010)). To simulate the effects of the policy, I reduce the wage penalty for working part-time in the model for all occupations to zero, for both men and women.

The series indicated by the green line in Figure 14 shows that the policy has one main effect on women's lifecycle labor supply: women choose to supply less labor to the market over most of their lifetime. The results of the simulation imply that when women can choose their desired number of hours worked without incurring any kind of wage penalty, they supply less labor on average. This large reduction in labor supply is observed even though the policy has a strongly positive effect on women's wages in the simulation. The result implies that households highly value the ability to specialize.³⁴ The only exception to the observed reduction in women's labor supply over the lifecycle is that women in their early twenties work at similar rates as they do in the baseline model. This is in line with intuition. Since almost all women in the model at this age are single or married without children, they do not value flexibility.

The policy decreases the gender gap in choice of major substantially. When there is no wage penalty, more women in the model enter science/business occupations, and as a result more choose the science/business major. The model implies that the share of women choosing a science/business major increases from 34% to 45%, whereas the share of men choosing the major increases marginally from 66% to 67%. Figure 14B shows that the part-time policy has almost no effect on men's labor supply. As a result, the effect on men's educational choices is also small. The net effect of the policy is to reduce the gender gap in majors by about a third, from 26 percentage points to 17 percentage points. The reason the model does not imply complete gender convergence in choice of major is that women continue to supply substantially less labor over their lifetime than men. Therefore, the additional financial return to choosing this major is still lower for women.

5.2.3 Subsidized Child Care

In the final experiment, I consider the effect of a child care subsidy, as has been implemented in a number of countries (OECD (2010)). In the baseline model, the household pays for childcare costs if there is a child under the age of six in the household and both spouses work. In that case, the household pays an hourly childcare cost for the number of hours worked by

³⁴This is in line with empirical evidence in Goldin and Katz (2012) on the pharmacy occupation, which has almost no wage penalty today for part-time work. Goldin and Katz document high part-time rates among female pharmacists despite the high compensation associated with the occupation.

the spouse with the lower labor supply. In this particular policy experiment, I provide a full subsidy, i.e. I reduce the cost of childcare to zero.³⁵

The series represented by the dotted red line in Figure 14 shows that subsidized child care has a small effect on women's labor supply patterns. The policy increases the labor supply of college women in the model mostly in their early childbearing years. In the baseline model, the childcare cost is usually an implicit tax on the woman's wage, since she is typically the one to provide the lower labor supply in the household. Among college-educated women in the model, those who respond to the policy are primarily women in science/business occupations with a low wage draw that period. The effective increase in their wage due to the subsidy is enough for some of these women to increase labor supply to avoid a wage penalty or to accumulate experience, which has a high future return. However, because these estimated effects are small, the implied effects on the returns to education are also minor.

Table 15 summarizes and compares the effects of the three family-friendly policies on educational choices. As a whole, the policy results suggest that a program that successfully increases the availability of part-time work would be the most effective in increasing women's participation in both science/business occupations and majors.

6 Conclusion

Even as women caught up to and rapidly outpaced men in college graduation rates, we have seen almost no convergence between men and women in choices of major since the mid-1980s. In 1985, U.S. men were about 1.5 times as likely as women to select high-paying science and business majors, and the same is still true today. A similar pattern is observed in almost every other developed country (Vincent-Lancrin (2006)).

I provide evidence that two factors help explain gender differences in college attainment and choice of major: first, college degrees provide insurance against very low income for women, especially in case of divorce; second, majors and their associated occupations differ substantially in the flexibility in hours they offer, such as availability of part-time work and the size of wage penalties for temporary reductions in labor supply. Because women draw from a lower wage distribution, they are more likely to seek insurance against very low income realizations when they are single or divorced, and more likely to specialize at least partly in non-market work when they are married. Their educational choices reflect this.

To analyze these drivers of educational decisions in greater detail, I construct and estimate a dynamic structural model of lifecycle marriage, labor supply, occupational and educational choices. Using the model, I show how changes in marriage patterns following divorce laws and changes in skill premiums over time affect the educational decisions of different cohorts.

³⁵I set the child care cost to \$5.60 per hour, based on data from the Census Bureau on weekly child care expenditures for mothers of children 5 or under who use child care (Laughlin (2013)).

I estimate that the insurance value of a degree for women today is equivalent to about 31% of their wage premium. I also estimate that the difference in the shares of men and women choosing science/business majors would decrease by about a third if penalties to labor supply reductions were equalized across occupations.

The findings in this paper suggest that many college-educated women select lower-paying occupations and majors to have flexibility to allocate more time to child care and home production, especially when their children are young. For this reason, I use the structural model to test several policies that potentially improve work-family flexibility for women across occupations. I find very large differences in the effects of these policies, with some, such as extended paid maternity leaves, even further widening both gender gaps in education. The findings call for more research in the future on flexible policies that make it easier for women to participate in science and technical occupations, especially as many developed economies grow increasingly more concerned about the low number of graduates in science and technical fields.

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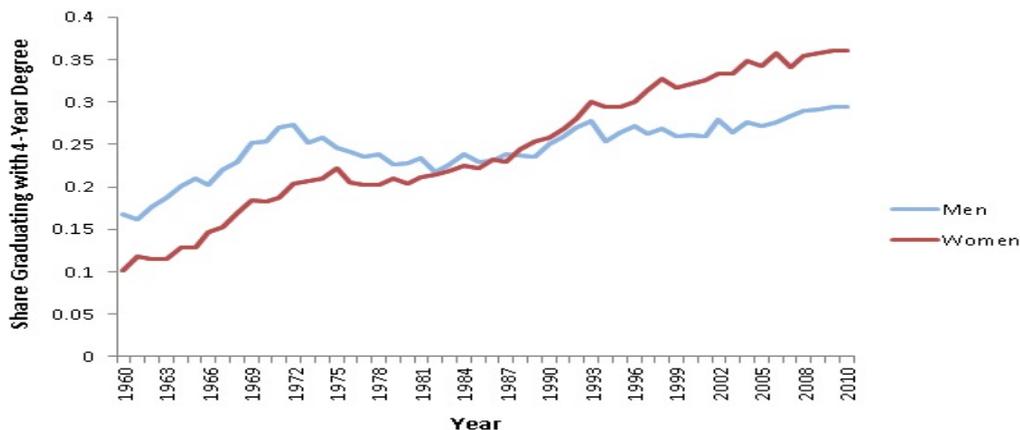
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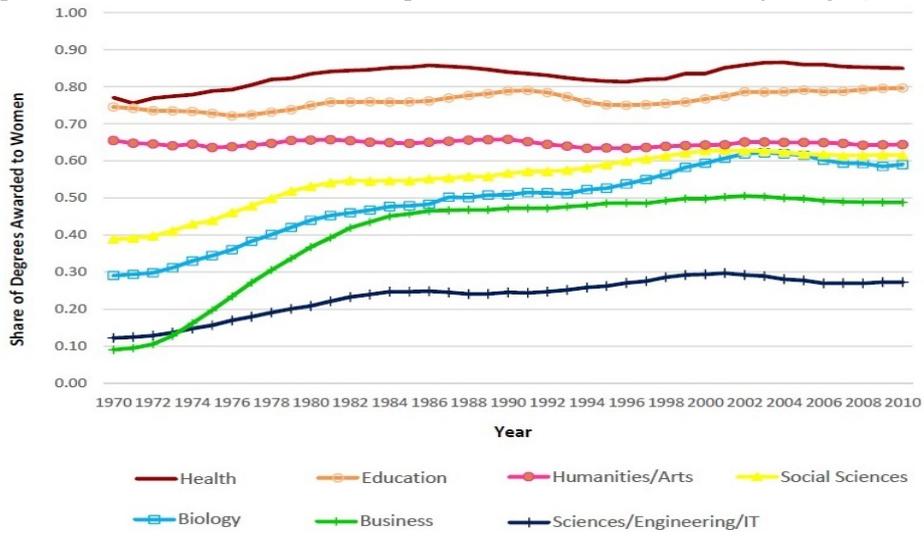
Tables and Figures

Figure 1: Share of Men and Women Graduating with 4-Year Degree, 1960-2010



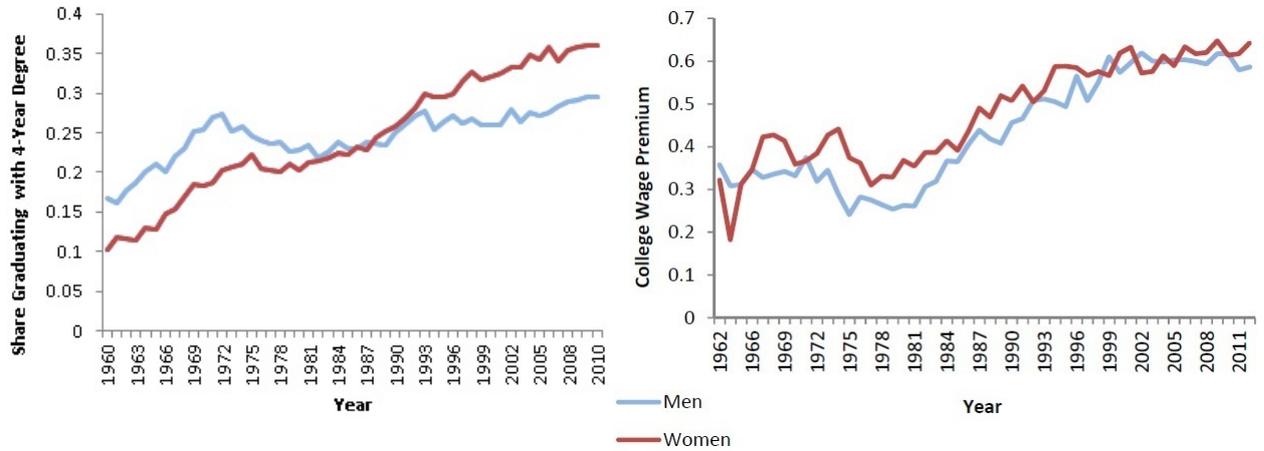
Sample includes individuals ages 24-30. Graduation year is the year individuals were 22 years of age. Graduation rates after 2008 are constructed using NCES data. Sources: CPS (1962-2012), NCES (2012).

Figure 2: Share of Bachelor's Degrees Awarded to Women By Major, 1970-2010



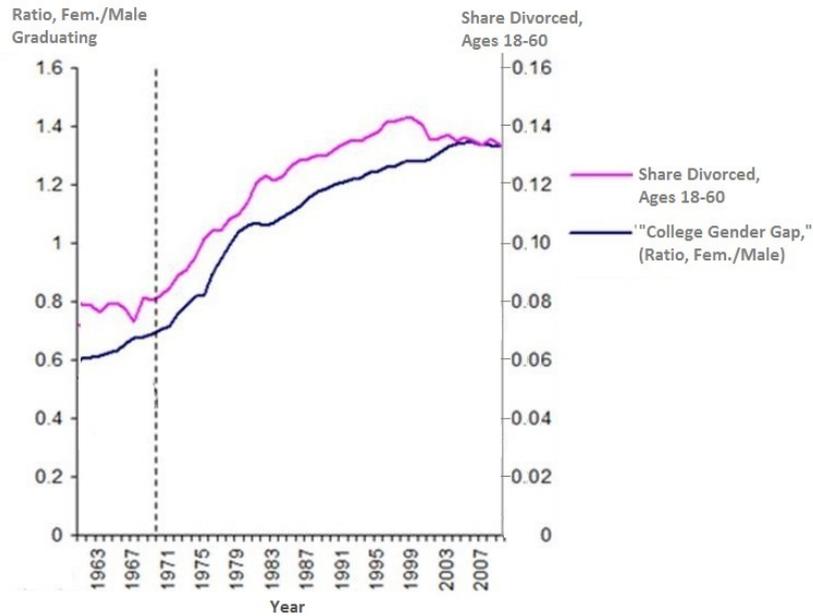
Data contains all students graduating from accredited U.S. colleges. See Appendix A.4 for major classifications. Source: NCES (2012), Tables 343-365.

Figure 3: Share Graduating and College Wage Premium, 1960-2012
 A. Share Graduating from College
 B. College Wage Premium



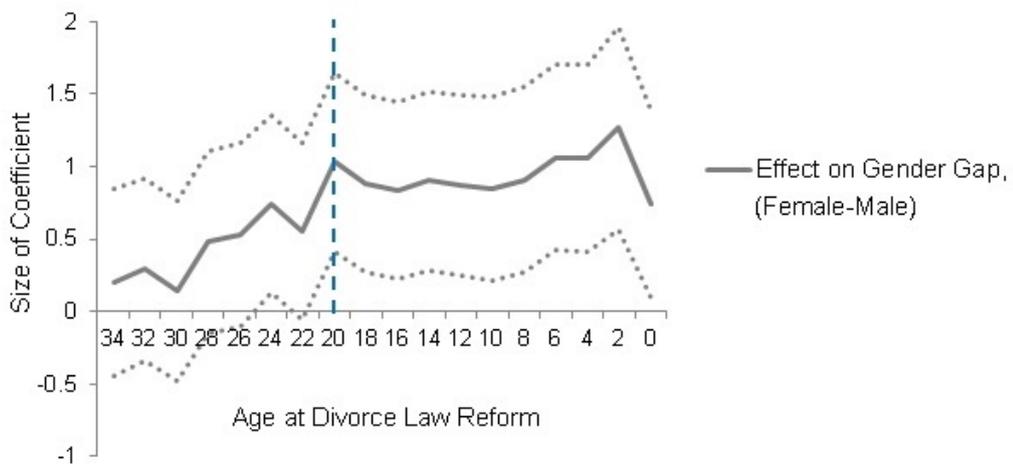
For Panel A, see notes in Figure 1. In Panel B, the sample includes all individuals ages 25-50, who worked 35+ hours in the past week and 48+ weeks in the past year. The wage premium is the difference in log income between college and high school graduates. Includes flexible controls for age and race. Source: CPS (1962-2012).

Figure 4: Share Divorced and the Ratio of Women to Men Graduating, by Year



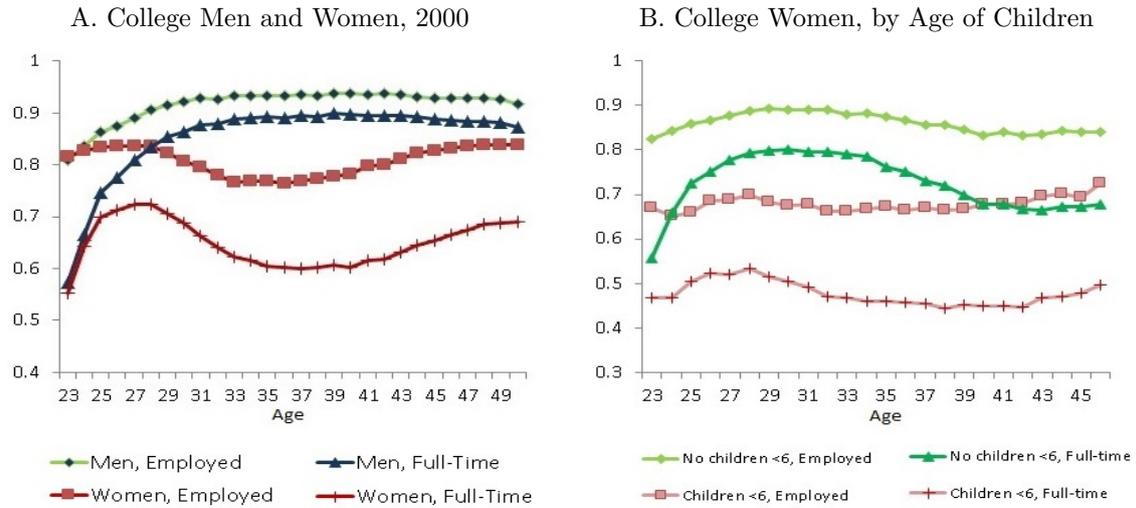
Share divorced refers to the share of all individuals ages 18-60 divorced each calendar year. The college gender gap is the ratio of women to men graduating that calendar year. Source: IPUMS CPS, 1962-2010; NCES, 1960-2010.

Figure 5: Coefficients from Regression of Gender Gap on Age at Time of Divorce Law Reform



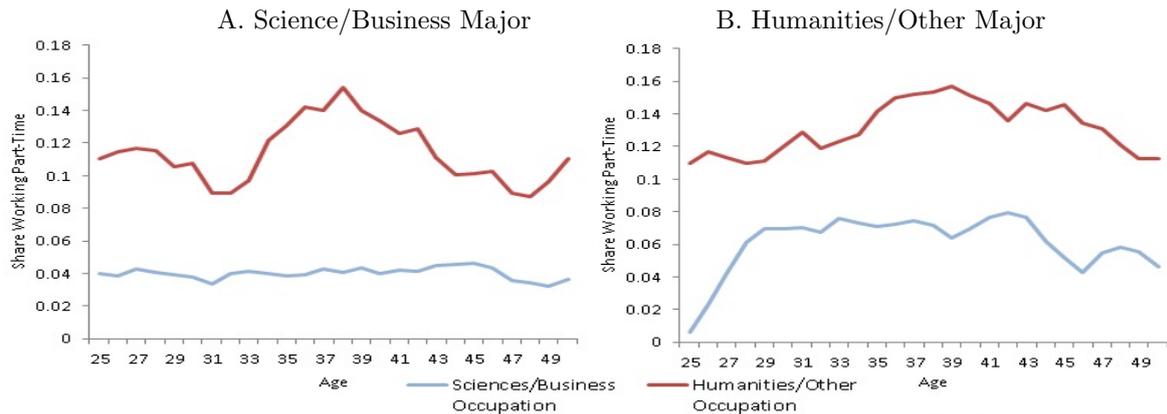
Robust standard errors. Additional controls include state and cohort fixed effects. Dotted series represent +/- one standard error.

Figure 6: Share Employed and Share Working Full-Time By Age, College Graduates



Full-time is defined as working 35+ hours per week. Sample includes college graduates only. Source: IPUMS USA (2000).

Figure 7: Share Working Part-Time, By Occupation and Major



Part-time is defined as working less than 35 hours per week. Sample includes female college graduates who are currently employed. Source: NSCG (2000).

Figure 8: Weekly Hours Worked in Labor Market, Data and Model

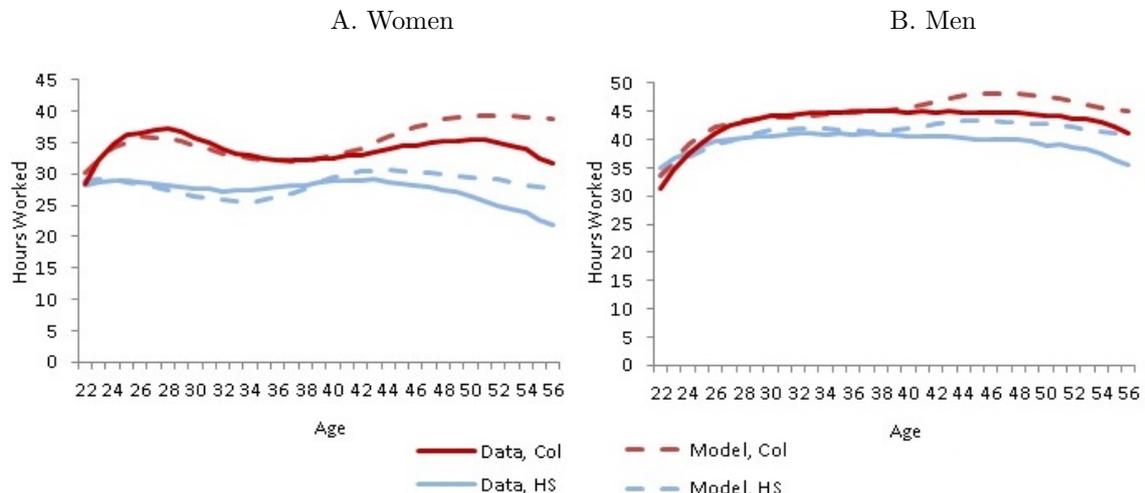


Figure 9: Weekly Hours Worked in Home Production, Data and Model

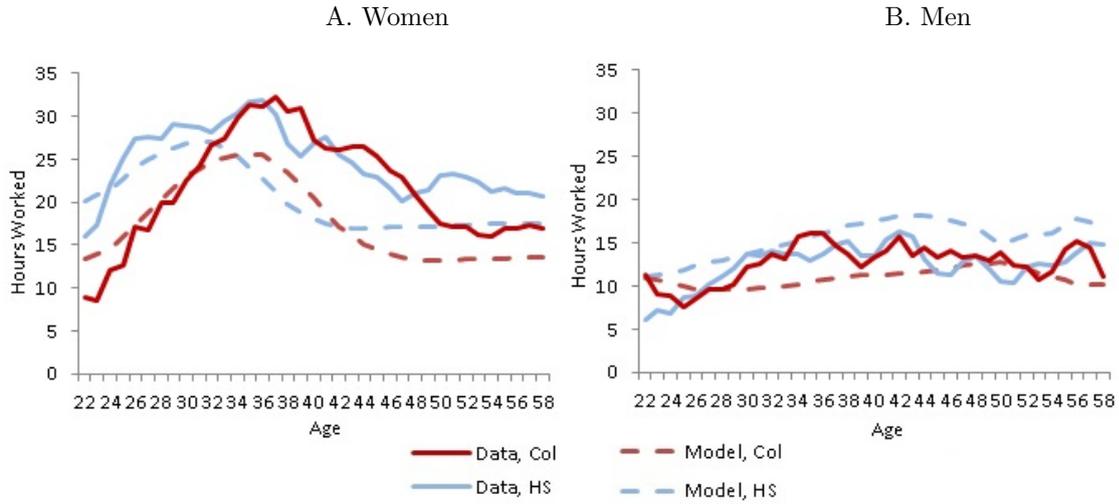


Figure 10: Share Married and Divorced (Women), Data and Model

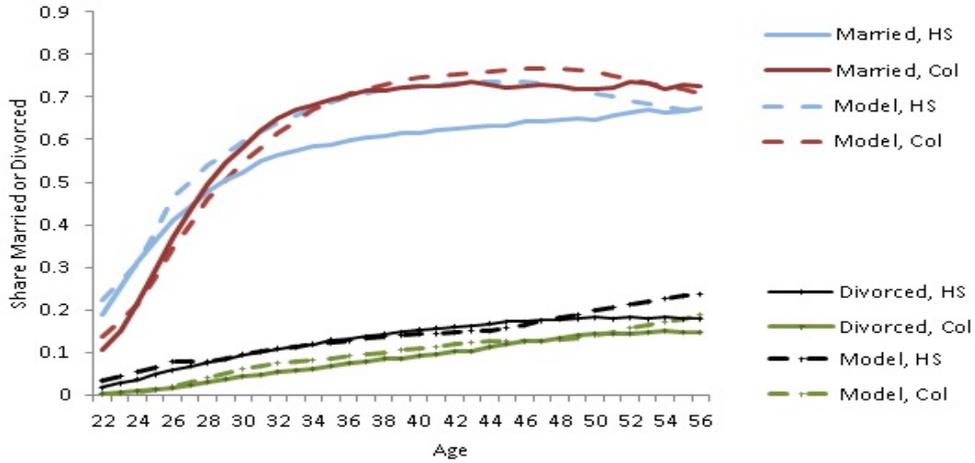


Figure 11: Share in \mathcal{H} -Type Occupation by Major, Data and Model

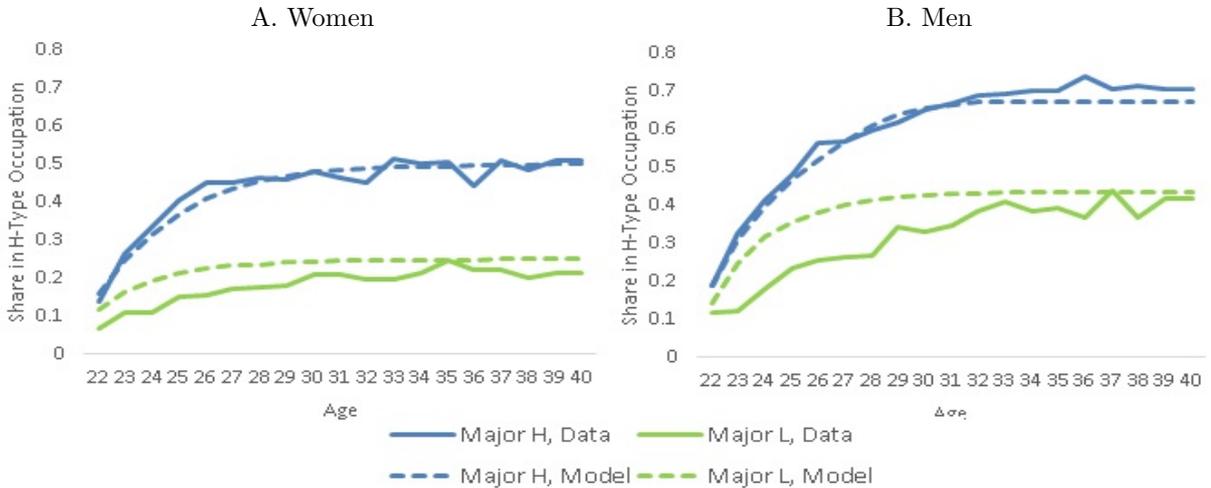


Figure 12: Men's and Women's Educational Choices Over Time, Data and Model

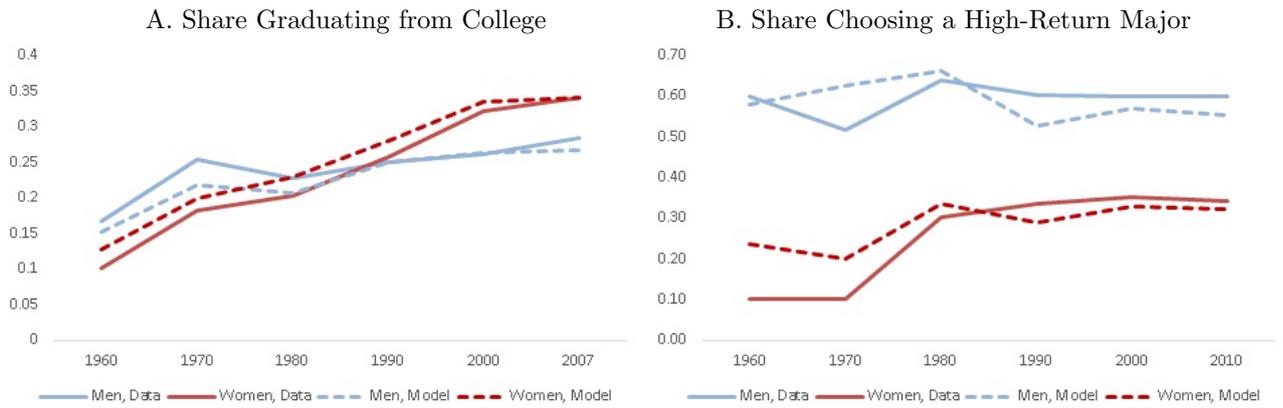


Figure 13: Share Married and Hours Worked Under Alternative Divorce Law Regimes, 2010 Graduating Cohort

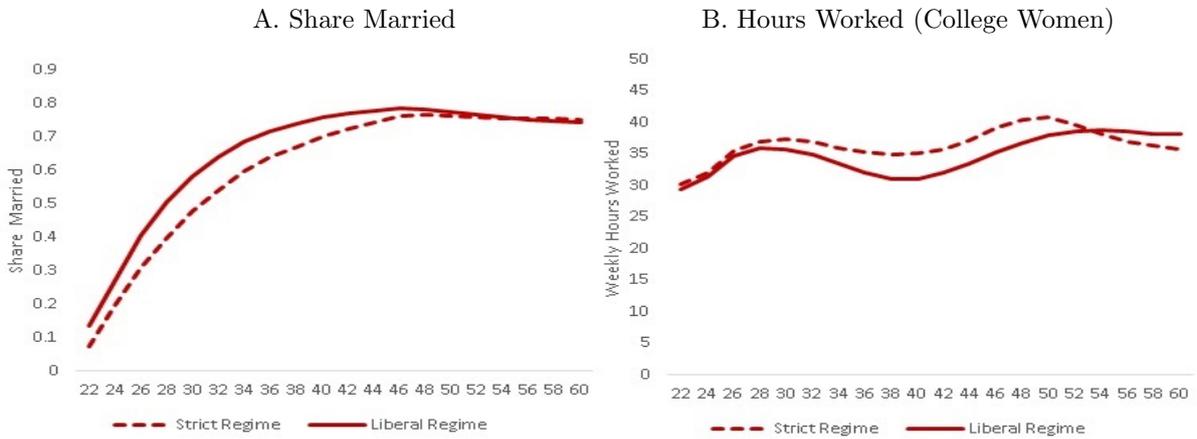


Figure 14: Simulated Labor Supply Under Family-Friendly Policies

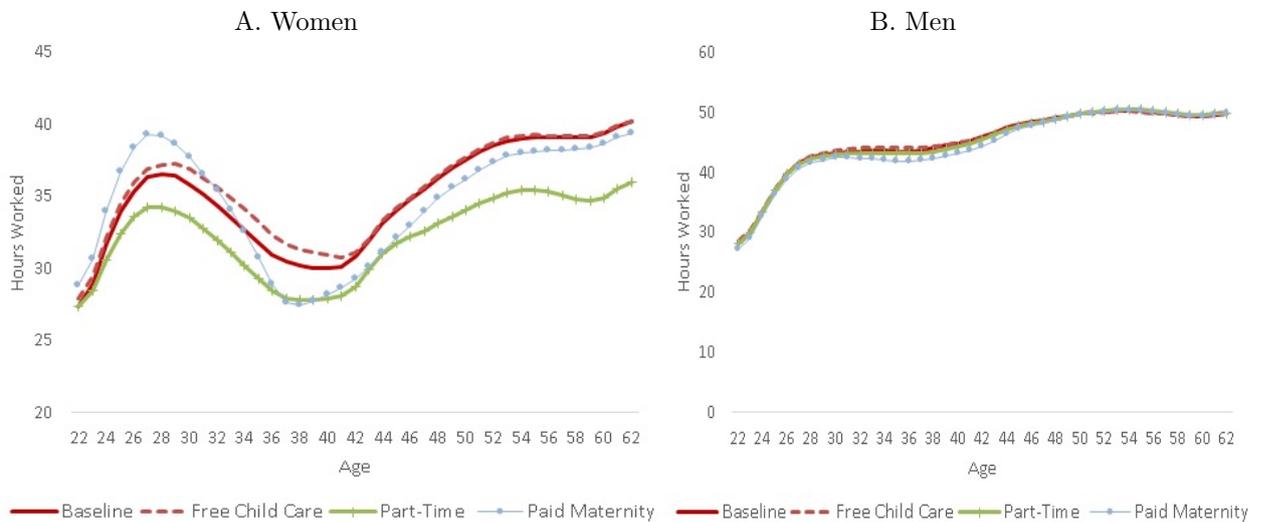


Table 1: Effect of Divorce Law Reforms on Gender Gap in Choice of College Major

Dep. Var.: Share Majoring in Science/Business (Women-Men)	
2 to 0 years until divorce law reform	0.003 (0.004)
1 to 3 years since divorce law reform	0.005 (0.004)
4 to 6 years since divorce law reform	0.008** (0.004)
7 to 9 years since divorce law reform	0.009* (0.005)
More than 10 years since divorce law reform	0.002 (0.008)

* Significant at 10%. ** At 5%. Source: NCES/HEGIS.

Table 2: Regression of Log Income on Field of Undergraduate Major, All College Graduates

	Women			Men		
	1993	2003	2010	1993	2003	2010
Sciences	0.137*** (0.011)	0.138*** (0.022)	0.196*** (0.042)	0.160*** (0.009)	0.224*** (0.020)	0.246*** (0.039)
Engineering	0.381*** (0.017)	0.375*** (0.037)	0.452*** (0.046)	0.306*** (0.009)	0.317*** (0.019)	0.355*** (0.040)
Business	0.164*** (0.010)	0.145*** (0.023)	0.202*** (0.053)	0.198*** (0.009)	0.234*** (0.021)	0.257*** (0.046)
Social Sciences	0.018* (0.010)	-0.053** (0.023)	0.053 (0.042)	0.002 (0.011)	0.043 (0.027)	0.068 (0.046)
Health	0.192*** (0.011)	0.143*** (0.026)	0.299*** (0.044)	0.161*** (0.020)	0.179*** (0.034)	0.276*** (0.053)
Education	-0.084*** (0.009)	-0.180*** (0.028)	-0.097 (0.061)	-0.082*** (0.012)	-0.151*** (0.031)	-0.070 (0.068)
Humanities ¹	-	-	-	-	-	-
N	33,111	16,432	13,209	54,992	28,075	20,117

¹ Humanities is the omitted category. * Significant at 10%. ** At 5%. *** At 1%. Coefficients are the outcome of a regression of log income on a set of indicator variables corresponding to each major. Controls include indicator variables for age, race, and highest degree earned. Sample includes individuals ages 25 to 50 employed full-time, full-year. Robust standard errors in parentheses. Sources: NSCG 1993, 2003, and 2010.

Table 3: Women's Employment and Rate of Part-Time Work in Different Majors

	No Children Under 6		Has Child Under 6	
	Employed	Part-Time	Employed	Part-Time
Sciences	0.89	0.12	0.77	0.23
Engineering	0.89	0.10	0.74	0.21
Business	0.88	0.12	0.70	0.23
Social Sciences	0.88	0.13	0.71	0.27
Health	0.91	0.18	0.80	0.43
Humanities	0.89	0.15	0.68	0.31
Education	0.93	0.10	0.72	0.20

Part-time rates are for individuals currently employed. Sample includes college graduates ages 25-50. Source: NSCG, 2003.

Table 4: Men's Employment and Rate of Part-Time Work in Different Majors

	No Children Under 6		Has Child Under 6	
	Employed	Part-Time	Employed	Part-Time
Sciences	0.94	0.03	0.97	0.02
Engineering	0.95	0.02	0.97	0.01
Business	0.95	0.03	0.97	0.01
Social Sciences	0.93	0.06	0.96	0.03
Health	0.96	0.04	0.98	0.02
Humanities	0.94	0.07	0.97	0.03
Education	0.94	0.03	0.99	0.01

See note in Table 3.

Table 5: Share Working in Science/Business Occupations, By Ages 30-35

	Women	Men
Science/Business Majors	0.574	0.808
Humanities/Other Majors	0.204	0.415

Source: National Survey of College Graduates, 2003.

Table 6: Wage Penalties for Labor Supply Reductions, by Major (Women)

	All Occupations		S/B Occupations		Other Occupations	
	S/B Major	Other	S/B Major	Other	S/B Major	Other
Part-Time	-0.126*** (0.016)	-0.116*** (0.011)	-0.178*** (0.023)	-0.162*** (0.028)	-0.083*** (0.028)	-0.108*** (0.028)
Time Off	-0.105*** (0.020)	-0.043*** (0.014)	-0.212*** (0.031)	-0.159*** (0.039)	-0.031 (0.028)	-0.026* (0.028)

* Significant at 10%. *** At 1%. Individual fixed effects regression. Log wage is the dependent variable. Additional controls for experience and experience squared. Robust standard errors in parentheses. Source: NLSY79.

Table 7: Wage Process Parameters for Baseline Cohort

	High School	Major <i>L</i>	Major <i>L</i>	Major <i>H</i>	Major <i>H</i>
	Occ. \mathcal{L}	Occ. \mathcal{L}	Occ. \mathcal{H}	Occ. \mathcal{L}	Occ. \mathcal{H}
Entry-Level Wage Gap	0.21 (0.04)	0.11 (0.03)	0.14 (0.03)	0.12 (0.04)	0.19 (0.05)
PT/Time-Off Penalty, Men	0.08 (0.006)	0.09 (0.017)	0.16 (0.033)	0.09 (0.023)	0.16 (0.020)
PT/Time-Off Penalty, Women	0.09 (0.006)	0.09 (0.11)	0.17 (0.026)	0.10 (0.06)	0.19 (0.022)
Experience, Men	0.05 (0.004)	0.08 (0.005)	0.09 (0.005)	0.09 (0.005)	0.11 (0.007)
Experience, Women	0.04 (0.004)	0.08 (0.003)	0.09 (0.004)	0.07 (0.004)	0.10 (0.006)
Experience ² , Men	-0.002 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.003 (0.000)
Experience ² , Women	-0.002 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.003 (0.000)	-0.003 (0.000)

Standard errors in parentheses. Source: NLSY79.

Table 8: Calibrated Parameters

Description:	Parameter:	Value
Risk aversion parameter	σ	2.50
Cobb-Douglas parameter on consumption/leisure	a	0.40
Discount factor	β	0.92

Table 9: Estimates of Home Good Technology Parameters

Description:	Parameter:	Estimate	Std. Error
Home labor productivity, by education and child status	α_1		
No Children:		0.178	(0.28)
High School, Children <6:		0.713	(0.29)
College, Children <6:		0.967	(0.15)
High School, Children 6+ Only:		0.591	(0.33)
College, Children 6+ Only:		0.821	(0.36)
Productivity of market good	α_2	0.344	(0.27)
Children's contribution to home good	α_3	2.511	(0.89)

Table 10: Estimates of Marriage Market Parameters

Description:	Parameter:	Estimate	Std. Error
Mean of initial match draw	μ_θ	-1.45	(1.20)
Variance of initial match draw	σ_θ	1.53	(0.80)
Mean of match quality shocks	μ_z	0.24	(0.34)
Variance of match quality shocks	σ_z	1.36	(0.49)
Probability of drawing a partner with the same education	p_m	0.81	(0.21)
Cost of divorce before reform	K_0	10.84	(1.28)
Cost of divorce after reform	K_1	1.08	(0.17)
Re-marriage penalty for individuals with children	P_{RM}	2.91	(1.91)

Table 11: Estimates of Utility Cost of College and Occupational Wage Draw Parameters

Description:	Parameter:	Estimate	Std. Error
Mean of utility cost, Type L major	μ_L	12.33	(2.62)
Variance of utility cost, Type L major	σ_L	2.39	(2.01)
Mean of utility cost, Type H major	μ_H	22.43	(2.77)
Variance of utility cost, Type H major	σ_H	6.67	(2.52)
Probability of wage draw from second occupation	μ_L	0.11	(0.15)

Table 12: Summary Statistics, Data and Model Simulation

Moment:	Data	Model
Share Married, Ages 22 to 60	0.61	0.65
Share Divorced, Ages 22 to 60	0.12	0.11
Weekly Hours Worked in the Labor Market:		
Men, HS	40.74	41.19
Men, College	42.99	43.97
Women, HS	28.43	29.04
Women, College	34.57	35.16
Share in \mathcal{H} -type occupations:		
Men, Major L	0.42	0.43
Men, Major H	0.68	0.66
Women, Major L	0.24	0.26
Women, Major H	0.51	0.51
Weekly Hours Spent in Home Production & Child Care, Married Men:		
No Children, HS	8.54	7.30
No Children, \mathcal{L}	10.74	7.93
No Children, \mathcal{H}	6.71	5.40
Children <6, HS	24.03	19.71
Children <6, \mathcal{L}	24.89	24.05
Children <6, \mathcal{H}	25.01	20.74
Weekly Hours Spent in Home Production & Child Care, Married Women:		
No Children, HS	25.11	20.98
No Children, \mathcal{L}	22.17	17.18
No Children, \mathcal{H}	19.47	14.51
Children <6, HS	44.36	47.31
Children <6, \mathcal{L}	48.14	49.30
Children <6, \mathcal{H}	45.03	36.63

Table 13: College Returns and Decisions for 1980 Graduating Cohort, Model and Data

	Women	Men
Discounted Lifetime Utility Returns, Model:		
Return to Major L , vs. HS	4.06	2.31
Additional return to Major H , vs. Major L	0.62	3.06
College Choices, Model:		
Share graduating	0.23	0.21
Share choosing Major H	0.33	0.66
College Choices, Data:		
Share graduating	0.20	0.22
Share choosing Major H	0.30	0.64

Table 14: Effect of Tuition Policy on Share Choosing Major H

	Baseline	Policy
Women	0.33	0.41
Men	0.66	0.67

Table 15: Main Effects of Family-Friendly Policies on Educational Choices

Policy	Main Effects
Paid Maternity Leave	Both college gender gaps increase:
	· Women major less frequently in science/business · Women increase their college attendance further
Part-Time Entitlement	Gender gap in majors narrows:
	· Women major more frequently in science/business · Women marginally increase their college attendance
Subsidized Child Care	Gender gap in majors narrows marginally:
	· Women major marginally more in science/business · No effect on attendance

A Appendix

A.1 Effect of Divorce Laws on College Graduation and Choice of Major

The specification used in equation (1) is very similar to the analysis in Stevenson and Wolfers (2006), which examined the effect of divorce law reforms on domestic violence. To estimate equation (1), I use data from Friedberg (1998) on the timing of unilateral, no-fault divorce law reforms, and Census data on educational attainment to construct four-year college graduation rates by birth cohort in each state. I construct the four-year graduation rates based on individuals ages 26 to 35 in the 1960 to 2000 Censuses, starting with the 1930 birth cohorts, up to the 1974 cohort, the youngest available for the analysis in the 2000 Census.

Unlike Stevenson and Wolfers (2006) who used indicators for the number of years since reforms occurred, I include indicators for age at the time of reform as the main independent variables of interest. The reason for this is that Census data is only available in decennial years. As a result, I cannot observe men and women in each calendar year at the typical college graduation age, 21 or 22, or how the shares graduating change with the number of years since reforms were passed. However, I can use a comparable cohort-based measure that focuses on the age that individuals were at the time of the reform. The measure similarly captures the number of years that have passed since the reform at the time those individuals made their educational decision. I assign a single indicator variable to all individuals who were not yet born when a divorce law reform occurred.

Because the Census does not have information on majors, to estimate equation (2) I use state-level data from the Higher Education General Information Survey (HEGIS), which provides data on undergraduate degrees earned yearly by gender and field between 1965 and 1985. The specification includes a full set of state and year-of-graduation fixed effects. The omitted category for the years-since-law indicators corresponds to the states in a given year that are three or more years away from passing a divorce law reform.

A.2 Choices of Major over Time

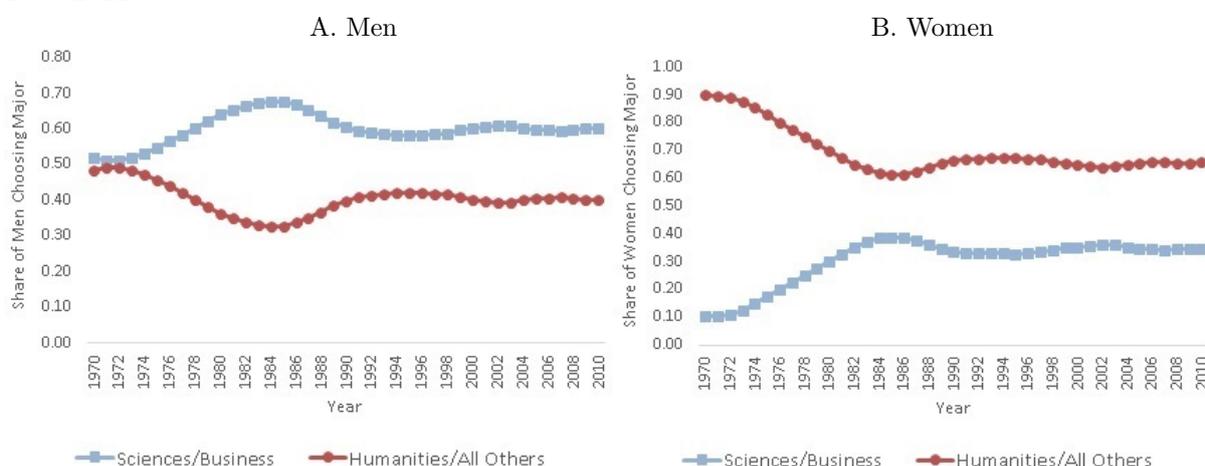
Figure 2 documents a significant increase in the share of women graduating with degrees in business and science, concentrated mostly in the 1970s. However, over time some traditionally “female” majors like education became less popular over time, while other majors that were historically “male” and became more gender-equal, such as business, increased in popularity (NCES (2012)). If these systematic shifts

in popularity persisted after the 1970s, Figure 2 may potentially understate changes in the share of women choosing science and business majors after 1980.

To account for this, Figure A1 graphs separately the share of men and the share of women choosing different categories of majors over time using NCES data. For simplicity, majors are aggregated, as in the previous subsection, into two categories: science/business and humanities/other. Figure A1 documents two patterns. First, for both men and women the popularity of science/business majors as a share of all degrees increased in the 1970s, although the increase was larger for women, meaning that men and women converged during this period. The share of women majoring in science/business quadrupled from about 10% in 1970 to almost 40% by the the mid-1980s. Men’s share increased from roughly 50% to a peak of 68% in 1986, before declining slightly. Secondly, after the mid-1980s the share of men and women choosing a science or business degree has remained roughly stable, at about 60% for men and 36% for women. This implies that convergence virtually ceased after the mid-1980s, as was also documented in Figure 2.

The period of interest in this paper is from 1960 to 2010, but NCES data on these measures begins in 1970. To check whether substantial changes occurred prior to 1970, I use the National Survey of College Graduates, which has data for cohorts that graduated between 1960 and 1970. In the NSCG the share of women graduating with a science/business degree between 1960 and 1970 was almost constant, 15% in 1960 and 16% in 1970. However, the NSCG sample overestimates the share graduating in 1970 relative to the NCES data (10%), which includes the entire population of graduation college students. The NSCG also overestimates the share of men with a science or business degree. It records a temporary decline in the measure over that decade, from 61% to 55%.

Figure A1: Share of Men and Women Choosing “Sciences or Business” vs. Other Major, 1970-2012



Data contains full universe of students graduating from accredited U.S. colleges. Shares sum to one in each year. See Appendix A.4 for details about the classification of majors. Source: NCES (2012), Tables 343-365.

A.3 Hours Worked by Major and Occupation

The time spent out of employment by women with young children, as documented in Table 3 may vary systematically not just with major but also with occupation. As discussed in Section 1, not all women who major in science/business work in a science/business occupation. Moreover, women may switch occupations after leaving the labor force for some period of time.

To address this, I use panel data from the NLSY79 to assign individuals to one of three occupational groups. Individuals are assigned to the first group if their current or most recent occupation is in science/business and they work again in a science/business occupation within the next 6 years. Individuals are assigned to the second group if their current or most recent occupation is in science/business, but they are not employed again in a science/business occupation in a subsequent survey wave within the next 6 years. Finally, individuals are assigned to a third group if they currently work in a non-science, non-business occupation. Note that the first two groups allow me to distinguish between women in science/business who stay in or re-enter their occupation, as compared to women who were in such an occupation but leave.

Table A1 records the labor supply for each of these three occupation groups, separately by major. For conciseness, the table lists annual hours worked. This allows me to analyze simultaneously multiple margins of flexibility, including employment, part-time work, and part-year work. If an individual did not work in the past year, the hours worked for that individual are recorded as zero.

The evidence in Table A1 shows that labor supply varies substantially more across the three groups, when occupations and occupational transitions are accounted for in this way. Among science and business majors, women with young children who ultimately stay in a science/business occupation work more than 1,800 hours annually, an average of 35 hours per week across all women in this group, equivalent to working full-time. By comparison, women with young children in the other two occupation groups worked 961 and 1,272 hours. The patterns for humanities/other majors by occupational group are similar to those for science/business majors.

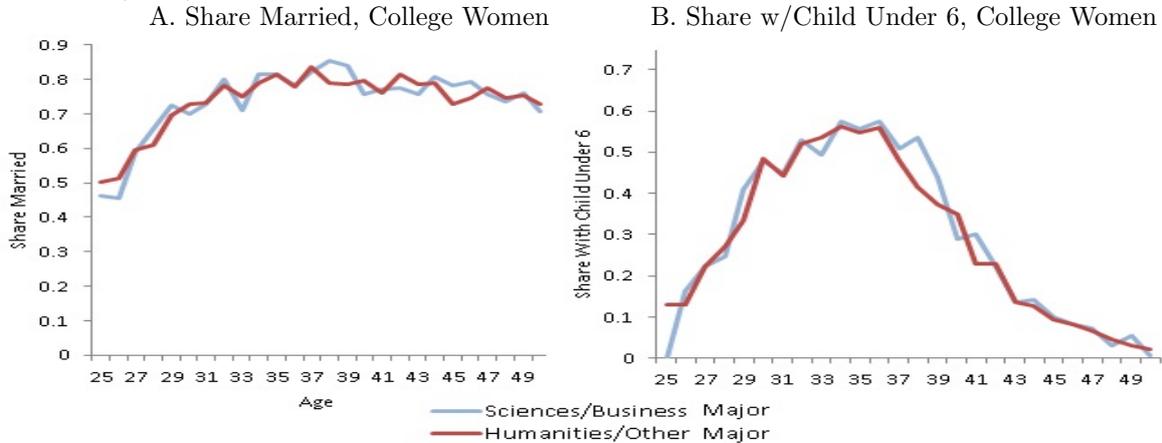
Table A1: Yearly Hours Worked in Different Majors and Occupational Groups

	Women		Men	
	No Children Under 6	Has Child Under 6	No Children Under 6	Has Child Under 6
Science/Business Majors:				
S/B Occupation, Now & In Future	2118.9	1816.7	2300.0	2459.5
S/B Occupation, Now Only	1850.0	961.0	2276.4	2354.4
Other Occupation	1730.7	1272.1	1950.0	2205.3
Other Majors:				
S/B Occupation, Now & In Future	2119.5	1696.9	2267.9	2450.1
S/B Occupation, Now Only	1827.8	1074.2	2177.8	2166.1
Other Occupation	1897.5	1299.5	2046.1	2266.8

S/B refers to science/business. Sample includes individuals ages 25 to 50. Individuals not employed in the current period are assigned the occupation they had in their most recent job. Source: NLSY79.

An important side-note to the previous tables is that they focus on women with and without children under 6, and do not take into account that there may be potential differences across majors in the overall share of women with a child under the age of 6 in the household. For example, if women with science and business are less likely to have a child under the age of 6 in the household, they may also be less likely to want “flexibility.” However, Figure A2 suggests that this is not the case. Figure A2 graphs by major the share of college women who are married (Panel A) and the share who have a child under the age of 6 (Panel B) in 2000. The figure shows that there are virtually no differences in these two measures for women across the two types of major.

Figure A2: Share Married and Share With a Child Under Age 6, College-Educated Women by Major (2000)



Sample includes all female college graduates. Source: NSCG (2000).

A.4 Classifications of Majors

The level of detail available about majors varies across datasets. The analysis categorizes majors as consistently across datasets as possible, but small differences remain. Note that in all the datasets, I assign individuals with pre-med majors preparing for advanced medical degrees with biology/pre-med majors, rather than health/nursing majors. I summarize the classifications used in the three main datasets below.

National Center for Education Statistics. The series for each major in Table 2 are constructed based on data from NCES Digest of Education Statistics, Tables 343-365. Majors are classified as follows. Hard science/engineering: computer and information sciences, engineering and engineering technologies, mathematics and statistics, physical sciences and science technologies, agriculture and natural resources, architecture and related. Biology: biological and biomedical sciences. Business: Business. Social Sciences: Social sciences and history, public administration and social services, communication, psychology. Humanities/Arts: English language and literature/letters, foreign languages and literatures, visual and performing arts. Health: health professions and related programs. In Table A1 the first three categories constitute the science/business category, and the remaining majors constitute sciences/other.

National Survey of College Graduates. The categories in Table 2 are constructed as follows in the year 2000 based on NSCG documentation. Sciences: Mathematical sciences, agricultural and food sciences, biological sciences, environmental life sciences, chemistry, earth science, geology and oceanography, physics and astronomy, other physical sciences. Engineering: Aerospace and related engineering, chemical engineering, civil and architectural engineering, computer and information sciences, electrical and related engineering, industrial engineering, mechanical engineering, other engineering, technology and technical. Business: Economics, management and administration, sales and marketing. Social Sciences: Political and related sciences, psychology, sociology and anthropology, social service and related, other social sciences. Health: Health and related. Education: Science and mathematics teacher education, other education. Humanities: Art and humanities, other. For health majors, I additionally use the more fine-grained classification variable available in the survey and assign all individuals who majored in medical preparatory programs to the sciences category, to distinguish them from individuals with nursing or health support majors. Those who major in health services administration are assigned to the business category. When majors are aggregated, science, engineering and business constitute the science/business category, and all remaining majors belong to the humanities/other category. In the 1993 and 2010 waves, the classification is almost identical.

NLSY79. The analysis using the NLSY79 groups majors into two categories, science/business, and all other majors. They are grouped as follows. Science/business: agriculture and natural resources, architecture and environmental design, biological sciences, business and management, computer and

information sciences, engineering, mathematics, military sciences, physical sciences, and selected interdisciplinary (biological and physical sciences, engineering and other disciplines). Humanities/other: area studies, communications, education, fine and applied arts, foreign languages, health professions (except pre-med), home economics, law, letters, library science, psychology, public affairs and services, social sciences, theology, and selected interdisciplinary (general liberal arts and sciences, humanities and social sciences, recreation, outdoor recreation, counseling, other).