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THE IMPACT OF STUDENT DEBT ON EDUCATION, CAREER, AND MARRIAGE CHOICES OF FEMALE LAWYERS

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ABSTRACT

We develop and estimate a dynamic model to study the impact of student debt on education, career, and marriage market choices of young female lawyers. Our model accounts for several important institutional features of the labor market for lawyers, including differences in the work hours across occupational tracks and learning about the prospects of promotion to partner. Some female students need to take on large amounts of student debt to finance their education and hence start their careers with large amounts of negative wealth. The empirical findings suggest that student debt has negative effects on marriage prospects, career prospects, and investments in educational quality of female lawyers. The analysis also provides new insights into the design of public policies that aim to increase public sector employment. We show that it is possible to design conditional wage or debt service subsidy programs that significantly increase public sector career choices at reasonable costs.

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1 Introduction

Law school tuition increased, on average, by 60 percent in real terms during the past 15 years in the U.S. Based on a recent survey by the U.S. Department of Education the average cost of obtaining a J.D. including tuition, fees, and living expenses was $175,000 in 2011.[1] Hence, many students need to take on substantial amounts of student debt to finance their education. Average debt of law students exceeded $105,000 in 2011. There has been much concern in the legal profession, among policy makers and researchers that the high levels of student debt may significantly distort career choices by discouraging careers in the public sector. Lawyers that are struggling to pay back debt accumulated during graduate school are more likely to accept higher paying jobs in the private sector. Less well-known is the fact that large amounts of debt may also affect the marriage prospects of female lawyers delaying marriage and child rearing. This means student debt may have both a direct effect on occupational choices, but also an indirect effect through marriage prospects. This indirect effect of student debt on marriage prospects may also drive females into private sector jobs since they need to pay back some of their student debts to increase their marriage prospects. Anticipating these negative effects, female lawyers with lower resources may systematically attend lower ranked, cheaper law schools underinvesting in the quality of education. The purpose of this paper is to develop and estimate a dynamic model to study the impact of student debt on education, career, and marriage market choices of young female lawyers and the effectiveness of different types of loan forgiveness programs.

Our model captures the observed heterogeneity among law schools which differ by quality and tuition. Since law school tuition rises substantially with quality, students face a palpable quality-price tradeoff.[2] Students differ with respect to their initial wealth or

[1] It remains as high as $152,000 even after including all grants.

[2] In 2014, the average cost of a J.D. at a top 10 school was $257,000, which was $58,000 higher than at schools ranked in the 31-40 range and $78,000 higher than at schools ranked in the 91-100 range.

resource endowments. If the initial wealth is not sufficient to pay the full costs of the education, a student graduates from law school with significant amounts of student debt or negative wealth. The magnitude of the accumulated student debt depends on the initial wealth endowment and the endogenously chosen quality of the law school attended.

Upon graduation students enter the labor market which offers a number of occupational tracks. In our model lawyers can work for private law firms, take a job in the public sector, work as an in-house lawyer for a private firm, or work part time. Labor markets for lawyers have some special institutional features that need to be modeled. First, a young lawyer employed at a private law firm often faces an up-or-out decision regarding promotion to partner. Promotion to partner is uncertain, but associates are evaluated on an annual basis. A key feature of the model is a learning process which allows associates to infer the likelihood of promotion based on their work experiences. We show that a learning model can explain the rapidly declining prevalence of employment in private law firms during the first 12 years after graduation observed in the data.[3] Second, different careers offer different combinations of hours and earnings. Private law firms require, on average, longer hours than public sector jobs, but offer higher earnings in return. Our model captures these observed differences among occupational tracks.

Young female lawyers are also active in the marriage market. The data suggest that student debt affects the quality of the match and the timing of marriage and child rearing. Our model captures these facts by assuming that potential marriages depend on the amount of wealth and individual characteristics. As a consequence, our model is consistent with the observed fact that female lawyers with large student debt tend to delay marriage and child rearing. Moreover, they tend to prefer higher paying jobs in the private sector to pay off their student debt.

We estimate the model using a combination of two data sets. Our main data set is

[3] Miller (1984) and Crawford and Shum (2005) also estimate dynamic discrete choice models with learning.

called *After the JD*, which is a nationally representative longitudinal dataset assembled by the American Bar Foundation and the National Association for Law Placement. It is drawn from J.D. students graduating in the year 2000. We supplement these data with the *National Postsecondary Student Aid Study*, a nationally representative financial aid survey of students conducted by the U.S. Department of Education. We discuss how to identify and estimate the parameters of our model using a simulated method of moments estimator.

The empirical findings suggest that our model accounts for the fact that negative wealth has large and significant negative effects on female career and marriage outcomes. Specifically, women with more student debt stay longer in private sector jobs, postpone marriage, marry men with lower earnings, and delay childbearing. Differences in female career choices are primarily driven by marriage market prospects. If one equalizes marriage market prospects for females with and without negative wealth, the differences in labor market choices shrink substantially. The intuition is that females with large negative wealth have fewer opportunities in the marriage market, and thereby experience poorer marriage outcomes. Consequently, it takes them longer to meet an acceptable spouse and to have children. Females also significantly under-invest in education quality in anticipation of the diminished marriage market prospects associated with the future debt burden.

The impact of debt on career and marriage choices is specific to female lawyers. We do not observe these negative effects in a corresponding sample of male lawyers. This study, therefore, documents the existence of significant gender differences in labor and marriage markets for lawyers.

Our empirical results speak to a long-standing concern of the legal profession that high costs of law school impel graduates to eschew public service jobs in favor of more lucrative positions in private practices. Much recent interest has focused on the design of public service loan forgiveness programs to partially offset these negative effects. We conclude the analysis by evaluating a variety of different loan repayment assistance programs. We compare an unconditional loan forgiveness policy to career-contingent wage or interest subsidy programs. We show that it is possible to design conditional subsidy programs that significantly increase public sector career choices at reasonable costs. Moreover, these conditional wage or debt service subsidies are more effective than traditional loan forgiveness policies.

This paper builds on the literature that has studied how the rising costs of attending law schools affects career choices. Using a sample consisting exclusively of male law students from the University of Michigan, Sauer (1998, 2004) finds that student debt has only a modest influence on career choices of male lawyers during the first 15 years after graduation. Our study complements this work by focusing on a nationally representative sample of female law students.

Our paper also builds on recent work by Azmat and Ferrer (2016) who use the same data to study the gender gap among young lawyers. They document that females have, on average, worse labor market experiences than males. We complement their empirical analysis by providing a structural analysis of joint education, marriage, and career decisions of female lawyers. This approach allows us to evaluate a variety of different policy options aimed at increasing access to public sector jobs.

Our paper is also related to Field (2009) who studies an experiment that was conducted with male and female students at NYU's law school. This study finds that student debt strongly discourages public sector employment in the first two years of a person's career.[4] Our work focuses on the underlying mechanisms that produce such a strong effect.

This study is also related to the literature that focuses on the relationship between student debt and marriage choices. Addo (2014), Bozick and Estacion (2014), and Gicheva (2014) document that the amount of accumulated student debt is negatively related to the probability of first marriage using nationally representative samples of the National Longitudinal Survey of Youth 1997 (NLSY97) participants, bachelor's degree recipients, and MBA students respectively. We also document significant differences in marriage quality,

[4]Rothstein and Rouse (2011) reach similar conclusion using an experiment with a sample of undergraduate students conducted a highly selective U.S. university.

in addition to differences in marriage rates.

Our paper also builds on the literature that has focused on the effects of liquidity constraints on schooling decisions. Important studies are Keane and Wolpin (2001), Carneiro and Heckman (2002), Cameron and Taber (2004), Stinebrickner and Stinebrickner (2008), Lochner and Monge-Naranjo (2011), and Johnson (2013). The main findings of these papers suggest that a relaxation of borrowing constraints does not significantly increase college enrollment. We evaluate a different set of student debt policies, namely, policies subsidizing repayments in the post-graduation stage.

Our paper is also related to a literature that has studied the gender gap in wages and career advancement in high-paying occupations such as corporate management, law, and academia. Recent studies include, among others, Ginther and Hayes (2003), Ginther and Kahn (2004), Bertrand, Goldin, and Katz (2010), Gayle, Golan, and Miller (2012), and Goldin (2014). We jointly model several elements identified as important in this literature, which include the promotion structure, the time cost of childcare, and the decision to exit an occupation. We incorporate these elements into a coherent structural framework. However, our analysis does not capture informational frictions of the type studied in Albanesi and Olivetti (2009). That paper develops a model in which gender differences in earnings and home hours arise from informational friction. Employers believe that women need more home hours and thus offer labor contracts with lower earnings, performance pay, and effort. As a consequence, the opportunity costs for women to work at home are indeed lower. Hence, women allocate more time to home production confirming firms' beliefs in equilibrium.[5]

The rest of this paper is organized as follows. Section 2 discusses the data used in the analysis and presents the most relevant stylized empirical facts. Section 3 presents the

[5]Albanesi, Olivetti, and Prados (2015) provide supportive evidence using data on pay structures of top corporate executives. Lehmann (2013) uses the first two waves of the After the J.D. to test for statistical racial discrimination.

model that is estimated in this paper. Section 4 discusses identification and estimation. Section 5 summarizes the key empirical results. Section 6 explores the policy implications of our results and evaluates a number of different loan forgiveness policies. Section 7 offers some conclusions.

2 Data

2.1 The Sample

The empirical analysis is based on a data set called *After the JD*, which is a nationally representative longitudinal data set constructed by the American Bar Foundation and the National Association for Law Placement. The data set follows students who graduated in 2000. The current version of the data set covers the first twelve years of student careers. The respondents were surveyed three times: once each in 2003, 2007, and 2012. After eliminating data points with missing information, our sample contains a total of 1193 females.

The data set contains detailed information about the law school that was attended by each student. For confidentiality reasons, law schools are grouped into four tiers according to the rankings in *U.S. News and World Reports Rankings 2003*, which ranks the top 100 law schools in the country, and then assigns all unranked schools into one of two groups, Tier 3 or Tier 4. In the dataset, the American Bar Association bundles the top 20 schools as Tier 1 and the remaining ranked schools as Tier 2.

The data set does not contain separate measures of wealth. However, it is well known that most young households in the U.S. do not have much wealth. In practice, all wealth that a student may have prior to entering law school is likely used to pay for the cost of attending law school. Each participant of the survey reports total student debt upon graduation and the remaining debt in 2006 and 2012. We treat this report as a measure of the negative wealth of a student.[6]

The data set contains the full employment history for each individual in the sample including organizational types and positions since 2000. It also reports salary and working hours for the jobs held in 2003, 2006, and 2012. Similarly marital status is reported in 2003, 2006, and 2012.[7] We also observe spousal salary in 2006 and 2012, and the ages of all children as of 2012.

We also need to characterize the initial conditions when making law school choices. In particular, it is important to have information about unpaid debt from prior education and available monetary resources. We, therefore, turn to the *National Postsecondary Student Aid Study*, a nationally representative survey of students conducted by the U.S. Department of Education in 2000, approximately the same cohort as the respondents in *After the JD*. The dataset contains 170 female J.D. students. The dataset provides measures of outstanding college debt, various sources of funding for law school education, tuition and expenses, and other demographics.

Finally, we need to characterize the admission rules of law schools. In both datasets, we observe the students' choices but not their choice sets. Without explicitly accounting for the admission rules, it is hard to separate a student's preferences from her constraints when choosing schools. We, therefore, exploit another data set called *Law School Numbers*, which was founded in 2003 as a free, publicly accessible database of user-supplied law school applicant information. Users provide LSAT, GPA, application and later admission portfolios. We extrapolate the admission rules in 1997 based on the 15,222 observations from the 2003-2008 cycles.

Table 1 provides selected summary statistics. *Prior debt* represents the unpaid college

[6]This treatment is consistent with our model below that abstracts from saving. Hence the remaining student debt is our measure of negative wealth. For the rest of the paper we will use debt and negative wealth synonymously.

[7]Cohabitation is counted as marriage. Cohabitation accounts for 3 percent of whole sample. The results change little by treating cohabitation as single.

Table 1: Descriptive Statistics

		Mean	SD	N	Dataset
Background	LSAT	157.9	6.8	170	NPSAS
	$I(3.75 \geq GPA \geq 4)$	25.9		219	AJD
	$I(3.50 \geq GPA \geq 3.75)$	26.4		223	AJD
	$I(3.25 \geq GPA \geq 3.50)$	24.1		204	AJD
	Age upon graduation	28.3	4.6	1174	AJD
	Prior debt	9.4	13.7	170	NPSAS
	Monetary resources	56.3	48.8	170	NPSAS
School Cost	Tuition	65.5	11.3	170	NPSAS
	Expense	55.7	2.6	170	NPSAS
Debt	Debt upon graduation	85.2	58.3	1193	AJD
	Unpaid debt after 6 years	45.4	46.6	1166	AJD
	Unpaid debt after 12 years	30.3	40.1	838	AJD
Pay and Hours (3 years post-graduation)	Private Law				
	Annual Salary	115.9	50.8	431	AJD
	Weekly Hours	47.8	12.7	405	AJD
	Public/Business				
	Annual Salary	80.0	80.7	279	AJD
	Weekly Hours	45.3	11.9	213	AJD
Pay and Hours (6 years post-graduation)	Private Law				
	Annual Salary	131.9	64.1	376	AJD
	Weekly Hours	48.9	13.4	442	AJD
	Public/Business				
	Annual Salary	98.9	40.6	403	AJD
	Weekly Hours	44.8	13.5	452	AJD
Pay and Hours (12 years post-graduation)	Private Law, Associates				
	Annual Salary	126.4	95.4	121	AJD
	Weekly Hours	47.0	14.0	146	AJD
	Private Law, Partners				
	Annual Salary	197.8	20.1	74	AJD
	Weekly Hours	48.1	11.2	95	AJD
	Public/Business				
	Annual Salary	119.0	70.5	357	AJD
	Weekly Hours	44.3	11.9	401	AJD

AJD refers to *After the JD*. NPSAS refers to *the National Postsecondary Student Aid Study*. All monetary values are in thousands of 2014 $.

debt, with an average of \$9,400, which is much lower than the total amount of *debt upon graduation*, which averages $\$85,200$ in our sample. *Savings* represents all the non-debt monetary resources students use to finance law school education, including family transfers, own savings, grants, etc. We treat grants as exogenous because merit-based institutional grants are very limited.[8] Students still owe on average \$45,400 six years after graduation, and \$30,300 twelve years after graduation.[9]

Females students graduate, on average, at age 28, further reinforcing the importance of modeling marriage and childbearing decisions in subsequent years. The median work week in the private sector is 48 hours, or 11 percent, longer than in the public or business sector (in-house council, legal adviser, etc), while the pay is approximately 35 percent higher. Note that these differences persist among time. Not surprisingly, we find that partners' earnings are significantly higher than associates' earnings.

Table 2: Market Shares of Law Schools

Share in Each Type of Education (%)				
	Tier 1	Tier 2	Tier 3	Tier 4
Enrollment	24	48	15	13

Table 2 reports the market shares of each law school type in our sample. It shows that Tier 2 law schools capture almost half of the market.

Table 3 reports the market shares of each occupation in four different years. Recall that our paper primarily focuses on the transition between private practice employment and other occupations. For that reason we aggregate all other occupations into two categories.

[8] In the sample, students on average receive \$7,000 of merit-based institutional grant, which accounts for only 6 percent of the cost of J.D. education. Only 11 percent of students receive merit-based institutional grant covering 20 percent or more of the cost.

[9] While the data set contains detailed information about financial transfers and resources of students, we find that the reported values do not fully reflect all the resources available to students and are typically too low to explain the observed levels of debt after graduation. We impute values of the financial endowments that are consistent with our key equations (4) and (5) that characterize the evolution of debt before graduation, i.e. we impute resources that are consistent with posted tuitions, estimated living expenditures, undergraduate debt, and observed levels of debt upon graduation from law school.

The first category captures public employment and employment in the business sector. The second category captures females who work part-time or are not employed in the labor market.

Table 3: Occupational Sorting

	Share in Each Occupation (%)			
	Private Practice		Public or Business Sector	Not Employed or Part-time
	Associates	Partner		
2003	52	0	33	15
2005	43	0	36	21
2007	31	5	39	25
2012	16	12	47	25

We observe a significant decline in the participation of female lawyers in private law firms. At the same time, the share of female lawyers rises in all other sectors.

2.2 Some Stylized Facts

We document four facts about the relationship between negative wealth (measured by outstanding student debt) and career choices, marriage, and childbearing outcomes for female lawyers. We divide the sample into three groups of similar size by the amount of student debt upon graduation. We call these groups *Low Debt*, *Medium Debt*, and *High Debt*. The average student debt for the three groups are $18,300, $84,900 and $145,500, respectively. We then calculate work experience, marriage rates, spousal earnings and the probability of having children for each group. We also calculate the differences in these outcomes between each group and the *Low Debt* group.[10]

Stylized Fact 1 *Females with high debt are more likely to work for private law firms than females with low debt.*

[10] Appendix B shows that all findings reported in this section are robust to including a standard set of controls in a regression analysis.

We calculate the choice probability at private practice in the 7th and the 12th year post-graduation for each debt group. As displayed in Table 4, in the 7th year, 42% of the *High Debt* group work in the private law firms, while only 29% of the *Low Debt* group do. In the 12th year, the corresponding choice probabilities are 35% and 21%. T-tests and F-test show these gaps are statistically significant.[11]

Table 4: Choice Probability at Private Practice

In the 7th Year Post-Graduation					
Group	Prob	Group Differences			
Low Debt ($18,300)	0.29		Mean	S.E.	t-stat
Medium Debt ($84,900)	0.37	Medium - Low	0.08	0.03	2.45
High Debt ($145,500)	0.42	High - Low	0.13	0.03	4.04
In the 12th Year Post-Graduation					
Group	Prob	Group Differences			
Low Debt ($18,300)	0.21		Mean	S.E.	t-stat
Medium Debt ($84,900)	0.28	Medium - Low	0.07	0.04	2.02
High Debt ($145,500)	0.35	High - Low	0.14	0.04	3.93
No differences across groups : p-value = 0.000					

Stylized Fact 2 *High-debt females are more likely to postpone marriage than low-debt females.*

We calculate marriage rates by age 34 and 40 for each debt group. Table 5 shows that the marriage rates for the three groups are 74 percent, 69 percent and 65 percent respectively by age 34. A *High Debt* individual is 12 percent less likely to be married by age 34 than a *Low Debt* individual. These gaps are statistically significant.[12]

[11]This fact is consistent with Rothstein and Rouse (2011), who find that student debt causes undergraduate students at a highly selective university to avoid low-paid "public interest" jobs and choose substantially higher paying jobs instead.

[12]We also calculate the marriage rates by other ages, but the pattern remains both quantitatively and statistically the same.

This marriage gap persists at age 40. The marriage rates are 85 percent for low debt females and 77 percent for high-debt females.[13] We thus find that the gap narrows by age 40, but it is still persistent.

Table 5: Marriage Rates

By Age 34					
Group	Group Average	Group Differences			
Low Debt ($18,300)	74		Mean	S.E.	t-stat
Medium Debt ($84,900)	69	Medium - Low	4.7	3.6	1.30
High Debt ($145,500)	65	High - Low	8.8	3.6	2.48
No differences across groups : p-value = 0.047					
By Age 40					
Group	Group Average	Group Differences			
Low Debt ($18,300)	85		Mean	S.E.	t-stat
Medium Debt ($84,900)	81	Medium - Low	3.8	3.5	1.09
High Debt ($145,500)	77	High - Low	7.1	3.5	2.07
No differences across groups : p-value = 0.039					

Stylized Fact 3 *Spouses of high-debt females have lower earnings than spouses of low-debt females.*

Not only do females with high debt delay marriage, they also seem to, at least, initially obtain worse matches in the marriage market. We illustrate this feature by comparing the spousal earnings conditional on getting married. Spousal earnings is our best measure of the "quality" of match.

Table 6 shows that spouses of *Low Debt* females earn an average of $113,000 annually, which is $16,000, or 16.5 percent, higher than their *High Debt* counterparts. Hence, there are significant differences in match quality at age 34.

[13] This fact is consistent with Addo (2014), Bozick and Estacion (2014) and Gicheva (2014), all of whom document that accumulated student debt is negatively related to the probability of first marriage using national representative samples of NLSY97 participants, bachelor's degree recipients, and MBA students respectively.

It is, however, important to point out that these differences disappear over time. Differences in spousal earnings are not significant 12 years after graduation. We, therefore, conclude that the gap between low- and high debt females closes over time as females pay down their debt.

Table 6: Spousal Earnings

6 Years Post-Graduation					
Group	Group Average	Group Diff			
Low Debt ($18,300)	113,000		Mean	S.E.	t-stat
Medium Debt ($84,900)	99,000	Medium - Low	14,000	9,000	1.52
High Debt ($145,500)	97,000	High - Low	16,000	8,000	1.97
No differences across groups : p-value = 0.120					
12 Years Post-Graduation					
Group	Group Average	Group Diff			
Low Debt ($18,300)	138,000		Mean	S.E.	t-stat
Medium Debt ($84,900)	117,000	Medium - Low	21,000	15,000	1.38
High Debt ($145,500)	135,000	High - Low	3,000	16,000	0.15
No differences across groups : p-value = 0.878. Earnings are in 2014 constant dollars.					

Stylized Fact 4 *Females with high debt are more likely to postpone childbearing than females with low debt.*

Lastly, we compare the probability of having a child by age 34 and 40 across debt groups. Table 7 shows that *Low Debt* females are 30 percent more likely to have children by age 34 than *High Debt* females. The gap shrinks to 6.3 percent by age 40. Again, there are significant differences early, but the gap closes over time as one would expect.

In summary, female lawyers with large amounts of negative wealth have different labor market, marriage, and child rearing outcomes than their more wealthy peers. One might be concerned that the differences in outcomes may not reflect differences in debt of females lawyers, but differences in wealth among the parents of these lawyers. Unfortunately, “After the JD” does not include parental wealth as a variable. Hence, we cannot directly

Table 7: Probability of Having a Child

By Age 34					
Group	Group Average	Group Diff			
Low Debt ($18,300)	0.49		Mean	S.E.	t-stat
Medium Debt ($84,900)	0.43	Medium - Low	0.06	0.04	1.64
High Debt ($145,500)	0.38	High - Low	0.11	0.03	3.19
No differences across groups : p-value = 0.007					
By Age 40					
Group	Group Average	Group Diff			
Low Debt ($18,300)	0.68		Mean	S.E.	t-stat
Medium Debt ($84,900)	0.66	Medium - Low	0.02	0.04	0.45
High Debt ($145,500)	0.64	High - Low	0.04	0.04	0.98
No differences across groups : p-value = 0.328					

test the hypothesis that differences in outcomes reported above are due to differences in parental wealth. However, the data set includes variables such as parental education and an indicator whether parents have been lawyers. These variables are likely to be correlated with parental wealth. We have included these additional regressors in the key outcome regressions reported in Appendix B. We find that the estimates of the impact of debt on the two most important outcomes – marital status and spousal earnings – are not affected by including these additional parental background characteristics. Father's education and mother's education are not significantly related to marriage status or spousal earnings. It also does not matter whether the father or mother has been a lawyer. In contrast, debt at graduation is still significant even after controlling for these additional regressors. As a consequence, our main empirical findings do not appear to be driven by omitted variables such as parental wealth.[14]

[14] These results also suggest that we do not need to control for these parent background variables in our structural model discussed below.

2.3 Gender Differences

The findings reported above suggest that debt affects the careers of female lawyers. However, debt does not strongly affect male lawyers. To illustrate these important gender differences we also compute the same statistics reported in Section 2.2 for the male sample.[15] We find that there are no significant differences in outcomes for males among the three different debt groups.

It is interesting to speculate why we observe these gender differences. One important difference between male and female lawyers is that male lawyers tend to have more traditional marriages than female lawyers. Table 8 compares the earnings and labor market participation rates among couples with male and female lawyers.

Table 8: Spousal Earning and Employment Status by Gender

	Male Lawyers	Married Male Lawyers	Spouses of Female Lawyers
Earning	133.2	135.0	103.2
Being Employed	98.1%	98.4%	93.0%
Earning, employed	135.4	137.0	110.1
	Female Lawyers	**Married Female Lawyers**	**Spouses of Male Lawyers**
Earning	101.9	97.9	50.5
Being Employed	90.6%	88.5%	62.3%
Earning, employed	110.8	109.2	80.4

All monetary values are in thousands of 2014 dollars.
The table combines part time and full time work.

Note that spouses of female lawyers work less and have on average lower earnings than male lawyers. The differences in participation rates are, however, small. Female lawyers in our sample have significantly higher earnings than spouses of male lawyers. The difference in participation rates is more than 25 percentage points. Moreover, most female lawyers –

[15]These relevant tables are available in an online appendix.

especially those with high debt – tend to work full time and hence are in marriages where both partners work full time.

To gain some additional insights into the underlying mechanisms that may explain the effects of debt on female lawyers we develop and estimate a dynamic model of decision making. In our model, negative wealth affects both the attractiveness of females in the marriage market and the consumption opportunities via the budget constraint.

3 Model

3.1 The Timeline

We model the sequence of decision problems of a female that has decided to pursue a career in law. The model consists of two stages: a schooling stage and a labor market stage. The first three periods correspond to the schooling stage. Students choose a law school among a set of differentiated schooling options. After graduating from law school, female lawyers are active in the labor market during the remaining periods of their careers. Each lawyer can choose among job offers from different occupational tracks. In addition, each female participates in the marriage market which is characterized by stochastic assortative matching. Job offers, promotions, marriage offers, and children arrive stochastically over time. The timeline of decisions and key outcomes are illustrated in Table 9. We discuss each of the three markets in detail below.

3.2 The Marriage Market

We follow Keane and Wolpin (2010) and assume that marriage markets are characterized by stochastic assortative matching. The empirical evidence suggests that the probability that a single individual receives a marriage offer is primarily a function of age. As a consequence

Table 9: Timeline

$t = 1$	Applies to all law schools and receives admissions. Marriage offer arrive. Makes joint schooling and marriage decisions. May have a newborn child.
$t \in \{2, 3\}$	Marriage offers may arrive. Makes marriage decisions. May have a newborn child.
End of $t = 3$	Draws a signal for match value for a private law profession.
$t = 4, ..., \tau$	Marriage offers and job offers arrive. Makes joint marriage and labor market decisions. Consumes and makes debt repayment. Receives signals and updates beliefs. May have a newborn child.
Note: This table illustrates the timing of decisions in our model.	

we assume:

$$Pr(\text{Receives a marriage offer}) = \beta_0^M + \beta_1^M A_t + \beta_2^M A_t^2 \tag{1}$$

Age effects capture the fact that marriage rates peak early and then decline sharply.[16] The quality of a marriage offer is characterized by spousal earnings given by:

$$\ln W_t^S = \beta_1^S dm_t(D_j) + \beta_2^S X_t^S + \beta_3^S X_t^S dm_t(D_j) + \sum_{j=1}^{J} \beta_{4j}^S S_j + \epsilon_t^S \tag{2}$$

This specification captures the idea that the quality of an individual's pool of potential husbands depends on the female's outstanding debt, denoted by $dm_t(D_j)$.[17] Our model thus

[16]We only report the specification that we use in the final version of the paper. We explored alternative specifications in our previous work. In general, we tended to select the most appropriate parsimonious model specification.

[17]The law of motion for debt is explained in detail below.

reflects stochastic assortative matching in the marriage market by wealth and education. Note that all females receive offers at the same rate conditional on age, but the quality of the offers depends on the outstanding student debt. We also observe systematic differences by law school attended which is captured by the terms denoted by S_j. This component is observed by the female at the time of the match. The husband's earnings also grow over time with experience, X_t^S.[18] The interaction term captures a catch-up effect since earnings of spouses of high debt lawyers tend to rise slightly faster in the data. In addition, there is an i.i.d. random component ϵ_t^S that reflects a permanent unobserved characteristic of a potential husband.

Marriage is a terminal state in our model. We do not model divorce since divorce rates are low in our data set. Only 6% of marriages end up in divorces over the 12-year sample period.

We model childbearing as an exogenous process rather than a direct choice. That said, we find that being married is associated with a substantial increase in the probability of having children. Childbearing is an indirect endogenous choice realized through marriage decisions. Children arrive stochastically, with arrival rates depending on age and marital status:

$$Pr(\text{new child at period } t) = logistic\{\beta_0^K + \beta_1^K A_t + \beta_2^K A_t^2 + \beta_3^K m_t + \beta_4^K m_t A_t + \beta_5^K m_t A_t^2\} \quad (3)$$

We also find that after controlling for the aforementioned variables, income or wealth (debt) are not significantly related to the probability of having children.

[18]We proxy experience using age of the husband which is consistent with the fact that many males work full time in most periods after graduation.

3.3 The Education Market

Students initially differ by ability, which is measured by undergraduate GPA and $LSAT$.[19] Students have monetary resources, E, which consist of parental transfers, own savings, grants, and other non-debt monetary resources that can be used to pay for tuition. Finally, students differ by unpaid student debt from undergraduate education D^U.

There are J different types of law schools. Each school charges tuition T_j, requires living expenses P_j, and implements admission rules $\Psi_j(GPA, LSAT) \in [0, 1]$. Compared with undergraduate schools, law schools offer fewer merit-based grants and scholarships. Therefore, we assume a common tuition rate for all students. The admission rules accommodate uncertainty in the admission process, since individuals with the same ability can have different admission results.

In the first period a student applies to all schools and selects one from among those to which she is admitted. She needs to finance the cost of education $T_j + P_j$ with monetary resources E. If these prove insufficient, then she must borrow D_j^G, where

$$D_j^G = \max(T_j + P_j - E, 0) \tag{4}$$

The total accumulated debt upon graduation from school j is

$$D_j = D_j^G + D^U \tag{5}$$

A student can only borrow to finance tuition and basic living expenses. She cannot borrow to boost consumption in the schooling stage. Schooling choices are only made once and are

[19] We do not include unobserved ability into the model specification for two reasons. First, our specification is already quite complicated and allows for unobserved state variables in the learning process. Second, we have access to a number of different observed measures of ability such as GPA and LSAT which should capture the most important differences in ability. Future research should evaluate more sophisticated models that also allow for unobserved differences in ability.

irrevocable; students do not drop out.[20]

Since we do not observe consumption during the education stages, we proxy consumption with school specific living expenditures given by:

$$C_{jt} \;=\; P_j \tag{6}$$

Leisure is determined by school specific work requirements. We also include a time cost for taking care of children denoted by λ.

$$L_{jt} \;=\; H \;-\; H_j \;-\; \lambda\, k_t \tag{7}$$

H_j denotes average study time as a graduate student at school j. k_t denotes the presence of children in the household.[21]

We assume that the deterministic part of the flow utility function associated with each school choice j conditional on marriage status is given by:

$$U_{jt} \;=\; \phi_0 \ln(C_{jt}) + (1-\phi_0)\ln(L_{jt}) + \mu_1 m_t + \zeta_j \tag{8}$$

Note that the first term captures general preferences over consumption and leisure which is given by a Cobb-Douglas function. The next term captures non-pecuniary benefit from marriage. The last term captures non-pecuniary benefit from attending law school.

In addition, there is an additively separable idiosyncratic preference shock for each potential school-marriage choice. These shocks follow a Type I extreme value distribution (McFadden, 1974).

[20] 3-year attrition rates are as low as 5 percent, as calculated by the authors using the enrollment and degrees awarded data published on the American Bar Association.

[21] We also solved versions of the model that included pecuniary costs of raising children as discussed in detail below.

3.4 The Labor Market

Hours and Earnings

Upon graduating from law school, females enter the labor market. We assume that there are four potential occupational choices: a private law firm associate position ($l = 1$), a partner position ($l = 2$), a public sector or business sector position ($l = 3$), and part-time employment ($l = 4$).[22]

Each period, a female obtains an earnings-hour draw from an occupation specific distribution. Let W_{lt} denote the earnings in occupation l and H_{lt} the required number of hours. Each period a earnings-hour pair is drawn from a multivariate lognormal distribution that depends on ability, schooling and work experience. Job offers in occupation $l \in \{1, 2, 3, 4\}$ at year t are specified as:

$$\ln(W_{lt}) = \sum_{j=1}^{J} \beta_{1jl}^{W} S_j + \beta_{2l}^{W} GPA + \beta_{3l}^{W} X_t^R + \beta_{4l}^{W} X_t^P + \beta_{5l}^{W} (X_t^R)^2 + \beta_{6l}^{W} (X_t^P)^2 + \varepsilon_{lt}^{W} \quad (9)$$

$$\ln(H_{lt}) = \beta_{0l}^{H} + \varepsilon_{lt}^{H} \quad (10)$$

where X_t^R denotes the working experience in private law firms, and X_t^P denotes the working experience in public/business sector.[23] The specification of the hours equations reflects the fact that observed hours do not systematically vary with ability, education, or experience, but they do vary across occupational tracks in our sample.

[22] The number of women that do not work at all is surprisingly small in the After the JD. As a consequence, we do not differentiate between part time work and unemployment. Our earlier analysis also suggests that there are few gains from differentiating between public sector jobs and business sector positions. The share of business sector jobs is small and the observed hours and earnings are similar to the public sector.

[23] For simplicity, we assume that income and hours are independent from each other and serially uncorrelated. Our model generates persistence in occupational choices by allowing for switching costs.

Preferences and Budgets

Next we derive the budget set which depends on two components: family income and debt repayment. The schedule for debt repayment is given by:

$$dp_t(D) = D\frac{r}{(1+r)(1-(1+r)^{-T_0})} \tag{11}$$

$$dm_t(D) = D\frac{1-(1+r)^{(t-T_0-1)}}{1-(1+r)^{-T_0}} \tag{12}$$

where t denotes the time period, dp_t is the annual repayment, dm_t is the remaining debt in the beginning of period t. T_0 is the initially scheduled length of repayment. r is the interest rate. Individuals pay equalized repayments during T_0. T_0 is set to be 15 years and r to 7 percent.[24]

If both spouses are active in the labor market, we allow for income sharing between spouses. The rate of income sharing is denoted by γ. The budget constraint is, therefore, given by:

$$C_{lt} = W_{lt}\,(1-m_t) + \gamma\,(W_{lt} + W_t^S)\,m_t - dp_t(D_j) \tag{13}$$

The time constraint is given by:

$$L_{lt} = H - H_{lt} - \lambda\,k_t \tag{14}$$

We assume that the deterministic part of the flow utility function associated with occupational choice l conditional on marital status is given by:

$$U_{lt} = \phi_0 \ln(C_{lt}) + (1-\phi_0)\ln(L_{tl}) + \mu_1 m_t + \psi_l \tag{15}$$

[24]Appendix D discusses how well this model tracks the observed levels of debt over time.

As before, the first two terms capture preferences over consumption and leisure. Note that our specification of the utility function does not allow us to disentangle risk aversion from substitution between leisure and consumption. The parameters of the utility function are, therefore, primarily identified of the observed leisure-consumption trade-offs. The next term capture the non-pecuniary benefits from marriage. The last term captures non-pecuniary benefit from each occupation. This captures the role of work schedule flexibility, stress, social status, and other unobserved amenities.[25]

We also include asymmetric switching costs between each occupation to our utility specification to generate persistence in occupational choices. These additional parameters are omitted from the equation above to simplify the notation. Alternatively, one could generate persistence in occupational choices by including time dependence in the error structure of the earnings.[26]

Finally, there is an additively separable idiosyncratic preference shock for each potential occupation-marriage choice. These shocks follow a Type I extreme value distribution.

Learning and Promotion to Partner

Private law firms feature a promotion process for associates to advance to partners. Since promotion is uncertain, we allow for learning about the likelihood of being promoted to partner. Each individual is characterized by a unique time-invariant match value for the private law sector, denoted by $\xi \in (0, 1)$. We assume that ξ is not directly observed by the individual. Instead, she receives experience signals, denoted by s_t, in each period she works in private practice. These experience signals can be interpreted as reviews from senior partners. Individuals have prior beliefs about match values and have an incentive to learn their match values through the experience signals.

[25]Our estimated model also allows the attractiveness of public sector jobs to depend on the presence of children to explain the increasing attractiveness of these jobs for working mothers.

[26]In addition, it may be desirable to allow for contemporaneous correlation in earnings shocks among sector. For a more detailed discussion, see Sauer(1998, 2004).

The match value is drawn from a $Beta(\eta_1, \eta_2)$ distribution upon graduation. The individual receives signal s_t about her match value at the end of t if she takes an associate position. s_t is a Bernoulli random variable such that

$$Pr(s_t = z) = \begin{cases} \xi & \text{if} \quad z = 1 \\ 1 - \xi & \text{if} \quad z = 0 \end{cases} \tag{16}$$

Binary signals can be interpreted as "good" or "bad". The probability of promotion to partner is given by:

$$logistic\{\sum_{j=1}^{J} \alpha_{0j} S_j + \alpha_1 GPA + \alpha_2 X_t^R + \alpha_3 (X_t^R)^2\} \times \frac{\sum_{s=1}^{t-1} s_s O_{1s}}{\sum_{s=1}^{t-1} O_{1s}} \tag{17}$$

where O_{1s} is an indicator variable that is equal to one if the individual works as an associate in a private firm and zero otherwise.

Parameters α_2 and α_3 capture the idea that the promotion probability varies with experience in private law firms. Once promoted to partner, the position is permanent. In addition, we assume individuals have to work in private law firms to receive partner offers. That is, the arrival rates of partner offers to public/business sector employees is zero.[27]

The individual does not know the true value of ξ. Instead, she has beliefs about this value given by $Beta(B_t^1, B_t^2)$, which she updates at the end of each period. The initial beliefs at the end of period $t = 3$ are specified as:

$$\begin{aligned} B_3^1 &= \xi \ \exp(\eta_0) \\ B_3^2 &= (1 - \xi) \ \exp(\eta_0) \end{aligned} \tag{18}$$

[27] These assumptions do not contradict any data. Although it is possible for an experienced public defender to directly receive a partner offer, it rarely happens for younger lawyers.

Individuals update beliefs according to Bayes' rule:

$$\begin{aligned} B_t^1 &= B_3^1 + \sum_{s=4}^{t-1} s_s \, O_{1s} \\ B_t^2 &= B_3^2 + \sum_{s=4}^{t-1} (1 - s_s) \, O_{1s} \end{aligned} \tag{19}$$

3.5 Dynamic Choices

Each individual maximizes expected lifetime utility by choosing one of the feasible discrete alternatives in her time-dependent choice set in each period, until a known terminal period. The maximization problem can be recast as a recursive, finite-horizon, dynamic programming problem. Females differ by a vector of time invariant state variables such as test scores and initial student debt. In addition, key state variables that change over time are the unpaid student debt, the occupation specific experience levels, and the two variables that characterize the beliefs regarding promotion to partner.

We assume that each discrete choice has an additively separable idiosyncratic error. Moreover, these errors follow a Type I extreme value distribution. We can therefore use the techniques discussed in Rust (1994) to simplify the calculation of the conditional and expected value functions. We can solve the model using backward induction.[28] Given the optimal decision rules, we simulate the model to compute the key moments used in estimation discussed below.

[28] To minimize the impact of functional form assumptions, we approximate the terminal value functions by solving the model for an additional two years past the 12 years covered in our data set. Different approaches to deal with this issue are discussed, for example, in Sauer (2004), and Kaplan (2012).

4 Estimation

We have adopted a method of simulated moments approach to estimate the key parameters of our model. While a likelihood based approach may be more efficient, computing the likelihood for our model would be challenging given that the presence of latent state variables due to the learning process.[29]

Denote the parameter vector by ϕ. Let ϕ_0 denote the vector that characterizes the data-generating process. Let N denote the sample size of the After the JD Sample. Combine all empirical moments used in the estimation procedure into one vector m_N and denote with $m_S(\phi)$ their simulated counterparts, where S denotes the number of simulations. The orthogonality conditions are then given by:

$$g_{N,S}(\phi) = m_N - m_S(\phi) \tag{20}$$

Following Hansen (1982), the parameters of our model can be estimated using the following moments estimator:

$$\hat{\phi}_{N,S} \;=\; \arg\min_{\phi \in \Phi} \;\; g_{N,S}(\phi)' \, W_N \, g_{N,S}(\phi) \tag{21}$$

for a weighting matrix W_N that converges in probability to a positive semi-definite matrix W_0.[30]

The estimator $\hat{\phi}_{S,N}$ is a consistent estimator of ϕ_0 and the asymptotic covariance matrix of the estimator is given in Newey and McFadden (1994). It is straightforward to correct for the sampling error induced into the estimation procedure by the simulations. However, if the number of simulations is large, these errors will be negligible.[31] To understand the

[29]See, for example, Eisenhauser, Heckman, and Mosso (2015), for a discussion of the trade-offs between SMLE and SMM.

[30]We use the inverse of estimated variances of the sample statistics as weighting matrix.

[31]Note that the simulation error can be made arbitrarily small by letting S be large relative to N. The

basic ideas behind our approach to identification and estimation, we offer a few additional observations.

First, consider the parameters that characterize labor market outcomes. These include the parameters of the job offer distributions and the arrival rate of partner promotions. Recall that job offers depend on law school quality, academic skills as measured by test scores, and sector-specific work experience. These parameters are primarily identified by the conditional means of the accepted job offers. Note that we explicitly model the selection process using functional form assumptions on the distribution of wage offer distributions. Moreover, we choose spousal income as a plausible exclusion restriction assuming that it affects occupational choices by altering the budget constraint. Spousal income does not affect the earnings equations of the three occupations. Similarly, arrival rates of partner promotion depend on a similar set of variables. These parameters are identified based on the observed conditional promotion probabilities.

Second, consider the parameters that relate to marriage market outcomes, which include the parameters in the marriage offer arrival rates and the parameters of the marriage offer distribution. Marriage offer arrival rates depend only on age. The marriage offer distribution also depends on law school rankings. We observe conditional marriage rates and conditional means of spousal income. A difficulty is to disentangle the arrival rate of marriage offers from the distribution that characterizes spousal quality. To this end, we exclude variables that affect the marriage offer distributions but not the offer arrival rates such as school quality. Similarly age affects the probability of receiving an offer, but not spousal income.

Third, consider the preference parameters which are largely identified using moments generated by interacting observed occupational choices with variables such as school quality,

simulated moments are generated for any given set of parameters by simulating 30000 histories. For a discussion of the theoretical properties of these estimators, see McFadden (1989) or Pakes and Pollard (1989).

experience, test scores, debt, marital status, whether children are present, and spousal earnings. The idea is that these interacted variables may affect occupational choices by altering the marginal utility derived from consumption and leisure. Similarly, we can identify the preference parameters in the schooling stage by matching matriculation rates, average academic skills, monetary resources, remaining debt, and total borrowing by school.

One particularly salient pattern concerns the high attrition rates in the private law sector. The share of employment in the private law sector shrinks by close to 50 percent for females from top schools. Similar patterns can be observed for graduates from lower ranked schools. It is worth noting that most of these attritions occur less than seven years after graduation, and thus far in advance of the partner promotion evaluations. The learning process then generates sufficiently high attrition rates in the private law sector.[32]

An alternative explanation of high attrition rates and of low public employment rates by students with high debt is that starting a career in the private sector tends to be more reversible than starting a career in the public sector. If this is the case, debt might discourage public sector employment only temporarily. Furthermore, if starting a career in the public sector is less reversible, it might not be as desirable to encourage public sector participation in early career stages. We have, therefore, also included asymmetric occupational switching costs to capture the fact that easier to move from the private sector to the public sector than the other way around.

We use outside estimates for a small number of parameters. The discount factor is set equal to 0.96. Tuition and living expenses are set equal to the average level in NPSAS. Admission rules are recovered using *Law School Numbers*. The time cost of childcare is set equal to 600 hours a year, and the intra-family income sharing rule is 0.6 (Keane and Wolpin, 2010).

[32]Note that Sauer (1998) generates a decline in private sector employment without relying on a learning model. Instead he uses permanent unobserved discrete types. We abstract from these unobserved differences. But note that in our data the share of private sector employment declines from 52% in Year 3 to 36% in Year 7 which is much steeper than the decline observed for males.

Instead of using a MSM estimator, we could have estimated the model using an indirect inference approach (Gourieroux, Monfort, and Renault, 1993). To assess the potential gains from implementing an indirect inference approach we have also estimated the regressions reported in Appendix B using simulated data from our estimated model.[33] We find that our model replicates the key regression results rather well. Note that we do not directly fit these conditional moments in our MSM estimation approach. These findings provide an additional validation of our estimation approach. They also suggest that the gains from adopting an indirect inference approach that exploits the regressions reported in Appendix B may be small.

5 Empirical Results

5.1 Parameter Estimates

We estimate the parameters of our model using a MSM estimator. Table 14 in Appendix A reports key parameter estimates and estimated standard errors. We find that there are large monetary benefits from attending top law schools. First, graduating from a Tier 1 law school increases earnings in all sectors, promotion to partner as well as earnings of potential spouses. There are also substantial benefits from attending Tier 2 law schools although the effects are generally smaller than the effects of top tier schools. Our estimates also imply that the non-pecuniary benefits from attending law school are inversely related to the quality of the law school. Attending Tier 1 law schools takes apparently more effort than attending lower ranked law schools.

In the online appendix we also report the OLS earnings regression coefficients and compare these estimates to our structural estimates. We find that the estimates of the returns to experience are of similar magnitude in both models. However, there are two notable

[33]The results of this exercise are shown in Tables 6-9 in the online appendix.

differences among the set of parameter estimates. First, our structural estimates imply that the returns to law schools are higher for private sector employments. Second, our structural estimates imply lower returns to law schools for public sector employment. We thus conclude that accounting for selection into occupations primarily affects the estimates for the returns to schooling.

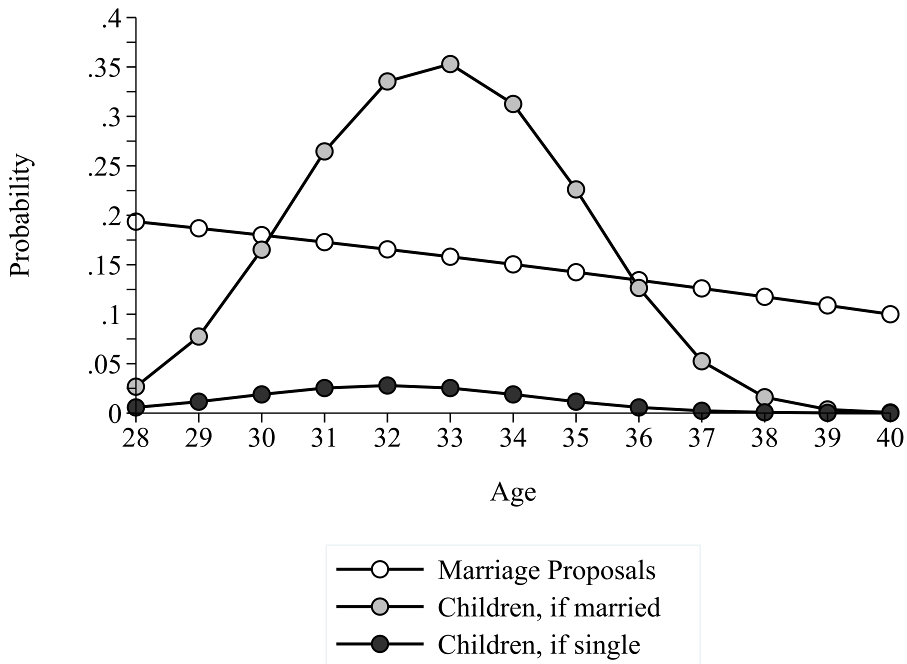
The probability of being promoted to partner positively depends on work experience as one would expect. Earnings in each occupation also increase with experience and ability. We also find that hours of work differ among occupations, but do not systematically differ by any observed characteristics. Finally, there are significant costs associated with switching occupations.

The estimates of the parameters of the flow utility function indicate that females get some significant non-pecuniary benefits from marriage. Public sector occupations are more valuable when having children. Being partner in a law firm provides strong pecuniary benefits which are partially off-set by negative non-pecuniary benefits.

We find that the arrival rate of marriage proposals declines substantially over time. The probability of meeting a potential spouse for a 28-year-old is 0.20. The probability declines to 0.12 when she reaches 38. Children arrival rates are much higher for a married individual than a single one. Female lawyers in our sample have very few children out of wedlock. For the married individual, the arrival rates of children peak at 0.35 at age 33, and decline to 0.02 when she reaches 38. As individuals value marriage, it is costly to postpone marriage. These findings are illustrated in Figure 1.

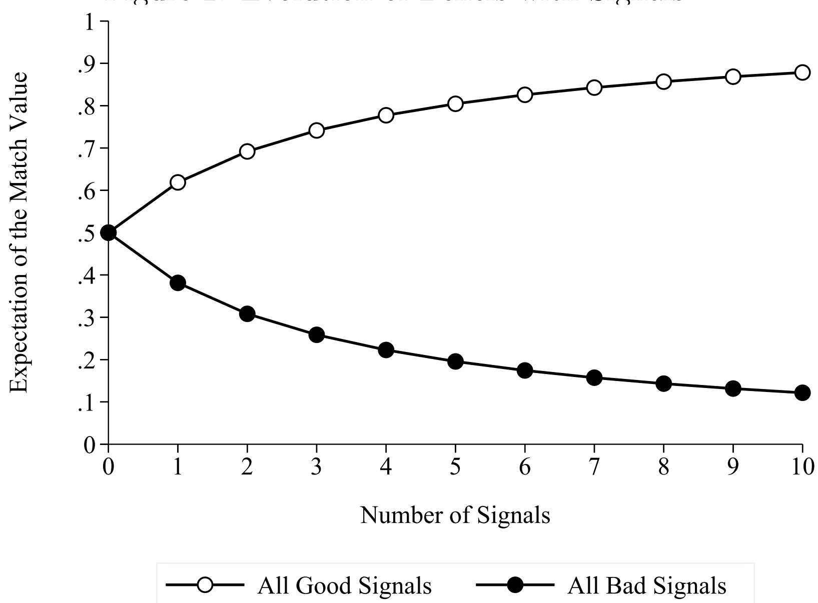
The quality of the spouse, as measured by spousal earnings, depends on the school attended. Not surprisingly we find that females that graduate from better law schools meet higher quality spouses, on average. More importantly, there is a large negative impact of debt on the quality of potential marriages. Our estimates indicate that a $10,000 increase in debt implies a 3.8% decrease in annual spousal earnings. There is a small catch-up effect over time as the quality of spouses with debt increase as time goes by.

Figure 1: Arrival Rates of Marriage Proposals and Children



Note: This figure illustrates the estimated arrival rates of marriage proposal for female lawyers. It also shows the estimated arrival rates of children for single and married females.

Figure 2: Evolution of Beliefs with Signals



Note: This figure illustrates the learning process in our model, we plot the speed of learning for two different realizations of signals. The first realization is a sequence of positive signals. The second realization is a sequence of bad signals.

To illustrate the learning process in our model, we plot the speed of learning for two different realizations of signals. The first realization is a sequence of positive signals. The second realization is a sequence of bad signals. Figure 2 illustrates the properties of our model. Overall our estimates imply that individuals learn reasonably fast about their prospects of promotion.

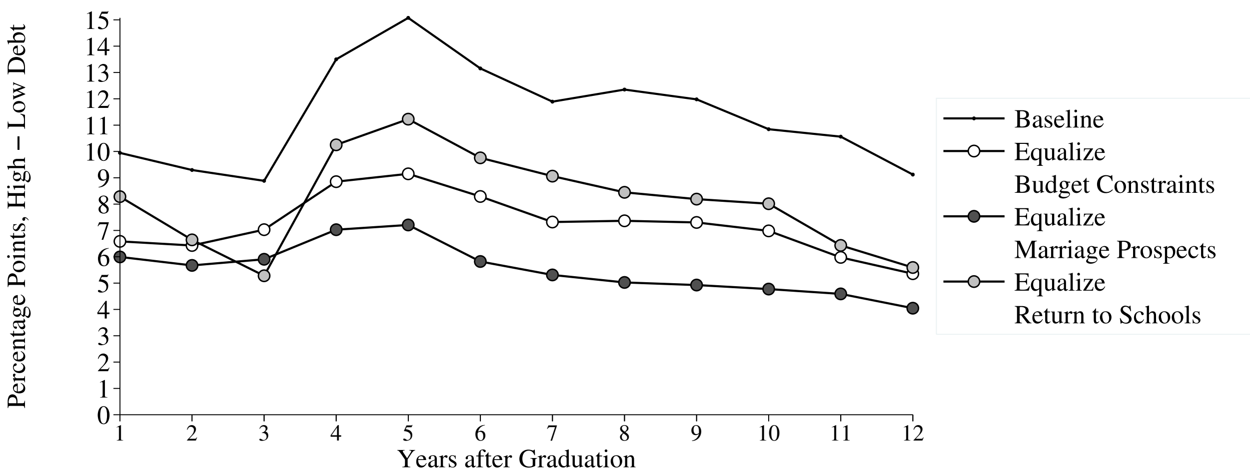
To generate some additional insights into the properties of our model, we predict private sector career choices for low-debt and high-debt females under three different scenarios. First, we assume that high-debt females face the same sequence of budget constraints as low-debt females, holding their school choices fixed. Hence differences in outcomes are only driven by differences in marriage market opportunities. Second, we consider the opposite case, where low- and high-debt females face the same marriage market prospects, but face a different sequence of budget constraints, holding school choices fixed. Finally, we predict choices for low- and high-debt females under the assumption that they have the same baseline schooling choices.

Figure 3 illustrates the results of this exercise. In the baseline model, the share of high-debt individuals employed in private practice is up to 15 percentage points higher than for their low-debt peers. Even after 12 years the gap is still approximately 10 percentage points. Equalizing marriage prospects explains approximately a half of this gap. Equalizing the budget constraint explains approximately 35% of the gap while equalizing the initial school choices explains approximately 30% of the gap between low- and high-debt females. We thus conclude that equalizing marriage prospects has a larger impact on career choices than equalizing budget constraints or equalizing educational choices.[34]

We also consider the impact of equalizing budget sets or marriage opportunities on initial law school choices. The results are illustrated in Figure 4. Overall we find that attendance is shifted from Tier 2 to Tier 1 law schools by up to four percentage points. Recall that

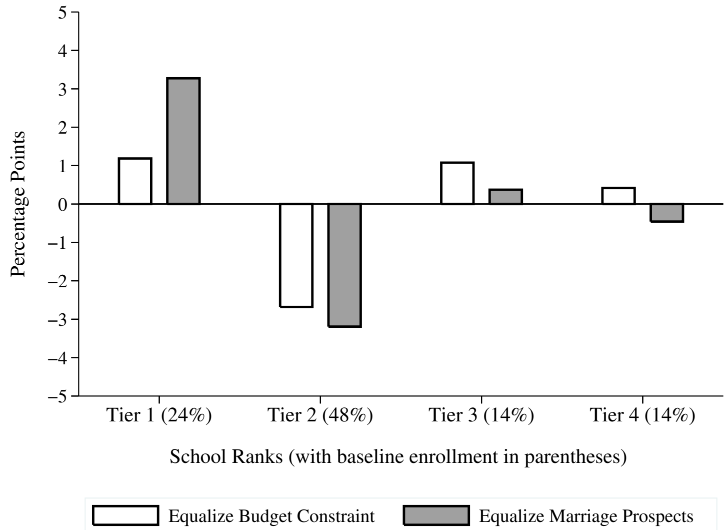
[34]These findings are broadly consistent with the previous literature. Sauer (1998, 2004) find that the impact of debt via the budget channel on career choices for male lawyers is small.

Figure 3: Differences in Private Sector Employment Rates by Debt Levels



Note: This figure illustrates private sector career choices for low-debt and high-debt females under three different scenarios. First, we assume that high-debt females face the same sequence of budget constraints as low-debt females, holding their school choices fixed. Hence differences in outcomes are only driven by differences in marriage market opportunities. Second, consider the opposite case, where low- and high-debt females face the same marriage market prospects, but face a different sequence of budget constraints, holding school choices fixed. Finally, we predict choices for low- and high-debt females under the assumption that they have the same baseline schooling choices.

Figure 4: Matriculation Rates



Note: This figure illustrates the impact of equalizing budget sets or marriage opportunities on initial law school choices.

school quality has a large impact on the job offer distributions in the labor market. In the public sector, the mean salary for Tier 1 graduates is 24 percent higher than for Tier 2 graduates, 31 percent higher than for Tier 3 graduates, and 46 percent higher than for Tier 4 graduates. The compensation gap is even more pronounced in the private sector, where the mean associates salary for Tier 1 graduates is 23 percent higher than for Tier 2 graduates, and 33 percent higher than for graduates of Tier 3 and 45 percent higher than for those of Tier 4 schools. The corresponding numbers for partner are 45, 43, and 103 percent. We also find a high degree of assortative matching in the marriage market. After controlling for other characteristics, spousal earnings for Tier 1 graduate are 15 percent higher than for Tier 2 graduates, 30 percent higher than for Tier 3 graduates, and 40 percent higher than for Tier 4 graduates. We conclude that the high price of Tier 1 law schools deters a significant fraction of qualified low wealth students from attending these highly selective schools.

5.2 Model Fit and Robustness Analysis

Next we discuss the overall fit of the model and conduct some robustness checks. Table 10 reports some of the most relevant moments that we match in estimation. These include moments characterizing career choices, marriage rates, spousal earnings, childbearing outcomes conditional on debt levels.

Table 10: Model Fit: Occupational Choices, Marriage Rates and Children

	2003		2012	
	Data	Model	Data	Model
Share of Associates at Private Practice				
Low Debt	0.47	0.47	0.12	0.14
High Debt	0.56	0.56	0.20	0.18
Overall	0.52	0.51	0.16	0.16
Share of Partners at Private Practice				
Low Debt	0.00	0.00	0.11	0.11
High Debt	0.00	0.00	0.14	0.17
Overall	0.00	0.00	0.12	0.14
Share of Employment in the Public Sector				
Low Debt	0.35	0.36	0.46	0.46
High Debt	0.31	0.34	0.48	0.48
Overall	0.33	0.35	0.47	0.47
Marriage Rates				
Low Debt	0.59	0.58	0.82	0.84
High Debt	0.50	0.46	0.77	0.77
Overall	0.54	0.53	0.79	0.81
Spousal Earning				
Low Debt	109.4	105.6	130.0	130.9
High Debt	96.5	93.2	130.3	130.5
Overall	102.9	100.5	130.2	130.7
Presence of a Child				
Low Debt	0.13	0.13	0.68	0.68
High Debt	0.10	0.13	0.63	0.62
Overall	0.12	0.13	0.65	0.65

All the monetary values are in thousands of 2014 $.

Overall our model fits the data well. Note that the model captures the differences in initial career choices conditional on debt level. We observe in the data that private sector employment of females with high debt is approximately 9 percentage points higher than that of females with low debt initially. The model predicts a gap of 9 percentage points. The main drawback of the model is that it predicts that the gap closes faster than observed in the data. With respect to family outcomes, the model slightly over-predicts the gap observed in the data. Finally, model also captures the gap in accepted spousal earnings and the differential probability of having a child.

We also find that the model captures the important life-cycle trends. One such trend is the decline in private practice employment between 2003 and 2012. The data show drops of 22 and 24 percentage points for the high-debt and low-debt females, respectively. The model produces similar declines.

Table 11: Model Fit: Enrollment and Debt

	Top 20		21-100		Tier 3		Tier 4	
	Data	Model	Data	Model	Data	Model	Data	Model
Enrollment	0.24	0.25	0.48	0.47	0.15	0.15	0.13	0.13
Total Debt	92.3	103.5	76.3	69.2	74.2	82.8	89.9	73.6

All the monetary values are in thousands of 2014 dollars.

Table 11 considers the model fit at the law school attendance level. We find that the model accurately captures matriculation rates by tier. The model is also consistent with the fact that students at top 20 schools accumulate more debt than students at lower quality schools.

Table 12 reports the key transition moments. We find that our model captures the features of the data reasonably well. In particular, our model generates enough persistence in occupational choices.

Note that our baseline specification also does not include monetary costs for raising children. We have explored the impact of adding pecuniary costs of having children to the model. Since we do not have any data in our sample that would be informative about the

Table 12: Model Fit: Transitions of Careers

Four-Period Transition Rate						
	Year 7:					
	Private		Public		Not Employed	
Year 3:	Data	Model	Data	Model	Data	Model
Private	0.61	0.64	0.24	0.22	0.15	0.14
Public	0.10	0.07	0.76	0.80	0.13	0.13
Not Employed	0.17	0.16	0.14	0.18	0.68	0.66
Average One-Period Transition Rates						
	Year $t+1$:					
	Private		Public		Not Employed	
Year t:	Data	Model	Data	Model	Data	Model
Private	0.87	0.84	0.07	0.11	0.06	0.05
Public	0.03	0.06	0.92	0.91	0.04	0.04
Not Employed	0.06	0.10	0.06	0.02	0.86	0.89

magnitude of these costs, we consider two scenarios. In the first case we set costs equal to $\$10,000$. In the second case we use an estimate of $\$15,000$. If we assume that monetary costs are equally shared by the couple, then these correspond to \$20,000 and \$30,000 of total monetary childcare costs. Overall, we find that there are only small differences among the model specifications.[35] The main difference is that females are more likely to work in the private sector. The relative difference between low and high debt females remains almost constant. Hence, including these costs does not affect the relative impact of debt on occupational choices. The effects of including these costs are similar when we consider marriage outcomes. We thus conclude that our characterization of the relative impact of debt on key outcomes is robust with respect to including reasonable estimates of the monetary costs of raising children.

[35] A tables that summarize this comparison between the three models is reported in the online appendix.

6 Policy Analysis

Encouraging public sector employment has been an important policy concern. One reason is the significant shortage of public sector lawyers. For example, the New York Times reported in 2013 that "professional guidelines recommend that public defenders handle no more than 400 misdemeanor cases in a year, yet a 2009 report found that part-time public defenders in Orleans Parish handled the equivalent of 19,000 misdemeanor cases per attorney annually, which means an average of about seven minutes spent by a lawyer on each case." Similar shortages are observed in more severe criminal cases. Another reason of concern is a perceived lack of high quality lawyers in the public sector (Iyengar, 2007). A lack of high quality public defenders undermines the legal system and provides a serious disadvantage for individuals who cannot afford to hire their own lawyers.

Our baseline model predicts that females work on average 5.81 years in public or business sector jobs during the first 14 years of their careers, which closely matches the data. (Recall that our model does not differentiate between business sector and public sector occupations.) We have also seen that female lawyers with high debt are more likely to avoid or postpone careers in the public sector than females with low debt. This raises the question of whether one can design public policies that would encourage participation in public sector careers at reasonable costs.

An example of a traditional loan forgiveness policy implemented in the U.S. is the Public Service Loan Forgiveness Program administered by the U.S. Department of Education. It forces participants to enroll in an income-contingent repayment scheme during the first 10 years of the career. After ten years of public service, the remaining debt is then discharged. Our analysis suggests that this policy is likely to be ineffective since 10 years are too long given the importance of the indirect marriage market effects. We, therefore, focus on shorter term policies in this section.

We can use our estimated model to evaluate a variety of shorter-term policies that are aimed at increasing public sector employment. The first policy is a conditional loan forgiveness program that provides a payment of principal and interest for each year of working in the public sector conditional on having accumulated a certain experience in the public sector. We consider a variety of policies that differ by the required years of service (5, 6, or 7 years) and the generosity in subsidy.

The second policy is a conditional earnings subsidy. The idea is to subsidize public sector employment by providing a fixed percentage earnings subsidy conditional on having worked a number of years in the public sector. We consider subsidy rates between 10 and 12 percent which are approximately as expensive as the loan forgiveness policies studied above. Note that the two policies are similar. The earnings subsidy provides large payments to females with high earnings while the repayment subsidy provides large payments to females with high debt. Otherwise, these two policies are identical.

Finally, we consider a traditional loan forgiveness policy that applies to all lawyers that have worked a certain number of years in the public sector. In contrast to traditional loan forgiveness policies, conditional loan forgiveness policies provide additional incentives for each additional year of public service independently of how many years have been previously served.

We characterize the impact of these policies on career choices and compute the implied costs of an additional year in public sector employment. Table 13 reports the key findings of these policy experiments. We report the parameters of the policy in Columns 1-3. We also report the implied price per year of extra service in Column 4, spending per capita in Column 5, and the average years worked in the public or business sector in Column 6.

There are several interesting findings. All policies consider above are expensive. The prices for an additional year of public sector work range from 10 to 40 thousand dollars for conditional earnings subsidies or conditional loan forgiveness programs. The estimated prices are much larger for traditional loan forgiveness programs. The significant costs of these programs are also reflected in the predicted spending per capita.

Table 13: Policy Analysis

1 Policy	2 Eligibility (Yrs)	3 Generosity	4 Price (in 1000$)	5 Spending (in 1000$)	6 Avg Yrs in Pub Sector (Out of 14 Years)
Baseline					5.81
Conditional Loan	5	100%	10.1	16.7	7.47
Forgiveness	6	100%	10.6	12.3	6.96
	7	100%	13.0	8.6	6.48
Conditional Earnings	5	11.5%	15.5	25.7	7.47
Subsidy	6	10.5%	15.3	17.7	6.97
	7	10.0%	17.7	12.2	6.51
Traditional Loan	5	100%	40.0	20.2	6.32
Forgiveness	6	100%	34.3	16.1	6.28
	7	100%	33.0	12.4	6.19

Conditional subsidy programs are more effective than traditional loan forgiveness programs. The overall impact of the program depends on the generosity and the eligibility criteria. Not surprisingly, we find that more generous policies have a larger overall impact. The first two policies – the conditional earnings subsidy and the conditional loan forgiveness programs – have similar effects on public sector employment and are almost equally expensive. Conditional loan forgiveness programs tend to be slightly more effective and cheaper than conditional earnings subsidies because they target a more responsive sub-population of female lawyers. The traditional loan forgiveness policy has much smaller overall effects on public sector employment and is more expensive. We thus conclude that conditional earnings subsidies and conditional loan forgiveness programs are more efficient policies than traditional loan forgiveness policies.

As we discussed above, an alternative explanation of high attrition rates and of low public employment rates by students with high debt is that starting a career in the private sector tends to be more reversible than starting a career in the public sector. To explore this issue in more detail, we have explored another counterfactual with reduced mobility costs from the public to the private sector. In particular, we have considered the case in which we reduce the switching costs from the public to the private sector by 50 (100) percent. The average number of years in public sector increases from 5.81 years to 5.85 (6.02) years. Overall, we conclude that these policies only have moderate impacts on public sector employment.

We have primarily focused in this section on the problem of attracting more lawyers to the public sector. As we discussed above, one may also be concerned that the lawyers attracted to the public sector may be of lower quality than the lawyers that work in private practice. More research is clearly needed to explore these issues in more detail.

7 Conclusions

We have developed and estimated a dynamic model that captures schooling, career, and marriage choices by aspiring young female lawyers. Our model accounts for several important features of labor markets for lawyers, including differences in hours and earnings across occupational tracks, and learning about the uncertain prospects of promotion to partner. We have shown that our model provides new insights into the effects of debt or negative wealth on marriage and career prospects of females. We find that the observed gap in career paths, marriage and child rearing outcomes is primarily driven by the worse match that high-debt females obtain in the marriage market. Finally, we use the model to study the design of policies that aim to increase public sector employment. We have shown that it is possible to design conditional earnings subsidies or conditional loan forgiveness programs that significantly increase public sector career choices at reasonable costs.

The main insights and empirical results of this study are promising for future research. We find that females tend to choose lower-ranked, cheaper law schools to avoid debt. Loan repayment subsidies increase a law student's willingness to borrow and hence the demand for high-quality education. A relevant concern for policy makers is whether top private schools will respond to these aid policies by increasing tuition.[36] It is worth noting that higher tuitions at law schools do not necessarily imply an inefficient outcome if law schools use the additional revenues to increase the quality of education, thereby raising labor market returns. It would be interesting to study these issues within an equilibrium framework that would properly endogenize tuition and admission policies, and law school quality. We leave these ideas for future research.

[36]There exists a small literature studying the general equilibrium effects of financial aid policies on the schools' tuition levels. Epple, Romano, and Sieg (2006) and Epple, Romano, Sarpca, and Sieg (2017) develop an equilibrium models of the college education market to study access and affordability of college education. Their quantitative analysis suggests that private schools may increase tuition in response to an increase in publicly provided grants. Epple, Romano, Sarpca, Sieg, and Zaber (2017) show that this model is consistent with observed price discrimination in the U.S. market for higher education. Grey and Hedlund (2016) extend the model to account for dynamics in the labor market outcomes and show that their model can explain the rise in college tuitions observed over time. Turner (2014) finds that colleges capture 12 percent of their students' Pell Grant aid through price discrimination, using a regression discontinuity design. Cellini and Goldin (2014) document that the for-profit colleges eligible for federal student aid programs charge tuition that is 78 percent higher than that charged by comparable non-eligible ones. Lucca, Nadauld, and Shen (2015) find that institutions more exposed to changes in the subsidized federal loan program increased their tuition disproportionately around these policy changes. Overall, these studies suggest that part of the aid will be captured by the schools. But the effect of policies subsidizing repayments, especially the policies that depend on labor market outcomes, have not yet been studied.

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A Parameter Estimates and Standard Errors

Table 14 reports the parameter estimates and estimated standard errors. The symbols correspond to the ones used in Section 3. We have also added a brief description of each parameter to make the table self-explanatory.

Table 14: Key Parameter Estimates and Standard Errors

Children Arrival Rates			
Symbol	Meaning	Estimates	Std Error
β_0^K	Constant	-105.95	17.90
β_1^K	Age	6.40	0.01
β_2^K	Age Squared	-0.10	0.02
β_3^K	Married	-34.51	5.43
β_4^K	Married$\times$ Age	2.13	0.01
β_5^K	Married$\times$ Age Squared	-0.03	0.00
Marriage Proposal Arrival Rates			
Symbol	Meaning	Estimates	Std Error
β_0^M	Constant	0.30	0.03
β_1^M	Age	-0.00	0.00
β_2^M	Age Squared	-0.00	0.00
Spousal Earning			
Symbol	Meaning	Estimates	Std Error
β_{41}^H	Tier 1	1.97	0.08
β_{42}^H	Tier 2	1.82	0.06
β_{43}^H	Tier 3	1.67	0.07
β_{44}^H	Tier 4	1.57	0.06
β_1^H	Debt	-0.04	0.01

β_2^H	Experience	0.04	0.01
β_3^H	Catch-up	0.00	0.00
σ^H	Shock of Variance	0.56	0.11
	Preference for Schools		
Symbol	Meaning	Estimates	Std Error
ζ_{11}	Non-pecuniary Benefit: Tier 1	-0.54	0.10
ζ_{12}	Non-pecuniary Benefit: Tier 2	-0.05	0.01
ζ_{13}	Non-pecuniary Benefit: Tier 3	-0.10	0.07
	Earnings in the Private Sector: Partners		
Symbol	Meaning	Estimates	Std Error
β_{112}^W	Tier 1	2.74	0.18
β_{122}^W	Tier 2	2.29	0.20
β_{132}^W	Tier 3	2.32	0.21
β_{142}^W	Tier 4	1.71	0.28
β_{22}^W	GPA	0.01	0.00
β_{42}^W	Private Sector Experience	0.10	0.02
β_{52}^W	Private Sector Experience Squared	-0.00	0.00
σ_2^W	Variance of Shocks	0.54	0.22
	Earnings in the Private Sector: Associates		
Symbol	Meaning	Estimates	Std Error
β_{111}^W	Tier 1	2.10	0.03
β_{121}^W	Tier 2	1.87	0.03
β_{131}^W	Tier 3	1.77	0.04
β_{141}^W	Tier 4	1.65	0.04
β_{21}^W	GPA	0.01	0.00
β_{41}^W	Private Sector Experience	0.11	0.01

β_{61}^{W}	Private Sector Experience Squared	-0.00	0.00
σ_{1}^{W}	Variance of Shocks	0.51	0.18
	Earnings in the Public Sector		
Symbol	Meaning	Estimates	Std Error
β_{113}^{W}	Tier 1	1.85	0.03
β_{123}^{W}	Tier 2	1.62	0.04
β_{133}^{W}	Tier 3	1.55	0.04
β_{143}^{W}	Tier 4	1.39	0.04
β_{23}^{W}	GPA	0.01	0.00
β_{43}^{W}	Private Sector Experience	0.08	0.01
β_{53}^{W}	Public Sector Experience	0.05	0.01
σ_{3}^{W}	Variance of Shocks	0.45	0.15
	Hours in the Private Sector: Partners		
Symbol	Meaning	Estimates	Std Error
β_{02}^{H}	Constant	0.95	0.03
σ_{2}^{H}	Variance of Shocks	0.24	0.06
	Hours in the Private Sector: Associates		
Symbol	Meaning	Estimates	Std Error
β_{01}^{H}	Constant	0.92	0.01
σ^{H}	Variance of Shocks	0.25	0.08
	Hours in the Public Sector		
Symbol	Meaning	Estimates	Std Error
β_{03}^{H}	Constant	0.82	0.01
σ_{3}^{H}	Variance of Shocks	0.28	0.08
	Preferences over Leisure and Consumption		

Symbol	Meaning	Estimates	Std Error
ϕ_0	weight on consumption	0.76	0.05
μ_1	Non-pecuniary Benefit: Marriage	0.20	0.07
ψ_1	Non-pecuniary Benefit: Associates	-0.59	0.05
ψ_2	Non-pecuniary Benefit: Partner	0.26	0.11
ψ_3	Non-pecuniary Benefit: Public	-0.27	0.04
ψ_4	Non-pecuniary Benefit: Public$\times$ Kids	0.18	0.03
σ	Variance of Preference Shocks	0.50	0.03

Promotion Probabilities

Symbol	Meaning	Estimates	Std Error
α_{01}	Tier 1	-12.10	1.08
α_{02}	Tier 2	-12.63	0.91
α_{03}	Tier 3	-12.38	0.98
α_{04}	Tier 4	-12.64	1.56
α_2	Experience	1.79	0.10
α_3	Experience Squared	-0.03	0.01

Learning Process

Symbol	Meaning	Estimates	Std Error
η_0	Initial	1.17	0.46
η_1	η_1	2.75	0.24
η_2	η_2	10.49	2.64

Transition Costs

Symbol	Meaning	Estimates	Std Error
c_{pr}	Public to Private	0.77	0.16
c_{ur}	Non-employed to Private	0.57	0.12
c_{pu}	Public to Non-employed	1.11	0.20

c_{ru}	Private to Non-employed	0.71	0.15
c_{rp}	Private to Public	0.67	0.15
c_{up}	Non-employed to Public	2.16	0.36

Calibrated Parameters:

Discount Factor: $\beta = 0.96$.

Income Sharing Rule: $\gamma = 0.6$.

Time Costs of Raising Children: $\lambda = 600$.

B Stylized Facts: Additional Evidence

B.1 Females with high debt prefer private law firms

Table 15 reports reports the marginal effects in probability of working at private practice through logistic regressions. Columns (1) and (3) do not use controls while Columns (2) and 4) control for undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age. The top panel uses debt upon graduation while the lower panel uses remaining debt as of debt. The finding that females with more debt have more work experience in private law firms is robust among all specifications.

Table 15: Debt and Probability of Working at Private Practice

	Probability of working at Private Practice			
	In the 7th Yr After Graduation		In the 12th Yr After Graduation	
	(1)	(2)	(3)	(4)
Debt upon Graduation	0.0009***	0.0011***	0.0011***	0.0012***
(in thousands of 2014 $)	(3.97)	(4.40)	(4.03)	(4.34)
Controls		Yes		Yes
Observations	1193	1176	876	868
	Probability of working at Private Practice			
	In the 7th Yr After Graduation		In the 12th Yr After Graduation	
	(1)	(2)	(3)	(4)
Remaining Debt	0.0011***	0.0013***	0.0010***	0.0010***
(in thousands of 2014 $)	(3.59)	(3.92)	(2.76)	(2.67)
Controls		Yes		Yes
Observations	1166	1149	838	830

t statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[a] Reports the marginal effects in probability of working at private practice through logistic regressions.
[b] Control variables: undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age.

B.2 Females with high debt are likely to postpone marriage

Table 16 reports estimates form conditional log-log models for discrete time proportional hazard. Time is bundled in 2 periods, each period corresponds to 3 years. We report the marginal effects evaluated at the means of the regressors. We cluster by individual. Control variables are undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age. The results are for 2006. The top panel uses debt upon graduation while the lower panel uses remaining debt as of debt. The finding that Females with more debt are more likely to postpone marriage is robust among all specifications.

Table 16: Debt and Marriage Rates

	Being Married			
	(1)	(2)	(3)	(4)
Debt upon Graduation	-0.0008***	-0.0006**	-0.0005**	-0.0004
(in 2014 $1000)	(-3.57)	(-2.53)	(-2.20)	(-1.61)
Controls		Yes	Yes	Yes
Sector-Specific Work Exp			Yes	
Work Hours				Yes
Observations	1642	1622	1622	1426
	Being Married			
	(1)	(2)	(3)	(4)
Remaining Debt	-0.0009***	-0.0007***	-0.0007***	-0.0005**
(in 2014 $1000)	(-3.60)	(-2.84)	(-2.70)	(-1.98)
Controls		Yes	Yes	Yes
Sector-Specific Work Exp			Yes	
Work Hours				Yes
Observations	1627	1607	1607	1411

t statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

[a] Conditional log-log models for discrete time proportional hazard, time is bundled in 2 periods, each period corresponds to 3 years.

[c] Reports the marginal effects on Probability of (Event happens in current period given it has not happened before) evaluated at mean. Average marginal effects are similar.

[d] Clusters by individual, control variables: undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age.

[e] In data, only marital status in 2003 and 2006 are observed.

B.3 Spouses of females with high debt have lower earnings

Table 17 reports result obtained by regression spousal income on debt without controls in Column (1) and controlling for undergraduate GPA, age, school tier, year of bar admission, whether a parent is a lawyer, parents' education, and race in Column (2). In Columns (3) - (5) we conduct additional robustness checks and control for sector specific work experience, own salary and own work hours. The top panel uses debt upon graduation while the lower panel uses remaining debt as of debt. The finding that spouses of females with more debt have lower earnings is robust among all specifications.

Table 17: Debt and Spousal Earnings

	Spousal Earning 6 Yrs Post-Graduation				
	(1)	(2)	(3)	(4)	(5)
Debt upon Graduation	-0.13**	-0.14**	-0.11*	-0.16**	-0.11*
(in 2014 $1000)	(-2.11)	(-2.23)	(-1.74)	(-2.50)	(-1.85)
Controls		Yes	Yes	Yes	Yes
Sector-Specific Work Exp			Yes		
Own Salary				Yes	
Own Work Hours					Yes
Observations	718	711	711	711	711
	Spousal Earning 6 Yrs Post-Graduation				
	(1)	(2)	(3)	(4)	(5)
Remaining Debt	-0.42***	-0.39***	-0.35***	-0.42***	-0.32***
(in 2014 $1000)	(-5.42)	(-4.86)	(-4.33)	(-5.02)	(-4.09)
Controls		Yes	Yes	Yes	Yes
Sector-Specific Work Exp			Yes		
Own Salary				Yes	
Own Work Hours					Yes
Observations	708	701	701	701	701

t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

[a] Clusters by individual, control variables: undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age.

B.4 Females with high debt are likely to postpone childbearing

Table 18 reports estimates of conditional log-log models for discrete time proportional hazard, time is bundled in 7 periods, each period corresponds to 1 year. It reports the marginal effects evaluated at mean. Average marginal effects are similar. Clusters are by individual. Control variables are undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age. The finding that females with more debt are more likely to postpone childbearing since they delay marriage is robust among all specifications.

Table 18: Debt and Probability of Having a Child

	Having a Child			
	(1)	(2)	(3)	(4)
Debt upon Graduation	-0.00006	-0.00004	-0.00002	-0.00002
(in 2014 $1000)	(-1.45)	(-0.89)	(-0.71)	(-0.65)
Married			0.0918***	0.0883***
			(17.19)	(15.53)
Own Salary				Yes
Controls		Yes	Yes	Yes
Observations	7112	7013	6061	5340

t statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

[a] Conditional log-log models for discrete time proportional hazard, time is bundled in 7 periods, each period corresponds to 1 year.

[b] Reports the marginal effects on Probability of (Event happens in current period given it has not happened before) evaluated at mean. Average marginal effects are similar.

[c] Clusters by individual, control variables: undergraduate GPA, school tier,whether mother is a lawyer, whether father is a lawyer, mother's education, father's education, and age.

C Initial Conditions

There are five initial variables: age A, undergraduate GPA, $LSAT$ scores, undergraduate debt D^U, and monetary resources E. We first assume that the joint distribution of the five variables can be approximated by a multivariate normal distribution:

$$\begin{pmatrix} A \\ GPA \\ LSAT \\ D^U \\ E \end{pmatrix} \sim N \left[\begin{pmatrix} \mu_A \\ \mu_{GPA} \\ \mu_{LSAT} \\ \mu_{D^U} \\ \mu_E \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} \\ \sigma_{12} & \sigma_{22} & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ \sigma_{13} & \sigma_{23} & \sigma_{33} & \sigma_{34} & \sigma_{35} \\ \sigma_{14} & \sigma_{24} & \sigma_{34} & \sigma_{44} & \sigma_{45} \\ \sigma_{15} & \sigma_{25} & \sigma_{35} & \sigma_{45} & \sigma_{55} \end{pmatrix} \right]$$

We then truncate the distribution of GPA at 4 which is the maximum possible value for the GPA.[37]

D The Evolution of Debt

Table 19 compares the observed debt values with the ones predicted by the model. The table shows that the predicted remaining debt matches up with observed remaining debt 6 and 12 years after graduation. The main difference is that the model slightly under-predicts the initial levels of debt. Moreover, the model slightly over-predict the rate at which females pay of their debt. Notice that females in different sectors pay down their debt at roughly the same speed using a uniform schedule that is similar to the one we use in our model.

In Appendix B we have also shown that the key stylized facts reported in Section 2.2 of the paper are robust to using different measures of debt. We, therefore, conclude that the main results reported in this paper do not depend on the specific definition of the debt measure used in the analysis.

[37] Table 11 in the online appendix reports the estimated or calibrated parameter values for the joint distribution. It also explains which data sources were used to estimate each parameter.

Table 19: Summary Statistics of Debt (in thousands of 2014 dollars)

		Graduation		6 Yrs Later		12 Yrs Later	
		Data	Model	Data	Model	Data	Model
Overall	Mean	85.2	82.6	45.4	50.4	30.3	23.7
	%Paid			46.7	38.9	64.4	71.4
High Debt	Mean	132.3	138.5	71.2	84.7	48.1	39.6
	%Paid			46.2	38.9	63.6	71.4
Low Debt	Mean	37.5	35.9	19.4	22.0	10.9	10.3
	%Paid			48.3	38.9	70.9	71.4
Working in PS	Mean	93.1	93.8	51.6	57.3	33.6	26.9
6 Yrs Post-Grad	%Paid			44.6	38.9	63.9	71.4
Not Working in PS	Mean	80.5	74.6	41.7	45.6	28.4	21.4
6 Yrs Post-Grad	%Paid			48.2	38.9	64.7	71.4