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ESSAYS ON GENDER ISSUES IN HUMAN CAPITAL ATTAINMENT AND THE LABOR MARKET

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To my parents,

for their continual support and never once asking when I was going to graduate

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ABSTRACT

This dissertation explores gender issues in three distinct and important life decisions: education, fertility, and labor supply. The first chapter examines whether legislation affected female human-capital investment decisions. It finds a sharp and dramatic convergence between female and male graduate-degree fields coincident with the 1972 passage of Title IX, which banned gender discrimination in graduate admissions. Using a well-known convergence measure in Computer Science called the Earth Mover's Distance Algorithm, I find that the distributional change occurred as females predominantly moved into male-dominated fields. In addition to providing evidence of successful anti-discrimination legislation, this chapter sheds new light on the factors responsible for the college gender gap reversal.

The second chapter examines how career concerns affect fertility-timing decisions differently by gender. A growing literature reveals that the adverse effect of children on career advancement falls disproportionately on women. This raises the possibility that women respond to career concerns by delaying family formation more than men. Using a novel dataset on lawyers, we find that females are less likely to have their first child before the promotion decision. The results imply that the focus on the gender wage gap understates gender inequality in the labor market.

The last chapter examines how economic conditions affect labor-supply decisions of married couples. Exploiting variation in local housing demand shocks from the recent U.S. housing crisis, it finds that wives of construction workers were more likely to join the labor force and be employed in areas that experienced larger housing busts. The study of the added worker effect is especially interesting in light of advancements made by women in the labor market.

These chapters relate to each other as human capital investments are closely tied to occupational choices. To the extent that there is gender-based sorting into educational decisions (e.g., types of degrees, fields of study), this may in part explain the observed gender-sorting into occupations and the gender pay gap. Chapter 1 explores this relationship. Even

with the same training and within the same occupation, however, gender disparities may arise in the labor market. Chapter 2 examines this question with respect to fertility. Last, growing similarity between male and female human-capital attainment and occupational choices have important implications for household labor supply. Chapter 3 examines the value of marriage as a risk-sharing device. Another common thread among the three chapters is the comparison of male and female decisions. This dissertation provides insight into how and why decisions pertaining to human capital attainment and the labor market may differ by gender.

CHAPTER 1

THE EFFECT OF TITLE IX ON GENDER DISPARITY IN GRADUATE EDUCATION

1.1 Introduction

A phenomenon that has been extensively documented is the convergence in the U.S. occupational distribution between men and women over the past 50 years. Current explanations, such as a decreasing gender wage gap and changing social norms sped up by the introduction of the birth control pill and legal abortion, attest to a gradually changing world and female view during this era (Goldin & Katz, 2002; Bailey, 2006; Blau & Kahn, 2016; Myers, 2017). Interestingly, less attention has been paid to the possible role of Title IX of the Education Amendments of 1972, which banned the use of admission quotas in graduate schools.

This mechanism is worth exploring, especially when one considers that the types of degrees that women were pursuing also changed drastically over this same time period. For example, the share of law degrees increased four-fold between 1962 and 1990 while the share of education degrees, the most popular field-of-study among women in 1962, decreased by 28 percent.[1] By making it illegal to discriminate against female applicants in admissions decisions, Title IX allowed women to pursue degree fields – and thus, occupations – previously open mainly to men, such as law and medicine. The primary goal of this paper is to empirically assess whether legislation was successful in eliminating discrimination in graduate education.

It is not obvious that Title IX would have an impact on graduate education. First, admissions quotas may have simply reflected the preferences of young women at the time rather than discriminatory tastes. A state commission on one medical school's admission

1. These statistics are based off the 1993 National Survey of College Graduates and pertain to all graduate degrees earned by age 35.

policy found that it admits very few women because they "[get] married and [do] not persist in the profession" (Discrimination Against Women, 1970, p. 312). This was the prevailing view among school officials and was often cited as a reason for admitting few women to graduate programs. Second, there is scant evidence of policy successfully eliminating discrimination.[2] Racial discrimination continued well after the Civil Rights Act of 1875, which dictated equal treatment of African Americans in public accommodations and public transportation. The 1954 Supreme Court case *Brown v. Board of Education of Topeka* did little to end segregation in schools. More than 50 years after the Civil Rights Act of 1964, we are still dealing with gender and racial bias in the workplace. These examples suggest that it takes more than well-intentioned legislation to have an actual impact.

I find results to the contrary. Focusing on the distribution of fields of study, I find strong evidence that Title IX was successful in eliminating gender disparity in graduate education. Moreover, the sharp and dramatic convergence between female and male graduate-degree fields was driven by female movement into male-dominated fields, suggesting that female preferences were not the barrier. I use two different methods to measure gender convergence: the Segregation Index, also known as the Index of Dissimilarity, and the Earth Mover's Distance algorithm (EMD). Although the segregation index is a popular method for measuring distributional change, EMD is a better measure when studying discrimination as it takes into account which bins people move out of and into, and, more importantly, the distance between bins (using expected salary of the different fields as a measure of distance). This is an important detail because women were barred from entering certain fields prior to Title IX, and those fields were precisely the more lucrative fields. My results do not change by convergence measure, though EMD estimates greater convergence.

I also find that female growth after Title IX was concentrated in fields in the top salary tercile. This suggests an indirect role that Title IX played on the labor market. By grant-

2. The notable exceptions are Heckman and Payner (1989), which found that Title VII of the 1964 Civil Rights Act had a sizable effect on black employment in the South Carolinian textile industry, and Donohue and Heckman (1991), which expanded the geographic focus of the previous study to the entire south.

ing women access to high-skilled occupations, which were also the highest-paid occupations, Title IX led to higher expected returns on human capital investment for women thereby encouraging labor market participation. Indeed, I find that occupational convergence between men and women increased starting with the birth cohort who was first exposed to Title IX in college.

There is one important identification concern that warrants discussion. Since Title IX is a national policy, there is no natural comparison group against which to measure the impact of the law. This is an issue if the law were anticipated or if it were passed in response to the changing social attitude at the time, especially regarding admissions policies. In these cases, a simple event-study may result in a biased OLS estimate as I would be unable to disentangle the trend from the impact. These concerns are mitigated when I study the history behind Title IX's passage. The law came at a time when women's rights were expanding, but the main impetus was persistent gender discrimination in educational institutions. This is supported by data, which show that female enrollment trends changed after Title IX's passage.

The coincidence in timing does not, of course, prove causation; there were a lot of other changes occurring between the late 1960s and early 1970s that may be responsible for the change in female educational choices. However, alternative explanations were gradual changes and cannot explain the large, national shift in graduate-field distribution that occurred between 1972-73 and 1974-75. I consider two possible explanations that are often cited as causes of change in women's education and labor force behavior: young, single women's increased access to the birth control pill in the late 1960s; and abortion legalization by the Supreme Court in 1973. These two events may have affected women's decisions to pursue graduate studies by lowering the cost of investment. My robustness checks exploit state-level variation in the adoption of these policies and still finds an increase in convergence right after Title IX's passage.

This paper relates to a number of existing literature. First and foremost, this paper contributes to the literature on Title IX. Title IX is largely associated with high school and college athletics; one of the seminal papers on Title IX finds that it increased female college attendance and labor market participation by increasing female participation in high school athletic programs (Stevenson, 2010). Other researchers have examined its effect on educational outcomes, but most are historical accounts or qualitative studies (Buek & Orleans, 1973; Stromquist, 1993; Valentin, 1997; DOJ, 2012; Mason & Younger, 2014). Unlike the previous studies on education, my paper conducts a robust quantitative analysis. To my knowledge, this is the first study that seeks to estimate causal effects of Title IX on graduate education.

In addition to expanding the literature on the college gender gap reversal, this paper relates to research on gender convergence in the U.S. occupational distribution as one's degree of study is closely linked to one's occupation. The large-scale movement of women into the U.S. labor market and the occupational convergence between men and women over the past 50 years has long been of interest to researchers (Polachek, 1981; Blau, Simpson, & Anderson, 1998; Blau, Ferber, & Winkler, 2014; Olivieri, 2014; Pan, 2015). Much of the literature that seeks to explain this phenomenon focuses on demand factors, specifically the decreasing gender wage gap (Heckman & Sedlacek, 1985; Smith & Ward, 1985, 1989; Blau & Kahn, 1997, 2000, 2006; Black & Juhn, 2000; Mulligan & Rubinstein, 2008). Less work has been done on the supply factors with most of them focusing on the fertility consequences of labor force participation (Goldin, 1988, 1990; Angrist & Evans, 1998; Goldin & Katz, 2002; Bailey, 2006; Myers, 2014). Noting that much of the convergence occurred among high-skilled occupations, my paper suggests that barriers to higher education also affected females' occupational choices.

Finally, this paper adds to the empirical toolbox of convergence measures. Measures of distributional change have broad applications, ranging from studies of residential segregation (Massey & Denton, 1988) to occupational segregation (Blau, Brummund, & Liu, 2013) to income-achievement gaps (Nielsen, 2015). As such, the literature on convergence measures is long and ever-growing (Duncan & Duncan, 1955; Taeuber & Taeuber, 1976; Cowell, 1985; Massey & Denton, 1988; Ruber, Tomasi, & Guibas, 2000; Reardon & Firebaugh, 2002; Reardon, 2009). I contribute to this literature by introducing a well-known measure in computer science, the Earth Mover's Distance algorithm, and applying it to an economics question. As mentioned before, the advantage of EMD is that it takes into account the distance between bins that people are moving into and out of when measuring convergence. This is something the segregation index does not do, but is an important detail when studying discrimination.

I begin the remainder of the paper by providing an historical account of Title IX. Section 1.3 discusses the empirical evidence on whether colleges and universities complied with Title IX. I describe the data in Section 1.4 and my main results in Section 1.5. Section 1.6 unpacks the distributional change, and Section 1.7 discusses alternative explanations. I discuss implications from my results in Section 1.8 before concluding.

1.2 A Brief History of Title IX

1.2.1 The status of education for women

The 1960s saw a colossal expansion of women's rights. President John F. Kennedy was elected into office on the promise of a New Frontier, ready to confront previously unconquered problems of social and civil injustice. As such, he signed the Equal Pay Act of 1963 into law, abolishing wage disparity based on sex. One year later, the Civil Rights Act of 1964 was passed – a landmark piece of civil rights legislation that ended racial segregation in schools but made no explicit mention of gender discrimination in educational institutions. The fight for women's rights continued, however, and in 1965, President Lyndon B. Johnson signed an executive order banning federal contractors from discrimination in employment based on sex as well as race, color, religion, and national origin (Executive Order 11246).

Despite these advancements, gender discrimination in educational institutions was still pervasive as it was technically not banned. This sparked a national conversation about gender inequalities in pay, rank, and admissions in higher education. A Special Subcommittee on Education in the House of Representatives was formed, and Congressional hearings on Section 805 of H.R. 16098 (Omnibus Post-Secondary Education Act of 1970) began on June 17, 1970. For days, hearing after hearing, statement after statement revealed the dire status of a woman's place in education (Discrimination Against Women, 1970). The statement of Professor Ann Sutherland Harris, Assistant Professor of Art History at Columbia University, summarized it best:

> The rule is a simple one: the higher, the fewer. Although more women than men finish high school (and this has been true since 1920), fewer women than men go on to college, largely because it is harder for a woman to gain entrance to college with the necessary financial support. Fewer women than men go on to get higher degrees, again largely because graduate departments discriminate against women in admissions policies and in the distribution of fellowships. Once they qualify, the higher-the-fewer rule continues to apply: the higher in terms of rank, salary, prestige or responsibility, the fewer the number of women to be found. (Discrimination Against Women, 1970, pp. 244-245).

Three clear facts about admissions discrimination emerged from the Hearings. First, gender discrimination existed in both undergraduate and graduate admissions, but it was more egregious at the graduate level and prevalent across all disciplines. Moreover, the use of admissions quotas for women was well-known by school administrators and applicants alike. For example, undergraduate admission to University of North Carolina was restricted to females "who are especially well-qualified", but no such restriction for male applicants existed (Discrimination Against Women, 1970, p. 739). In the State of Virginia, 21,000 women were rejected for college entrance over a 3-year period while not one male student was rejected (Discrimination Against Women, 1970, p. 739). When the Dean of Admissions at New York University Law School was approached with the idea of actively recruiting women law students, he responded that there were already too many women and that NYU did not need classes composed of 50 percent women (Discrimination Against Women, 1970, p. 587). Studies of the status of women at Cornell University found that "there were quotas on women applicants operating at all the schools" (Discrimination Against Women, 1970, p. 1077). The Dean at Harvard Law School announced to the class of 1967 that female enrollment at Harvard Law had reached 5 percent for each class and would probably stay there as "that was Yale Law School's percentage; and that, after all, there could never be a great influx of women into the school...because the policy was never to give any man's place to a women" (Discrimination Against Women, 1970, p. 587).

Second, there were plenty of highly-qualified female applicants to various graduate school programs. Because women faced discrimination in admissions, those who decided to pursue graduate studies were exceptional students, drawn from the right-tail of the ability distribution. Professor Ann Sutherland Harris recounted stories of her colleagues complaining that women undergraduates needed A or A- grades for graduate school admission while their male counterparts were admitted with B averages (Discrimination Against Women, 1970, p. 248). A University of Chicago Report (Chicago Report) on the status of its women found that 34 percent of graduate women had grade point averages of A or A-, while the corresponding grade point average for graduate men was 27 percent (Discrimination Against Women, p. 798). In the State School of Agriculture at Cornell, "the mean SAT scores of entering women freshmen are higher than those of men by 30-40 points" (Discrimination Against Women, 1970, p. 1077).[3] Considering that female applicants were more qualified than male applicants, admission criteria that is based on merit alone would result in a higher acceptance rate for women than for men. However, all accounts report that female acceptance rates were tied to their percentage of applicants. For example, 25% of the applications to the School of Journalism at Columbia were female and 20% of its places were offered to women. Colleges and universities boasted that the acceptance rate for women was proportional to their application percentage, unaware that such a fact belied their unfavorable attitudes towards female applicants.

Third, the notion that women were less committed students than men is not true. This

3. Whether these estimates are statistically significantly different is unknown.

notion was widely-held by school administrators at the time despite a lack of accurate data on attrition rates. It was also used as an explanation by school officials, who were mainly men, when asked why women were discriminated against in admissions (Discrimination Against Women, 1970, p. 248). The Chicago Report, administered in October 1969, was the first of its kind to publish attrition statistics by department. It found that the difference in attrition at the undergraduate level is small, with women being 2 percentage-points more likely to drop out (Discrimination Against Women, 1970, p. 806). At the graduate level, however, there were no consistent differences between men and women in regards to leaving before finishing a degree. Moreover, women stop at the master's level more frequently than men but the reasons for doing so are widely varied – including inadequate performance for the PhD – whereas men are more likely than women to stop due to poor performance (Discrimination Against Women, 1970, p. 806). The Report also found that women at the University of Chicago have high career commitment. The questionnaire found that 92% of women want to have a career compared to 81% of men (Discrimination Against Women, 1970, p. 867). Relatedly, 62% of women respondents would be "very disappointed" if they left school before completing their education compared to only 53% of men (Discrimination Against Women, 1970, p. 871).[4] In summary, admissions quotas in graduate schools discriminated against highly-qualified female applicants who were also committed students. Therefore, when Title IX banned gender discrimination in graduate-school admissions, the effect on female enrollment would be immediate and consequential.

1.2.2 Title IX regulations

On June, 23, 1972, Title IX was signed into law by President Richard Nixon. It mandated that:

> No person in the United States shall, on the basis of sex, be excluded from

4. Again, it is unclear whether these differences are statistically significantly different, but the magnitudes are large.

> participation in, be denied the benefits of, or be subjected to discrimination under any education program or activity receiving Federal financial assistance.

The law was broad in scope, covering many aspects of education discrimination, but in regards to admissions, Title IX applied specifically to "institutions of vocational education, professional education, and graduate higher education, and to public institutions of undergraduate higher education."

Preparations to draft compliance regulations began shortly after its passage. Between August 2-4, 1972, the Department of Health, Education, and Welfare (HEW) held national hearings to discuss Title IX regulations. In June 1974, an initial draft of the regulations was published in the Federal Register. After reviewing nearly 10,000 comments, HEW edited the regulations, and they were signed into law by President Gerald Ford in May 1975.

Title IX regulations state:

> Compliance with any requirement adopted pursuant to this section may be effected (1) by the termination of or refusal to grant or to continue assistance under such program or activity to any recipient as to whom there has been an express finding on the record, after opportunity for hearing, of a failure to comply with such requirement, but such termination or refusal shall be limited to the particular political entity, or part thereof, or other recipient as to whom such a finding has been made, and shall be limited in its effect to the particular program, or part thereof, in which such noncompliance has been so found, or (2) by any other means authorized by law.

As is made clear in the language, Title IX had severe consequences for non-compliance; any program, department, or school that was found to be practicing gender discrimination after it was notified of the violation would no longer receive federal assistance. As such, schools had an incentive to comply with Title IX regulations. But it had been three years since Title IX was passed. Without these regulations, did universities and colleges have an incentive to comply? We examine this question in the next section.

1.3 Did universities comply with Title IX?

The 1975 Congressional Hearings before the Subcommittee on Postsecondary Education took place in June 1975, one month after Title IX regulations were signed into law. Their purpose was to review the regulations and hear any contestations. The main opposition was on Title IX's coverage of athletic programs (Sex Discrimination Regulations, 1975, p. 69, 285, 385). Its coverage of sex discrimination in admissions was not contested, likely because it was a well-acknowledged problem by that time. According to Nellie M. Varner, who testified on behalf of the National Association of State Universities and Land-Grant Colleges, the American Council on Education, and the Association of American Universities, "many institutions [had] already begun to respond to the spirit of Title IX" even though the regulations had not be been passed and therefore Title IX technically could not be enforced (Sex Discrimination Regulations, 1975, p. 416).

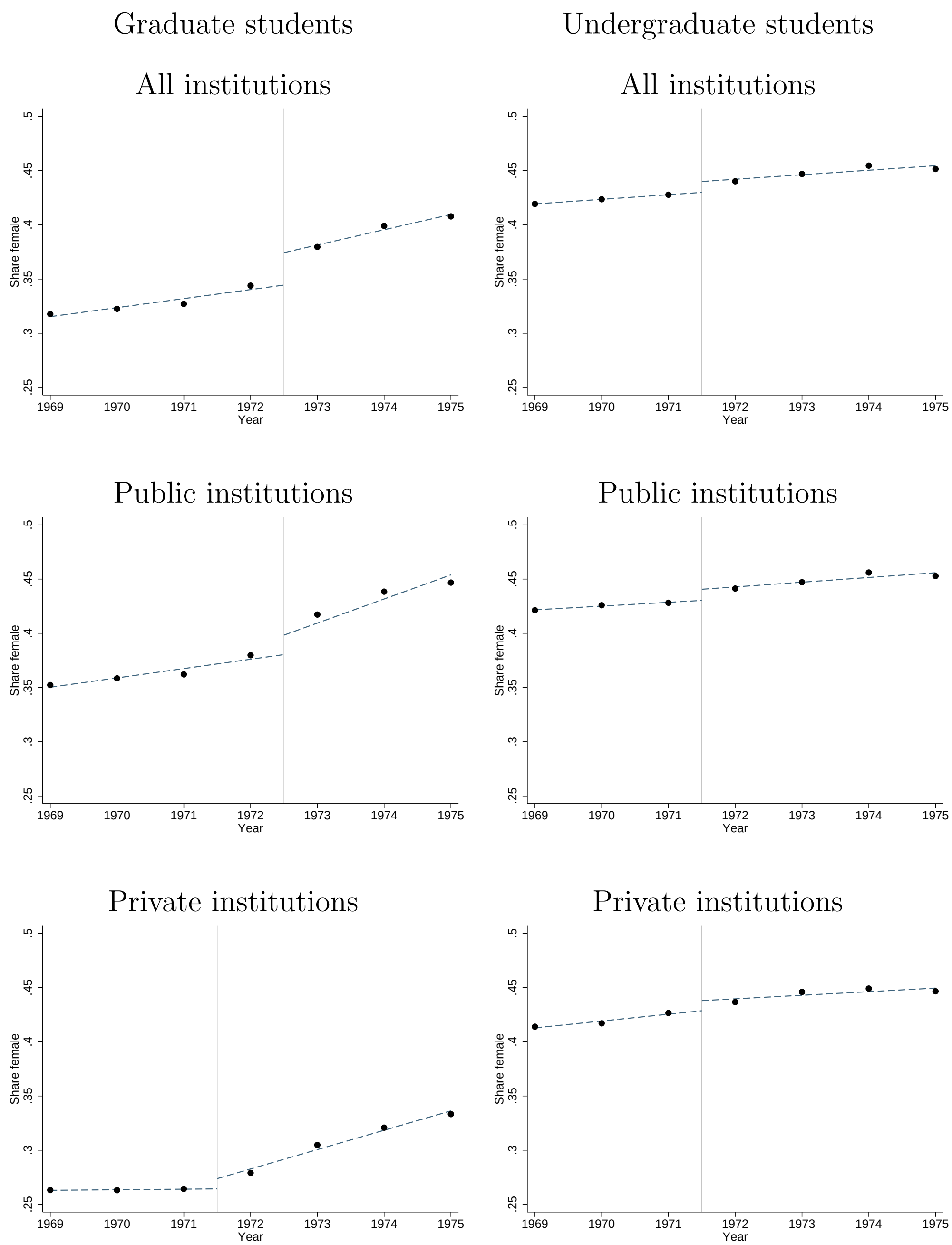
The data agree. Using fall enrollment data from the Higher Education General Information Survey (HEGIS), I examine how the female share of enrolled students evolved between 1969 and 1975. The HEGIS series were issued by the United States Department of Education to all public and private two-year and four-year institutions in an effort to provide comprehensive information on various aspects of postsecondary education in the U.S. and its territories. Figure 1.1 plots the share of female students between 1969 and 1975. The left column depicts the female share of enrolled graduate students, and the right column depicts the female share of enrolled undergraduate students. The dots are the annual mean shares, weighted by the institution's total enrollment. The vertical line represents the year of a structural break in the enrollment trend. The dashed lines are linear fitted values allowing for a structural break in the trend. The year of the break was found by maximizing the following regression, separately for graduate students and undergraduate students:

$$F(t) = \beta_0 + \beta_1 \cdot \mathbb{1}\{t > t^*\} + \tau \cdot t + \delta \cdot (t - t^*) \cdot \mathbb{1}\{t > t^*\} + \varepsilon_t \tag{1.1}$$

where $F(t)$ is the share of female students in year t and t^* is the year of the structural break in the time series.[5] The parameter τ is a linear time trend before the structural break, β_1 is the size of the structural break, and δ is the linear time trend after the structural break.

5. The range of the structural break excludes the first and last years of the time period.

Figure 1.1: Trends in female share of enrolled students



Source: HEGIS 1968-1975 Fall Enrollment data.
Notes: Each dot is the mean female share of enrolled students in each year. The dashed line is a fitted linear trend allowing for a break. The break-year was determined by looking for a structural break in the data.

All of the graphs show a structural break that occurred right around the time of Title IX's passage in June 1972. There is a larger break in graduate-school enrollment, which is not surprising as the law applied specifically to all graduate institutions. As explained before, the immediate reaction by colleges and universities is unsurprising as there were many qualified female students applying to graduate programs before Title IX's passage.

A second check of whether universities responded to Title IX is to look at enrollment trends by funding source. Since Title IX is a federal law, one would expect schools that receive more money from the federal government would feel more pressure to comply with Title IX. I use 1968 and 1969 financial statistics data from HEGIS to calculate the percentage of their general revenue that comes from the federal government.[6] I consider federal government appropriations and federally sponsored research and programs as federal funds, and categorize schools into terciles based on their federal funds share.[7]

Table 1.1 compares the median growth rate in the female share of enrolled students by tercile. Tercile 1 comprises of schools where the federal funds share is in the bottom third. Tercile 3 comprises of schools where federal funds make up larger portions of revenue. One would expect that schools in Tercile 3 would experience faster growth rates post-Title IX, relative to schools in Tercile 1. Column (3) tells us that the difference in growth rates is actually negative between 1969 and 1971. That is, the median growth rate in female enrollment share among Tercile-1 schools is larger than the median growth rate among Tercile-3 schools. Starting in Fall 1972, however, right after Title IX's passage, the median growth rate among Tercile-3 schools nearly tripled, and the difference turns positive.

6. I am only able to use 1968 and 1969 data because starting in 1970, I cannot differentiate federal funds.

7. There is quite some variation in federal funding shares; the average federal share of revenue between 1968-1969 is 8.7 percent and the median share is 4.9 percent. The 10th and 90th percentiles are 0.1 percent and 21.5 percent, respectively.

Table 1.1: Median growth rate in female enrollment share

Year	Percentage of revenue from federal funds		
	Tercile 1 (Low)	**Tercile 3 (High)**	**Difference**
	(1)	(2)	(3)
1969	0.9%	0.3%	-0.6%
1970	1.2%	0.9%	-0.3%
1971	1.9%	1.0%	-0.9%
1972	2.2%	2.9%	0.7%
1973	1.6%	2.5%	0.9%
1974	2.5%	3.1%	0.7%
1975	-0.03%	1.0%	1.0%

Source: HEGIS 1968-1975 Fall Enrollment data and 1968-1969 Financial Statistics data.
Note: Numbers depict the median growth rate in the female share of total enrollment. (3) = (2) - (1).

In summary, the data support the argument that universities responded immediately to Title IX, and that there were enough qualified female applicants to meet the demand. Using enrollment data, I find a structural break in the female-share trend right after Title IX's passage. I also find stronger evidence of compliance among graduate schools, which is consistent with the 1970 Congressional Hearings and Title IX regulations. Informed by these findings, the rest of my analysis will focus on graduate degrees.

1.4 Data and Summary Statistics

The National Survey of College Graduates (NSCG) is a longitudinal, biennial survey of U.S. college graduates that began in the 1970s. I use data from the 1993 survey, which surveyed all non-institutionalized, U.S. individuals under the age of 73 with at least a bachelor's degree as of 1993. The individuals who lived through Title IX would have been roughly 40-50 years old in 1993 and, therefore, in this dataset. Most importantly, the 1993 survey is the first of its kind to ask about field of study.

The survey asks respondents to report their field of study and year of degree for their (1) bachelor's degree, (2) most-recent degree, and (3) second most-recent degree. I classify graduate degree as any degree other than a bachelor's degree. This includes master's degrees, professional degrees, and doctoral degrees. All results reported in this paper use data on the highest degree.[8] There are 255 reported fields of study in the NSCG data. I consolidate these into 28 main fields, as categorized by the 2010 Classification of Instructional Programs (CIP).[9] My main analysis sample considers all graduate degrees obtained before age 35 between 1964 and 1987.[10] I combine two-year cells to increase power.

Table 1.2 provides a sense of the status of education before Title IX. In 1965, there were about almost 15,000 or 11 percent more male BAs than female BAs. Similarly, in 1970, there were nearly twice as many males with graduate degrees, relative to females. By 1980, however, the number of female graduate degrees more than doubled, and the male-to-female graduate degree ratio was almost at parity. Second, Education is the most popular graduate field of study for both males and females in 1970. But whereas nearly half of all females in graduate school are in education, only 20 percent of males chose that field. In other words, males were more evenly distributed across fields in graduate school whereas females were clustered in education.

The next two most popular graduate fields for men are business, at 14.1 percent, and legal, at 10.3 percent. By contrast, only 1.9 percent of females are in business school and 2.5 percent are pursuing an law degree in 1970. The disparity between male and female educational choices becomes starker when we consider undergraduate majors. In 1965, back

8. The highest degree very closely corresponds with most-recent degree. 99.6 percent of respondents in the NSCG 1993 survey have matching highest-degree and most-recent degree types. Of the 447 respondents whose highest degree type and most-recent degree type differ, 134 of them (30 percent) are in the same field-of-study.

9. CIP was originally developed in 1980 by the U.S. Department of Education's National Center for Education Statistics for the purpose of accurate tracking, assessment, and reporting of fields of study. Please see the online appendix for the crosswalk between NSC 1993 reported field of study and the 2010 CIP major code.

10. I choose age 35 as an arbitrary cutoff age as most graduate degrees are obtained by then. The average age of a graduate-degree-holder was 30 between 1960-71 and 31 between 1973-90.

when these graduate students were in college, 6.2 percent of female BAs studied health but only 2.5 percent of males did so. However, males made up 68 percent of graduate health degrees in 1970; men were severely over-represented in medical school. A similar story can be seen for legal degrees. Female and male BAs majored in legal professions in similar proportions (around 0.3-0.4 percent), but males were 4 times more likely to pursue a graduate law degree.

Table 1.2: Summary Statistics of Major Fields of Study in 1965, 1970, and 1980

	1965 BAs		**1970 Grad. Degrees**		**1980 Grad. Degrees**	
Fields of Study	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
Legal	0.4%	0.3%	10.3%	2.5%	13.8%	6.7%
Health	2.5%	6.2%	8.1%	6.8%	16.1%	12.5%
Engineering	12.9%		9.9%	0.1%	5.0%	2.1%
Phys. Sci.	3.4%	0.2%	6.2%	1.1%	2.8%	0.7%
Business	30.1%	4.4%	14.1%	1.9%	19.6%	14.4%
Comp. Sci.	0.1%	0.6%	0.8%		2.4%	0.5%
Engin. Tech.	2.2%		0.3%		0.5%	0.1%
Math	5.2%	1.7%	3.6%	1.5%	0.9%	0.8%
Soc. Sci.	5.9%	5.9%	3.8%	1.3%	1.7%	1.9%
Architecture	0.9%		0.4%		1.2%	0.5%
Nat. Resources	1.1%		0.0%		0.2%	0.8%
Agriculture	3.4%		1.6%		1.3%	0.4%
Bio. Sci.	3.0%	2.7%	1.8%	2.7%	2.4%	1.7%
Comm.	1.3%	0.4%	1.7%	2.5%	1.4%	0.7%
Ethnic Stud.		0.4%			0.0%	
Homeland Sec.				0.1%	1.3%	0.3%
History	3.9%	2.9%	1.2%	1.0%	0.4%	0.1%
Pyschology	2.2%	1.3%	3.6%	6.4%	5.0%	5.5%
Pub. Admin.	0.5%	1.5%	2.5%	5.3%	2.6%	5.5%
For. Lang.	0.8%	2.1%	0.5%	3.4%	0.3%	0.2%
Education	11.7%	47.6%	19.6%	47.6%	14.2%	35.0%
Liberal Arts	1.1%	2.1%		0.7%		0.2%
English	1.2%	5.0%	2.2%	4.4%	0.8%	1.3%
Parks & Rec.	0.4%	0.3%	0.4%		0.4%	0.8%
Family Sci.	0.3%	4.8%		2.3%	0.1%	1.2%
Library Sci.		1.2%	0.9%	4.2%	0.4%	2.3%
Perf. Arts	1.8%	8.3%	2.2%	2.1%	1.3%	3.3%
Philosophy	2.9%		3.7%	1.4%	2.9%	0.5%
Not classified	0.6%		0.4%	0.7%	1.0%	0.2%
Total	99.4%	100.0%	99.6%	99.3%	99.0%	99.8%
Number of graduates	150,373	135,576	105,248	58,307	143,458	122,361

Source: NSCG 1993 data.
Notes: Reported fields of study were consolidated into 28 major fields using CIP 2000.

1.5 Effect on Graduate-field Distributions

1.5.1 Convergence Measures

This section examines the effect of Title IX on the convergence between male and female distributions of graduate fields of study. I use two different methods to measure gender convergence. The first is the Segregation Index, also known as the Index of Dissimiliarity, developed by Duncan and Duncan (1955). The segregation index is used to measure change in the distribution of an unordered, categorical variable and has been used in a variety of applications, from measuring racial segregation in neighborhoods (Massey & Denton, 1988) to gender segregation in occupations (Blau, Brummund, & Liu, 2013). It is calculated as follows:

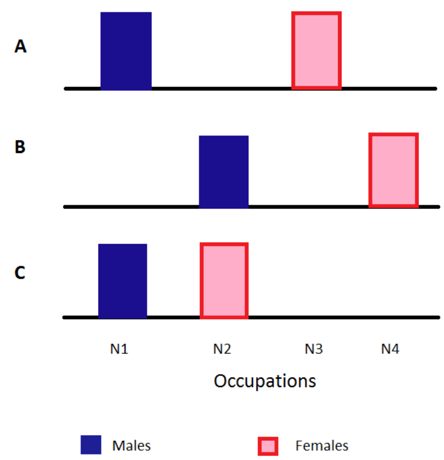
$$S_t = (0.5) \cdot \sum_i |m_{it} - f_{it}| \tag{1.2}$$

where m_{it} is the share of all male graduate students in degree-field i in year t and f_{it} is the share of all female graduate students in field i in year t. This measure indicates the percentage of women (men) who would have to change graduate fields for the overall distributions of men and women to be identical. For example, if the share of women in all fields is the same as their share of total graduate degrees, then the segregation index is 0. Therefore, larger values indicate greater segregation (divergence) and smaller values indicate greater integration (convergence).

As is clear from the formula, the segregation index does not consider the ordering of the fields of study. For example, a segregation index of 30 means that 30 percent of women (or 30 percent of men) need to change their degree-field but there is no constraint on where these women (men) move to or where they moved from. In some cases, however, this is an important detail. I illustrate my point with a simple example below.

Say we would like to measure gender segregation in the occupation distribution. For simplicity, assume there are four occupation categories: N1, N2, N3, and N4. Figure 1.2 presents three different examples of occupation distributions by gender: A, B, and C. The segregation index for all three scenarios is equal to 100. According to the segregation index, these three distributions have the same level of gender segregation.

Figure 1.2: Convergence Measure Example



Now, say that N1 is Lawyers, N2 is Doctors, N3 is Teachers, and N4 is Secretaries. Now it becomes less clear that the level of gender segregation is equal across the three scenarios. Distribution A and Distribution B seem similar, but Distribution C, where all men are lawyers and all women are doctors, is different from the other two. The reason is that, when assessing the level of gender segregation, we inherently assign values to each occupation category.[11] For example, in a society where all men are lawyers, there is less resulting gender segregation if a female secretary becomes a doctor than if she became a teacher. Put another way, the "distance" an individual moves to switch occupations is non-constant across occupations. A secretary and a lawery are further apart on a "distance" metric than a secretary and a teacher. This distance is something that I would like to incorporate in my convergence measure. To relate this to the segregation index, we care about *where* we move the 30 percent of women (or men) relative to where they came from. This is an important detail for this case as we are studying discrimination and the fact that women were barred

11. Wage is one example of a "value" of an occupation.

from entering certain fields and subsequently, occupations. Therefore, a woman moving to an occupation from which she was previously banned would indicate greater integration in comparison with her moving to an occupation that is female-dominated.

The Earth Mover's Distance is a metric that measures the difference between two distributions by taking into account both within-category and cross-category differences. It is the minimal cost that must be paid to transform one distribution into the other. For example, say we have a male distribution of I graduate fields, $M = [m_1, \cdots, m_i, \cdots, m_I]$, and a female distribution of J graduate fields, $W = [w_1, \cdots, w_j, \cdots, w_J]$. To transform distribution M to distribution W, the EMD is defined as follows:

$$\text{EMD}(M, W) = \frac{\sum_{i=1}^{K} \sum_{j=1}^{K} d_{ij} f_{ij}}{\sum_{i=1}^{K} \sum_{j=1}^{K} f_{ij}} \tag{1.3}$$

where i, j denote graduate-field category for distributions M and W, respectively, d_{ij} is the distance between graduate-field categories m_i and w_j, and f_{ij} is the total number of people who are being moved between m_i and w_j. Appendix A.1 describes EMD in more detail. Because EMD considers cross-category differences, the ordering of categories is non-trivial. In my application, I order graduate fields by decreasing expected salary. I define a field's expected salary as the median salary for everyone who obtained a graduate degree in that field between 1962 and 1991. Because EMD considers categories that are further away from each other to have a higher "moving cost", the ordering by expected salary is a logical one.

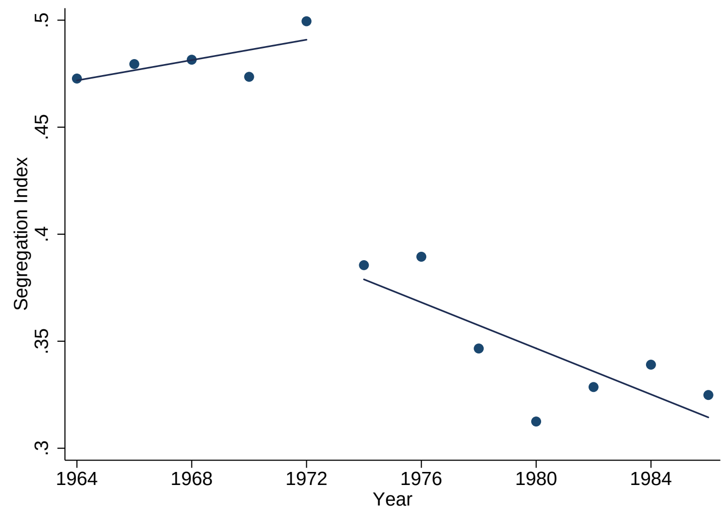
1.5.2 Results

Next, I provide graphical evidence of gender convergence in graduate-field distribution after Title IX's passage. Figure 1.3 plots the segregation index between the male distribution and the female distribution from 1964 to 1986. In 1964, the segregation index is 47 percent. This means that 47 percent of the women with graduate degrees would need to change their field of study in order to have the same overall graduate-field distribution as men. By 1986, the index drops down to 32 percent. There is a marked jump in the segregation index between 1972 and 1974 as depicted by the solid lines. The solid lines in the graph are fitted linear trends allowing for a break. The break-point was found by looking for a structural break in the data (equation (1.1)). I find that the male and female distributions became 13 percentage-points more similar, as measured by the segregation index, after Title IX's passage. Notice that the timing is consistent with what we found in Figure **??**. A majority of graduate degrees are master's degrees, so it is not surprising that we see a structural break in convergence trend starting in 1974.[12]

Figure 1.4 compares distributional change as measured by the Segregation Index and EMD. Both convergence measures are normalized to their respective 1964 values. The two measures show the same picture. I find a structural break between 1972 and 1974 whether I use the Segregation Index or EMD. Both measures estimate that distributional convergence increased around 20 percent after Title IX's passage, relative to its 1964 value. EMD, however, estimates greater convergence. Considering how these two measures are calculated, this implies that most of the convergence were in fields that were further apart. I explore this further in Section 1.6. For the rest of my analysis, I report estimates using the preferred EMD measure.

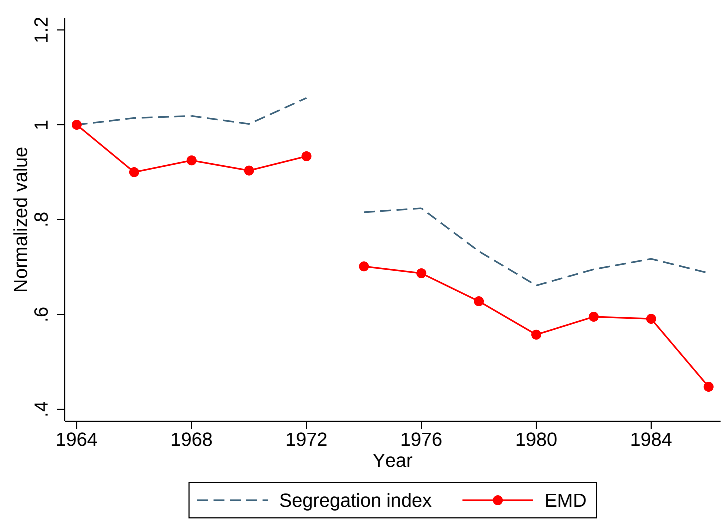
12. The average share of graduate degrees that are master's degree is 75 percent between 1965 and 1981. The range in this time period is 74 percent to 77 percent.

Figure 1.3: Level of Segregation between Female-Male Distributions



Source: NSCG 1993 data.
Note: The dots are mean values for each year. Lines are fitted linear trends allowing for a break between 1972-73 and 1974-75. The break year was determined by looking for a structural break in the data.

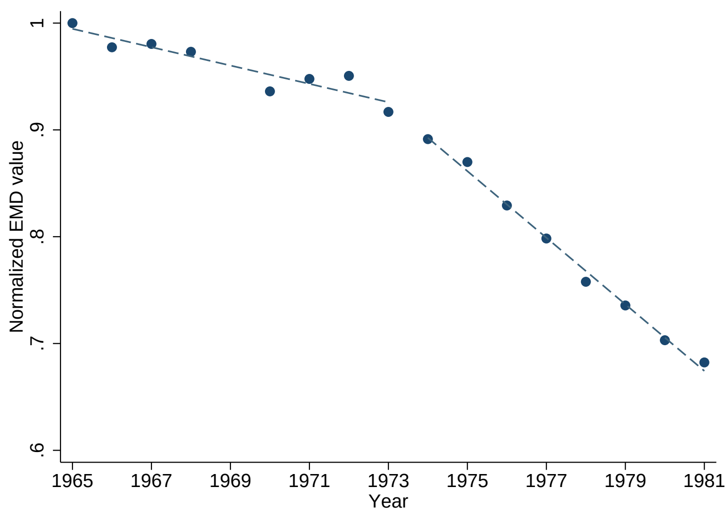
Figure 1.4: Female-Male Convergence in Distributions of Graduate Fields



Source: NSCG 1993 data.
Note: Normalized values have been normalized to 1964-65, separately for Segregation Index and EMD. Lined are connected values allowing for a break between 1972-73 and 1974-75. The break year was determined by looking for a structural break in the data.

Next, I conduct the same analysis using a different dataset. The HEGIS survey also asks about earned degrees and the specific fields by gender.[13] Using data from 1965 to 1981, I estimate the EMD distance between male and female distributions of graduate degree-fields and plot them in Figure 1.5.[14] Similar to my analysis using NSCG data, I find that the two distributions were converging over time with a break between Fall 1973 and Fall 1974. This break-point coincides with the earliest year that we would expect to see a change in earned degrees post-Title IX. Before 1973, convergence moved more slowly relative to the period after 1973. For example, the slope in the pre-Title IX period is -0.01, while the slope steepens to -0.03 in the post-Title IX period.

Figure 1.5: Female-Male Convergence using HEGIS data



Source: HEGIS 1965-1981 Earned Degrees data.
Note: Each dot is the normalized EMD distance between male and female distributions in that year. The dashed line is a fitted linear trend allowing for a break between 1973 and 1974. The break-year was determined by looking for a structural break in the data.

I also conduct a secondary analysis by birth-cohort rather than degree-year. This spec-

13. Although HEGIS, being an administrative source of graduate degree data, has some advantages over the NSCG 1993 survey, my preferred data source for my main analysis is the NSCG because it contains information on individuals, such as geographic location and birth-year.

14. There are no data available for 1969.

ification will inform us which *cohort* was most affected by the Title IX policy. As a result, the interpretation differs slightly from the degree-year analysis. In the previous analysis, we see an immediate impact on earned degrees - as soon as spring 1975. I argue that this is not surprising as there were many qualified female graduate school applicants who, prior to Title IX, would have been rejected solely on the basis of admissions quotas.

A cohort analysis, however, empirically assesses the impact of Title IX on an entire birth cohort. To the extent that a decision to pursue graduate studies in a particular field requires some advance planning and preparation, we expect that younger cohorts, who are able to make human capital investments and decisions accordingly, would be more affected. In other words, we would expect initial effects of Title IX to be concentrated among freshmen and sophomores in college, who have time to react to the new policy, as opposed to juniors and seniors who would not be able to change their major or post-college plans as easily.

Under the argument that Title IX was unexpected and sudden, our estimate from the degree analysis can be thought of as the impact on "always takers", whereas the estimate from the cohort analysis can be thought of as the impact on "always takers" plus "compliers". The cohorts born between 1942 and 1953 began their college years under the assumption that admissions quotas would still be operating when they graduated from college. Therefore, women who applied to graduate school in the fall of 1972 and were accepted "randomly" when Title IX passed, can be thought of as a variant of an "always taker".[15]

Figure 1.6 graphs the results. Consistent with my hypothesis, I find a structural break between cohorts born in 1952-1953 and 1954-1955. The first cohort turned 19-20 years old in 1972, and the second cohort turned 17-18 years old.

15. These women may also be considered compliers in terms of their decision to pursue graduate studies as Title IX's passage induced them to apply to graduate school the following fall. However, they would be restricted in the graduate field of study, which would most likely to similar to their undergraduate major choice. In terms of the graduate degree-field, therefore, these women can be considered as a type of "always taker".

Figure 1.6: Female-Male Convergence by Birth Cohort

Source: NSCG 1993 data.
Note: Each dot is the normalized EMD distance between male and female distributions in that year. The dashed line is a fitted linear trend allowing for a break between 1952-53 and 1954-55 cohorts. The break-year was determined by looking for a structural break in the data.

Under the assumptions that Title IX is relevant (it affected admissions rates for women), excludable (it did not directly affect the graduate degrees except through its impact on admissions), and valid (it is uncorrelated with other determinants of female graduate degrees), its passage can be used as a natural experiment or an instrument. These assumptions are trivially satisfied. Title IX explicitly addresses gender discrimination in graduate school admissions, and Section 1.3 provides evidence that female enrollment numbers increased relative to male's after its passage. Moreover, a review of the history of the passage of Title IX reveals that it was passed because of persistent gender discrimination in educational institutions. This invalidates the argument that other determinants of increased female graduate degrees, say a decreasing wage gap, is correlated with Title IX's passage. In fact, historical testimony shows the exact opposite. Therefore, these results can be interpreted as a causal estimate of the effect of the removal of admissions quotas for women on gender disparity in graduate education. More importantly, my findings hold despite using different analysis methods and data sources.

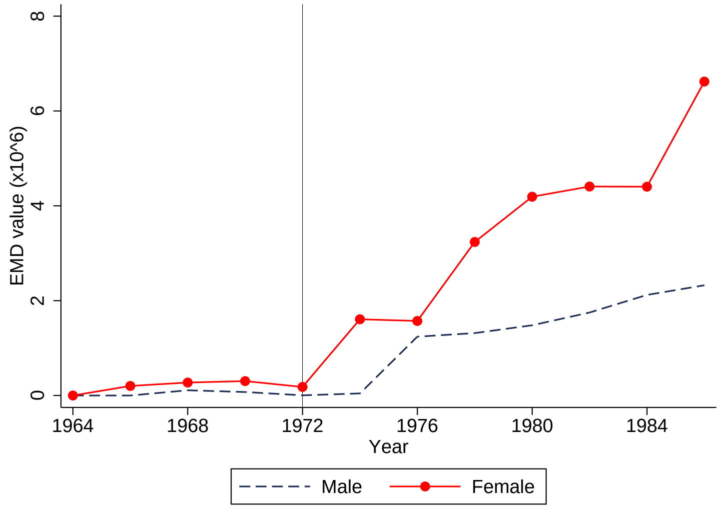
1.6 Unpacking distributional change

1.6.1 Female versus Male Movement

The previous section established a large, discrete, nationally-observed jump towards gender convergence in graduate-field distributions. Here, I explore Title IX's effect at a more granular level. I am interested in unpacking the observed distributional changes to better understand the drivers of the observed change. As a first step, I examine whether the structural break is due to predominantly female movement, predominantly male movement, or both. I compare the female distribution of graduate fields to the female distribution from 1964-65, and similarly for the male distributions. This analysis is another advantage of EMD over the Segregation Index; we cannot do this with the segregation index because it uses absolute gender differences in its formula.

Figure 1.7 tells us that gender convergence in graduate fields was driven by female movement. Larger EMD values relate to greater distributional divergence whereas smaller EMD values relate to distributional convergence. Prior to 1972, the female graduate-field distribution did not look very different from the distribution in 1964 and the same is true for males. After 1972, however, females and males begin entering different fields from their 1964-peers, but the change among females begins earlier and is larger.

Figure 1.7: Distributional change in graduate fields by gender



Source: NSCG 1993 data.
Note: This figure plots distributional change in graduate-field distributions relative to the 1964 distribution, separately for each gender. The vertical line depicts the year that Title IX was passed.

1.6.2 By Salary Tercile

In this section, I examine which degree-fields contributed to the distributional change. Since EMD orders degree-fields by salary in its calculation, I classify each field into terciles based on its expected salary.[16] I then estimate a difference-in-differences regression model, comparing the female-male difference in graduate degrees obtained before and after Title IX's passage. Because my DID methodology compares female degrees to male degrees, there is a mechanical relationship between the two especially when comparing gender differences within a particular degree field. To bypass this issue, I restrict my analysis sample to whites. Whites make up 90 percent of the NSCG sample allowing the white-male share to vary

16. See Appendix A.1 for the list of degree fields by tercile.

independently of the white-female share. The regression model is as follows:

$$
\begin{aligned}
Y_{it}^{c} &= \beta_0^c + \beta_1^c \cdot F_i + \beta_2^c \cdot \mathbb{1}\{\texttt{Title IX}\} + \delta^c \cdot \Big(F_i \times \mathbb{1}\{\texttt{Title IX}\}\Big) \\
&\quad + \tau_0^c \cdot t + \tau_1^c \cdot (F_i \times t) + + \tau_2^c \cdot \Big((t - \texttt{Title IX}) \times \mathbb{1}\{t > \texttt{Title IX}\}\Big) \\
&\quad + \tau_3^c \cdot \Big(F_i \times (t - \texttt{Title IX}) \times \mathbb{1}\{t > \texttt{Title IX}\}\Big) + X'\gamma^c + \varepsilon_{it}^c
\end{aligned}
\tag{1.4}
$$

where $Y_{it}^c = 1$ if individual i obtained a graduate degree in tercile c in year t, F_i is a female dummy; the indicator dummy, $\mathbb{1}\{\texttt{Title IX}\}$, is equal to 1 if the graduate degree was earned in 1974 or later and equal to 0 otherwise; X is a vector including fixed effects for the highest degree-granting school's region and birth-year. The parameter τ_0^c is a linear time trend for male graduate degrees, and τ_1 is the female-male difference in pre-trend. The parameter τ_2^c is the post-Title IX time trend for male degrees, and τ_3^c is the female-male difference in post-trend. The parameter of interest is δ^c, which gives us the female-male difference in graduate degrees in tercile c due to Title IX.

Before Title IX, 31 percent of men had a graduate degree, with 61 percent of these in the top salary tercile. Women, by contrast, were 38 percent less likely to hold a graduate degree in comparison with men, and two-thirds of their degrees were in the *bottom* salary tercile. If Title IX were successful in removing gender discrimination, which was more salient in more-lucrative fields, we would expect to see monotonically decreasing effects by salary tercile. Table 1.3 confirms this. Title IX led to a 14 percentage-point increase in female graduate degrees in the top salary tercile, relative to males'. By contrast, female graduate degrees in the bottom salary tercile dropped by 11 percentage-points, relative to males'. To understand the magnitude of these effects, consider the overall increase in female share in these fields. The share of female graduate degrees in the top salary tercile increased by 19.5 percentage-points between 1964-72 and 1974-87. Title IX explains about 73 percent (= 14.3/19.5) of the growth in this tercile during this period.

The identifying assumption for DID is that the treatment group and the comparison group were exhibiting similar trends in the outcome variable prior to the treatment. This allows us to obtain counterfactual estimates of the treatment group's outcome in the absence of treatment. For the purposes of this study, this means that male share of graduate degrees should be on a similar trend as female graduate degrees before Title IX's passage. We see from Table 1.3 that this assumption holds; the coefficient on τ_1 is very small (from -0.7 percent to 0.6 percent) and statistically insignificant.

Table 1.3: Gender difference in graduate degrees by salary tercile

Dependent variable: Graduate degree in tercile t before age 35			
Salary tercile	**Top (Highest)** (1)	**Middle** (2)	**Bottom (Lowest)** (3)
Female	13.32	-2.065	-11.26
	(8.710)	(3.694)	(8.878)
Title IX	-0.0445*	0.0156	0.0290
	(0.0239)	(0.0109)	(0.0205)
Female x Title IX	0.143***	-0.0355**	-0.107***
	(0.0274)	(0.0130)	(0.0246)
Time trend	-0.0160***	0.00646***	0.00955*
	(0.00448)	(0.00127)	(0.00465)
Female x Time trend	-0.00699	0.00107	0.00593
	(0.00442)	(0.00188)	(0.00451)
Post-Title IX time trend	0.00882	-0.00310	-0.00572
	(0.00508)	(0.00229)	(0.00508)
Female x Post-Title IX time trend	0.0140**	0.00406	-0.0181***
	(0.00537)	(0.00329)	(0.00533)
Male distribution of baseline outcome	0.609	0.118	0.273
Female distribution of baseline outcome	0.185	0.149	0.666
Observations	20,544	20,544	20,544
Controls	Yes	Yes	Yes

Source: NSCG 1993 data.
Notes: Salary terciles are created using the field's median salary between 1961-1991. Baseline outcome is the mean outcome before 1972. Controls include fixed effects for birth-year and the region of highest degree-granting school. Standard errors are in parentheses and are clustered by region. *** p< 0.01, ** p< 0.05, * p< 0.1

1.6.3 By Gender Parity

Admissions quotas for women existed across all graduate fields of study, but data and testimonies reveal that they were more egregious in some. This may be one explanation for why there were few women in law and engineering in 1970, as we saw in Table 1.2. Although Title IX was a national policy aimed at eliminating gender discrimination in admissions at all graduate schools, if there were differing levels of discrimination across fields, then a removal of these barriers-to-entry would have differing effects by field. Specifically, one would expect Title IX to have larger effects on female degrees in fields where women faced greater discrimination and smaller effects in fields with less discrimination.

Another explanation for low female representation in certain fields may be that female preferences differ from male preferences. That is, there may be few females in law or engineering because males differentially prefer these fields. If this were true, a removal of barriers-to-entry would have no effect on female share in these fields. That is, even if law school admissions quotas for women were removed, we would still see few women in law school, relative to men, because they did not prefer that field of study. In this section, I explore this issue further and examine whether Title IX had heterogeneous effects by gender parity. This also provides an indirect test for the presence of gender discrimination in graduate education.

I proxy for the level of gender parity in the degree field by using the field's average female share of degrees between 1962 and 1970. Appendix A.2 lists the fields that are in these three groups. This list is highly correlated with the grouping by expected salary, indicating that the graduate fields that were male-dominated were also the most lucrative. I estimate equation (1.4) separately for each gender-parity tercile and report results in Table 1.4.

Not only did Title IX decrease gender disparity most in fields where females were historically under-represented, its effects decrease by increasing female representation. After Title IX, women are 9.5 percentage-points more likely than men to pursue male-dominated degrees, and 12 percentage-points less likely to pursue a female-dominated degree. If gender discrimination in graduate admissions existed and Title IX accomplished what it had set out to do, then these results and patterns are exactly what we would expect to see. Again, the pre-trends are not statistically significantly different between men and women, allowing us to interpret these coefficients as causal estimates.

Table 1.4: Gender difference in graduate degrees by gender parity

Dependent variable: Graduate degree in tercile t before age 35			
Gender parity tercile	**Top (M-dom.)** (1)	**Middle** (2)	**Bottom (F-dom.)** (3)
Female	1.008	14.94	-15.94
	(9.121)	(8.462)	(9.216)
Title IX	-0.0462*	0.0103	0.0359
	(0.0233)	(0.0226)	(0.0313)
Female x Title IX	0.0949***	0.0210	-0.116**
	(0.0202)	(0.0279)	(0.0366)
Time trend	-0.00562	-0.00904**	0.0147**
	(0.00522)	(0.00284)	(0.00584)
Female x Time trend	-0.000726	-0.00760	0.00833
	(0.00463)	(0.00430)	(0.00468)
Post-Title IX time trend	0.00748	0.00116	-0.00864
	(0.00514)	(0.00369)	(0.00493)
Female x Post-Title IX time trend	0.00403	0.0133**	-0.0173***
	(0.00703)	(0.00529)	(0.00487)
Male distribution of baseline outcome	0.483	0.255	0.262
Female distribution of baseline outcome	0.073	0.217	0.710
Observations	20,544	20,544	20,544
Controls	Yes	Yes	Yes

Source: NSCG 1993 data.
Notes: Gender parity terciles are created using the field's mean share of females between 1962-1970. Baseline outcome is the mean outcome before 1972. Controls include fixed effects for birth-year and the region of highest degree-granting school. Standard errors are in parentheses and are clustered by region. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

1.7 Alternative explanations

In this section, I address alternative explanations that may have contributed to gender convergence in graduate education in the absence of Title IX. The 1960s and 1970s were a time of great social change so it is not hard to imagine that other factors may explain the sharp gender convergence in graduate-field distribution. Two events that are often cited as causes of change in female education and labor force behavior are increased access to birth control by young, single women in the late 1960s and the legalization of abortion in 1973. I will address both of these in turn.

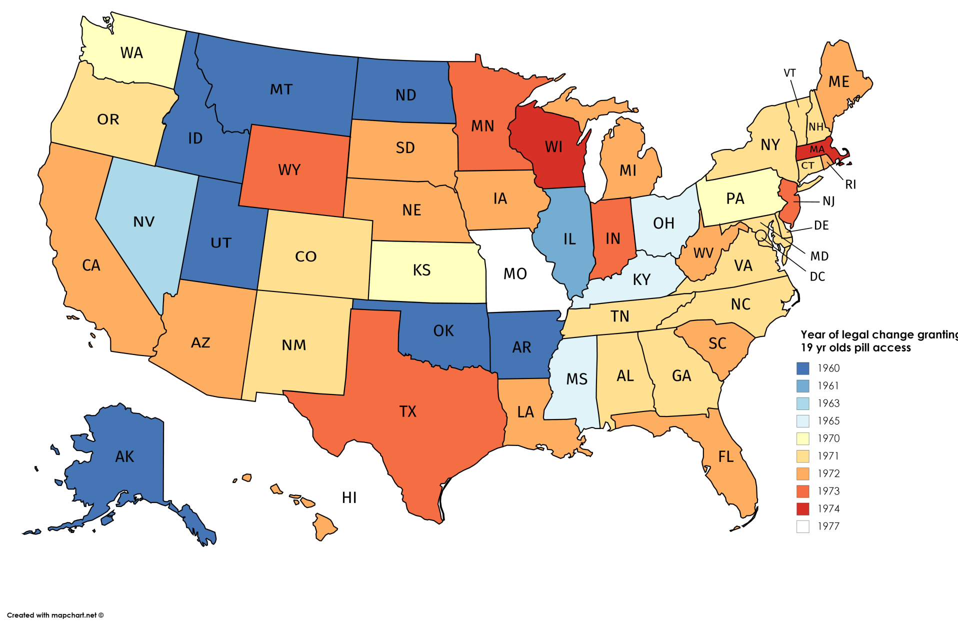
1.7.1 Access to the Birth Control Pill

The introduction of the birth control pill in 1960 as an oral contraceptive was an important milestone in advancing female rights and civil liberties. It not only gave women sexual freedom, but it also lowered the cost of making long-term career investments. With greater certainty over the pregnancy consequences of sex, women no longer needed to worry about an unintended pregnancy interrupting their education or career.

The concern in estimating a causal effect of Title IX is that young, single women gained access to the pill around the same time that Title IX was passed. When *Enovid* first became publically available, it was first available only to married women or to those above the age of majority. During the late 1960s, several states lowered their age of majority thereby granting a large set of young women access to the pill. These legal changes came about mainly in response to the discrepancy in minor's rights highlighted by the ongoing Vietnam War. In particular, 18-year old men were being drafted but were not allowed to vote until they were 21 (Paul, Pilpel, & Wechsler, 1974). Aside from changes in the age of majority, there were other legal ways that single, female minors could obtain the pill. Some states enacted a medical consent law that granted unmarried minors capacity to consent, while others had judicial or legislative recognition of a mature minor doctrine. Figure 1.8 illustrates each state's year of legal change granting 19 year olds pill access.

Although there is a lot of variation across states, a large majority of the states changed their law between 1971 and 1973. To examine whether my nationally-observed jump in convergence is driven by these states, I drop them from my analysis sample and plot gender convergence over time.[17] Figure 1.9 graphs the results using HEGIS Earned Degrees data.[18] The structural break is found after Title IX's passage, but it is one year earlier than the break-year found in the main analysis sample. One possible explanation for this is that these results are driven by states that changed their law in 1960. To the extent that the pill affected female educational choices and graduate school aspirations, we would expect to see earlier impact for this more motivated group.

Figure 1.8: Year of legal change granting 19 year olds pill access

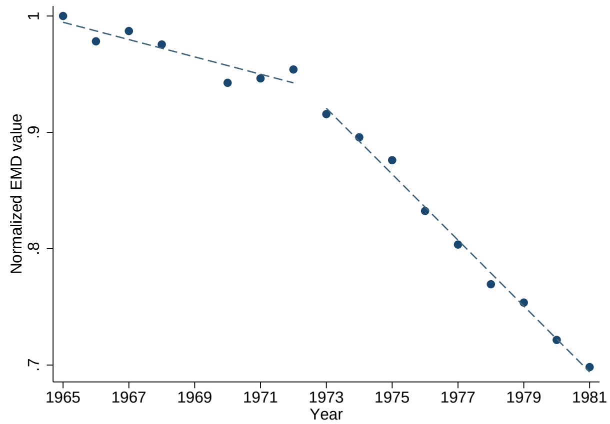


Source: Myers (2017), Appendix Table A-1.
Note: This map displays the legal codings preferred by Myers (2017).

17. There are five papers that exploit state-level variation in which minors gained access to the birth control pill (Myers, 2017). The legal codings used by these authors all differ. I drop the 30 states in which at least four of the five codings agree that the year of legal change for that state was between 1971 and 1973. These states are Alabama, Arizona, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Indiana, Iowa, Louisiana, Maine, Maryland, Michigan, Minnesota, Nebraska, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Vermont, Virginia, and West Virginia.

18. I use HEGIS data for this analysis rather than NSCG data because state restriction severely limits the number of observations in the NSCG data, which is a sample survey.

Figure 1.9: Gender convergence after dropping states with legal changes between 1971-1973



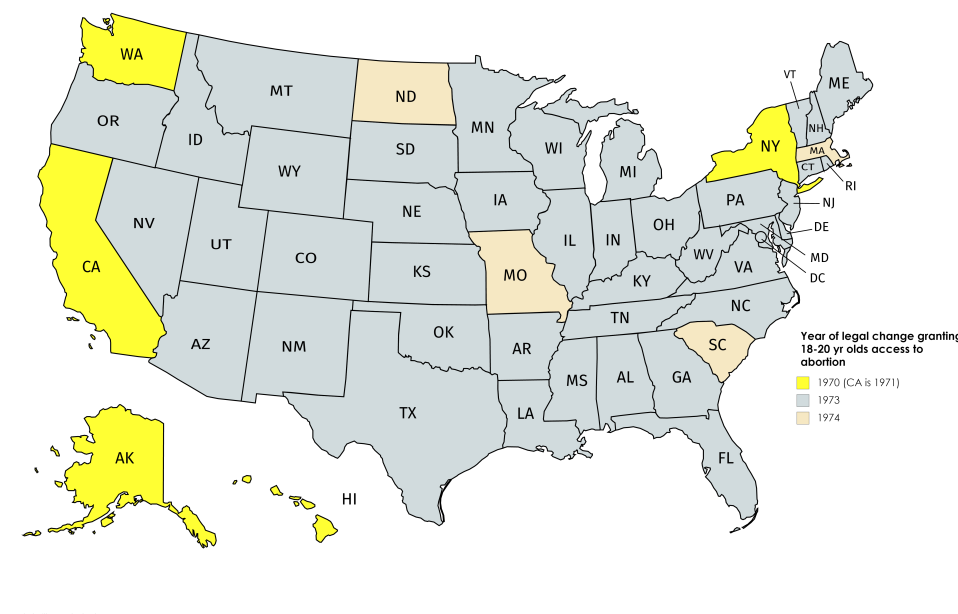
Source: HEGIS 1965-1981 Earned Degrees data; Myers (2017), Appendix Table A-1.
Note: The sample is restricted to states that passed laws granting 19 year olds pill access before 1971 or after 1973, the same time period that Title IX was passed. Normalized values have been normalized to 1965. Lines are fitted linear trends allowing for a break between 1972 and 1973. The break year was determined by looking for a structural break in the data.

1.7.2 Legalization of Abortion

A second alternative explanation to Title IX is the 1973 landmark U.S. Supreme Court case *Roe v. Wade* that legalized abortion. Just as the birth control pill lowered the cost of long-term investments for women, abortions gave women more choice and control over their lives. If a woman became pregnant while in college or graduate school, she would have had no choice but to drop out of her program. Therefore, by allowing females to terminate their pregnancies, we would expect *Roe v. Wade* to increase the number of female graduates. As a result, any positive, significant effects I see in my analysis would be due to both *Roe v. Wade* and Title IX.

Unlike pill access, there is much less state variation in when single, college-aged women gained access to legal abortions. Figure 1.10 is very monochromatic as nearly all of the states legalized abortion in 1973. Fortunately, there are five states that legalized abortion in 1970-1971. To control for the potentially confounding effects of *Roe v. Wade*, which passed in 1973, I restrict my analysis to these five states.[19] Figure 1.11 plots the normalized EMD values for degrees conferred in these five states and finds a structural break right after Title IX's passage. Similar to my results when controlling for pill access, I find that the structural break occurred one year earlier than in my main analysis. This is not surprising as these young women had access to legal abortions in 1970, three years before Title IX's passage. It is important to note that these five Repeal States are different from the states in my pill-access sample, so my results from this robustness check are not being driven by the same few states.

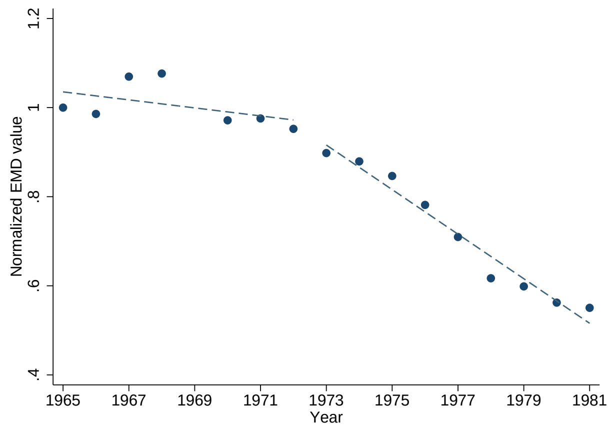
Figure 1.10: Year of legal change granting 18-20 year olds access to abortion



Source: Myers (2016), Table 2.

19. As with the pill analysis, I use HEGIS data for this robustness check as opposed to NSCG data due to the small sample size.

Figure 1.11: Gender convergence after restricting sample to Repeal States



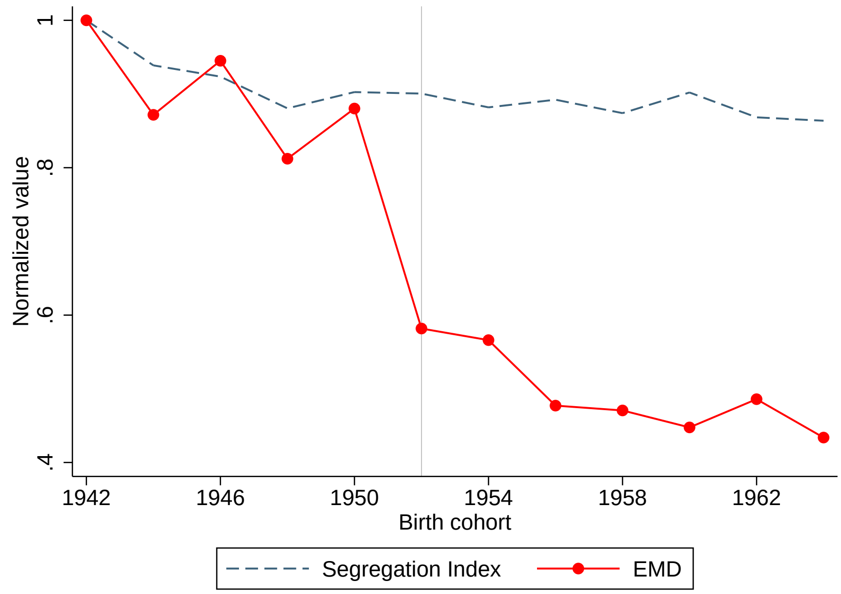
Source: HEGIS 1965-1981 Earned Degrees data; Myers (2016), Table 2.
Note: The sample is restricted to the 5 repeal states that allowed 18-20 year olds to obtain abortions in 1970, before Title IX was passed. Normalized values have been normalized to 1965. Lines are fitted linear trends allowing for a break between 1972 and 1973. The break year was determined by looking for a structural break in the data.

1.8 Discussion

In Section 1.6, I found that Title IX increased the relative number of female graduate degrees in more-lucrative fields. A natural question is whether Title IX had any second-order effects on the occupational distribution. As females pursue graduate degrees in increasing numbers, their return on human capital investment increases, also increasing the opportunity cost of not joining the labor force. As a result, we would expect to see gender convergence in occupations as well, for the cohorts who are exposed to Title IX.

Figure 1.12 plots the normalized segregation-index and EMD values for occupational distributions by birth cohort. Following my previous analysis, I focus on birth cohorts between 1942 and 1964 and collapse the data into two-year cohort cells. I use each cohort's occupation between ages 35 and 39 and aggregate them into the 25 broad categories as classified by the Census Bureau. For the EMD calculation, I order occupations by their median hourly wage for full-time workers aged 18-55 between 1960 and 1990.

Figure 1.12: Female-Male Convergence in Occupation Distributions



Source: 1960-2000 Census data; 1965-1999 CPS data.
Note: The sample is restricted to all persons aged 35-39 and born between 1942-1964. Values have been normalized to 1942-43 birth cohorts, separately for Segregation Index and EMD.

When measuring occupational convergence using the Segregation Index, we see that there is some convergence over time but it is slight and pretty stable; the index never changes more than 15 percent of its 1942 value. Although EMD starts off on a similar path as the Segregation Index, it diverges greatly starting with the 1952-53 cohort (denoted by the vertical gray line). As mentioned before, the 1952-53 cohort were juniors and seniors in college when Title IX was passed and corresponds with the results of my degree analysis. Specifically, EMD estimates around 30 percent *greater* convergence in the occupational distributions in comparison with the segregation index. This highlights the importance for taking into account which occupation categories experienced movement.

1.9 Conclusion

During the 1960s, there were essentially three career choices for women: nurse, secretary, or teacher. Graduate school admissions quotas prevented women from pursuing different career paths. Title IX of the Education Amendments of 1972 removed this barrier by making gender discrimination in admissions illegal. This paper provides evidence that legislation played a role in female higher-educational choices. My analysis finds that Title IX sped up the gradual change that was occurring in graduate education during this time.

Because Title IX is a national policy, it is difficult to find useful variation to measure the impact of the law. This is a concern if the law were anticipated or if it were passed in response to the changing social attitude at the time. However, graduate-school enrollment data reveal that enrollment patterns changed after discrimination became illegal. This is in line with historical accounts that state that the main impetus for Title IX's passage was gender discrimination in educational institutions. As a result, Title IX's passage can be thought of as a natural experiment.

I find that its effect on graduate-field distribution was large, discrete, and nationally-observed. I also find that the distributional change was driven by a reduction in gender disparity among the most-lucrative fields, which also happen to be male-dominated. I specifically consider two alternative explanations that are often cited as causes of change in female education and labor force behavior and find they cannot fully explain my results. Ultimately, it is difficult to find causal factors other than Title IX that would have an effect focused so specifically on graduate-degree fields, and also limited so sharply to the years immediately surrounding the passage of Title IX.

One interesting question is why Title IX was successful in eliminating discrimination while past policies were not. To answer this question, I turn to two papers that found that Title VII of the 1964 Civil Rights Act had a sizable effect on black employment in the south, specifically in the South Carolinian textile industry (Heckman & Payner, 1989; Donohue & Heckman, 1991). The general takeaway from this research is that the overall social climate was open and ready for change. We see a similar story when we read historical accounts of the 1960s. It was an era marked by social change, and the 1970 Congressional hearings revealed that a growing minority was protesting the widespread gender discrimination in education. Another possible explanation may be the existence of an enforcement mechanism. Although *Brown v. Board of Education* ruled that segregated schools is unconstitutional, it offered no guidelines on how to comply with the ruling. By contrast, compliance regulations for Title IX were clearly stated and communicated to all schools, which may have strengthened the policy's effect.

The implications for my findings also extend to a more aggregate level. Hsieh and co-authors (2013) find that improved allocation of talent in the occupational distribution explains 15-20 percent of growth in aggregate output per worker between 1960 and 2008. To the extent that banning gender discrimination in admissions improves the allocation of talent by allowing qualified women to pursue any career path, this policy also has important implications for the macroeconomy.

CHAPTER 2

THE GENDERED EFFECTS OF CAREER CONCERNS ON FERTILITY (WITH KYUNG PARK)

2.1 Introduction

A well-known and controversial statistic is that women earn 80 cents on average for each dollar that men make.[1] A large body of research explores various determinants of the gender wage gap; gender differences in human capital investment and productivity (Polacheck, 1981; Altonji & Blank, 1999; Mulligan & Rubinstein, 2008; Gallen, 2015), bargaining skills (Reuben, Wiswall, & Zafar, 2015; Card, Cardoso, & Kline, 2016), and gender norms (Bertrand, Kamenica, & Pan, 2015) are known contributors.[2] Recent economic research, however, has begun to coalesce around a principal explanation for this result. A growing body of evidence shows that career interruptions tied to child-birth account for a large fraction of the gender disparity both in the cross-section and over time (Wood, Corcoran, & Courant, 1993; Bertrand, Goldin, & Katz, 2010; Kleven, Landais, & Søgaard, 2015; Adda, Dustmann, & Stevens, 2016).[3] These findings are consistent with a theoretical literature that suggests the female-male gap in earnings may reflect optimal responses to a gender-specific comparative advantage in child-rearing rather than an employer's taste for discrimination (Lazear & Rosen, 1990). However, far less attention is given to the possibility that, in equilibrium, gendered effects of children on career advancement have important implications for fertility and family formation. Our paper explores the extent to which women respond to

1. According to the Institute for Women's Policy Research (2016), the gender wage gap is 79 cents on the dollar in 2014.

2. See Blau and Kahn (2016) for a survey of current explanations.

3. For example, Bertrand, Goldin, and Katz (2010) find no wage gap between women MBAs with no career interruptions and male MBAs after controlling for pre-MBA traits and MBA-training. Similarly, Adda, Dustmann, and Stevens (2016) find that the wage profile for German women without children follows a similar, though more muted, growth pattern to German men, while wages for women with children start to diverge at age 27 and never recover.

gendered career concerns[4] by reducing family size more or less in comparison with men.

It is theoretically ambiguous as to whether career concerns should have a differential impact on fertility decisions by gender. On one hand, a pervasive narrative in the literature is that firms should endogenously invest less in the career development of workers who are more likely to experience work disruptions. In this framework, firms are more likely to assign desirable tasks to men rather than women because gender predicts child-related career interruptions (Milgrom & Oster, 1987; Barron, Black, & Loewenstein, 1993; Lehmann, 2013).[5] In response, women may be more likely to delay or reduce fertility in comparison with men since the adverse effects of children on career advancement are disproportionately borne by women. On the other hand, numerous factors, including technological advances in household production, increasing accessibility to child care, and own-income and spousal-income effects, push in the opposite direction. To the extent that women can adjust along various margins, these forces may render the demand for children to be highly inelastic with respect to career concerns irrespective of gender. The primary goal of this paper is to empirically assess whether career concerns influence family formation differently by gender.

There are two important challenges to identification that warrant discussion. First and foremost, career concerns are not randomly assigned. It is plausible that workers sort both across occupations (e.g., lawyers versus teachers) and across fields within an occupation (e.g., corporate law versus family law) based on preference for work-family balance. In particular, if women who prefer smaller families sort into high-intensity occupations, then different fertility choices between men and women may reflect gender preferences rather than gender-specific shadow prices for children. Because the "price effect" is our empirical object of interest, the potential for gender-based sorting into occupations presents a first-order concern. Second, there are concerns related to data availability. A rich literature examines various aspects of

4. We use "career concerns" to mean workers' concerns about the effects of current performance on future compensation.

5. Lehmann (2013) examines discrimination in task-assignment based on race, but the model is easily applied to gender discrimination.

female fertility choices, but many of these studies use household surveys.[6] As our focus is how fertility choices between men and women differ, household surveys are not conducive to our study since there is no variation in fertility choices across gender within a household. Additionally, we require micro-level data on employment and wage histories that are linked to fertility histories. The stringent data requirements may be one reason that most empirical studies on timing of birth have looked to international data sources.[7] Unlike these studies, which examine the life-cycle model of fertility, however, this paper seeks to examine the fertility decision over the career trajectory.

Several advantages of our study mitigate these concerns. To begin, our data set is especially conducive to the study of our research question. The After the JD (AJD) survey is a panel data set that follows a nationally representative sample of lawyers throughout the first 12 years of their careers. Our focus on lawyers is appealing due to the fact that the career trajectory for young attorneys is well-known and typically standard across firms. For example, associate attorneys in large private firms are on a "partner-track" that is analogous to "tenure-track" positions in academia.[8] This facilitates analysis of fertility timing across the "partner clock" when career concerns are conceivably high or low. In addition, there is likely to be far more variation in fertility choices across gender in the AJD in comparison with household surveys.

Finally, the data set is exceptionally rich. The survey asks respondents to weigh the importance of various factors in their decision to select into their chosen career. The questions cover a wide range of reasons, from "medium-to-long-term earning potential" to "the potential to balance work and personal life" to "the opportunity to do socially responsible work". We use these survey questions to conduct factor analysis, which assumes that latent

6. For example, Moffitt (1984), Francesconi (2002), Autor, Dorn, and Hanson (2015), and Schaller (2016).

7. For example, Cigno and Ermisch (1989) use British data. Heckman and Walker (1990) use Swedish data. Del Bono, Weber, and Winter-Ebmer (2012) use Austrian data. Adda, Dustmann, and Stevens (2016) use German data.

8. There are two levels of partners in private law firms: equity partners or senior partners and non-equity partners or junior partners. In our analysis, we use the term "partner" to mean an equity partner.

preferences affect the lawyer's responses on the survey and uses the variation in observed survey responses to find the common, underlying factors. Crucially, this allows us to control for heterogeneous latent preferences, such as career ambition or fertility preferences, when we examine how career concerns affect fertility decisions.

We find that female lawyers are less likely than males to start their family formation before the partnership decision and more likely to start after the decision. Moreover, this gender difference in fertility timing nearly doubles among lawyers who face greater career concerns at work. We identify these lawyers by predicting their mid-career billed hours using intrinsic characteristics and classifying them as "high-intensity lawyers" if their predicted work-intensity is in the top quartile. The idea is that high-intensity lawyers face greater career concerns because they have a greater chance of making partner, relative to their predicted low-intensity peers. Constructed factor scores mitigate concerns about gender-based selection into occupations based on fertility preferences. Additionally, we do not find a gender difference in completed fertility, suggesting that family-size preferences are not driving our results.

Our conceptual framework highlights two key mechanisms for our results. The first is that women face a greater career cost of having children. We find that several factors can mitigate this trade-off between career and children, such as increased spousal income and more family-friendly work conditions. We also find that gender norms are at play, reinforcing the gender imbalance in child-raising responsibilities. This is consistent with Bertrand, Kamenica, and Pan (2015), who find that the gender identity norm that "a man should earn more than his wife" impacts the division of home production. The second mechanism occurs through the firm's promotion thresholds. Specifically, the firm has higher promotion thresholds for mothers because they are more likely to have child-related career interruptions. We test this mechanism by comparing the gender difference in ability of equity partners who were parents at the time of promotion. We find that mothers are significantly more likely to have participated in general law review, held a judicial clerkship, and worked on more cases early in their career than their male counterparts. Moreover, women are less likely to be promoted than men, even conditional on ability proxies, billed hours, and caseload.

As a robustness check, we investigate two alternative mechanisms that can explain our results in the absence of career concerns. First, we consider the empirical fact that female lawyers are less likely to be married than male lawyers. In this case, we may observe women starting their family formation later in their careers because they are more likely to enter marriage later in their careers, relative to men. But our results still hold when we focus on lawyers who were ever-married at the start of their careers. A second potential explanation is the gender difference in spousal occupation. This relates to the intensity of the spousal occupation. That is, male lawyers are more likely to marry women with less-intensive careers while female lawyers are more likely to marry men with intensive careers. This alternative explanation is similar to Becker's theory on time allocation in the household which predicts that males, as primary-earners, will specialize in the market while their spouses will specialize at home (Becker, 1965). But when we focus on primary-earners - the ones in the household who theoretically should specialize in the market - we still see that high-intensity female lawyers time their first child to the partnership decision.

We begin the remainder of this paper with a literature review. In Section 2.3, we describe the conceptual framework wherein career concerns lead to a gender gap in fertility. Section 2.4 describes the data. Section 2.5 describes the empirical methodology and specifically how we deal with the potential for gender-based selection. Section 2.6 discusses results, and Section 2.7 considers alternative explanations. We turn to an exploration of the mechanisms through which career concerns operate in Sections 2.8 and 2.9. Section 2.10 concludes.

2.2 Literature Review

Ever since Becker's seminal 1960 paper that modeled the fertility decision as an economic one, researchers have been interested in the price and income effects of having children. Gronau (1973) examines the effect of children on the housewife's value of time. He finds that the "opportunity cost of children" varies with the child's age and the mother's education. Other studies reveal that children increase the value of time for working women as well. Del Bono, Weber, and Winter-Ebmer (2008) find that women have fewer children after losing their jobs due to firm closures. This effect is driven by white-collar workers, who have higher expected returns to firm-specific training relative to blue-collar workers. Because they are at crucial stages of their careers, these women face a higher opportunity cost of having children. Relatedly, Schaller (2012) finds that improved labor market conditions for women decrease fertility. Using an instrumental variables strategy based on in vitro fertilization, Lundborg, Plug, and Rasmussen (2016) find that children have a negative effect on female hourly earnings. Heckman and Walker (1990) examine fertility-timing decisions, or the distribution of births across the life-cycle, and find that increased female wages delay times to all conceptions.

The fertility decision has become an important factor in the inequality literature, where researchers have found that a gender wage gap persists despite shrinking gender differences in pre-market factors, such as human capital attainment and training. An extensive literature finds that career interruptions tied to child-birth account for a large part of the gender wage gap. This finding is true whether we look at the entire population or within specific occupations. For example, children are the main reason female MBAs have less accumulated experience, greater career discontinuity, and shorter work hours (Bertrand, Goldin, & Katz, 2010). Similarly for lawyers, women's greater child-care responsibilities explain 23 percent of the wage gap (Wood, Corcoran, & Courant, 1993). Women physicians in the U.S. earn 13-20 percent less than male physicians if they have children (Sasser, 2005). This relationship is also robust whether we use data from the U.S. (Wood, Corcoran, & Courant, 1993; Sasser, 2005; Bertrand, Goldin, & Katz, 2010), Austria (Del Bono, Weber, & Winter-Ebmer, 2012), Denmark (Gallen, 2015; Kleven, Landais, & Søgaard, 2015), Germany (Adda, Dustmann, & Stevens, 2016), or Sweden (Angelov, Johansson, & Lindahl, 2016). Juhn and McCue (2017) provide a nice overview of the gender wage gap as it relates to marriage and parental status.

One important question is how fertility and labor-supply decisions interact. This question has only recently been addressed with increasing availability of better data. Adda, Dustmann, and Stevens (2016) develop a structural model of dynamic labor supply, fertility, and occupational decisions to decompose the career costs of children. The authors use detailed German data and estimate that three-quarters of the cost stem from lost earnings due to reduced labor supply while the rest is due to depreciation or loss of investment in skills. That children are associated with adverse career consequences is not new. Thomas (2014) finds that a mandated leave policy decreases promotion prospects for women. Similarly for economists in academia, a gender-neutral tenure clock stopping policy reduces female tenure rates but increases male tenure rates (Antecol, Bedard, & Stearns, 2016). However, these findings raise the question whether women make family-formation decisions in anticipation of career penalties associated with child-birth.

Although researchers have studied the female fertility decision in relation to human-capital investments and occupational decisions (Polacheck, 1981; Herr & Wolfram, 2012; Wasserman, 2015), none have looked explicitly at the effect of career concerns. Further, the current literature focuses on age at first-birth. A more appropriate measure is a woman's career timing, or the point in her career when children are first present (Herr, 2012). This is an important question as a woman's prime childbearing years overlap with her early-career years, when the return to career investment is high. The recent public debate underscores the relevance of better understanding the conflicting demands of work and family (Mead, 2014; Parsons, 2014; Sandberg, 2013; Slaughter, 2015). In the next section, we discuss the conceptual framework.

2.3 Conceptual Framework

What are the predicted effects of career concerns on fertility timing, and how do they differ by gender? To answer this question, we start with the firm's decision of whether to invest in the worker's human capital.[9] Because the firm's investment decision (promotion decision) is profitable only if the worker is high-ability, the firm will seek to promote only high-ability workers.[10] In a world with perfect information, this is an easy problem to solve. The firm observes the workers' effort levels (assuming that ability is analogous to effort) and knows which ones to promote. If the firm cannot observe the worker's ability level, however, the promotion decision becomes difficult. A key feature of these career concern models is that firms observe a signal of the worker's ability and updates its beliefs accordingly. The worker is concerned about his current performance on future compensation. The firm is concerned about moral hazard, where low-ability workers will masquerade as high-ability workers.[11]

An additional fact that complicates this scenario. As raising children takes time and effort, mothers and parents, in general, have less to spend at work, thereby making less money for the firm. A gender difference in the child-rearing cost is enough to induce this result, even if men and women are equal in terms of their ability and value for children. Now as investment is costly, the firm acts to minimize its losses from providing firm-specific training to (promoting) women and parents (Barron, Black, & Loewenstein, 1993). It sets the highest promotion threshold for mothers, then for fathers, and the lowest threshold for childless workers.[12]

How do workers respond to this statistical discrimination? Lang and Manove (2011) provide some answers. They find that in the face of statistical discrimination on race, blacks

9. Remember, career concerns refer to the worker's uncertainty about his promotion prospects.

10. This assumption is necessary to make the question interesting. If it were profitable to invest in everyone, then the firm would promote everyone. Likewise, if it were unprofitable to promote everyone, then the firm would invest in no one.

11. There are different types of contracts (explicit or implicit) that solve this problem (Fama, 1980; Radner, 1981; Rubinstein, 1981; Holmstrom, 1999). However, the focus of this paper is on the fertility decision and not the worker's effort-level. Therefore, we simply assume a linear contract where firms and workers share the profit and firms bear the full cost of investment (promotion). This will lead to a separating equilibrium, where high-types will exert more effort to distinguish themselves from the low-types (Spence, 1973, 2002; Akerlof, 1976; Landers, Rebitzer, & Taylor, 1996).

12. Another method of discrimination is to assign less-productive tasks to women and parents. We do not examine this mechanism in this paper but in a current research project.

over-invest in education relative to whites in an attempt to send a stronger signal of their ability. This example can easily be applied to our case of statistical discrimination on the basis of parental status and gender. Like race, gender is not manipulable. But parental status is. Therefore, workers have an incentive to delay their fertility so that they are not subject to the higher promotion threshold for parents. Moreover, as the child penalty is stronger for women than for men, this perverse incentive is stronger for female lawyers.

Delaying one's fertility is a non-trivial decision, but the cost of doing so is mitigated by the increased chance of being promoted. In our example case of lawyers, the incentive to make partner is huge as it comes not only with a large pay-raise but also with the ability to purchase an equity stake in the organization. For example, the average equity partner at a law firm earned $971,000 in 2014 (MLA, 2014). The median salary for a first-year associate, by comparison, was $160,000 (NALP, 2014a). An important note is that the increased promotion probability from fertility delay is large enough to warrant such action only for those at the margin. In other words, a worker whose effort-level is so far below the promotion threshold has no benefit from delaying fertility because the lowering of the threshold does not exceed his current deficit.

In summary, we make the following empirical predictions about fertility:

- EP1. Fewer females than males will have children before the promotion decision.
- EP2. The gender difference in fertility timing (EP1) will be larger among workers with high effort-levels relative to the gender difference among those with low effort-levels.

2.4 Data and Summary Statistics

2.4.1 After the JD dataset

The After the JD study was borne out of a strong interest from practicing attorneys, law schools, and academics to understand the career choices of lawyers. As such, the American

Bar Association (ABA) commissioned a longitudinal survey that would focus on the first 12 years of a lawyer's career. Survey respondents answered detailed questions on current job characteristics, employment history, educational background, and family background. The sampling frame is a 2-stage sampling process that was stratified by region and size of the new lawyer population. The target population is any individual living in the U.S. who graduated from a U.S. law school between July 1, 1998 and June 30, 2000 and entered the bar for the first time in 2000. Thus, the AJD study is intended to be nationally representative of all lawyers first admitted to the bar in 2000.[13]

There were three waves of data collection. Wave 1 was administered between May 2002 and May 2003 and aimed to capture the early careers of lawyers, about 2-3 years after they began practicing law. Wave 2 was administered between July 2007 and May 2008, about 7-8 years into their careers. This time marks a crucial period in the careers of young lawyers as it is when they are begining to face important career decisions such as the partnership decision. Wave 3 was administered between May 2012 and January 2013, roughly 12-13 years into a lawyer's career. As such, we expect it to contain a clear picture of the lawyer's early career trajectory as well as a nearly-complete fertility history.[14]

We use time-invariant, baseline characteristics from the Wave 1 survey to minimize memory bias and employment history and fertility history from the Wave 3 survey as it will provide the most complete and consistent histories. Income information (both respondent's and spouse's) is reported only for the current job at the time of the survey. Therefore, we predict the respondent's income trajectory and spousal income trajectory using the three data-points from each survey wave. For respondents who reported spousal income in only one wave or did not report income for an employed spouse, we use data from the Census and the American Community Survey to impute the spouse's income trajectory. Details on the imputation methodology can be found in Appendix B.1.2.

13. For more detail on the sampling process, please see Appendix B.1.1.

14. The average lawyer in our data is 42 years old in Wave 3. The median lawyer is 40 years old.

Because our analysis uses data from all three waves, we account for sample attrition. The sample size from Wave 1 to Wave 3 drops from 4,538 to 2,984, a 34 percent decline. We predict an individual's likelihood of attrition as a function of gender, birth year, race and ethnicity, marital status, BA graduation year, U.S. News' law school ranking in 2003, law school graduation date, standardized undergraduate GPA, standardized law school GPA, respondent's employment status, respondent's firm type, respondent's salary, and household income.See Appendix B.1.3 for a complete list of firm types. All variables are from the Wave 1 survey, and we account for item non-response by including dummy variables.[15] The new weight is equal to the inverse of (1 − predicted probability of attrition) times the sampling weight. We are unable to calculate new weights for 28 individuals who do not show up in both Wave 1 and Wave 3.

Our final analysis-sample size is 2,087 after dropping 869 people who have missing or inconsistent information. There are 783 people who have missing or inconsistent job start- and end-dates and are missing birth year, gender, and law school graduation date, and 86 people who did not list their children's ages. We need children's ages to determine when an individual had his or her first child.

2.4.2 Summary statistics

Male lawyers and female lawyers in our analysis sample are pretty similar on observable traits (Table 2.1). Females tend to be more diverse racially, but there are no gender differences in birth year or law school graduation year. The median birth year is 1972, placing the median lawyer at the start of the survey at 30 years old.[16] The average lawyer in our sample graduated from law school in 2000, which is consistent with the survey's target sampling population. There is also no significant gender difference in the type of law school attended. Nearly half of our sample attended a law school ranked between 21 and 100 on U.S. News'

15. Regression results are in the Online Appendix.

16. The average lawyer was born in 1970.

2003 rankings, with almost 9 percent attending a Top 10 school. Females are more likely to hold a foreign law degree, and though this difference is statistically significant, foreign degrees make up less than 1 percent of all degrees. There is also no significant gender difference along different ability proxies, such as participation in general law review, judicial clerkships, and law school GPA. Females have higher undergraduate GPAs than males, suggesting that there is positive selection into law school.

Table 2.1: Summary statistics

		Share of Respondents			
Characteristic	**N**	**Everyone**	**Males**	**Females**	**p-value**
Female	2,087	45.8%			
Race and ethnicity	2,061				
White		82.2%	84.0%	80.2%	0.04
Black		4.1%	3.1%	5.3%	0.01
Hispanic		3.5%	3.3%	3.8%	0.46
Asian		5.9%	5.3%	6.6%	0.28
Other		4.2%	4.3%	4.2%	0.92
U.S. News' 2003 law school ranking	2,068				
Ranked 1-10		8.8%	9.1%	8.6%	0.74
Ranked 11-20		9.0%	8.9%	9.2%	0.76
Ranked 21-100		49.3%	49.8%	48.8%	0.70
Tier 3 (101-137)		17.7%	16.6%	19.0%	0.31
Tier 4 (138-178)		13.0%	13.4%	12.6%	0.64
Foreign degree		0.5%	0.1%	0.9%	0.07
Unaccredited school		1.6%	2.1%	1.0%	0.06
General law review	2,002				
Member		20.7%	20.8%	20.5%	0.89
Editor		12.3%	11.8%	13.0%	0.51
Judicial clerkship	483	14.9%	13.5%	16.3%	0.50
Ever-married status					
In early-career	2,066	64.8%	66.9%	62.3%	0.09
In late-career	2,056	90.2%	92.0%	88.1%	0.02
Have children	2,087				
By law school graduation year		9.4%	11.7%	6.7%	0.00
10 years after law degree		61.0%	64.5%	56.8%	0.00
Birth year (median)	2,087	1972	1972	1973	
Law school graduation year	2,087	1999.5	1999.5	1999.5	0.63
		(0.6)	(0.6)	(0.6)	
Undergraduate GPA (standardized)	1,428	0.0	-0.2	0.1	0.00
Law school GPA (standardized)	1,277	0.0	0.0	0.0	0.24
Number of positions	1,801	3.1	3.0	3.1	0.76
Length of stay at a position (years)	1,801	4.1	4.2	4.0	0.24
Initial number of cases	1,199	8.3	8.3	8.3	0.67
Early-career weekly hours	1,695	48.2	49.7	46.3	0.00
Early-career salary	1,904	$ 82,910	$ 88,046	$ 76,698	0.00
Late-career salary	1,869	$ 165,773	$ 198,802	$ 125,082	0.00
Mid-career annual billed hours	771	1,549	1,622	1,434	0.01

Source: AJD restricted data.
Notes: N is the number of individuals. "Early-career" variables are from the Wave 1 survey (2002-2003), "mid-career" variables are from the Wave 2 survey (2007-2008), and "late-career" variables are from the Wave 3 survey (2012-2013). Salary is total gross annual salary including bonus, profit sharing/equity distribution, and stock options. Billed hours is reported only for those in private law firms.

When we look at family formation and career decisions, however, a gender difference emerges. Most of our sample are ever-married at the start of the survey (65 percent), but male lawyers are more likely than female lawyers to be ever-married and this gender difference is weakly significant.[17] By the end of our survey, however - about 10 to 12 years into these lawyers' careers - the vast majority of our sample is now married and the gender difference of 4 percentage-points becomes statistically significant at the 5-percent level. Very few lawyers have children before they graduate from law school: about 9 percent. However, male lawyers are again more likely to be parents in the year of law school graduation, and this difference is statistically significant. Ten years after their JD, 61 percent of lawyers in our sample are parents but female lawyers are still more likely to be childless relative to their male peers (0.65 versus 0.57).

Weekly hours worked is high for both men and women in their early careers - well above the full-time threshold of 40 hours. Although weekly hours is a useful metric of a person's work ethic, for our purposes a more relevant measure of a person's productivity is billed hours and caseload. Billable hours are used in private law firms to determine bonuses, promotions, and salary increases.[18] This is an important measure because the partner clock we are exploiting is predominantly a feature of private law firms. To provide some context for the numbers, the average firm required associates to bill at least 1,884 hours a year in 2014 (NALP, 2014a). Meeting this requirement is not easy, as revealed by Table 1. The average mid-career lawyer billed 1,538 annual hours, about 346 annual hours or 6.6 weekly hours short of the requirement. Men billed an average of 200 more annual hours than women, which amounts to 3.8 additional hours a week. Although this gender difference is statistically significant, it is economically small. Moreover, men and women are similar in terms of initial

17. "Ever-married" is mainly composed of those currently married or in a domestic partnership (90 percent). About 7 percent are divorced or separated and around 3 percent are widowed or in another arrangement.

18. About 88 percent of lawyers who reported annual billed hours worked in a private law firm. Ten percent were solo practitioners, and the remaining 1.8 percent worked in a non-traditional law setting such as government or in industry.

caseload; both work on 8 cases. One interesting fact is that the career trajectories of female and male lawyers are similar: the average number of positions for a lawyer is three for both males and females. Both also stay at a position for four years, on average.

Table 2.2: Labor supply and fertility by years since JD

	Years since law school graduation:				
	1	**3**	**5**	**7**	**10**
Share working full-time					
Male	98.8%	97.6%	98.0%	97.8%	97.6%
Female	95.8%	94.5%	92.0%	89.4%	85.4%
N	1,278	1,310	1,212	1,197	1,430
Share working in private firm					
Male	65.5%	67.9%	63.1%	56.4%	49.9%
Female	60.4%	62.8%	56.7%	48.7%	43.3%
N	1,477	1,619	1,597	1,597	1,651
Share practicing law					
Male	90.3%			88.0%	82.1%
Female	89.5%			82.4%	78.2%
N	2,001			1,651	1,973
Share of equity partners in law firms with 30+ lawyers					
Male	0.0%	0.1%	0.4%	4.9%	18.8%
Female	0.0%	0.0%	0.0%	0.9%	14.4%
N	1,474	1,616	1,594	1,590	1,634
Share of parents					
Male	15.3%	23.9%	37.0%	50.5%	64.5%
Female	8.4%	15.8%	25.5%	39.7%	56.8%
N	2,087	2,087	2,087	2,087	2,087

Source: AJD restricted data. Share practicing law are taken from each survey wave with Wave 1 listed under year 1, Wave 2 listed under year 7, and Wave 3 listed under year 10.

Table 2.2 shows how labor supply and fertility decisions evolve over time. Early in their careers, full-time work among lawyers is extremely high for both males and females. Over time, however, a gender gap emerges as female lawyers increasingly decide to work part-time. In terms of firm-types, the majority of JDs first enter private law firms (63 percent). Attrition out of private law firms increases for both males and females over time, but is slightly stronger for women. The gender difference of 5.1 percentage-points in year 1 is not statistically significant. Ten years after law school, however, the gender difference increases slightly to 6.7 percentage-points and becomes statistically significant at the 5 percent level.

In terms of the law profession, nearly 90 percent of our analysis sample are practicing lawyers in Wave 1, and the gender difference is negligible at 0.87 percentage-points. By Wave 3, the last wave of our survey, this percentage decreases to 80 percent and the gender difference of about 4 percentage-points becomes statistically significant. Although some lawyers do leave the profession, the percentage doing so is small - likely because of the large, occupation-specific, human-capital investment required.

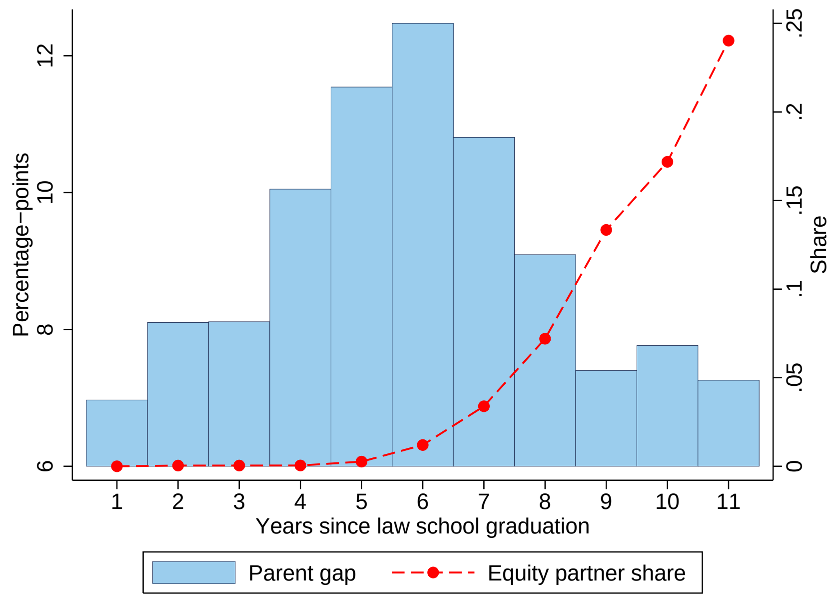
We now turn to a dynamic picture of fertility decisions that illustrates the essence of our paper. Figure 2.1 plots the percentage-point difference between the share of parents among male lawyers and the share of parents among female lawyers over time. The male-female difference grows over the lawyer's career, peaks in year 6 at 12.5 percentage-points, then decreases and levels out starting in year 9. A closer look at the data reveals that the shrinking of the gender parent gap starting in year 7 is because female lawyers are "catching-up" to their male peers (see Table 2.2). This is an interesting point because there is no age difference between male lawyers and female lawyers in our sample. Both were born around the same year and graduated from law school in the same year, on average.

When we consider the timing of partnership decisions, this "catching-up" phenomenon makes more sense. A 2012 survey by ALM Legal Intelligence found that 41 percent of new partners worked for 7-9 years before being promoted.[19] Our data are consistent with the survey's findings: the equity partner share begins to increase significantly in year 7 and the largest increase occurs in year 9.[20] We posit that career concerns arising from the partnership decision are influencing female decisions on when to start their family more so than male decisions. The remainder of this paper will explore this coincidental timing between partnership decisions and the decreasing gender parent gap and move towards a causal interpretation.

19. The wait-times in decreasing order of prevalence are: 7-9 years (41%), 4-6 years (35%), 1-3 years (13%), 10 years or more (9%), less than one year or new to the firm (3%).

20. Equity partner share is defined as the number of equity partners in private law firms with at least 30 lawyers. We filter on firms larger than 30 to clean out small, boutique firms. The average size of a private law firm in our data is 270, so this restriction does not hugely affect our analysis.

Figure 2.1: Male-female difference in share of parents over time



Source: AJD restricted data.
Notes: Share of equity partner is the number of equity partners in private law firms with at least 30 lawyers.

2.5 Empirical Methodology

2.5.1 Dealing with selection

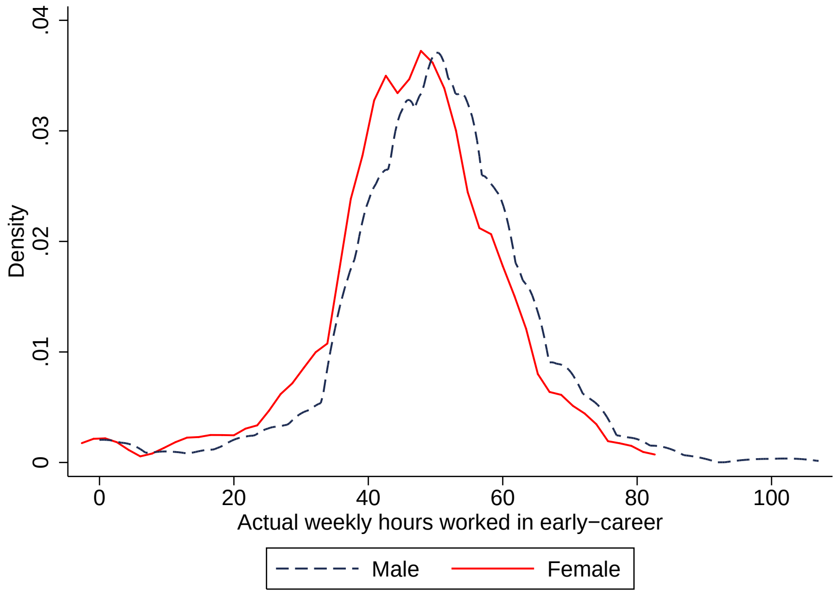
Before describing the empirical specification, we first address the main identification concerns. Our goal is to estimate the gender difference in fertility outcomes and to see how it changes by effort-levels. There are two major issues with this approach. First and foremost, there may be gender-based sorting into occupations due to fertility preferences. If it exists, any observed gender difference in fertility may reflect gender differences in preferences rather than the gender-specific shadow prices of children. Second, observed effort-levels may be endogenous to the extent that lawyers are adjusting their levels based on signal they receive from the firm about their promotion prospects. We will discuss both of these issues in turn.

Differential selection into careers by gender

A major concern for our identification strategy is that women who choose to become lawyers may be characteristically different from male lawyers in terms of their fertility preferences. For example, women who want a family may be less likely to pursue a law degree in anticipation of the demanding career lifestyle ahead of them as lawyers. Similarly, female lawyers may choose different types of sectors or areas of law based on future fertility. This theory is in line with economic research that has found that women make human-capital investment decisions and occupational choices based on their future fertility and in anticipation of the pecuniary penalties associated with career interruptions (Polacheck, 1981; Francesconi, 2002; Wasserman, 2015; Adda, Dustmann, & Stevens, 2016). More importantly, it leads to an important identification issue when estimating the effect of career concerns on fertility: fertility and career decisions are not independent of each other.

Indeed, the distribution of weekly hours worked in early-career is different between men and women (Figure 2.2). There appears to be a mean shift between the male distribution and the female distribution, with female lawyers more likely to work fewer hours. Specifically, there is greater mass between 20 and 40 hours in the female distribution relative to the male distribution, implying that females are more likely to work part-time, and the right-tail of the male distribution stretches out beyond 100 hours a week while the right-tail of the female distribution ends around 80 hours a week. The observed gender difference in hours-worked is especially interesting given that male lawyers and female lawyers are pretty homogenous in our analysis sample. Summary statistics in Table 2.1 reveal that men are similar to women in terms of age, law school ranking, and ability (as measured by law school GPA, participation in general law review, and judicial clerkships). Therefore, a more crucial concern may be gender differences in unobservable traits rather than differences in observable traits. In particular, we are concerned about latent career ambition or fertility preferences that determine the lawyer's career choice, but would not be captured by observable variables in our data.

Figure 2.2: Distribution of hours worked by gender



Source: AJD restricted data.

This selection problem can be framed as a latent variables model, where the lawyer's decision rule (to enter a prestigious and highly competitive law firm, for example) is determined by a latent variable that is unobserved by the econometrician. For example, the indicator variable D_i is generated by a latent variable D_i^*:

$$D_i^* = \beta_D \cdot Z_i - U_{Di} \tag{2.1}$$

$$D_i = \begin{cases} 1 & \text{if } D_i^* \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

where Z_i is a vector of observed random variables and U_{Di} is an unobserved random variable. D_i^* is the net utility to the lawyer from choosing to enter a prestigious law firm, and is the decision rule for D_i.

Now, let Y_i be the measured fertility outcome variable such that:

$$Y_i = D_i \cdot Y_{1i} + (1 - D_i) \cdot Y_{0i} \tag{2.3}$$

where $D_i = 1$ denotes lawyer's decision to enter a prestigious law firm, and $D_i = 0$ denotes the decision to not. Y_{1i} and Y_{0i}, therefore, are the fertility outcomes for lawyers at prestigious law firms and lawyers not at prestigious law firms, respectively. We want to estimate the effect of career concerns (i.e., working at a prestigious law firm) on fertility outcomes:

$$\begin{aligned} \underbrace{\mathbb{E}(Y_i|D_i = 1) - \mathbb{E}(Y_i|D_i = 0)}_{\text{observed difference in average fertility}} &= \underbrace{\mathbb{E}(Y_{1i}|D_i = 1) - \mathbb{E}(Y_{0i}|D_i = 1)}_{\text{average treatment effect on treated}} \\ &+ \underbrace{\mathbb{E}(Y_{0i}|D_i = 1) - \mathbb{E}(Y_{0i}|D_i = 0)}_{\text{selection bias}} \end{aligned} \tag{2.4}$$

The second term, $\mathbb{E}(Y_{1i}|D_i = 1) - \mathbb{E}(Y_{0i}|D_i = 1)$, captures the average causal effect of career concerns on those at prestigious law firms. This term captures the average difference between the fertility outcome of lawyers at these firms, $\mathbb{E}(Y_{1i}|D_i = 1)$, and what would have happened to them *had they chosen a different sector*, $\mathbb{E}(Y_{0i}|D_i = 1)$. The observed difference in average fertility also captures a term called "selection bias". This term is driven by unobserved differences in the decision rule that led lawyers to enter or not enter a prestigious law firm (U_{Di}). If they are not equal ($U_{1i} \neq U_{0i}$), the selection bias term is not equal to 0, resulting in a biased estimate for the treatment effect.

There are several empirical methods to deal with this selection problem (Heckman & Navarro-Lozano, 2004; Aakvik, Heckman, & Vytlacil, 2005). We decide to leverage the richness of our data and conduct a factor analysis. We employ a two-step process where we compute individual "scores" based on extracted factors in the first step and use these factor scores in an OLS regression to obtain treatment effect estimates in the second step.

The theoretical motivation behind a factor structure model is identical to the latent variable model. The factor structure model, however, imposes a particular structure on the unobservables of the latent decision rule:

$$
\begin{aligned}
U_{Di} &= -\varphi_i + \epsilon_{Di} && (2.5)\\
U_{1i} &= -\alpha_1 \cdot \varphi_i + \epsilon_{1i} && (2.6)\\
U_{0i} &= -\alpha_0 \cdot \varphi_i + \epsilon_{0i} && (2.7)
\end{aligned}
$$

where $U_{1i} = Y_{1i} - X_i\beta_1$, $U_{0i} = Y_{0i} - X_i\beta_0$, X_i is a set of observable random variables, and φ_i is the factor or the latent variable driving the decision rule. With a normality assumption regarding $\varphi, \epsilon_D, \epsilon_1, \epsilon_0$ and i.i.d. data, we are able to recover the average treatment effect if we observe φ. To relate this to our case of lawyers, the factor φ can be seen as career ambition or fertility preferences, which lead a lawyer to enter a prestigious law firm or not. These traits are typically unobserved by the econometrician, but luckily we have several proxies for them in our data:

$$q_k = \gamma_k \cdot \varphi + \upsilon_k \tag{2.8}$$

where q_k is the k^{th} proxy measure, $\gamma_k > 0$ is the scale coefficient, and υ_k is measurement error. Equation (2.8) is referred to as a measurement equation. The k measurement equations together are referred to as a measurement system. Under the assumed error structure in equations (2.5)-(2.7), we are able to identify all the parameters in the measurement system, in particular the factor loadings. We point the reader to the many papers that discuss the conditions under which the factor model is identified, rather than reproducing them here (e.g., Carneiro, Hansen, & Heckman, 2003; Aakvik, Heckman, & Vytlacil, 2005; Heckman, Stixrud, & Urzua, 2006; Heckman, Pinto, & Savelyev, 2013).

Using the identified factor loadings, we then construct a factor score for each individual, which is a linear combination of the factor loadings and the proxies:

$$F_j = A_j \cdot q, \quad j = 1, \cdots, f \tag{2.9}$$

where F_j is the score for the j^{th} factor, A_j is a factor score matrix, and q is a vector of the k proxy variables. The computation of A_j depends on the method used for the prediction of the factor score. An issue is that there is an infinite set of factor scores that are consistent with the same factor loadings. To see this, consider that we have $k + f$ unknowns and k equations. It is possible, therefore, that an individual with a high ranking on ambition according to one set of factor scores, may also receive a low ranking on the same common factor according to another set of factor scores. The researcher has no way of determining which ranking is "true" from the results of the factor analysis. This issue is known as factor score indeterminacy. Grice (2001) provides a nice history and overview.

Indeterminacy becomes an even more important concern when the factor scores are subsequently used in an OLS regression to obtain treatment effect estimates. Factor scores contain a degree of uncertainty that is not accounted for in the second-stage OLS regression and causes the regression coefficient estimate to be biased (Skrondal & Laake, 2001; Croon, 2002; Bolck, Croon, & Hagenaars, 2004; Lu & Thomas, 2008; Devlieger, Mayer, & Rosseel, 2016). Devlieger, Mayer, and Rosseel (2016) show that in a model with latent independent variables and an observed dependent variable, the Regression method of computing factor scores yields an unbiased estimate. See Appendix B.2 for the proof. Thus, we use Regression factor scores as explanatory variables in our main regression model. Next, we discuss the survey questions used as proxy variables.

The Wave 1 survey asks several questions about the determinants of the lawyer's initial career choices and motivating factors to attend law school. Figure 2.3 presents one example question on the lawyer's decision to start his or her career in a particular sector.[21] The crux of our methodology is that these survey questions capture the latent variables that drive a lawyer's career choices. The possible answer choices cover a wide range of reasons, from earning potential to social responsibility to work-life balance. More importantly, they were asked in the initial survey thereby mitigating reverse causality concerns. We find

21. See Appendix B.1.4 for the other survey questions.

seven factors that drive lawyers' career decisions.[22] They are, in order of importance: social responsibility, earning potential, prestige, career development, firm's ranking, mission match, and financial security.

Figure 2.3: Survey question about the determinants of lawyer's initial career choices

38. Thinking about the principal types of settings in which lawyers work (e.g., government, large law firms, business), how important was each of the following factors in determining the sector in which you began your professional career? *(Exclude clerkships.) Check one box on each line.*

		NOT AT ALL IMPORTANT						EXTREMELY IMPORTANT	NA
a.	Medium-to-long-term earning potential	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
b.	Substantive interest in a specific field of law	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
c.	Salary to pay off law school debts	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
d.	Availability of loan repayment assistance or loan forgiveness programs	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
e.	Opportunity to develop specific skills	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
f.	Potential to balance work and personal life	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
g.	Opportunity to do socially responsible work	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
h.	Prestige of the sector	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
i.	Opportunities for future career mobility	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
j.	Other (*Specify:* ______________________________)	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐

Source: AJD restricted data.

We conduct several robustness checks. First, we examine whether factors differ by gender. They remain largely the same with the exception that women care most about the office environment and "fit" and men care most about earning potential.[23] To capture this gender heterogeneity in preferences, we compute two factor scores: "ambition", taking into account male preferences, and "family", taking into account female preferences. Results are in Table B.7. Next, we examine whether conditioning on other observable characteristics affects the calculation of factor scores. This is equivalent to including other explanatory variables in equation (2.8). Specifically we control for gender, race and ethnicity, marital status, number of children, undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of job offers and bar exam attempts, license status, and amount of debt. All measures are from the Wave 1 survey.

22. See Appendix B.2 for empirical methodology, tests, and detailed results.

23. See Appendix B.2.

Results are in Table B.8. Last, we include the survey questions directly rather than using factor scores. Results are in Table B.9. For all of these robustness checks, our fertility timing results do not change significantly.

Last, we conduct a validity test to check that factor analysis adequately addresses the selection issue. Table 2.3 examines whether there is gender selection in initial entry into a private law firm. Female lawyers are 5 percentage points less likely than their male peers to enter a private law firm right after law school, and this difference is weakly statistically significant. The addition of demographic controls takes away the significance, but the magnitude remains similar (around -0.04). The addition of ability proxies, spousal employment, and income reduces the estimate slightly to -0.035. Columns (5)-(8) include the respondent's answers to the survey questions that we use for the factor analysis. When we include all three sets of questions, the gender difference in initial entry into private law firms disappears. These results provide assurance that our factor scores are capturing unobservable heterogeneity that lead to a gender difference in these lawyers' career decisions.

Table 2.3: Gender selection into initial job

	Entry into private law firm							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female-male difference	-0.0497*	-0.0426	-0.0347	-0.0349	0.00441	-0.0214	-0.0244	0.00224
	(0.0299)	(0.0286)	(0.0283)	(0.0284)	(0.0277)	(0.0285)	(0.0277)	(0.0275)
Observations	1,780	1,780	1,780	1,780	1,780	1,780	1,780	1,780
Controls for:								
Demographic characteristics		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ability proxies			Yes	Yes	Yes	Yes	Yes	Yes
Income and spousal employment				Yes	Yes	Yes	Yes	Yes
Why sector					Yes			Yes
Why law						Yes		Yes
Why job							Yes	Yes

Source: AJD restricted data.
Notes: Demographic characteristics account for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Educational attainment controls account for standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, and number of bar exam attempts. Spousal employment and income controls include spousal employment status at time of initial survey, and early-career household income. In Panel B, it also includes the area of law. "High-stress" law firm is defined as a firm with at least 350 lawyers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Endogeneity of observed effort-levels

Our second empirical prediction is that the gender fertility difference will be more pronounced among lawyers who have high effort-levels (EP2). Our proxy for work intensity is the lawyer's mid-career billed hours.[24] For lawyers who are not in a private law firm, we set their billed hours to 0.[25] The identification concern is that, because there is a long partner clock, the lawyer's effort-levels may endogenously adjust over time as the lawyer receives signals from the firm about his or her chances of making partner. The strategy of using observed billed hours in mid-career, therefore, is suspect. As a solution, we predict which lawyers will be "high-intensity" using intrinsic characteristics.

We use an extensive set of controls including demographic information (race and ethnicity, birth year, law school graduation date, geographic region at time of initial survey, parental educational attainment, initial marital status, and initial number of children), ability proxies (GPAs from law school and college, law school tier, participation in exclusive activities such as general law review and judicial clerkships, and the number of initial job offers and bar exam attempts), and initial firm-type.[26] The regression model is as follows:

$$\text{Work-intensity}_i^g = \beta_0^g + X'\beta_1^g + \varepsilon_i^g \tag{2.10}$$

where work-intensity is mid-career billed hours for lawyer i of gender g and X is the set of baseline characteristics described above. We classify a lawyer as "high-intensity" if the lawyer's predicted work-intensity is in the top quartile and as "low-intensity" otherwise. Our predicted measure of intensity captures the portion of the lawyer's work ethic that is solely associated with baseline, observable traits. Because we predict intensity-levels for every

24. Billed hours were not asked in the Wave 1 survey.

25. Billed hours is used only at private law firms.

26. We conduct a robustness check by including desire for work-family balance as a control. To the extent that, at the start of these lawyer's careers, their fertility preferences are going to determine their future career decisions, this inclusion is important. Our results remain very similar. They can be found in Figure B.3.

lawyer in our sample, we have counterfactual measures of work-intensity even for lawyers not working at private law firms.[27]

We check the strength of our predicted intensity measure by examining its predictive power in the lawyer's probability of becoming equity partner. A 1 standard-deviation increase in predicted intensity is associated with an 11 percentage-point increase in the probability of becoming equity partner. This estimate reduces to 8 percentage-points with the inclusion of demographic controls, ability proxies, and job characteristics (initial firm's size, initial hours worked, and area of law) but remains highly statistically significant. Results are in Table B.10.

2.5.2 Empirical specification

Gender difference in early parenthood and late parenthood

Our first empirical approach uses cross-sectional data and binary outcome variables to examine whether there is a gender difference in early parenthood and late parenthood. We use equity partner decisions to determine the approximate year that partnership decisions are made and use this threshold to differentiate between early parenthood and late parenthood. To find this threshold, we plot the distribution of equity partners by their promotion year in Figure 2.4. The most common post-JD year that equity partners were promoted is year 8. Our data are consistent with external surveys that ask about the length of the partner clock (ALM Legal Intelligence, 2012). Using year 8 as a threshold, we define "early parenthood" as having one's first child within seven years of law school graduation, and "late parenthood" as having one's first child at least nine years after law school.[28]

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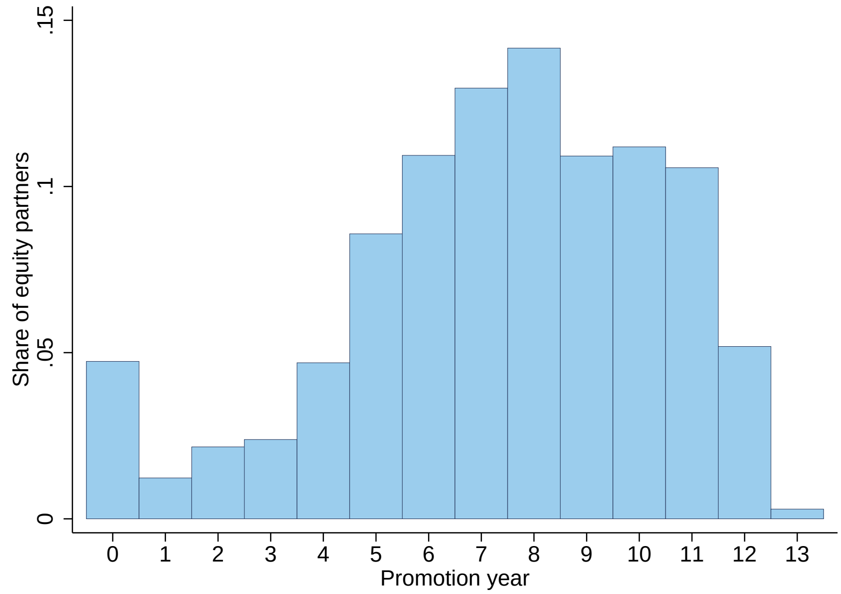
27. Regression results for the intensity prediction measure are in the Online Appendix.

28. Alternatively, we defined a threshold by parent-share. We regressed a year indicator variable and a quartic time trend against the change in share of parents and chose the year that maximized the R^2 of the regression. The growth rate in parent share peaks in year 6, so pregnancies before year 6 are classified as "early" and pregnancies after year 6 are classified as "late" (Table B.11). Fertility results using this alternative threshold are in Table B.12; the patterns still hold.

Figure 2.4: Distribution of equity partners by promotion-year



Source: AJD restricted data.
Notes: N = 305.

To estimate the gender fertility gap, we run the following regression model separately for early parenthood and late parenthood:

$$Y_i = \beta_0 + \beta_1 \cdot F_i + \beta_2 \cdot \mathbb{1}\{\texttt{High-Intensity}\} + \beta_3 \cdot \Big(F_i \times \mathbb{1}\{\texttt{High-Intensity}\} \Big) + X' \gamma + \varepsilon_i \quad (2.11)$$

where Y_i is a binary fertility outcome for lawyer i, F_i is a dummy variable indicating whether the individual i is female, and X contains a set of individual-level, baseline characteristics including race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of initial job offers, number of bar exam attempts, spousal employment status at time of initial survey, early-career household income, respondent's early-career salary, initial firm's size, early-career weekly hours worked, area of law, and factor scores.

The parameter of interest is β_1, which gives us the female-male difference in probability of early parenthood (or late parenthood) for those predicted to be low-intensity workers. To obtain the gender difference for predicted high-intensity lawyers, we flip the indicator variable, $\mathbb{1}\{\texttt{High-Intensity}\}$, so that the reference group becomes high-intensity males and look at the analogous β_1.

Gender difference in rate of exiting childless state

Our second empirical approach usees panel data to explore how fertility decisions evolve over the lawyer's career. In particular, we estimate the annual likelihood of becoming a parent conditional on being childless in the year before.[29] The regression model is as follows:

$$\begin{aligned} Y_{it} =& \alpha_i + X'\gamma + \sum_{t=1}^{12} \tau_t^M \cdot \mathbb{1}\{T = t\} + \sum_{t=1}^{12} \tau_t^F \cdot \Big(F_i \times \mathbb{1}\{T = t\}\Big) \\ &+ \sum_{t=1}^{12} \mu_t \cdot \Big(\mathbb{1}\{\texttt{High-Intensity} \times \mathbb{1}\{T = t\}\}\Big) \\ &+ \sum_{t=1}^{12} \delta_t \cdot \Big(F_i \times \mathbb{1}\{\texttt{High-Intensity}\} \times \mathbb{1}\{T = t\}\Big) + \varepsilon_{it} \end{aligned} \tag{2.12}$$

where t indexes years since the JD, Y_{it} is equal to 1 if lawyer i had his or her first child t years after the JD, α_i is an individual fixed-effect, and X is a vector of the respondent's firm-type (private law firm or not), firm-size, respondent's lagged predicted income, and spouse's lagged predicted income. The variables in X are all time-varying. The individual fixed-effect takes care of any *time-invariant* gender differences in fertility preferences or in career ambitions. But to the extent that these may change over the course of the lawyer's career, the fixed effect will not capture that variation. Therefore, we also include time-varying job characteristics and (lagged) income. These will capture any unobservable changes in family-size preference or in career ambitions that manifest in firm type, firm size, and earnings.

The reference category here is low-intensity males in year 0, the year they graduated from

29. To be clear, the analysis sample is at the level of an individual-year and, for each individual, stops in the year that the lawyer had his or her first child.

law school. The parameter of interest is τ_t^F, which tells us each year's contribution to the low-intensity female's hazard relative to low-intensity males' in year 0. To get the analogous τ_t^F for high-intensity lawyers, we flip the indicator function, $\mathbb{1}\{\texttt{High-Intensity}\}$, so that the reference category becomes high-intensity male lawyers in year 0.

2.6 Results

2.6.1 Gender difference in timing of first-child

In this section, we test our empirical predictions. EP1 states that females are less likely than males to have their first-child before the partnership decision. Our results are presented in Panel A of Table 2.4. On average, female lawyers are 11 percentage-points less likely than male lawyers to have their first child within seven years after law school (Column 1). As we add in baseline controls, this gender gap shrinks but does not disappear, even after we include the factor scores. Because of the way we define early parenthood, these results are consistent with EP1. We also examine whether there is a gender difference in late parenthood, defined as having one's first child at least nine years after law school. If women are delaying their family formation until after the promotion decision, we may expect there to be a positive female-male difference in first-time births later in these lawyer's careers - assuming that demand for having children is relatively inelastic. Indeed, for late parenthood, the gender gap is about 10 percentage-points (Panel B of Table 2.4). The addition of demographic characteristics shrinks the gap to about 6 percentage-points, but it is persistent even after controlling for factor scores. In sum, we find that female lawyers are nearly 8 percentage-points less likely than male lawyers to have their first child before the partnership decision, and are around 6 percentage-points more likely to wait until after the partnership decision.

Table 2.4: Gender difference in early parenthood and late parenthood

	Panel A: Early parenthood					
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.108***	-0.0772***	-0.0805***	-0.0920***	-0.0803***	-0.0787***
	(0.0277)	(0.0241)	(0.0239)	(0.0243)	(0.0246)	(0.0247)
Observations	2,087	2,087	2,087	2,087	2,087	2,087
Controls for:						
Demographic characteristics		Yes	Yes	Yes	Yes	Yes
Ability proxies			Yes	Yes	Yes	Yes
Job characteristics				Yes	Yes	Yes
Income and spousal employment					Yes	Yes
Factor scores						Yes

	Panel B: Late parenthood					
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	0.0909***	0.0597**	0.0624***	0.0648***	0.0572**	0.0580**
	(0.0280)	(0.0240)	(0.0238)	(0.0245)	(0.0248)	(0.0248)
Observations	2,087	2,087	2,087	2,087	2,087	2,087
Controls for:						
Demographic characteristics		Yes	Yes	Yes	Yes	Yes
Ability proxies			Yes	Yes	Yes	Yes
Job characteristics				Yes	Yes	Yes
Income and spousal employment					Yes	Yes
Factor scores						Yes

Source: AJD restricted data.
Notes: Probability of early parenthood is 0.51 (males) and 0.40 (females). Probability of late parenthood is 0.44 (males) and 0.53 (females). Early parenthood is defined as having one's first child within the first 7 years after law school. Late parenthood is defined as having one's first child at least 9 years after law school. Demographic characteristics account for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of initial job offers, and number of bar exam attempts. Job characteristics control for initial firm's size, early-career weekly hours worked, and area of law. Income and spousal employment controls include spousal employment status at time of initial survey, early-career household income, and respondent's early-career salary. Factor scores are: social responsibility, earning potential, prestige, career development, firm's ranking, mission match, and financial security. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

In Table 2.5, we examine how this gender gap differs by predicted intensity level. Our second empirical prediction is that the gender gap in timing will be more negative among high-intensity lawyers relative to low-intensity lawyers. When we look at the data, we see that a majority of lawyers start their family formation later in their careers (the likelihood of late parenthood ranges from 0.34 to 0.54). However, women are more likely to wait until later in their career and men are more likely to start within the first 7 years of their career. Further, high-intensity men are the least likely group to experience late parenthood (34 percent) and the most likely to experience early parenthood (61 percent), while the opposite is true for high-intensity women.

Columns 1 and 2 examine gender differences in early parenthood, and columns 3 and 4 examine differences in late parenthood (from equation (2.11)). Females who we predict to be high-intensity are 15 percentage-points less likely than males predicted to be high-intensity to have their first child before the partnership decision. The gender gap in early parenthood for low-intensity lawyers is much smaller, at -5 percentage-points.[30] Similarly for late parenthood, the gender difference is large and positive for high-intensity lawyers (0.12) and much smaller and not statistically significant for low-intensity lawyers (0.04). The interpretation of these results is consistent with EP1 and EP2: females are more likely than males to wait until after the partnership decision, but the incentive to delay fertility is much stronger for high-intensity females, who have a greater chance of making partner, relative to low-intensity females.

Table 2.5: Gender fertility difference by intensity level

	Early Parenthood		**Late Parenthood**	
Predicted intensity level	High (1)	Low (2)	High (3)	Low (4)
Female-male difference	-0.152*** (0.0570)	-0.0490* (0.0275)	0.120** (0.0580)	0.0375 (0.0274)
Avg. male likelihood	0.61	0.45	0.34	0.49
Avg. female likelihood	0.40	0.40	0.54	0.53
Observations	2,087		2,087	
Baseline controls	Yes		Yes	

Source: AJD restricted data.
Notes: Early parenthood is defined as having one's first child within the first 7 years after law school. Late parenthood is defined as having one's first child at least 9 years after law school. See notes in Table 2.4 for description of baseline controls. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

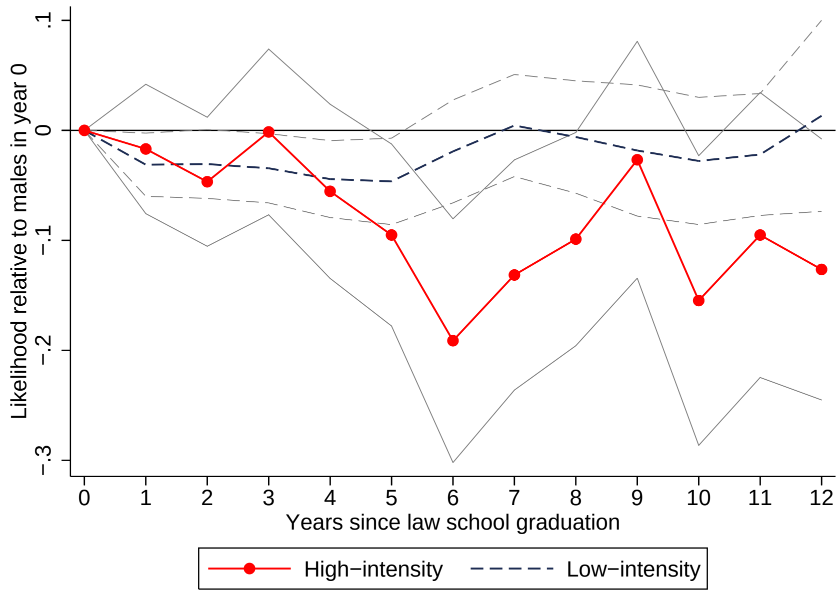
Next, we present graphical evidence of how the gender fertility gap evolves over the lawyer's career. Figure 2.5 plots the year-specific estimates of the gender difference and

30. The difference between these two estimates is very close to being statistically significant, with a t-statistic of 1.63.

their corresponding 95% confidence intervals from equation (2.12). Although female lawyers are always less likely than their male peers in year 0 to have a child, these estimates are statistically insignificant for the first few years. Interestingly, the gender differences for high-intensity and low-intensity lawyers are also similar for the first two years. Starting in year 5, the gender difference for high-intensity lawyers starts to widen, increases to -19 percentage-points in year 6, before shrinking to -2.7 percentage-points in year 9. The gender gap in years 5 through 8 are statistically significant and becomes insignificant in year 9, when the gap shrinks. Moreover, the sign-change and closing of the gap starting in year 7 corresponds with when partnership decisions are beginning to be made (see Figure 2.1). The drop in year 10 says that women are much less likely than men in year 0 to become parents after year 9, conditional on not having becoming parents. This makes sense when we consider that in year 10, the median female lawyer is 38 years old, when female fecundity is already in a decline (American College of Obstetricians and Gynecologists, 2014). In other words, if a female lawyer has not become a parent by year 9, the likelihood of her becoming a parent in the future is diminished due to biological reasons. The following is not true for men, whose fecundity does not begin to decline until age 45 (Harris et. al, 2011).

When we look at low-intensity lawyers - the ones that we predict do not have as strong an incentive to trade-off children for effort - we see much more muted effects. The female-male difference is negative, as predicted by EP1, but pretty stable throughout their careers (-0.02 to -0.05). Most importantly, they do not seem to react to career concerns faced by their high-intensity peers around year 8. The gender difference for low-intensity lawyers does shrink in year 7, and the explanation for this is biology. The median lawyer is aged 35 in year 7, which is when fecundity begins to decline rapidly for women.

Figure 2.5: Gender difference in hazard of exiting childless state



Source: AJD restricted data.
Notes: N = 18,081. This figure depicts each year's contribution to the hazard of exiting the childless state relative to males in year 0, separately for high-intensity and low-intensity lawyers. Lawyers are classified as "high-intensity" if their predicted intensity-level is in the top quartile and as "low-intensity" otherwise. Gray lines are 95% confidence intervals.

2.6.2 Gender difference in completed fertility

In this section, we examine whether there is a gender difference in completed fertility. This serves as a robustness check for whether our fertility timing results are due to gender differences in preferences for timing of first-child. Even though we construct factor scores to capture these latent preferences, to the extent that our factor scores are not perfect proxies, this exercise provides an additional robustness check. We estimate the following regression model:

$$Y_i = \beta_0 + \beta_1 \cdot F_i + \beta_2 \cdot \mathbb{1}\{\texttt{High-Intensity}\} + \beta_3 \cdot \Big(F_i \times \mathbb{1}\{\texttt{High-Intensity}\}\Big) + X'\gamma + \varepsilon_i \quad (2.13)$$

where Y_i is the fertility outcome (parent likelihood) for lawyer i, F_i is a dummy variable indicating whether the individual is female, and X contains a set of individual-level, baseline characteristics including race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of initial job offers, number of bar exam attempts, spousal employment status at time of initial survey, early-career household income, respondent's early-career salary, early-career weekly hours worked, area of law, and factor scores.

The parameter of interest is β_1, which gives us the female-male difference in probability of being a parent for those who are predicted to be low-intensity. To obtain the gender difference for predicted high-intensity lawyers, we flip the indicator variable, $\mathbb{1}\{\texttt{High-Intensity}\}$, so that the reference group becomes high-intensity males and look at the analogous β_1.

There is no gender difference in the probability of being a parent if we control for baseline characteristics; the female-male difference is -0.03 and is not statistically significant (Table 2.6). When we focus on high-intensity lawyers, the gender difference widens to -0.067 but is still not statistically significant. We confirm that we observe the (near) complete fertility decision of these lawyers by examining their responses to the Wave 3 survey question, "Do you want more children?". Around 75 percent of our sample - both males and females - reported "no".[31] This is unsurprising as lawyers in our sample are 40-42 years old at the end of the survey. Among high-intensity lawyers, females are 3 percentage-points more likely to report wanting more children, but this difference is not statistically significant. Among low-intensity lawers, females are 3 percentage-points less likely to report wanting more children, but again, this estimate is not statistically significant. Our results suggest that preferences for parenthood are not driving our fertility timing results; female lawyers in our sample want

31. This statistic is only among the 1,730 lawyers who reported either wanting more children or not wanting more children. There are 338 respondents who reported being uncertain about future children, and 19 respondents who did not answer the question. There is no gender difference in uncertainty about wanting more children.

to have children but they are delaying their child-birth until after the partnership decision due to career concerns.

Table 2.6: Gender difference in completed fertility

	Pr(Parent)			**Want more children?**		
Predicted intensity level		High	Low		High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.0253	-0.0673	-0.0143	-0.00810	0.0334	-0.0285
	(0.0248)	(0.0532)	(0.0278)	(0.0271)	(0.0559)	(0.0310)
Avg. male likelihood	0.72	0.80	0.68	0.25	0.21	0.27
Avg. female likelhood	0.67	0.64	0.67	0.24	0.24	0.24
Observations	2,087	2,087		1,730	1,730	
Baseline controls	Yes	Yes				

Source: AJD restricted data.
Notes: Baseline Controls account for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of initial job offers, number of bar exam attempts, spousal employment status at time of initial survey, early-career household income, respondent's early-career salary, early-career weekly hours worked, area of law, and factor scores. Columns (1) and (4) include predicted intensity level as a control. *** p< 0.01, ** p< 0.05, * p< 0.1

2.6.3 Difference between "law" and "non-law" females

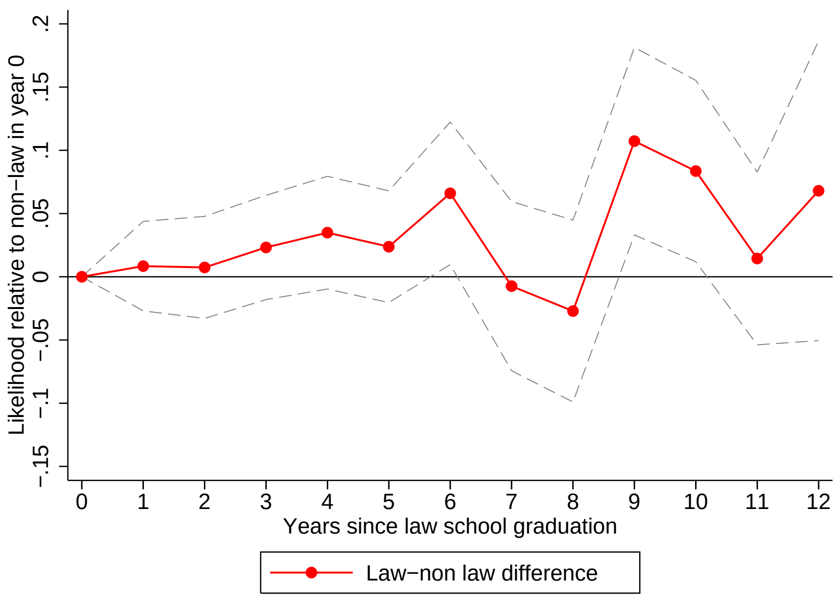
An additional method of estimating the effect of career concerns is to compare the fertility decisions of female lawyers at private law firms to female lawyers not at private law firms. The partner clock we exploit is a feature only of private law firms, so we would not expect to see female lawyers in other sectors time their first-child to the partner clock if career concerns were the mechanism. Our main hazard results in Figure 2.5 provide an indirect test of this; the pattern for low-intensity lawyers, who presumably face less career concerns, is very different from the pattern for high-intensity lawyers, who presumably face greater career concerns. In this section, we present an additional, more direct test by focusing on females.

We estimate the same model as equation (2.12), except our sample is restricted to females and the high-intensity indicator is replaced with an indicator for whether the lawyer's first job was at a private law firm, $\mathbb{1}\{\texttt{Law}\}$:

$$Y_{it} = \alpha_i + X'\gamma + \sum_{t=1}^{12} \tau_t \cdot \mathbb{1}\{T = t\} + \sum_{t=1}^{12} \tau_t^L \cdot \Big(\mathbb{1}\{\texttt{Law}\} \times \mathbb{1}\{T = t\} \Big) + \varepsilon_{it} \tag{2.14}$$

The reference category is "non-law" females (defined as those whose first job was not at a private law firm) in year 0. The parameter of interest is τ_t^L, which tells us each year's contribution to the "law" female's hazard relative to "non-law" female's in year 0.

Figure 2.6: Difference in hazard of exiting childless state between "law" and "non-law" females



Source: AJD restricted data.
Notes: N = 8,910. This figure depicts each year's contribution to the hazard of exiting the childless state relative to "non-law" females in year 0. "Law" are those whose first job was at a private law firm. "Non-law" are those whose first job was not at a private law firm. Gray lines are 95% confidence intervals.

If career concerns are driving our fertility-timing results, we would expect to see "law" females significantly more likely to become parents after the partnership decision (around year 8). The estimates and corresponding 95% confidence intervals are graphed in Figure

2.6. The results are as expected: there is no significant difference between these two groups of females until year 9, when females who started at private law firms are now 11 percentage-points more likely to become parents. There is also a statistically significant difference in year 6, but the estimate is about about half of the year 9 estimate (0.066). One potential explanation for this is female exit from high-stress firms (large private law firms) in year 5.[32] It is important to mention that though the probability of female exit from high-stress firms is high in year 5, the *gender difference* in exit from high-stress firms is not statistically significant. Therefore, a gender difference in exit likelihoods is not driving our fertility-timing results.

2.6.4 Alternative work-intensity measures

In this section, we conduct robustness checks by using alternative work-intensity measures to the predicted intensity measure, which predicts the lawyer's mid-career billed hours. We consider three different measures that also differentiate between those who face greater career concerns: (1) whether or not the lawyer's first job was at a private law firm, (2) whether or not the lawyer's first job title was "Associate", and (3) whether or not the lawyer's mid-career billed hours exceeded 1,561 (the 9-month threshold for a typical 2,000 annual requirement). These measures can also be seen as capturing the "effort-level" of lawyers.

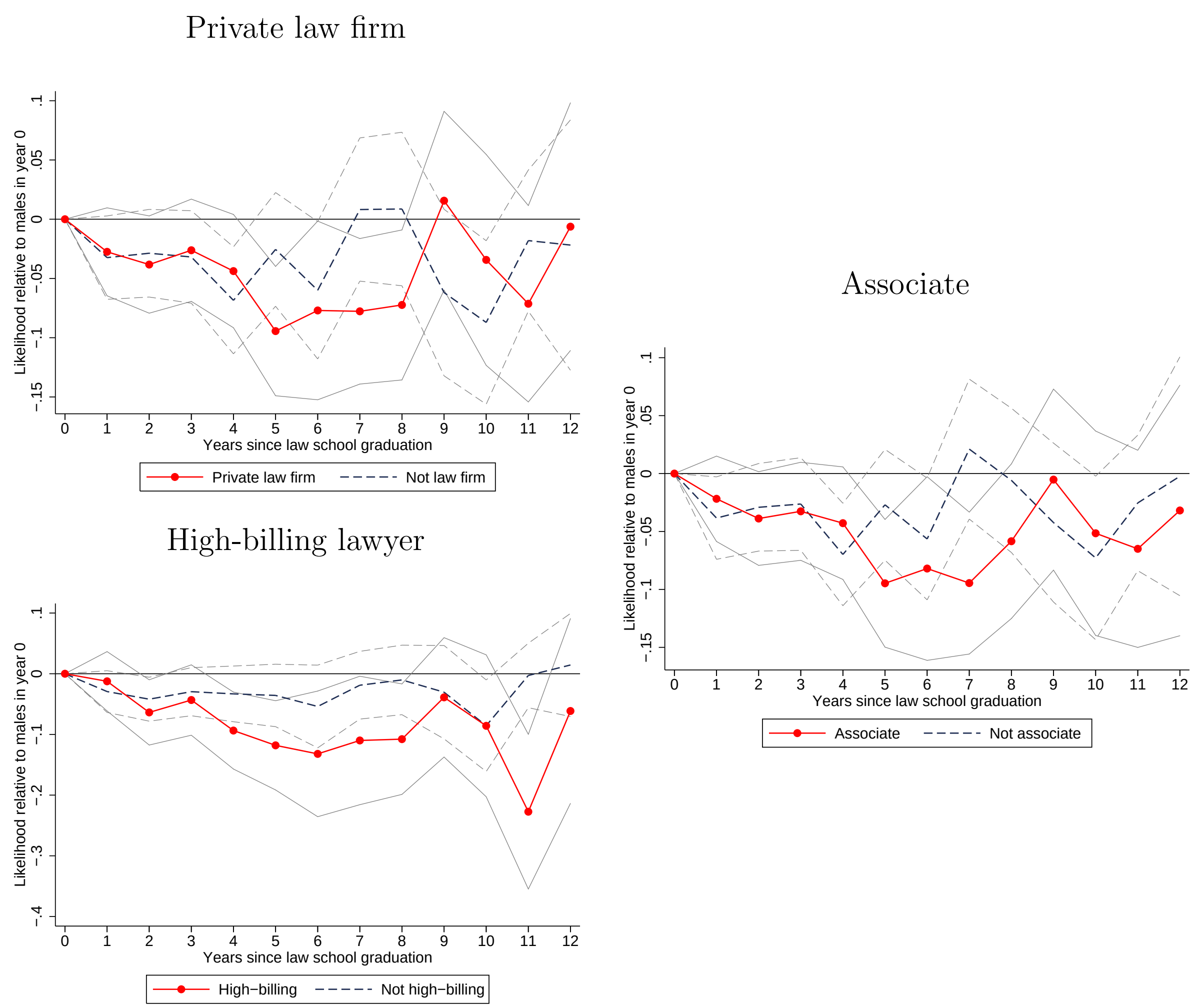
We estimate the rate of exiting the childless state using the same regression model as equation (2.12) and graph the results in Figure 2.7. The patterns are largely similar, with a larger female-male difference among those who face greater career concerns (in private law firms, working as associates, billing large hours) relative to their peers.[33] More importantly, the gender difference shrinks or disappears in year 9. Consistent with our results using the predicted intensity measure, the gender differences in years 4 through 8 are statistically significant. Additionally, the gender difference in the hazard rates for lawyers who do not

32. See Figure B.4.

33. The hazards when we delineate on private law firms and on associates are very similar. This is not surprising as 90 percent of law graduates who enter private law firms start as "Associate".

face strong career concerns is much smaller, more stable, and is not statistically significant after year 4.

Figure 2.7: Gender difference in rate of exiting childless state by alternative work-intensity measures



Source: AJD restricted data.
Notes: N = 8,910. This figure depicts each year's contribution to the hazard of exiting the childless state relative to "non-law" females in year 0. "Law" are those whose first job was at a private law firm. "Non-law" are those whose first job was not at a private law firm. Gray lines are 95% confidence intervals.

2.7 Alternative Explanations

2.7.1 Gender difference in timing of marriage

In this section, we explore alternative explanations to our theory that career concerns lead to a gender gap in fertility. One explanation is a gender difference in marriage timing. From Table 2.1, we know that female lawyers in our sample are less likely to be married than their male peers early in their careers. If females are more likely to marry later in life, then they will start their family formation later than their male peers. (This is assuming that very few births are out-of-wedlock.) Further, it is possible that among females, high-intensity females marry later in the life than low-intensity females because they are focusing on their careers right out of law school. In this case, we would expect there to be a gender difference in timing of first-child, and this gender difference to be larger among high-intensity lawyers relative to low-intensity lawyers. This may be one explanation for why we see females having their first child 9 years out of law school; it is mainly because they are single longer.

To test this alternative explanation, we subset our analysis sample to those ever-married at the start of the survey. To the extent that our results are being driven by gender differences in marital decisions, this concern should now be eliminated. The first graph in Figure 2.8 plots the same parameter estimates from equation (2.12) for this initially ever-married sample.[34] We see similar patterns in fertility timing as before: the magnitudes of the female-male difference among high-intensity lawyers remain large and negative, reaching -28 percentage-points six years after law school, before shrinking to -18 percentage-points in year 7 and disappearing in year 9. Similar to our main results, the gender-differences in years 5 through 7 are statistically significant. The gender difference among low-intensity lawyers, on the other hand, is never statistically significant. The magnitude also remains pretty consistent, ranging from -0.03 to -0.06.

A related concern is the age difference between husband and wife. In the population,

34. Full regression results are in the Online Appendix.

husbands tend to be younger than their wives, but in our sample male lawyers and female lawyers are the same age on average.[35] As a hypothetical example, say a 35-year-old male lawyer in our sample is married to a 33-year-old woman, while a 35-year-old female lawyer in our sample is married to a 37-year-old man. This indicates that the family formation of the 35-year-old female lawyer is more complete than that of her male peer. This would work against our favor; in the absence of career concerns, we would expect the female lawyer to start her family formation *before* the male lawyer, but this is not the case.

2.7.2 Gender difference in spousal occupation

A second potential explanation is the gender difference in spousal occupations. That is, male lawyers are more likely to marry women with less-intensive careers while female lawyers are more likely to marry men with intensive careers. Therefore, the gender difference in fertility-timing stems not from career concerns or the pressure to perform at work, but rather because male lawyers have spouses who are able to help around the house while female lawyers are married to spouses who are also in intensive occupations. This mechanism is similar to Becker's theory on time allocation in the household, which predicts that males, as primary-earners, will specialize in the market while their spouses will specialize at home.

To test for this, we restrict our analysis sample to lawyers who are primary-earners and estimate equation (2.12). We now expect both females and males in our sample to have a comparative advantage in the market and their secondary-earning spouses to specialize at home. If the allocation of time in the household were driving the results, then we would not expect to see gender difference in fertility timing.

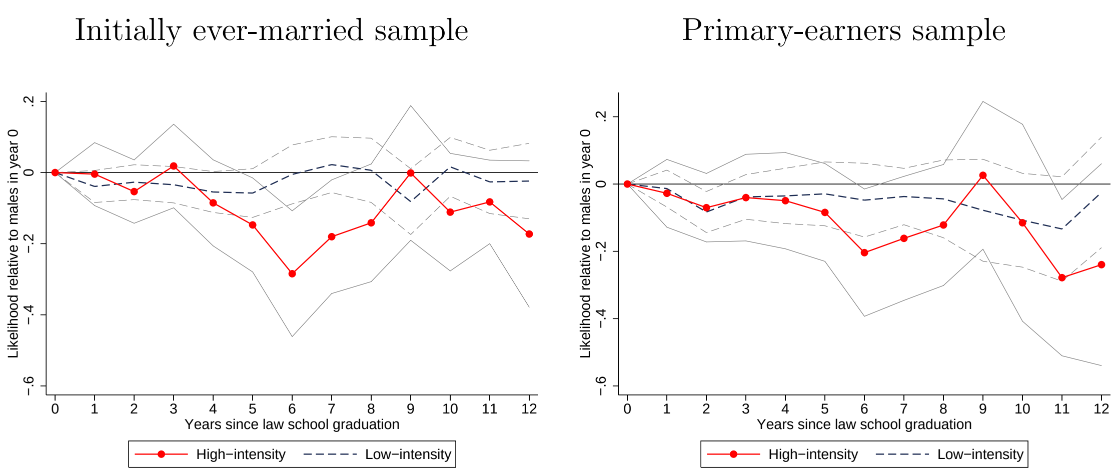
Our graphical results are presented in the second graph in Figure 2.8.[36] We still see that high-intensity females time their first-child to the partnership decision more so than their male counterparts. The estimates are not significant, likely due to the reduced sample

35. According to the 1990 and 2000 Census data, the mean husband-wife age difference in law households is 2.25 years. The median husband-wife age difference in law households is 1 year.

36. Full regression results are in the Online Appendix.

size. But the magnitudes are large and the timing pattern is very similar to our main result: the female-male difference goes from -7 percentage-points in year 3 to -20 percentage-points in year 6. It begins to shrink starting in year 7 and turns positive in year 9. For low-intensity lawyers, the female-male difference follows their high-intensity peers for the first four years. But whereas the high-intensity lawyers diverge and become more negative, the gender difference among low-intensity lawyers remains pretty stable before growing steadily after year 8.

Figure 2.8: Gender difference in hazard of exiting childless state by sample subset

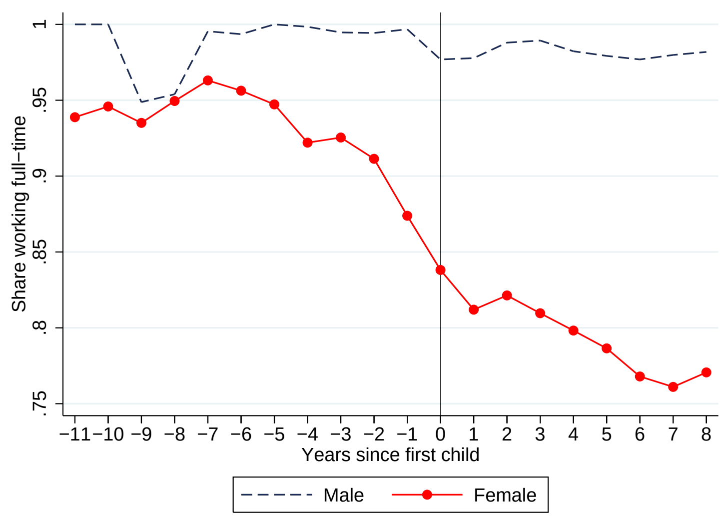


Source: AJD restricted data.
Notes: N = 9,297 (intially ever-married sample) and 5,324 (primary-earners sample). This figure depicts each year's contribution to the hazard of exiting the childless state relative to males in year 0. "Initially ever-married sample" is those who reported being ever-married in the first survey. "Primary-earners sample" is those who earn more than their spouse in mid-career. Lawyers are classified as "high-intensity" if their predicted intensity-level is in the top quartile and as "low-intensity" otherwise. Gray lines are 95% confidence intervals.

2.8 Mechanism 1: Gender difference in child-rearing costs

We now turn to an examination of the mechanisms that drive the gender difference in fertility timing. A main mechanism highlighted by the literature and our conceptual framework is the time cost of raising children. The reason that children have a negative effect on career advancement is that children require attention. They need to be fed, washed, clothed, and watched over. To the extent that these activities require effort on the parent's part, the parent then has less effort to exert at work. Consistent with evidence presented by the literature, we assume that this indirect cost is greater for women than for men. Indeed, our data corroborate this assumption. Figure 2.9 shows that male lawyers are less likely than female lawyers to adjust their hours after becoming a parent. In fact, men continue working full-time at impressive rates throughout their careers; not once does it dip below 95 percent. Women's full-time rates also do not dip below 90 percent - until one year before their first child. The percentage of women working full-time drops from 87 percent to 81 percent in the year immediately following the birth of their first-born. In this section, we examine how the higher price of children faced by women affects the gender difference in fertility-timing.

Figure 2.9: Share working full-time by birth of first child



Source: AJD restricted data.

2.8.1 *Spousal income*

If women face a greater time cost of children, then we would expect to see heterogeneous effects by cost-size. In particular, we would expect to see smaller female-male fertility differences among those for whom the time cost of children is smaller. One method to test this hypothesis is to use income as a proxy for the time cost. More well-off households can afford child-care or full-time nannies to watch over their children. The use of household income, however, is problematic as it includes the lawyer's salary, which is correlated with the lawyer's career decision. To bypass this concern, we use early-career spousal income. The use of *early-career* income mitigates the concern that spousal income is determined by the lawyer's career choices. Assortative matching presents a concern if partners are matching on intensity-level or career ambitions. In that case, spousal income will be positively correlated with the lawyer's career choices. This correlation may be true in the general population, but it is likely weaker in this more homogenous, highly-educated sample of lawyers. We create quartiles of spousal income conditional on geographic location at time of initial survey. Those in the top income quartile of each geographic location are classified as being in the top spousal-income quartile.

If lawyers with spouses in the top income quartile face a smaller time cost of children, then we expect that the gender difference in fertility timing for these lawyers will be less negative relative to the gender difference for lawyers whose spouses are not in the top quartile. The results, reported in Table 2.7, are largely in-line with this prediction. The signs for early parenthood and late parenthood are reversed between those with spouses in the top income quartile and those with spouses not in the top income quartile. Specifically, female high-intensity lawyers with top-earning spouses are more likely to have an early parenthood relative to their male counterparts, and are *less* likely to have an a late parenthood relative to their male counterparts. The estimates are not statistically significant, but the signs are informative as they are the opposite of the signs in our main results in Table 2.5. Additionally, there are little heterogeneous effects by spousal income for low-intensity lawyers, who are not as affected by career concerns. These results suggest that having a spouse in the top income quartile mitigates the adverse effect of career concerns on fertility timing for the marginal lawyers.

Table 2.7: Gender fertility difference by spousal income

Panel A: Early parenthood

Predicted intensity level	High		Low	
Spousal income quartile	Top (1)	Not top (2)	Top (3)	Not top (4)
Female-male difference	0.126 (0.149)	-0.317*** (0.0791)	-0.0104 (0.0771)	-0.0445 (0.0464)
Avg. male likelihood	0.55	0.79	0.56	0.63
Avg. female likelihood	0.64	0.40	0.57	0.57
Observations	1,296		1,296	
Baseline controls	Yes		Yes	

Panel B: Late parenthood

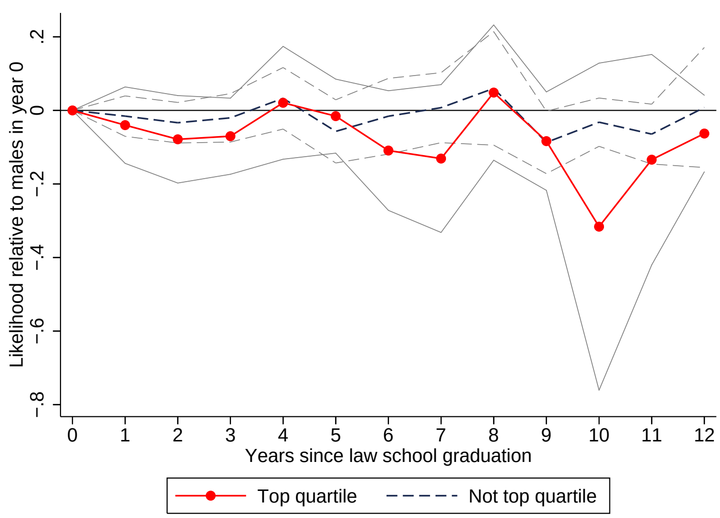
Predicted intensity level	High		Low	
Spousal income quartile	Top (1)	Not top (2)	Top (3)	Not top (4)
Female-male difference	-0.137 (0.148)	0.272*** (0.0801)	-0.0674 (0.0724)	0.0688 (0.0444)
Avg. male likelihood	0.42	0.17	0.40	0.32
Avg. female likelihood	0.32	0.53	0.33	0.38
Observations	1,296		1,296	
Baseline controls	Yes		Yes	

Source: AJD restricted data.
Notes: Early parenthood is defined as having one's first child within the first 7 years after law school. Late parenthood is defined as having one's first child at least 9 years after law school. Spousal-income quartiles are based off early-career income and account for geographic location. See notes in Table 2.4 for description of baseline controls. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

A look at the average likelihoods suggests that the positive female-male difference in early parenthood among high-intensity lawyers with top-earning spouses is coming mainly from an increase in female likelihood rather than a decrease in male likelihood. Specifically, the likelihood of early parenthood is 40 percent for a high-intensity female but increases to 64 percent for a high-intensity female with a top-earning spouse. The analogous likelihoods for males decreased from 61 percent to 55 percent, a much smaller change. A similar pattern is found when examining late parenthood for high-intensity lawyers; the gender difference is driven by a change in female fertility decisions rather than male fertility decisions.

Although we are interpreting these results to be driven by a change in the time cost of having children, it is possible that they may instead be driven by female movement from private law firms into less-intensive occupations. That is, maybe top-earning husbands are making enough money so that their lawyer wives do not have to work. That may be one reason that we see a positive and statistically insignificant gender difference in early parenthood among lawyers with top-earning spouses. To check this, we plot the hazard rates of exit from private law firms for high-intensity lawyers by spousal-income quartile (Figure 2.10). There is no gender difference. The magnitude for top-income quartile lawyers is larger in years 6 and 7, but all of the estimates are not statistically significant. This graph implies that the heterogeneous effects on early and late parenthood are not driven by female movement across sectors, but may be due to the time cost of having and raising children.

Figure 2.10: Gender difference in exit likelihood from private law firm by spousal-income quartile of high-intensity lawyers



Source: AJD restricted data.
Notes: This figure depicts each year's contribution to the hazard of exiting the childless state relative to males in year 0. Spousal-income quartiles are based off early-career income and account for location. Gray lines are 95% confidence intervals.

2.8.2 Work and family conditions

There are several ways in which the time cost of having children can be reduced. In the previous section, we examined the effect of income. In this section, we examine the accessibility of child-care and leniency of parental leave legislation. Greater accessibility to child-care, lower child-care costs, and more family-friendly policies all reduce the time cost of having children by reducing the work-child tradeoff the parent faces. In other words, women who live in an area with lots of affordable child-care options do not need to worry about keeping their children occupied during the work-day. To this end, we expect that the gender difference in fertility timing will be less negative for lawyers who live in areas with more family-friendly work conditions.

We use the Institute for Women's Policy Research's *Status of Women* 2015 report to obtain measures of work and family conditions in each state. This report assigns a letter grade for each state based on its paid leave legislation, elder and dependent care, child care, and the gender gap in parents' labor force participation rates. Table B.13 lists the letter grades of all the geographic regions in our dataset. We group the letter grades into 5 categories to increase power (B, B-/C+, C/C-, D+/D, and D-/F) and estimate the female-male difference in early parenthood and late parenthood separately for each category using equation (2.11). The results for high-intensity lawyers is reported in Figure 2.11.[37]

The circles represent the female-male difference in the fertility outcome. The size of the circles represents the geographic region's population. The red line is a fitted line of the estimates, weighted by population size. The fitted line indicates that the gender-difference becomes monotonically larger as the work and family conditions in the region gets worse. In regions that earned a B, the gender difference in early parenthood and late parenthood is close to 0. In regions that earned a D- or an F, however, the gender difference in early parenthood is more than -0.3 and about 0.3 for late parenthood. These results suggest there

37. We show estimates for high-intensity lawyers because they are the ones most affected by career concerns. We also estimate the gender difference for the entire sample and low-intensity lawyers. Those results can be found in Figure B.6.

is room for policy to have an impact. Better accessibility to affordable child-care and more family-friendly policies at work may help to reduce the greater time cost of children for women.

2.8.3 Gender norms

In previous sections, we explored how the time cost of children faced by women can be affected by income or child-care costs. One question that was not addressed is *why* women face a greater time cost. One explanation may be that women have a stronger preference than men for raising children. Another may be that women have a comparative advantage in non-market activities (Becker, 1960). In this case, it is possible that women adjust their hours to focus on non-market activities even if they also have a comparative advantage in the market. A third explanation that has been posited by the literature looks at gender norms. Bertrand, Kamenica, and Pan (2015) find that gender identity impacts the division of home production. Specifically, the gender-identity norm that "a man should earn more than his wife" leads women to undertake a larger share of home-production activities to appear less threatening to their husbands.

One implication of this theory is that the gender fertility difference should be more pronounced in areas that strongly prescribe to these gender norms. We obtain each Census region's measure of gender norms from Pan (2015), who constructed them using the 1977 to 1988 General Social Survey (GSS). The GSS, one of the most comprehensive sources of attitudinal data in the US, asks several questions related to the appropriate role of women in society. For example, survey respondents are asked whether they agree or disagree with the following statement: "It is much better for everyone involved if the man is the achiever outside the house and the women takes care of the home and family." Pan uses men's responses to these questions to construct a uni-dimensional index of gender-related attitudes held by men. She also constructs separate indices by white-collar and blue-collar occupations. To be more relevant to our sample of lawyers, we use the white-collar male index. The crosswalk of Census region to geographic regions in our data, with the corresponding sexism index, is reported in Table B.14. More positive values in the index correspond with more gender-prejudiced attitudes.

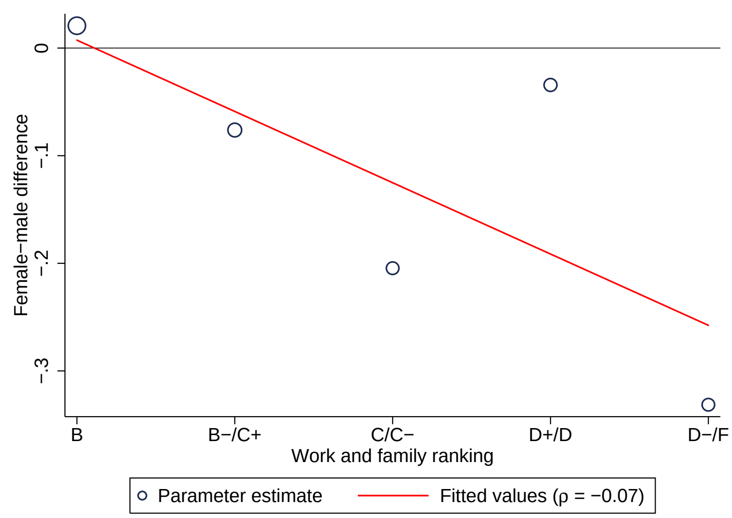
We estimate the female-male difference in early parenthood and late parenthood separately for each Census region using equation (2.11).[38] Our estimates for high-intensity lawyers are presented in Figure 2.12.[39]. Female lawyers in regions that prescribe more strongly to gender norms are more likely to delay their fertility relative to male lawyers in those regions, while the gender difference is smaller in regions with more open attitudes about gender norms. Although the previous analyses highlight the roles that policy may play in alleviating the higher price of children that women face, these results suggest that policy may have a limited effect as social attitudes and norms are also a factor.

38. The Mountain region was combined with the Middle Atlantic due to low power; with only 75 observations, we were unable to obtain estimates for the Mountain region. The gender fertility difference estimate is reported under a newly constructed sexism index for the Mountain-Middle Atlantic region, which is weighted by population.

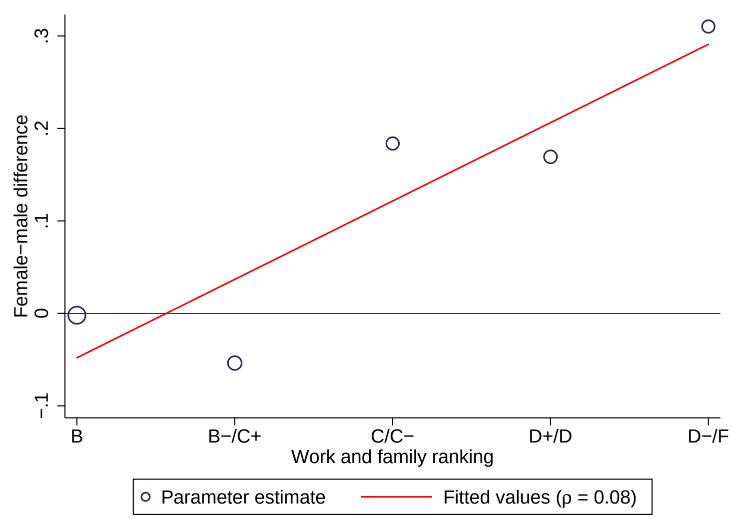
39. Results for the full sample and low-intensity lawyers are in Figure B.7

Figure 2.11: Gender fertility difference by state grade of work & family conditions

Early parenthood



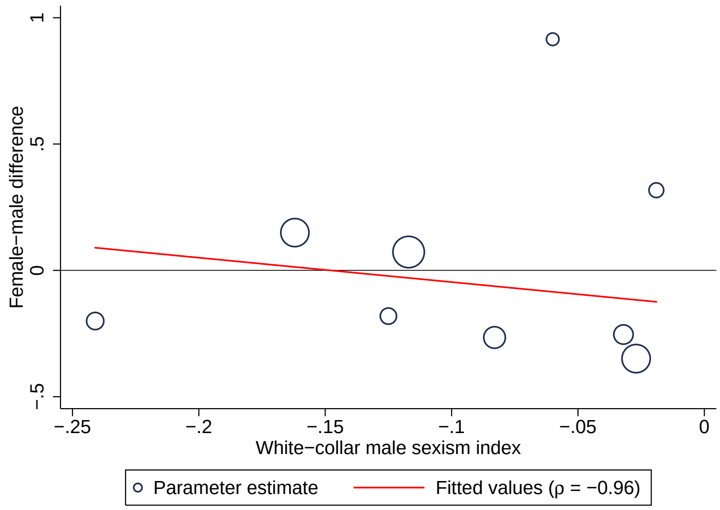
Late parenthood



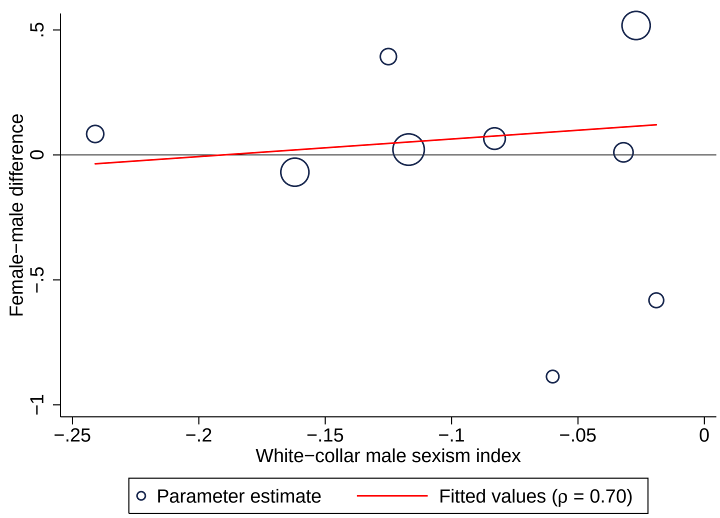
Source: AJD restricted data, Institute for Women's Policy Research's *Status of Women* 2015 report.
Notes: State grades for work and family conditions are taken from the Institute for Women's Policy Research's *Status of Women* 2015 report. Work and family conditions consider paid leave legislation, elder and dependent care, child care, and the gender gap in parents' labor force participation rates. Size of circles represents the region's population. Fitted values are weighted by population size.

Figure 2.12: Gender fertility difference by Census region's level of gender norms

Early parenthood



Late parenthood



Source: AJD restricted data, Pan (2015).
Notes: White-collar male sexism index is constructed from the GSS survey and is taken from Pan (2015). More positive values correspond with more gender-prejudiced attitudes. Size of circles represents the census region's population. Fitted values are weighted by population size.

2.9 Mechanism 2: Gender-specific thresholds

Our conceptual framework highlighted two main mechanisms that drive the gender difference in fertility-timing. In Section 2.8, we explored the first channel, which is that women face a greater career cost of having children. In this section, we consider the empirical evidence on whether firms have different promotion thresholds for mothers and parents.

2.9.1 Promotion thresholds

If it is true that firms have higher promotion thresholds for parents and mothers, then, in equilibrium, we expect that among those promoted: (1) lawyers with children at the time of promotion must be of higher ability than childless lawyers, and (2) female lawyers with children at the time of promotion must be of higher ability than male lawyers with children at the time of promotion.

In this section, we test these predictions using the following characteristics as proxies for ability: participation in general law review during law school, obtaining a judicial clerkship after law school, and initial caseload.[40] Most major American law schools publish a law review dealing with all areas of law ("general law review") with the purpose of promoting scholarship in the field of law. Historically, law review articles have been influential in the development of the law, and, thus, membership on the law review staff is highly sought-after by law students. Judicial clerkships are post-graduate opportunities for law students to work closely with a judge and assist in making legal determinants. These are prestigious, competitive opportunities usually reserved for law students at the top of their class. We also look at the lawyer's initial caseload. Because the law firm makes its promotion decisions on

40. We can also look at billed hours as a measure of ability. However, observed billed-hours may differ across firms as some firms have a larger client-base than others. Therefore, a direct comparison of observed billed-hours across the industry may be misleading: a top-billing lawyer at a mid-size firm may bill 1,600 annual hours, but a middling lawyer at a large firm may bill 1,800 annual hours. More importantly, from my conversation with a partner at a law firm, billed hours is too coarse a measure to determine whether an associate will make a good partner. Although billed hours is a factor in partnership decisions, more weight is put on the quality of the lawyer's work product. Therefore, ability proxies may be a more accurate measure.

the lawyer's signal rather than actual effort-choice, the lawyer's initial caseload is a proxy for the lawyer's signal.

To test for gender discrimination, we estimate the gender difference in ability outcomes separately for equity partners who were parents before being promoted to partner ("parents-first") and equity partners who were childless at time of promotion ("partners-first"). Our test for discrimination against parents is similar, except we estimate the difference in ability outcomes between the "parents-first" lawyers and the "partners-first" lawyers. If the firm does not have different promotion thresholds, then we would expect there to be no statistically significant differences or for them to be economically small.

Table 2.8: Ability levels of equity partners by gender and parental status

Panel A: Parent-first sample

	General law review		Judicial	Initial
	Member	**Editor**	**clerkship**	**caseload**
	(1)	(2)	(3)	(4)
Female-male difference	0.250**	0.290***	0.455**	1.196***
	(0.103)	(0.0912)	(0.205)	(0.433)
Avg. male likelihood	0.22	0.12	0.20	7.91
Observations	172	172	39	119
Baseline controls	Yes	Yes	Yes	Yes

Panel B: Partner-first sample

	General law review		Judicial	Initial
	Member	**Editor**	**clerkship**	**caseload**
	(1)	(2)	(3)	(4)
Female-male difference	-0.0546	-0.0914	0.550	-0.516
	(0.123)	(0.0931)	(1.630)	(0.369)
Avg. male likelihood	0.35	0.28	0.26	8.76
Observations	109	109	26	76
Baseline controls	Yes	Yes	Yes	Yes

Panel C: Everyone

	General law review		Judicial	Initial
	Member	**Editor**	**clerkship**	**caseload**
	(1)	(2)	(3)	(4)
Parent-not parent difference	-0.0330	-0.0650	0.0550	0.0214
	(0.0700)	(0.0555)	(0.123)	(0.259)
Avg. childless lawyer likelihood	0.28	0.22	0.20	8.61
Observations	281	281	65	195
Baseline controls	Yes	Yes	Yes	Yes

Source: AJD restricted data.
Notes: Each column is a separate OLS regression. Sample is subsetted to equity partners in a law firm, and partnership is defined as making equity partner in a private law firm. "Parents-first sample" are lawyers who had children before they became equity partner. "Partners-first sample" are lawyers who had children after they became equity partner. Baseline controls include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, and area of law. Column (3) does not include law area to reduce perfect collinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results suggest evidence of different promotion thresholds for mothers (Panels A and B of Table 2.8). Among those who had children before they were promoted to partner, women are 25 percentage-points more likely to have participated in general law review, 29 percentage-points more likely to have been in an editorial role, and 46 percentage-points more likely to have held a judicial clerkship. They also worked on one additional case than men did at the start of their careers. All of these estimates are statistically significant. Again, these results control for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, and area of law. More interestingly, we do not see similar patterns when looking at associates who did not have children before they became partners (Panel B of Table 2.8). Females are less likely than their male peers along all of our outcome measures with the exception of judicial clerkships, but these estimates are not statistically significant. The positive ability selection in the parents-first sample and the lack of a gender difference in the partner-first sample are consistent with what we would expect if firms set different promotion thresholds by gender for associates with children.

The evidence on different promotion thresholds for parents is mixed (Panel C of Table 2.8). Equity partners who were parents first are 3 percentage-points less likely than their "partners-first" peers to have participated in general law review, and are 6.5 percentage-points less likely to have been an editor. They are also 6 percentage-points more likely to have had a judicial clerkship and work on 0.02 more cases. Again, these results control for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, and area of law. Because of the small sample size, we exclude law area fixed-effects to reduce perfect collinearity issues when estimating differences in judicial clerkships. Why is it that we do not see strong evidence of discrimination against parents? One potential explanation, which we discussed in Section 2.8, is that the adverse career-costs of children are not gender-neutral. Females are more likely than males to adjust their labor supply after having a child so it may not make sense to discriminate against parents broadly.

It is important to note that the average female equity partner in the parent-first sample had her first child four years *after* law school and the average male equity partner had his first child three years *after* law school. This gender difference of 0.8 years is not statistically significant. This is important because it indicates that the ability proxies we are using are not contaminated by the child's presence. One potential reason that female equity partners in the parent-first sample are of higher ability than their male peers may be that having children is costly in terms of effort and these women, if they had them before or during law school, would need to be of higher ability anyway in order to participate in general law review or to obtain a judicial clerkship. Our results in Panel A, therefore, may simply be reflecting gender differences in the child-cost on our ability measures rather than actual gender differences in underlying ability. However, as 83 percent of lawyers in parent-first sample were not parents during law school, this concern is mitigated.

To be thorough, however, we include a control for child-care responsibility (see Table 2.9). In Wave 2, lawyers are asked who is primarily responsible for taking care of the child's needs at night. The answer choices are: the respondent, shared equally, my spouse/partner, and someone else. To the extent that having children affects the gender difference in our ability measures, this control should mitigate that concern. The estimates are very similar to the original estimates without the child-care control: female equity-partners in the parent-first sample are of higher ability, on average, than male equity-partners, but there is no gender difference among equity partners in the partner-first sample.[41]

41. We are unable to look at judicial clerkships due to a lack of power.

Table 2.9: Ability levels of equity partners by gender with child-care controls

Panel A: Parent-first sample

	General law review		**Initial**
	Member	**Editor**	**caseload**
	(1)	(2)	(3)
Female-male difference	0.250**	0.281***	1.242***
	(0.106)	(0.0943)	(0.440)
Avg. male likelihood	0.22	0.12	7.91
Observations	172	172	119
Baseline controls?	Yes	Yes	Yes
Control for child-care responsibility	Yes	Yes	Yes

Panel B: Partner-first sample

	General law review		**Initial**
	Member	**Editor**	**caseload**
	(1)	(2)	(3)
Female-male difference	-0.0443	-0.0559	-0.558
	(0.123)	(0.0994)	(0.418)
Avg. male likelihood	0.35	0.28	8.76
Observations	109	109	76
Baseline controls	Yes	Yes	Yes
Control for child-care responsibility	Yes	Yes	Yes

Source: AJD restricted data.
Notes: See notes in Table 2.8 for description of baseline controls. *** p< 0.01, ** p< 0.05, * p< 0.1

Table 2.10: Ability levels of "early-parenthood" lawyers

	General law review		**Judicial**	**Initial**
	Member	**Editor**	**clerkship**	**caseload**
	(1)	(2)	(3)	(4)
Female-male difference	0.00208	0.0477	0.0125	0.127
	(0.0401)	(0.0326)	(0.0140)	(0.204)
Observations	745	778	778	447
Baseline controls	Yes	Yes	Yes	Yes

Source: AJD restricted data.
Notes: See notes in Table 2.8 for description of baseline controls. *** p< 0.01, ** p< 0.05, * p< 0.1

Another method of testing whether there is positive female selection into early parenthood is to consider the average ability of all lawyers who experienced an early parenthood. The idea is that if positive female selection exists, then we would see a positive female-male difference in ability measures among *all* lawyers who had children before year 8 (our proxy year for when partnership decisions are made). The results are reported in Table 2.10. There is no significant gender difference in the four ability proxies among the "early parenthood" lawyers. Moreover, the estimates are small and nowhere near the magnitude found in Table 2.8. This suggests that the observed higher-ability female equity partners in the "parent-first" sample is not due to postive female selection into early parenthood.

2.9.2 Promotion probability

A second method for examining whether firms have different promotion thresholds for mothers is to look at the gender difference in the probability of promotion. If, conditional on ability and productivity measures, there is still a gender difference in the likelihood of becoming equity partner, this suggests that the firm may have different thresholds for female versus male lawyers. We test this hypothesis by examining how the gender difference in promotion probability changes as we add in more controls (Table 2.11). Initially, females are 10 percentage-points less likely to be equity partner. When we add in demographic controls and ability proxies, such as graduate school ranking, participation in general law review, and judicial clerkships, the gender difference shrinks but remains statistically significant at -8 percentage-points. The largest explanatory variables are whether the lawyer took parental leave and for how long and the number of billed hours. However, even after controlling for observable productivity measures and spousal employment, females are still about 4 percentage-points *less* likely to be promoted relative to men.

Panel B of Table 2.11 focuses on the "early parenthood" sample. This is all lawyers who had their first-child at most 7 years after their JD. We also see negative and statistically significant gender differences in promotion probabilities, but the significance disappears when we control for parental leave and the gender difference disappears when we control for billed hours and caseload. An interesting comparison is that the gender difference among all lawyers remains negative and statistically significant after including all controls, but it disappears among early-parenthood lawyers. This implies that the negative female-male difference in the overall sample is being driven by lawyers who did not have their first-child before year 8. One potential explanation for this is that firms have higher promotion thresholds for *all women* not just mothers, because of the possibility that a female lawyer may have a child after the promotion decision. However, we do not see any significant gender difference in ability proxies among the partner-first sample in Table 2.8 so these results should be interpreted with caution.

Table 2.11: Gender difference in promotion probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Everyone								
Female-male difference	-0.103***	-0.0905***	-0.0837***	-0.0731***	-0.0700***	-0.0552***	-0.0389*	-0.0364*
	(0.0234)	(0.0229)	(0.0213)	(0.0210)	(0.0209)	(0.0206)	(0.0199)	(0.0199)
Observations	1,780	1,780	1,780	1,780	1,780	1,780	1,780	1,780
Panel B: Early parenthood sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female-male difference	-0.116***	-0.107***	-0.0868**	-0.0623*	-0.0662*	-0.0444	-0.0127	-0.00780
	(0.0387)	(0.0381)	(0.0363)	(0.0346)	(0.0356)	(0.0374)	(0.0346)	(0.0347)
Observations	806	806	806	806	806	806	806	806
Controls for:								
Demographic characteristics		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ability proxies			Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics				Yes	Yes	Yes	Yes	Yes
Income and spousal employment					Yes	Yes	Yes	Yes
Parental leave						Yes	Yes	Yes
Billed hours in mid-career							Yes	Yes
Caseload in mid-career								Yes

Source: AJD restricted data.

Notes: "Early parenthood sample" consists of lawyers who had their first child within 7 years of the JD. Demographic characteristics include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, initial number of job offers, and bar exam attempts. Job characteristics include initial firm's size, initial hours worked, and area of law. Parental leave controls include whether or not the lawyer took parental leave for his or her first child and the number of weeks taken. Income and spousal employment controls are from Wave 1. *** p< 0.01, ** p< 0.05, * p< 0.1

2.9.3 Adverse child consequences at work

Last, we examine firm attitudes towards lawyers who have children. If firms indeed have different promotion thresholds based on parental status, then it is not surprising for lawyers to experience negative consequences at work. The Wave 2 survey asks whether the respondent experienced any adverse outcomes at work after becoming a parent. Table 2.12 highlights the results for four negative outcomes: delay in promotion, questioning of commitment to work, loss of challenging assignments, and loss of clients. While 5 percent of male lawyers report experiencing a delay in promotion after having a child, female lawyers are four times more likely to be penalized even after controlling for the lawyer's demographic characteristics, ability proxies and predicted intensity level, job characteristics, and division of child-care responsibilities. Female lawyers are ten times more likely than males to lose challenging assignments and three times more likely to lose clients. The loss of clients and challenging assignments have far-reaching consequences as they may affect future career trajectories and promotions. Interestingly, a relatively large percentage of male lawyers also report being questioned about their commitment to work after becoming a father (13.4 percent), but they do not seem to experience negative effects in terms of job assignments or promotions like their female peers. We also examine the consequences for equity partners, in case our results capture a "disgruntled employee" effect. But the estimates are very similar. The gender difference in promotion delay is smaller among equity partners, which is unsurprising as these lawyers are already promoted, but the loss of clients is larger, which is a bigger deal for equity partners who are expected to bring in new business.

Table 2.12: Gender difference in adverse child consequences at work

	Everyone			Equity partners		
	Avg male	**Estimate**	**N**	**Avg male**	**Estimate**	**N**
Adverse consequence at work						
Delay in promotion	0.047	0.198***	1,396	0.017	0.125**	1,204
		(0.0277)			(0.0539)	
Questioning of commitment to work	0.134	0.222***	1,388	0.057	0.272***	1,196
		(0.0334)			(0.0739)	
Loss of challenging assignments	0.015	0.159***	1,404	0.010	0.155***	1,209
		(0.0212)			(0.0514)	
Loss of clients	0.021	0.0778***	1,395	0.019	0.157***	1,203
		(0.0203)			(0.0559)	

Source: AJD restricted data.
Notes: Regressions control for race and ethnicity, age, law school graduation date, geographic location at time of initial survey, initial marital status, standardized undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, number of initial job offers, number of bar exam attempts, initial firm's size, early-career weekly hours worked, area of law, mid-career billed hours, spousal employment status at time of initial survey, early-career household income, respondent's early-career salary, and division of child-care responsibilities. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

2.10 Conclusion

A growing body of evidence shows that the adverse effect of children on career advancement falls disproportionately on women. We predict that women will respond by delaying family formation more than men. We test this theory using detailed survey data on a nationally representative sample of lawyers. We find considerable evidence that female lawyers are more likely than men to wait until after the partnership decision to have their first child, and these results are more pronounced among women who have the greatest chance of making partner. We mitigate concerns about gender-based selection into occupations by leveraging the richness of our data and conducting a factor analysis to construct measures of latent preferences that drive selection into different types of jobs. Our findings are not explained by gender differences in marriage timing or in spousal occupation. Moreover, we do not find a gender difference in completed fertility, suggesting that family-size preferences are not driving our results.

We explore two main mechanisms for our results. The first is that women face a greater career cost of having children. Consistent with the literature, we find that this trade-off is influenced by spousal income, family-friendly work conditions, and gender norms (Schaller, 2012; Bertrand, Kamenica, & Pan, 2013; Adda, Dustmann, & Stevens, 2016). A contribution of this paper is the consideration of an additional mechanism that affects female fertility decisions differently from male's: the possibility that firms have higher promotion thresholds for mothers because gender predicts child-related career interruptions. We find evidence in support of this mechanism. Not only are equity partners who were mothers at the time of promotion of higher ability, on average, than their male counterparts, but females are less likely to be promoted even conditional on measures such as billed hours and caseload. Women are also more likely to experience negative consequences at work after having a child, including a questioning of commitment to work and loss of challenging assignments.

One research question that stems from this paper is whether law firms assign less-desirable tasks to women - even before they have children - because gender predicts child-related career interruptions. This empirical question is consistent with the theory that firms endogenously invest less in the career development of workers who are more likely to experience work disruptions (Milgrom & Oster, 1987; Barron, Black & Loewenstein, 1993; Lehmann, 2013). Future work should explore this possible channel of statistical discrimination.

Another potential research topic is to better understand the complex relationship between workplace flexibility and fertility. This is analogous to Goldin's charge (2014) to address the "last chapter" in eliminating the gender pay gap. Significant progress has been made over the past fifty years in closing the gap between men and women in terms of college majors and occupations. Due to shrinking gender differences in labor force participation and hours-worked, the gender wage gap is now essentially a motherhood gap. This paper adds to the literature by focusing on non-pecuniary costs of career advancement. Our findings make clear that the current focus on the gender wage gap understates the level of gender disparity in the labor market.

CHAPTER 3

HOUSING BOOMS, BUSTS, AND THE ADDED WORKER EFFECT (WITH DAN A. BLACK AND KERWIN CHARLES)

3.1 Introduction

The recent U.S. housing crisis and the subsequent 2007-2009 recession have reinvigorated the study of income shocks and consumption smoothing. A long-standing literature finds that family labor supply is an important tool for risk-insurance (e.g., Mincer, 1962; Heckman and MaCurdy, 1980; Lundberg 1985; Dynarski and Gruber, 1997). For example, in a two-earner household, the wife may enter the labor force to make up for the loss in family income from her husband's unemployment during the recession. Labor economists refer to this phenomenon as the "added worker effect" (AWE).

The study of the added worker effect is especially interesting in light of advancements made by women in the labor market. Theoretically, it is ambiguous how these advancements would affect AWE. On one hand, a decrease in the labor-force participation cost of married women can strengthen the added worker effect (e.g., Mankart and Oikonomou, 2016b). On the other hand, these developments may decrease the value of marriage as a risk-sharing device (e.g., Juhn and Potter, 2007). Increasing co-movement of employment between couples limits the wife's ability to adjust her labor supply. This may lead to a "discouraged worker effect" (DWE) in economic downturns, counteracting any AWE.[1] This paper empirically assesses whether married women increased their labor supply during the housing bust of the 2000s.

Past studies have sought to quantify the added worker effect with mixed results.[2] The

1. The discouraged worker effect is when individuals leave the labor force after failed job searches.

2. Some studies find no evidence of an added worker effect (Layard, Barton, and Zabalza, 1980; Maloney, 1987, 1991), while others estimate a small effect size (Mincer, 1962; Bowen and Finegan, 1968; Heckman and MaCurdy, 1980, 1982; Lundberg, 1985; Spletzer, 1992; Cullen and Gruber, 1996). Still, others find a *discouraged* worker effect (Long, 1958; Mincer, 1962; Bowen and Finegan, 1965, 1968; Cain, 1966).

seemingly contradictory results are mainly due to differences in methodological approaches in measuring unemployment (Lundberg, 1985). One of the seminal works in this literature is Stephens (2002), which measures job displacement through reported plant closings and layoffs in the Panel Study of Income Dynamics (PSID). Our paper also utilizes an unexpected shock to the husband's permanent income to examine the wife's labor supply, but differs from Stephens in a number of key ways. First, we exploit a national housing shock, an arguably cleaner source of exogenous variation than self-reported job displacements. Second, we focus on non-college construction households in the Census and the American Community Surveys (ACS). As such, our analysis sample is larger and can speak more generally to the impact on low-skilled workers.[3] Further, whereas Stephens uses data between 1968-1992, our analysis focuses on the 2000s. Examining more recent years is an interesting exercise considering the growing similarity in women's human-capital investments and labor-supply decisions as men's. Given these differences, we believe our paper provides new and timely evidence of the AWE.

Our focus on the housing crisis is conducive to the research question for several reasons. First and foremost, its effects were massive, national, and concentrated in construction, where a majority of workers are male (90 percent) and married (60 percent).[4] This facilitates analysis of the added worker effect. Second, the start of the housing bust in 2006 was unexpected. A bubble is difficult to identify *ex ante*, and understandably, economists were split on this issue.[5] The unpredicted housing bust is an important detail as it limits the family's ability to prepare for upcoming negative income shocks.[6] Further, the collapse of

3. According to the 2000 Census, 13 percent of the male, non-college population were in the construction industry.

4. These estimates are from the 2000 Census data.

5. As early as 2002, Baker (2002) concluded that a housing bubble existed. Krugman (2006) warns that a "nasty correction" of the housing market lies ahead. Bernanke acknowledged that there was "a great deal of froth in housing markets" but did not think there would be a major fallout (Krugman, 2010). Tabarrok in Februray 2008 insisted that there was no housing bubble (Krugman, 2010).

6. Stephens (2002) finds pre-displacement added worker effects for plant closings, where presumably, information about an impending plant closing was relayed to workers. He did not find pre-displacement effects for layoffs.

the housing market led to a credit crisis, thereby limiting alternative channels through which families can smooth their consumption.[7] This helps us to better identify an added worker effect.

Figure 3.1 presents graphical evidence of the added worker effect. It plots labor market trends for construction husbands and their wives from 1981 to 2014. The two trends move in opposite directions during the housing boom period (light-blue shaded area) and the housing bust period (light-gray shaded area). The housing boom period is defined as years 2000 to 2006, and the housing bust period is defined as years 2006 to 2011.For example, the female labor force participation rate increased 2.6 percent between 2006 and 2011, while male employment-to-population rate *fell* by 11.2 percent.

Figure 3.1: Labor market trends for construction husbands and wives

Source: CPS data, 1981-2014.
Notes: Sample is restricted to non-institutionalized, non-college, married persons between 21-55, where the husband is in the construction industry and where both persons reported living in the same household as last year. Housing boom period, in light-blue, is defined as years 2000 to 2006. Housing bust period, in light-gray, is defined as years 2006 to 2011.

7. Cullen and Gruger (2002) find that unemployment insurance crowds-out spousal labor supply; a dollar of UI receipt reduces wives' earnings by 73 cents.

Our main analysis exploits variation across metropolitan statistical areas (MSA) to assess how local housing booms and busts affected the labor supply of wives of construction workers. To simplify our analysis, we use the size of the housing boom as a proxy for the magnitude of the housing bust. We are able to do this because cities that experienced the largest housing demand growth between 2000 and 2006 subsequently experienced the largest housing bust. Following Charles, Hurst, and Notowidigdo (2016a) (hereafter "CHN"), we use the sum of changes in local prices and local quantities as our measure of local housing demand. Because measures of local housing demand can be endogenous, we instrument for it by using the size of the structural break in an MSA.

We first examine how labor market outcomes for construction workers were affected by the housing boom and subsequent bust. We find that construction husbands were more adversely affected than their peers who were not in construction. We then examine labor market outcomes of construction wives and find strong evidence of an AWE. In MSAs that experienced a larger increase in housing demand between 2000 and 2006, construction wives were more likely to join the labor force and be employed. Further, we find stronger effects in MSAs where construction is more "skill-remote".[8] In other words, in cities where construction husbands cannot easily switch into other occupations that are similar to construction in terms of required skills, wives are more likely to increase their labor supply. We see weaker AWE among wives of non-construction husbands, supporting our argument that the U.S. housing crisis mainly affected construction workers. Our results are also not due to endogenous changes in marital status or migration patterns related to the housing bust.

In addition to contributing to the empirical literature on the added worker effect, this paper directly relates to three important strands of research. First, the added worker effect is part of a broader literature on unemployment spells and consumption smoothing. There are three general mechanisms for consumption smoothing: credit markets, family labor supply,

8. Skill-remoteness is a unit index developed by Macaluso (2017) that varies by occupation-MSA-year. It measures the similarity in required skills between two occupations in a particular MSA in a given year. See Section 3.4.2 for more information.

and the state through its welfare programs.[9] In a life-cycle model with perfect certainty and no credit market constraints, the added worker effect will be small. This is because the family can use market alternatives for risk-insurance. The added worker effect may be sizeable, however, if either of these conditions fails (Lundberg, 1985). Further, the permanent income hypothesis says that only reductions in permanent income (compared to transitory income) will be reflected in consumption patterns. Recently, the role of AWE has been examined in a macroeconomic context of the labor market. Mankart and Oikonomou (2016a) find that it resolves "an extremely persistent puzzle" that contradicts many business-cycle models.[10]

Second, the collapse of the United States housing bubble had serious consequences in multiple sectors, including mortgage markets, real estate, and hedge funds. An active literature examines its impact on future economic growth (Bhutta, 2015; Jorda, Schularick, and Taylor, 2014; Mian and Sufi, 2014). A lesser explored area is its impact on individuals. Research by Charles, Hurst, and Notowidigdo (2016a, 2016b) finds that the housing boom increased employment opportunities for non-college workers in construction, thereby decreasing college enrollment and masking the decline of manufacturing sector. This paper expands the literature by studying the impact of the housing boom and bust on family labor-supply decisions.

Last, this paper is related to the general literature on the economic decline of low-skilled workers. One often-cited contributor to wage inequality and polarization of the U.S. labor market is skill-biased technical change (e.g., Acemoglu, Katz, and Kearney, 2006; Acemoglu and Autor, 2011).[11] Growing wage inequality as a result of skill-biased technical change also

9. Blundell, Pistaferri, and Saporta-Eksten (2016) develop a life-cycle model with three potential channels for consumption smoothing: credit markets, family labor supply, and progressive taxation. The authors find that all three channels are important and, cumulatively, explains effectively all of the consumption movements in response to wage shocks.

10. Search-theoretic models of the labor market predict that participation rises during economic expansions. However, U.S. data show that while aggregate employment is procyclical, labor force participation is not correlated with aggregate economic activity. The discrepancy is due to the definition of the labor force as the sum of employed and unemployed individuals in search-theoretic models.

11. This phenomenon refers to technological progress that disproportionately helps higher-skilled workers (e.g., computers and financial modelers) and harms lower-skilled workers (e.g., machines and manufacturing

increases geographic sorting as higher-skilled workers concentrate in high-wage, high-rent cities (Diamond, 2016). This is a problem for low-skilled workers in small and more remote towns. Migration is one mechanism by which individuals may adjust to local employment shocks (e.g., Kennan and Walker, 2011). However, low-skilled workers are relatively immobile, thereby limiting their ability to improve their economic situation in an age where economic growth is increasingly concentrated in high-rent cities. (Topel, 1986; Bound and Holzer, 2000). For example, the benefits of migratory insurance over the Great Recession were accrued by above-average earners (Yagan, 2014). Poor economic conditions have implications for other outcomes as well; a recent working paper by Autor, Dorn, and Hanson (2017) finds that the decline of the manufacturing sector increases household instability, reducing the prevalence of marriage but raising the fraction of children born to young and unwed mothers and living in poor, single-parent households. Our paper adds to the literature by examining how non-college households adjust to adverse economic conditions.

The remainder of this paper is organized as follows. In Section 3.2 we discuss the data and empirical methodology. Section 3.3 examines the effect of the housing boom and bust on changes in labor market outcomes for construction husbands. Section 3.4 presents results from our main analysis. Section 3.5 describes our robustness checks. Section 3.6 concludes.

3.2 Data and Methodology

3.2.1 Local Housing Demand Shocks

For our measure of local housing demand shocks, we use the method described in CHN. This method exploits variation in the size of the housing-demand shock that the MSA experienced during the national housing boom and bust. The literature finds that the housing boom during the 2000s was primarily caused by large changes in housing demand, and that variation across MSAs is due to both differences in the magnitude of changes in local housing

workers).

demand *and* in the local housing supply elasticity (Shiller, 2008; Ferreira & Gyourko, 2011; Mian & Sufi, 2011; Davidoff, 2015). In a log-linear model of housing demand and housing supply, therefore, a housing demand shock in MSA k, $\triangle H_k^D$, produces both a price change and a quantity change:

$$\triangle H_k^D = \eta_k^D \cdot \triangle P_k + \triangle Q_k, \tag{3.1}$$

where $\triangle P_k$ is the change in the log of local housing prices in MSA k, η_k^D is the price elasticity of housing demand, and $\triangle Q_k$ is the change in log of new housing produced. We follow CHN in assuming that $\eta_k^D \approx 1$ and proxy for the change in local housing demand by simply summing the log difference in local housing prices and the log difference in new housing produced in the MSA.

Local housing price information is taken from the Federal Housing Finance Agency (FHFA) annual series on prices in FHFA metro areas, which were manually matched to Census/ACS MSAs by name. Local housing supply is measured using the number of new privately owned housing units authorized via permits within the market. Building permits from the Census Building Permits Survey are matched to Census and ACS metro areas using the MSA codes in the permits data. We have local housing demand proxies for 237 local labor markets or MSAs.[12]

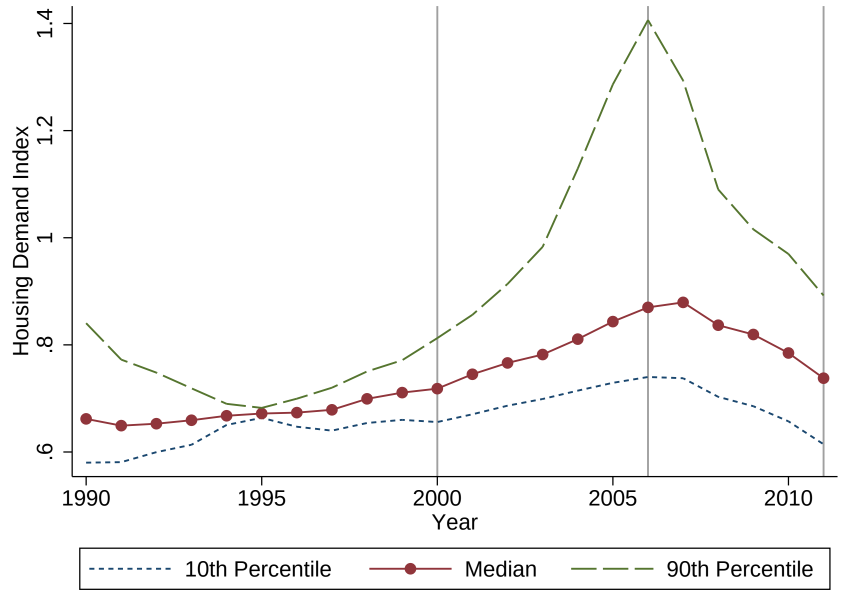
Because our empirical strategy exploits cross-MSA variation, we check that there is enough variation in the housing demand index. Figure 3.2 plots the 10th percentile, the 50th percentile, and the 90th percentile of the index between 1990 and 2011. The gray vertical lines indicate our three years of interest. We look at these years to focus on a base period before the housing boom (2000), after the start of the housing boom (2006), and the low of the housing bust (2011).[13] considerable amount of variation in housing demand, especially

12. These constructed proxies were obtained from CHN's Online Data Appendix. Please see CHN for more information on the data sources and methodology.

13. Although there is variation in when the housing boom began across different MSAs, Ferreira and Gyourko (2011) find that most MSAs experienced a boom beginning in the 2002-2004 period (43 metropolitan areas).

in 2006.

Figure 3.2: Housing demand index over time



Source: Federal Housing Finance Agency (FHFA) data and the Census Building Permits Survey.

One important concern is measurement error in the housing demand shock measure. As noted by CHN, there is some unavoidable error in dating the exact start and end of the housing boom, particularly in every MSA. This results in a noisy proxy of underlying housing demand, leading to an attenuation bias of the OLS estimate. A second concern is that changes in an MSA's housing demand may be correlated with latent factors that are also correlated with labor demand shocks for wives of construction workers. This would bias our OLS estimates. We use an instrumental variable to address both of these issues, as in CHN.

The instrument is based on rapid changes in housing prices that occurred in the local area between 2000 and 2006.[14] CHN contend that sharp breaks from the trend reflect variation

14. As we use annual housing price data provided by the Online Appendix from CHN and do not have access to the raw quarterly data, we are unable to reconstruct the instrumental variable. Therefore, please refer to CHN for details on the methodology, summary statistics, and supporting tables and figures. For the reader's convenience, we reprint the regression model to estimate the structural break in Appendix C.1.

that is the result of exogenous forces rather than unobserved changes in fundamental factors that may also affect labor market outcomes. As reassurance, the authors find that these sharp changes occurred at different times in different locations. This mollifies the extent to which national shocks can explain the sharp change in housing prices within local areas.

3.2.2 Labor Market Outcomes

We use data from the 2000 Census and from the 2005-2007 and 2010-2011 years of the American Community Survey to measure labor market outcomes. We focus on all non-institutionalized, married persons between the ages of 21 and 55, inclusive, who do not have a four-year college degree. We also restrict the sample to all construction households who reported living in the same household as of last year.[15] The same household restriction mitigates concerns from any potential endogenous migration that may be related to local demand shocks (Blanchard & Katz, 1992; Bound & Holzer, 2000; Notowidigdo, 2013). We focus on three time periods: 2000, 2006, and 2011. We use the 2000 Census for the year 2000, and we pool ACS data from 2005-2007 for the year 2006 and pool ACS data from 2010-2011 for the year 2011. We pool the ACS data to increase precision, given that our analysis is conducted at the MSA-level.[16]

We estimate the impact of local housing demand shocks on labor market outcomes with the following regression model:

$$\triangle \bar{Y}_{kt} = \gamma_0 + \gamma_1 \cdot \widehat{\triangle H^D_{kt}} + X'_{kt}\Gamma + \varepsilon_{kt} \tag{3.2}$$

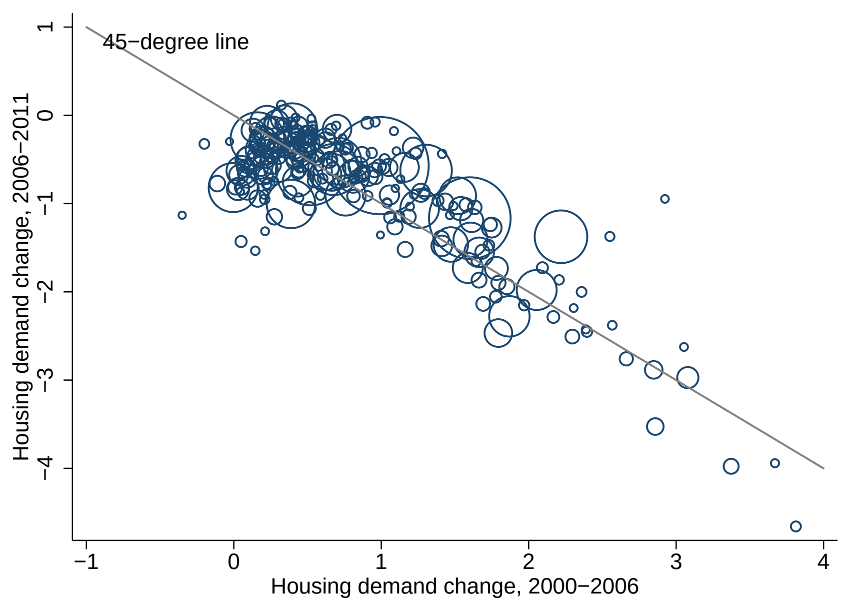
where $\widehat{\triangle H^D_{kt}}$ and $\triangle \bar{Y}_{kt}$ are, respectively, the change in housing demand and the change

15. Construction households are defined as married couples where the husband is in the construction industry.

16. In regards to house price data, the second- and third-quarter house price index values are averaged for each year. For the housing supply proxy, the change in average annual housing permits over the 1998-2000 period is used for the year 2000 and the change in average annual housing permits over the 2004-2006 period is used for the year 2006.

in the average labor market outcomes in MSA k. The first-difference specification deals with any latent fixed MSA-specific factors. We include control vector X_{kt} to capture any factors that are related to differential trends in labor market conditions across MSAs. Specifically, it includes controls for the share of employed workers with a college degree in 2000, the contemporaneous change in the marriage rate, and the MSA's log total population in 2000.[17] Standard errors are clustered by state, and all regressions are weighted by the MSA population (ages 21-55) in 2000.

Figure 3.3: Housing price growth, 2006-2011 versus 2000-2006



Source: FHFA data and the Census Building Permits Survey.
Notes: Correlation is -0.80. Circle size represents the total MSA population in 2000.

We calculate average labor market outcomes separately for construction husbands and for their wives. There are three outcomes of interest: the employment rate, the share of the population that is employed, and the share of the population in the labor force. Average change in labor market outcomes is calculated for two different time periods: between 2000

17. When calculating these MSA-level control variables, we restrict the population to all non-institutionalized persons aged 21-55.

and 2006 ("boom period") and between 2006 and 2011 ("bust period"). We use variation in house price growth during the boom period to examine labor supply in both the boom and bust periods. This approach is motivated by several facts about the housing boom and bust. First, cities that experienced larger housing booms subsequently experienced larger housing busts. Figure 3.3 depicts the negative relationship. The correlation is -0.80. Given this, we simplify our analysis and use the size of the housing boom as a proxy for the magnitude of the housing bust. Additionally, the housing bust was sudden and unexpected.[18] As a result, it is reasonable to assume that construction workers living in MSAs that experienced large housing booms were not anticipating a recession in a few years and adjusted their labor supply accordingly.

3.3 Change in Labor Market Outcomes of Construction Husbands

Before we turn to our main analysis of the added worker effect, we first examine whether local housing demand shocks affected labor market outcomes of construction workers.

We estimate equation (3.2) for changes in male labor-supply along extensive and intensive margins. Table 3.1 presents results. The OLS results in Panel A suggest that in an MSA experiencing a 100 log point larger increase in housing demand during the boom, mean employed share was 2.3 percentage points higher over the same period among non-college, construction husbands. The same MSA, however, saw a 4.1 percentage-point *decrease* in mean employed share over the subsequent bust period. The corresponding 2SLS estimates are 2.5 percentage-points and -5.2 percentage-points. Similar patterns are seen in estimates for other labor supply outcomes. During the bust period, these men became more likely to become unemployed, leave the labor force, more likely to work part-time, less likely to be a full-time full-year worker, and more likely to reduce their hours. All of these estimates are

18. See Introduction.

statistically significant.

We also examine outcomes for all non-college husbands and non-college husbands who are not in the construction industry. Broadly speaking, these workers were also positively affected during the housing boom and negatively affected during the bust period. One interesting fact is: the magnitudes of the 2SLS estimates of all labor market outcomes over the boom period are similar across the three subsamples (with the exception of full-time full-year share). This is not true when we compare outcomes during bust-period; those in construction were hardest hit. For example, the mean employed share between 2006 and 2011 for non-college construction husbands fell by 5.2 percentage-points in an MSA that experienced a 100 log point larger increase in housing demand during the boom period. This effect is statistically significant at the 1-percent level. The equivalent change for those not in construction was -0.3 percentage-points, and this estimate is not statistically significant. The change for all non-college husbands is -1.2 percentage-points, five times smaller than the estimate for those in the construction industry. We use these results to inform our decision to focus our analysis on the construction industry.

Table 3.1: Effect of housing boom and bust on husband's labor supply

	LFPR		**Share Employed**		**Employment Rate**		**Share FTFY**		**Share Full-Time**		**Hours Worked**	
	2000-2006	**2006-2011**	**2000-2006**	**2006-2011**	**2000-2006**	**2006-2011**	**2000-2006**	**2006-2011**	**2000-2006**	**2006-2011**	**2000-2006**	**2006-2011**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: OLS estimates												
Non-college Construction Husbands												
Housing demand change, 2000-2006	0.0150**	-0.00817**	0.0225**	-0.0412***	0.00710	-0.0338***	0.0365**	-0.0500***	0.00517*	-0.0280***	0.00193	-0.0342***
	(0.00599)	(0.00373)	(0.00934)	(0.0111)	(0.00617)	(0.00862)	(0.0145)	(0.0156)	(0.00303)	(0.00566)	(0.00640)	(0.00920)
Mean outcome in base year	0.93	0.94	0.88	0.89	0.95	0.94	0.80	0.77	0.96	0.96	42.49	41.99
All Non-college Husbands												
Housing demand change, 2000-2006	0.0151***	0.000362	0.0238***	-0.0108*	0.00836***	-0.0110***	0.0205***	-0.0160**	0.00444***	-0.00879***	0.00842	-0.00945
	(0.00443)	(0.00282)	(0.00638)	(0.00601)	(0.00262)	(0.00398)	(0.00536)	(0.00652)	(0.00133)	(0.00256)	(0.00506)	(0.00563)
Mean outcome in base year	0.97	0.97	0.86	0.88	0.89	0.92	0.87	0.85	0.97	0.96	41.84	41.96
Non-college Non-construction Husbands												
Housing demand change, 2000-2006	0.0120***	0.00208	0.0210***	-0.00479	0.00873***	-0.00661*	0.0180***	-0.00948	0.00417**	-0.00490**	0.00771*	-0.00512
	(0.00402)	(0.00176)	(0.00564)	(0.00490)	(0.00222)	(0.00366)	(0.00455)	(0.00655)	(0.00155)	(0.00240)	(0.00439)	(0.00447)
Mean outcome in base year	0.98	0.97	0.90	0.92	0.92	0.94	0.88	0.86	0.97	0.96	43.47	43.51
Panel B: 2SLS estimates												
Non-college Construction Husbands												
Housing demand change, 2000-2006	0.0173	-0.0103**	0.0246	-0.0521***	0.00704	-0.0431***	0.0503**	-0.0707***	0.00851*	-0.0418***	0.00213	-0.0456***
	(0.0124)	(0.00405)	(0.0179)	(0.0122)	(0.00770)	(0.0106)	(0.0235)	(0.0196)	(0.00457)	(0.0119)	(0.00895)	(0.00874)
All Non-college Husbands												
Housing demand change, 2000-2006	0.0182**	0.00197	0.0297***	-0.0118	0.0111***	-0.0136***	0.0250**	-0.0214***	0.00533**	-0.0147***	0.00841	-0.0134**
	(0.00821)	(0.00406)	(0.0111)	(0.00758)	(0.00386)	(0.00523)	(0.00986)	(0.00697)	(0.00213)	(0.00422)	(0.00651)	(0.00664)
Non-college Non-construction Husbands												
Housing demand change, 2000-2006	0.0149**	0.00378	0.0271***	-0.00387	0.0119***	-0.00733	0.0206**	-0.0109	0.00443*	-0.00874**	0.00767	-0.00832
	(0.00718)	(0.00248)	(0.00961)	(0.00610)	(0.00335)	(0.00495)	(0.00866)	(0.00708)	(0.00249)	(0.00343)	(0.00590)	(0.00571)
First-stage F-statistic	101.68	94.79	101.68	94.79	101.68	94.79	101.68	94.79	101.68	94.79	101.68	94.79
Observations	237	237	237	237	237	237	237	237	237	237	237	237
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: 2000 data are Census data. 2006 data are pooled 2005-2007 ACS data. 2011 data are pooled 2010-2011 ACS data. Local housing demand data are from FHFA and the Census Building Permits Survey.

Notes: Sample is restricted to non-institutionalized, non-college, married persons between 21-55, where the husband is in the construction industry and where both persons reported living in the same household as last year (2006, 20012) or as 5 years ago (2000). Regressions are at the MSA-level, and we instrument for local housing demand change with the size of the structural break in that MSA. Baseline controls include the log of MSA population in 2000, the MSA's share of employed BAs in 2000, and the contemporaneous change in marriage rate at the state-level. Standard errors are shown in parentheses and are clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4 The Added Worker Effect

3.4.1 Construction Wives

In this section, we examine the evidence for the added worker effect among construction wives. Table 3.2 estimates how labor outcomes during the boom and during the bust were affected by the housing bubble. We examine outcomes in both periods to contrast between the wife's labor supply response when her husband faces favorable economic conditions (boom period) and unfavorable conditions (bust period). The table presents OLS and 2SLS estimates. As overall patterns between OLS and 2SLS estimates are similar, subsequent tables show only the preferred 2SLS results.

Table 3.2: Change in labor market outcomes of wives of construction workers

	LFPR		**Share Employed**		**Employment Rate**	
	2000-2006 (1)	**2006-2011** (2)	**2000-2006** (3)	**2006-2011** (4)	**2000-2006** (5)	**2006-2011** (6)
Panel A: OLS estimates						
Housing demand change, 2000-2006	-0.00127	0.0460***	0.00346	0.0346***	0.00493	-0.00918*
	(0.00996)	(0.00933)	(0.0101)	(0.0109)	(0.00494)	(0.00492)
Panel B: 2SLS estimates						
Housing demand change, 2000-2006	-0.0276*	0.0760***	-0.0131	0.0571***	0.0153***	-0.0151*
	(0.0163)	(0.0181)	(0.0132)	(0.0210)	(0.00592)	(0.00787)
First-stage F-statistic	101.68	94.79	101.68	94.79	101.68	94.79
Mean outcome in base year	0.71	0.69	0.68	0.65	0.97	0.94
Observations	237	237	237	237	237	237
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Source: 2000 data are Census data. 2006 data are pooled 2005-2007 ACS data. 2011 data are pooled 2010-2011 ACS data. Local housing demand data are from FHFA and the Census Building Permits Survey.
Notes: Sample is restricted to non-institutionalized, non-college, married persons between 21-55, where the husband is in the construction industry and where both persons reported living in the same household as last year (2006, 20012) or as 5 years ago (2000). Regressions are at the MSA-level, and we instrument for local housing demand change between 2000-2006 with the size of the structural break in that MSA. Baseline controls include the log of MSA population in 2000, the MSA's share of employed BAs in 2000, and the contemporaneous change in marriage rate at the state-level. Standard errors are shown in parentheses and are clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A presents OLS estimates. Columns (1) and (2) show that the mean LFPR rate during the boom period was not affected by local housing demand, but it increased by 4.6 percentage-points during the bust period. We see similar patterns for share employed and weaker effects for the mean employment rate.

Panel B presents 2SLS estimates, where we instrument for local housing demand change, $\widehat{\triangle H_{kt}^{D}}$, with the size of the structural break. In MSAs that experienced a 100 log point larger increase in housing demand between 2000 and 2006, the mean LFPR was 7.6 percentage-points higher between 2006 and 2011. These MSAs also saw a 5.7 percentage-point higher mean share employed among wives of construction workers. Both of these estimates are statistically significant at the 1 percent level. In terms of the employment rate, we see negative growth; this can be explained by the influx of women entering the labor force.

3.4.2 Skill-remoteness of the Construction Occupation

One underlying assumption of the added worker effect is that the unemployed husband cannot find work. One factor affecting the size of AWE, therefore, is how easily the husband can find re-employment. We use the "skill-remoteness" of the construction occupation as our measure for how easily a construction worker can find employment in his city.[19] The skill-remoteness index, developed by Macaluso (2017), is a unit-distance measure of an occupation's similarity to other occupations in a given MSA and year. The distance between two occupations is measured using the different types of skills that are required for the respective jobs.

Consider a universe of J occupations and S skills. Assuming that each occupation requires a specific skill-set, it can be described as a vector of length S, where l_s denotes the skill level required by occupation j: $j = [l_{j1}, \cdots, l_{js}, \cdots, l_{jS}]$. Therefore, the "distance" between occupation j and occupation k can be defined by the distance between their respective skill vectors:

19. Our main analysis focuses on men in the construction *industry* while the skill-remoteness index focuses on the construction *occupation*. These may not be identical; for example, there are management occupations in the construction industry. According to the 2000 Census, 73.5% of non-college men in the construction industry also listed construction as their occupation.

$$d_k^j = \frac{1}{S}\sum_{s=1}^{S} |l_{js} - l_{ks}|, \quad \text{where } j \neq k \tag{3.3}$$

One issue with this measure is that it is geographic- and time-invariant, which may not be accurate. For example, a person in sales would be less skill-remote in Laredo, TX, which is the port of entry of around half of U.S.-Mexico international trade (Federal Reserve Bank of Dallas, 2008), than in Palo Alto, CA, the heart of Silicon Valley. To make the distance measure specific to an MSA and a year, it is weighted by the share of occupation j in total employment in MSA c in year t. A given occupation j's skill-remoteness in MSA c in year t is defined as:

$$\text{Skill Remoteness}_{ct}^j = \sum_{k=1}^{J} \omega_{kct} d_k^j, \quad \text{where } k \neq j \tag{3.4}$$

where d_k^j is the skill-distance between occupations j and k and ω_{kct} is the share of occupation k in total employment in MSA c in year t.

For our analysis, we use the skill-remoteness of the construction occupation in the year 2000 to categorize MSAs into terciles.[20] We compare MSAs where construction is least skill-remote (first tercile) to MSAs where construction is most skill-remote (third tercile). We use the 2000 index to avoid any issues of endogenous changes in skill-remoteness arising from the housing boom and bust. In Appendix Table C.1, we plot the 2000-2006 local housing demand change against the construction skill-remoteness index to examine whether they are correlated. The fitted line has a slope of 0.046, mitigating our concerns.

We expect that in cities where construction is more skill-remote, construction workers will have a harder time finding work during the bust period, thereby strengthening the added worker effect. In cities where construction is less skill-remote, construction workers are more easily able to find alternative employment, thereby weakening the added worker effect. Table 3.3 tests these predictions.

20. A list of the MSAs by tercile is in Appendix Table C.1.

Table 3.3: Change in labor market outcomes by construction skill-remoteness

	LFPR		**Share Employed**		**Employment Rate**	
Construction's skill-remoteness:	Least remote (1)	Most remote (2)	Least remote (3)	Most remote (4)	Least remote (5)	Most remote (6)
Change in Wife's outcomes						
Housing demand change	0.0682**	0.0938***	0.0667*	0.0818**	-0.00106	-0.00794
	(0.0294)	(0.0285)	(0.0352)	(0.0342)	(0.0137)	(0.0185)
Change in Husband's outcomes						
Housing demand change	-0.00150	-0.0127	-0.0362**	-0.0553**	-0.0366**	-0.0438**
	(0.0122)	(0.00931)	(0.0173)	(0.0253)	(0.0149)	(0.0206)
First-stage F-statistic	160.78	68.93	160.78	68.93	160.78	68.93
Mean outcome for wives	0.70	0.70	0.66	0.66	0.94	0.95
Mean outcome for husbands	0.94	0.94	0.88	0.90	0.94	0.95
Observations	79	78	79	78	79	78
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Source: 2000 data are Census data. 2006 data are pooled 2005-2007 ACS data. 2011 data are pooled 2010-2011 ACS data. Local housing demand data are from FHFA and the Census Building Permits Survey.
Notes: This table presents 2SLS estimates of local housing demand shocks on the change in labor market outcomes between 2006 and 2011. See Notes of Table 3.2. We use the MSA's skill-remoteness of the construction industry in 2000. Least remote MSAs are those in the top tercile of the construction skill-remoteness index. Most diverse MSAs are those in the bottom tercile. Mean outcomes for wives and husbands are from the base year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The change in share employed among constructions wives increased by 8.2 percentage-points in MSAs that are most skill-remote and by 6.7 percentage-points in MSAs that are least skill-remote. The magnitude is larger for MSAs in the top tercile of the construction skill-remoteness index, but the two estimates are not statistically significantly different. Similarly, construction husbands were more likely to be non-employed in MSAs where construction is most skill-remote. These estimates are all statistically significant. The overall patterns indicate that the added worker effect is stronger in MSAs where construction is more skill-remote. Additionally, the employment outcomes for construction husbands in these MSAs are worse.

3.5 Robustness Checks

In this section, we conduct several robustness checks.

3.5.1 Non-construction wives

First, we examine if there is an added worker effect in households where the husband is not in the construction industry. In Table 3.1, we saw that in MSAs that experienced larger housing booms, non-construction husbands were not as hard-hit as construction husbands during the bust period, in terms of labor market outcomes. For example, the mean change in employment-to-population for construction husbands over 2006-2011 is -5.2 percentage-points. The equivalent change for non-construction husbands is -0.4 percentage-points. Therefore, one would expect that AWE would be weaker among wives of non-construction husbands. We test this prediction in Table 3.4.

Table 3.4: Change in labor market outcomes of non-construction wives

	LFPR		**Share Employed**		**Employment Rate**	
	2000-2006	**2006-2011**	**2000-2006**	**2006-2011**	**2000-2006**	**2006-2011**
	(1)	(2)	(3)	(4)	(5)	(6)
Housing demand change	-0.00926*	0.0219***	0.00156	0.00369	0.0106**	-0.0169***
	(0.00541)	(0.00622)	(0.00701)	(0.00760)	(0.00474)	(0.00575)
First-stage F-statistic	101.68	94.79	101.68	94.79	101.68	94.79
Mean outcome in base year	0.97	0.95	0.71	0.70	0.73	0.74
Observations	237	237	237	237	237	237
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Source: 2000 data are Census data. 2006 data are pooled 2005-2007 ACS data. 2011 data are pooled 2010-2011 ACS data. Local housing demand data are from FHFA and the Census Building Permits Survey.
Notes: Sample is restricted to non-institutionalized, non-college, married persons between 21-55, where the husband is not in the construction industry and where both persons reported living in the same household as last year (2006, 20012) or as 5 years ago (2000). Regressions are at the MSA-level, and we instrument for local housing demand change with the size of the structural break in that MSA. Baseline controls include the log of MSA population in 2000, the MSA's share of employed BAs in 2000, and the contemporaneous change in marriage rate at the state-level. Standard errors are shown in parentheses and are clustered by state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In MSAs that experienced a 100 log point larger increase in housing demand over the boom period, the mean employed share for wives of non-construction workers did not change over the bust period. Contrast this with a 5.7 percentage-point increase for wives of construction workers. This result is not surprising as those in the construction industry were harder hit by the housing crisis. We see weak AWE in terms of labor force participation rate (2.2 percentage-points). This is not surprising as the general economy between 2006 and 2011 was weak. However, the point remains that the magnitudes of these estimates are smaller than the effect-sizes of construction wives.

3.5.2 Change in marital status

One concern is that household structure may change as a result of the housing boom and bust, and this change may also affect labor market outcomes. For example, Charles and Stephens (2004) find that the likelihood of divorce is greater when the husband loses his job. If the likelihood of remaining married is correlated with the likelihood that the wife looks for work, then we may see a spurious result arising from the changing composition of married couples. In other words, in MSAs that experienced a larger housing bust, finding an added worker effect may be an artifact of higher divorce rates occurring among couples where the wife would not have joined the labor force or looked for employment (*had they stayed together*). This results in our analysis sample consisting of more "committed couples" in MSAs that experienced stronger housing busts relative to the types of couples in MSAs that experienced weaker housing busts.

To control for this potential issue, we include the change in the state's marriage rate as a control in all of our regressions. Here, as an added robustness check, we plot the share currently married over time by the housing boom quartile (Figure 3.4). The trends are very similar between the MSAs that experienced the smallest boom (bottom quartile) and MSAs that experienced the largest boom (top quartile). This mitigates concerns that the composition of married couples in our analysis sample differs between MSAs that experienced a larger housing bust and those that did not.

Figure 3.4: Share currently married

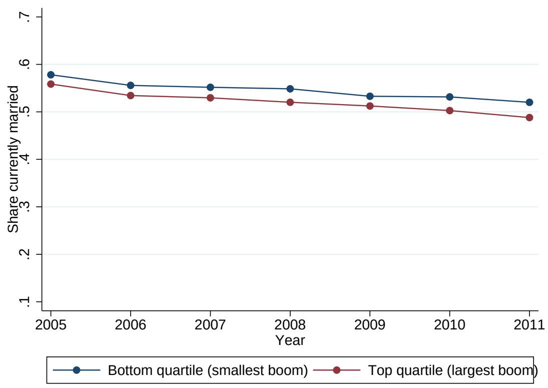
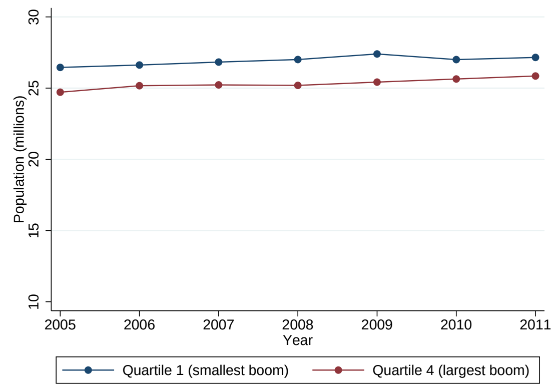


Figure 3.5: MSA Population



Source: 2005-2011 ACS data. Local housing demand data is from FHFA and the Census Building Permits Survey.

3.5.3 Change in migration

Another potential concern is our AWE results may be due to endogenous migration that relate to local economic shocks (Yagan, 2014).[21] In particular, we are worried that those who are not be able to find work leave the city, thereby biasing upwards our estimates of labor market outcomes. To examine this concern, we plot the change in MSA population by the housing-boom quartile. Figure 3.5 shows that population trends were pretty stable over this time period.

3.6 Conclusion

This paper finds strong evidence of AWE among construction households during the housing bust of the 2000s. We exploit variation across MSAs and instrument changes in local housing demand between 2000 and 2006 with the size of the structural break in the trend of local housing prices. We find that negative changes in local housing demand adversely

21. Although the empirical literature largely finds that low-skilled workers, our population sample, are relatively immobile (Topel, 1986; Bound and Holzer, 2000; Yagan, 2014), we include this robustness check for the sake of completeness.

affected construction husbands' employment outcomes, and that their wives increased their labor supply as a result. Changes in marital status and migration do not seem to be driving these results. These results add to the empirical literature on the added worker effect as well as shedding light on the impact of the recent U.S. housing crisis on low-skilled workers.

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APPENDIX A
THE EFFECT OF TITLE IX ON GENDER DISPARITY IN GRADUATION EDUCATION

A.1 The Earth Mover's Distance (EMD) Algorithm

The Earth Mover's Distance is a metric that measures the difference between two distributions that considers both within-bin and cross-bin differences. In a nutshell, it is the minimal cost that must be paid to transform one distribution into the other. Computation of EMD is borne from the transportation problem. Suppose that several suppliers, each with a given amount of goods, are required to supply several consumers, each with a given limited capacity. For each supplier-consumer pair, the cost of transporting a single unit of goods is given. The transportation problem is then to find a least-expensive flow of goods from the suppliers to the consumers that satisfies the consumers' demand. The following formalization of EMD is reproduced from Rubner, Tomasi, and Guibas (2000) for the reader's convenience. The notation has been adapted to apply to the context of occupational convergence.

The computation of EMD can be formalized by the following linear programming problem:

Let

$$M = \{(m_1, s_1^m), \cdots, (m_K, s_K^m)\}$$

be the male occupation distribution with K occupation categories, where m_i is occupation i and s_i^m is the share of males in occupation i.

Analogously, let

$$W = \{(w_1, s_1^w), \cdots, (w_K, s_K^w)\}$$

be the female occupation distribution with K occupation categories; and let $\mathbf{D} = [d_{ij}]$ be the difference matrix where d_{ij} is the difference between occupations m_i and w_j, that minimizes the overall cost

$$WORK(M, W, \mathbf{F}) = \sum_{i=1}^{K} \sum_{j=1}^{K} d_{ij} f_{ij},$$

subject to the following constraints:

$$f_{ij} \geq 0, \quad 1 \leq i \leq K, \quad 1 \leq j \leq K \tag{A.1}$$

$$\sum_{i=1}^{K} f_{ij} \leq s_i^m, \quad 1 \leq i \leq K \tag{A.2}$$

$$\sum_{j=1}^{K} f_{ij} \leq s_i^w, \quad 1 \leq j \leq K \tag{A.3}$$

$$\sum_{i=1}^{K} \sum_{j=1}^{K} f_{ij} = \min\left(\sum_{i=1}^{K} s_i^m, \sum_{j=1}^{K} s_i^w\right) \tag{A.4}$$

Constraint (A.1) allows moving people from M to W and not vice versa. Constraint (A.2) limits the number of males who can be moved in an occupation to their share (i.e., if 30 percent of males are doctors, the number of male doctors who can be moved to another occupation is limited to that 30 percent). Constraint (A.3) is the analog for occupation categories in F; and constraint (A.4) forces to move the maximum number of people possible. This maximum number is called the total flow. Once the transportation problem is solved, and the optimal flow F is found, the earth mover's distance is defined as the resulting work normalized by the total flow:

$$EMD(M, F) = \frac{\sum_{i=1}^{K} \sum_{j=1}^{K} d_{ij} f_{ij}}{\sum_{i=1}^{K} \sum_{j=1}^{K} f_{ij}}$$

The normalization factor is the total weight of the smaller distribution, because of constraint (A.4). Thus, the EMD naturally extends the notion of the dissimilarity between two distributions.

Table A.1: List of Major Fields of Study by Salary Tercile

Fields in the Top Tercile
Architecture and Related Services
Business, Management, Marketing, and Related Support Services
Computer and Information Sciences and Support Services
Engineering
Engineering Technologies and Engineering-Related Fields
Health Professions and Related Programs
Legal Professions and Studies
Mathematics and Statistics
Physical Sciences
Social Sciences
Fields in the Middle Tercile
Agriculture, Agriculture Operations, and Related Sciences
Area, Ethnic, Cultural, Gender, and Group Studies
Biological and Biomedical Sciences
Communication, Journalism, and Related Programs
History
Homeland Security, Law Enforcement, Firefighting and Related Protective Services
Natural Resources and Conservation
Psychology
Public Administration and Social Service Professions
Fields in the Bottom Tercile
Education
English Language and Literature/Letters
Family and Consumer Sciences/Human Sciences
Foreign Languages, Literatures, and Linguistics
Liberal Arts and Sciences, General Studies and Humanities
Library Science
Parks, Recreation, Leisure, and Fitness Studies
Philsophy and Religious Studies; Theology and Religious Vocations
Visual and Performing Arts

Source: NSCG 1993 data.

Table A.2: List of Major Graduate Fields of Study by Gender Parity

Fields in the Top Tercile (Lowest 1962-1970 Female Share)
Agriculture, Agriculture Operations, and Related Sciences
Architecture and Related Services
Business, Management, Marketing, and Related Support Services
Computer and Information Sciences and Support Services
Engineering
Engineering Technologies and Engineering-Related Fields
Homeland Security, Law Enforcement, Firefighting and Related Protective Services
Legal Professions and Studies
Philsophy and Religious Studies; Theology and Religious Vocations
Physical Sciences
Fields in the Middle Tercile
Biological and Biomedical Sciences
Communication, Journalism, and Related Programs
Health Professions and Related Programs
History
Mathematics and Statistics
Natural Resources and Conservation
Parks, Recreation, Leisure, and Fitness Studies
Social Sciences
Visual and Performing Arts
Fields in the Bottom Tercile (Highest 1962-1970 Female Share)
Area, Ethnic, Cultural, Gender, and Group Studies
Education
English Language and Literature/Letters
Family and Consumer Sciences/Human Sciences
Foreign Languages, Literatures, and Linguistics
Liberal Arts and Sciences, General Studies and Humanities
Library Science
Psychology
Public Administration and Social Service Professions

Source: NSCG 1993 data.

APPENDIX B

THE GENDERED EFFECTS OF CAREER CONCERNS ON FERTILITY (WITH KYUNG PARK)

B.1 After the JD study

B.1.1 Sampling process

In the first stage of the sampling process, the nation was divided into 18 strata by region and size of the new lawyer population. Within each stratum, one primary sampling unit (PSU) was selected. A PSU can be a metropolitan area, portion of a state outside large metropolitan areas, or the entire state. The PSUs included the four "major" markets, those with more than 2,000 new lawyers (Chicago, Los Angeles, New York, and Washington, D.C.); 5 of the 9 "large" markets, those with between 750-2,000 new lawyers; and nine of the remaining "smaller" markets. In the second stage, researchers sampled individuals from each of the PSUs from databases of individuals addmitted to a bar in 2000. This made up 7,727 individuals. An oversample of 1,465 minority lawyers (Black, Hispanic, and Asian American) yielded a final sample of 9,192 lawyers.

However, 20 percent of the sample could not be located and another 20 percent of those located were identified as lawyers moving from one state bar to another rather than having entered the bar for the first time in 2000. These "movers" were left in the sample as long as they graduated from law school no earlier than 1998. The response rate for Wave 1 was 71 percent, yielding an analysis sample of 4,538 lawyers.

B.1.2 Imputation of spousal income trajectory using Census and ACS data

We predict the spousal income trajectory using the three waves of cross-sectional data on spouse's income. However, for respondents who reported spousal income in only one wave or did not report income for an employed spouse, we use Census and ACS data to impute the spouse's income trajectory (288 respondents). This section describes our imputation methodology.

We use the ACS data from years 2001-2014 and 1990 and 2000 Census data. We keep only adults aged between 17 and 64, inclusive. We drop those living in group quarters and unmarried couples. That is, we keep married couples where at least spouse is in the legal profession (OCC2010 code 2100). We also double-check the lawyer's education by dropping those who do not have a graduate degree.

After adjusting the top-coded income responses (we multiply the top-coded value by 1.5), we calculate hourly wages and trim extreme wages (dropping wages that are between \$0-\$1 and greater than 1/35 of the annual maximum weekly wage.

We predict the spousal income using the lawyer's gender, race and ethnicity, and years of experience. Years of experience is defined as: $\max\{\texttt{Age} - 19 - 5, 0\}$. The reason we have a sparse specification is that the AJD survey has very little information on the spouse; we only know the spouse's employment status and income. We run the following OLS regression model on logged spousal hourly wage:

$$\begin{aligned}\texttt{log(spousal hrly wage)} &= \beta_0 + \beta_1 \cdot F_i + \beta_2 \cdot R_i + \beta_3 \cdot \Big(F_i \times R_i\Big) \\ &\quad + \delta_1 \cdot exp_i + \delta_2 \cdot exp_i^2 + \delta_3 \cdot exp_i^3 + \delta_4 \cdot exp_i^4 \\ &\quad + \delta_5 \cdot \Big(F_i \times exp_i\Big) + \delta_6 \cdot \Big(F_i \times exp_i^2\Big) + \delta_7 \cdot \Big(F_i \times exp_i^3\Big) \\ +\delta_8 \cdot \Big(F_i \times exp_i^4\Big) + \varepsilon_i\end{aligned} \tag{B.1}$$

These coefficients are then used to predict spousal income in the AJD data. For respondents who reported spousal income in Wave 1 (2001), we back out what it would have been in the year that the respondent graduated from law school, which was not necessarily in 2001.

B.1.3 Comprehensive List of Firm Types

1. Private Law Firm
2. Solo Practice
3. Federal Government
4. State or Local Government
5. Educational Institution
6. Legal Services or Public Defender
7. Public Interest Organization
8. Other Non-Profit
9. Professional Service Firm
10. Other Fortune 1000 Industry/Service
11. Other Business/Industry
12. Labor Union or Trade Association
13. Military
14. Legal Temporary Firm
15. Insurance Company

B.1.4 Wave 1 questions on important factors and determinants of respondent's initial career decisions

40. Comparing specific job offers you received from employers you considered, how important were the following factors in making your choice? *Check one box on each line.*

I received one offer ➔ **Skip to Question #41 on page 12.**

	Not At All Important						Extremely Important	NA
a. Salary	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
b. Benefits	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
c. Office environment/collegiality	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
d. Hours expected	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
e. Pro bono opportunities	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
f. Prospects for advancement	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
g. Good match of employer's mission and my own	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
h. Location	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
i. Size	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
j. Prestige	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐
k. Training/mentorship opportunities	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐	☐

65. How important was each of the following goals in your decision to attend law school?
Check one box on each line.

	Irrelevant				Very Important
a. Intellectual challenge of law school and the law	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
b. Desire to help individuals as a lawyer	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
c. Desire to develop a satisfying career	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
d. Desire to defer entry into the job market	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
e. Desire for eventual financial security	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
f. Desire to change or improve society	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
g. Becoming influential in a powerful profession	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
h. Desire to build a set of transferable skills	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐
i. Other (*Specify:* ________________________)	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐

B.2 Factor Analysis

B.2.1 Factor Score Regression

This section describes the factor indeterminancy problem that arises when using the two-step process of Factor Score Regression (FSR). In the first step, the scores on the latent variables are predicted using a factor analysis. These scores are referred to as factor scores. In the second step, the factor scores are used in an OLS regression as explanatory variables.

Devlieger, Mayer, and Rossel (2016) show that in a model with a latent independent variable and an observed dependent variable, constructing factor scores using the Regression method in the first-step will yield an unbiased coefficient estimate in the second-step. For the sake of the reader, we reproduce their proof here:

Say the structural equation is:

$$Y = \delta\varphi + \varepsilon \tag{B.2}$$

As φ is latent, the following measurement model is used:

$$q = A_q\varphi + \upsilon \tag{B.3}$$

where $q = (Q_1, \cdots, Q_i, \cdots, Q_k)^T$ are vectors of mean-centered proxy variables measuring φ, A_q is a vector of the factor loadings and υ is a vector of measurement error variables.

In the first step of FSR, we use this measurement system to calculate factor scores for φ:

$$F_\varphi = \Lambda_\varphi q \tag{B.4}$$

where $F_\varphi = (F_1, \cdots, F_j)$ for j total factors. The factor scores are calculated by multiplying a factor score matrix Λ_φ with proxy variables q. We fix the metric scales of φ by fixing one factor loading per latent variable to 1 (also known as unstandardized parameterization). The computation of Λ_φ depends on the method used for the prediction of the factor score. There is a variety of possible methods; Grice (2001) discusses several options.

In the second step of FSR, a linear regression is performed between the factor scores, resulting in a regression coefficient. In a simple linear regression, the true regression coefficient is defined as follows:

$$\delta = \frac{cov(\varphi, Y)}{var(\varphi)} \tag{B.5}$$

When performing the linear regression with factor scores, the regression coefficient becomes:

$$\beta = \frac{cov(F_\varphi, Y)}{var(F_\varphi)} \tag{B.6}$$

which is not necessarily the same as the true regression coefficient, δ. The relationship between δ and β is depicted as follows:

$$\begin{aligned}
\beta &= \frac{cov(F_\varphi, Y)}{var(F_\varphi)} && \text{(B.7)}\\
&= \frac{cov(\Lambda_\varphi q, Y)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi} && \text{(B.8)}\\
&= \frac{\Lambda_\varphi cov(q, Y)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi} && \text{(B.9)}\\
&= \frac{\Lambda_\varphi cov(A_q \varphi + \upsilon, Y)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi} && \text{(B.10)}\\
&= \frac{\Lambda_\varphi A_q cov(\varphi, Y)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi} && \text{(B.11)}\\
&= \frac{\Lambda_\varphi A_q cov(\varphi, \delta\varphi + \varepsilon)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi} && \text{(B.12)}\\
&= \frac{\Lambda_\varphi A_q var(\varphi)}{\Lambda_\varphi \Sigma_q \Lambda'_\varphi}\delta && \text{(B.13)}
\end{aligned}$$

This equation makes clear that the estimated regression coefficient β does not necessarily equal δ.

Now we discuss the Regression method of constructing factor scores used to predict Λ_φ. The Regression method gives the following estimate for the factor score matrix:

$$\Lambda_\varphi^R = \Phi A'_q \Sigma_q^{-1} = var(\varphi) A'_q \Sigma_q^{-1} \tag{B.14}$$

This means that $var(F_\varphi)$ can be simplified:

$$
\begin{aligned}
var(F_\varphi) &= \Lambda_\varphi^R \Sigma_q \Lambda_\varphi^{R'} && \text{(B.15)}\\
&= \left(var(\varphi) A_q' \Sigma_q^{-1}\right) \Sigma_q \Lambda_\varphi^{R'} && \text{(B.16)}\\
&= var(\varphi) A_q' I \Lambda_\varphi^{R'} && \text{(B.17)}\\
&= \Phi' \Lambda' \Sigma_q^{-1} \Lambda \Phi && \text{(B.18)}\\
&= \Lambda_\varphi^R A_q var(\varphi) && \text{(B.19)}
\end{aligned}
$$

Plugging this into the denominator of equation $(B.7)$ yields (the numerator does not change):

$$
\begin{aligned}
\beta &= \frac{cov(F_\varphi, Y)}{var(F_\varphi)} && \text{(B.20)}\\
&= \frac{\Lambda_\varphi A_q var(\varphi)}{\Lambda_\varphi^R A_q var(\varphi)} \delta && \text{(B.21)}\\
&= \delta && \text{(B.22)}
\end{aligned}
$$

B.2.2 Exploratory Factor Analysis

This section describes the empirical methodology for our factor analysis. First, we impute missing item responses using gender-specific averages to minimize the number of dropped respondents due to missing reponse. To minimize bias, we impute responses only for those with one or two missing responses in each question set. There are three question sets (Question 38, Question 40, and Question 65), each with 9-11 potential reasons that are to be ranked by the lawyer. (See Appendix B.1.4 for exact text of the questions.) If the lawyer ranked all but one or two of the potential reasons, then we replace the missing ranking(s) with a gender-specific average ranking. We leave out the "Other" category in our factor analysis as it is too broad to systemically capture a common underlying factor. Question 40, which asks about the important determinants in choosing between multiple job offers, was asked only for those who received more than one job offer. A majority of respondents received multiple job offers (64 percent). But for those with only one offer, we impute their rankings of each potential reason using gender-specific averages. As a robustness check, we use an alternative imputation method where we use individual-specific means. Our main results do not change much.

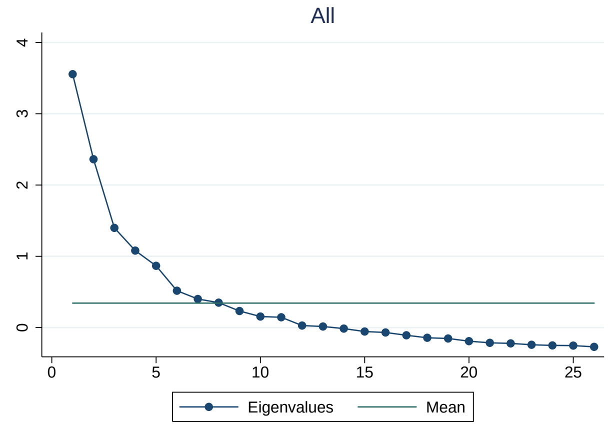
We run two specifications for the factor analysis. First, we construct scores for everyone in the sample. Second, we construct scores separately for males and females. Our factor analysis finds that there are seven factors that, cumulatively, explain all of the variance in survey responses for all lawyers. The eigenvalues are reported in Table B.1. The Kaiser test says that only factors with an eigenvalue of 1.0 or greater are meaningful, which tells us to keep the first five factors. The second test is the scree test (Figure B.1). This test uses a graphical method to determine which factors to keep. The criterion is to keep the factors up until the line becomes flat or flatter. According to this visual test, there are seven common factors. We chose to keep the seven factors that explain all of the variance.

Table B.1: Principal factor analysis/correlation for everyone

Factor #	Eigenvalue	Proportion	Cumulative
1	1.71	0.19	0.19
2	1.69	0.19	0.38
3	1.43	0.16	0.54
4	1.42	0.16	0.70
5	1.00	0.11	0.81
6	0.97	0.11	0.92
7	0.89	0.10	1.02

Source: AJD restricted data.
Note: Only the seven factors with a cumulative proportion reaching 1 are shown. For full results, see the Online Appendix. LR test: independent vs. saturated: chi2(136) = 4062.42 Prob>chi2 = 0.0000

Figure B.1: Scree plot



The rotated factor loadings in Table B.3 report the correlation between the survey question and the factor. They provide a picture of the most important "factors" in the lawyer's career decisions, as captured by the survey questions and lawyer's responses. Factor analysis is designed to maximize the amount of variation explained by the first factor; each additional factor tries to explain as much leftover variation as possible. Looking at this table, we define the first factor as social responsibility. The remaining six are classified as: earning potential, prestige, career development, firm's ranking, mission match, and financial security.

Table B.2: Principal factor analysis/correlation by gender

	Males			**Females**		
Factor #	**Eigenvalue**	**Proportion**	**Cumulative**	**Eigenvalue**	**Proportion**	**Cumulative**
1	1.79	0.19	0.19	1.80	0.20	0.20
2	1.69	0.18	0.37	1.63	0.18	0.38
3	1.62	0.17	0.54	1.63	0.18	0.56
4	1.50	0.16	0.70	1.62	0.18	0.74
5	1.06	0.11	0.81	1.44	0.16	0.90
6	1.05	0.11	0.93	0.90	0.10	1.00
7	0.89	0.09	1.02	0.83	0.09	1.09

Source: AJD restricted data.
Note: Only the seven factors with a cumulative proportion reaching 1 are shown. For full results, see the Online Appendix. LR test: independent vs. saturated: chi2(136) = 4062.42 Prob>chi2 = 0.0000

Table B.3: Rotated factor loadings and unique variances for everyone

Survey question	**Factor1**	**Factor2**	**Factor3**	**Factor4**	**Factor5**	**Factor6**	**Factor7**	**Uniqueness**
Why sector?								
Medium-to-long-term earning potential							0.5631	0.4761
Substantive interest in a specific field of law				0.5360				0.6488
Salary to pay off law school debts							0.5205	0.6295
Opportunity to develop specific skills				0.5929				0.5300
Potential to balance work and personal life				0.5213				0.5747
Opportunity to do socially responsible work	0.5063			0.5257				0.3839
Prestige of the sector			0.6920					0.4710
Opportunities for future career mobility			0.5302					0.5599
Why law school?								
Intellectual challenge of law school and the law								0.8161
Desire to help individuals as a lawyer	0.7279							0.4430
Desire to develop a satisfying career								0.6842
Desire to defer entry into the job market								0.8653
Desire for eventual financial security								0.6012
Desire to change or improve society	0.7977							0.3491
Becoming influential in a powerful profession								0.6721
Desire to build a set of transferable skills								0.7716
Why job offer?								
Salary		0.7795						0.3487
Benefits		0.7616						0.3763
Office environment/collegiality								0.5728
Hours expected								0.5163
Prospects for advancement						0.5142		0.5485
Good match of employer's mission and my own						0.5545		0.5130
Location								0.7925
Size					0.5536			0.6219
Prestige			0.4702		0.5083			0.5005
Training/mentorship opportunities								0.6213

Source: AJD restricted data.
Notes: Blanks represent loadings where the absolute value is less than 0.4.

We also conduct our factor analysis separately for males and females to see if there are any gender differences in latent preferences driving career decisions. Our factor analysis again finds seven factors that explain all of the variance in survey responses. The eigenvalues are reported in Table B.2. The scree test also confirms that there are seven factors.

Tables B.4 and B.5 report the rotated factor loadings for males and females, respectively. Perhaps not surprisingly, the first and most important factor differs by gender. Specifically, males care most about earning potential in making their career decisions while females care most about the office environment and "fit". The factors for men are: earning potential, social responsibility, prestige, career development, financial security, office environment, and career goals. The factors for women are: office environment and "fit", earning potential, social responsibility, prestige, career development, financial security, and stability.

Figure B.2: Scree plot

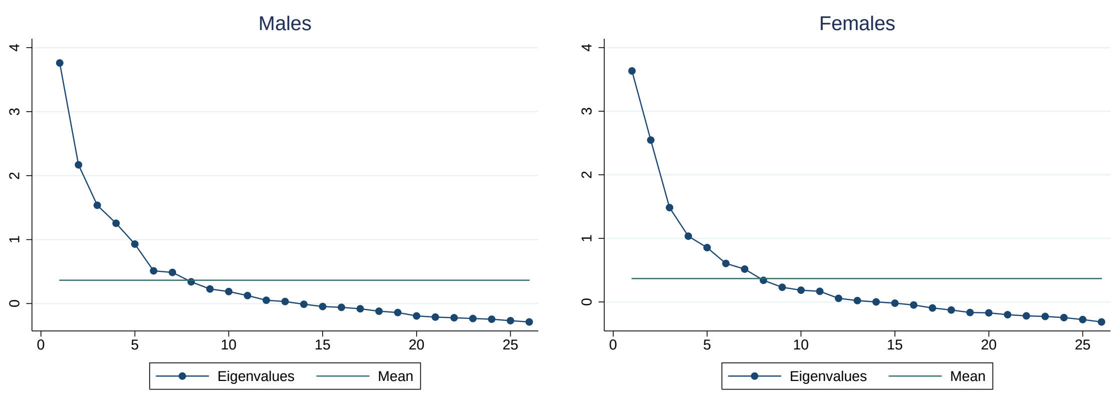


Table B.4: Rotated factor loadings and unique variances for males

Survey question	**Factor1**	**Factor2**	**Factor3**	**Factor4**	**Factor5**	**Factor6**	**Factor7**	**Uniqueness**
Why sector?								
Medium-to-long-term earning potential					0.5891			0.4740
Substantive interest in a specific field of law				0.5736				0.5950
Salary to pay off law school debts					0.5356			0.6387
Opportunity to develop specific skills				0.6434				0.5047
Potential to balance work and personal life				0.4550		0.4528		0.5465
Opportunity to do socially responsible work		0.5490		0.4539				0.3692
Prestige of the sector							0.5580	0.4926
Opportunities for future career mobility							0.4878	0.5205
Why law school?								
Intellectual challenge of law school and the law								0.7810
Desire to help individuals as a lawyer		0.6916						0.4913
Desire to develop a satisfying career								0.7055
Desire to defer entry into the job market								0.8482
Desire for eventual financial security								0.6264
Desire to change or improve society		0.7974						0.3572
Becoming influential in a powerful profession								0.6929
Desire to build a set of transferable skills								0.7864
Why job offer?								
Salary	0.8030							0.3152
Benefits	0.8073							0.3071
Office environment/collegiality						0.4604		0.5586
Hours expected						0.6193		0.4843
Prospects for advancement								0.5226
Good match of employer's mission and my own								0.4994
Location								0.7772
Size			0.6223					0.5646
Prestige			0.7093					0.4407
Training/mentorship opportunities			0.5013					0.5686

Source: AJD restricted data.
Notes: Blanks represent loadings where the absolute value is less than 0.4.

Table B.5: Rotated factor loadings and unique variances for females

Survey question	**Factor1**	**Factor2**	**Factor3**	**Factor4**	**Factor5**	**Factor6**	**Factor7**	**Uniqueness**
Why sector?								
Medium-to-long-term earning potential						0.5792		0.4704
Substantive interest in a specific field of law					0.5153			0.6672
Salary to pay off law school debts						0.5164		0.5976
Opportunity to develop specific skills					0.5728			0.5345
Potential to balance work and personal life					0.5477			0.5816
Opportunity to do socially responsible work			0.4336		0.5836			0.3974
Prestige of the sector				0.7470				0.4143
Opportunities for future career mobility				0.5097				0.5662
Why law school?								
Intellectual challenge of law school and the law								0.8353
Desire to help individuals as a lawyer			0.7467					0.4160
Desire to develop a satisfying career								0.6510
Desire to defer entry into the job market								0.8484
Desire for eventual financial security							0.4986	0.5480
Desire to change or improve society			0.7898					0.3483
Becoming influential in a powerful profession								0.6356
Desire to build a set of transferable skills							0.4700	0.7204
Why job offer?								
Salary		0.7564						0.3770
Benefits		0.7223						0.4255
Office environment/collegiality	0.5192							0.5852
Hours expected	0.5224							0.5247
Prospects for advancement	0.5371							0.5550
Good match of employer's mission and my own	0.6168							0.5211
Location								0.7405
Size								0.6411
Prestige								0.5281
Training/mentorship opportunities	0.4987							0.6384

Source: AJD restricted data.

Notes: Blanks represent loadings where the absolute value is less than 0.4.

Factor analysis assumes that the error terms are governed by a single latent factor, and therefore uses a correlation matrix of observed variables to extract this latent factor. If the observed variables are completely non-collinear, then factor analysis would extract as many as factors as variables from the correlation matrix. That is, each observed variable would be its own factor. A good validity test, therefore, would be one that measures the degree to which the observed variables share a common factor. That is, is the correlation matrix "factorable"?

There are two tests for this. Barlett's test of sphericity calculates the determinate of the matrix, which is then converted to a chi-square statistic and tested for significance. If it is statistically significant, then we can reject the null hypothesis that the observed variables are non-collinear. The determinant of the correlation matrix is 0.001 for both males and females, providing a p-value of 0. Since this is highly statistically significant, we can proceed with factor analysis.

The Kaiser-Meyer-Olkin measure of sampling adequacy test (KMO) tests the validity of the observed variables sharing a common factor. If two variables share a common factor with other variables, their partial correlation, which indicates the unique variance they share, will be small. In particular, the KMO is calculated as follows:

$$KMO = \frac{\sum_i \sum_j r_{ij}^2}{\sum_i \sum_j r_{ij}^2 + (\sum_i \sum_j a_{ij}^2)}$$

Scores between 0.9 and 1.0 are ideal, while scores below 0.6 are "miserable" and factor analysis is not recommended. The table of KMO interpretations is below. Our values of 0.739 for males, 0.745 for females, and 0.754 for everyone is "middling" indicating that the factors extracted will account for a fair amount of variance, but not a substantial amount.

Cronbach's alpha is a rule-of-thumb rather than a statistical test, but it tells us how correlated the set of items being tested are correlated with one latent factor. The rule-of-thumb is that the coefficient should be least 0.50, with it ideally being at 0.70 or higher.

Table B.7: Gender difference in fertility timing with gender-specific factors

	Early parenthood			Late parenthood		
Predicted intensity level		High	Low		High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.0846***	-0.155***	-0.0557**	0.0620**	0.124**	0.0416
	(0.0249)	(0.0572)	(0.0277)	(0.0251)	(0.0581)	(0.0277)
Observations	2,087	2,087	2,087	2,087	2,087	2,087
Controls for:						
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Ability proxies	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income and spousal employment	Yes	Yes	Yes	Yes	Yes	Yes
Ambition and Family preference	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Demographic characteristics include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, initial number of job offers, and bar exam attempts. Job characteristics include initial firm's size, initial hours worked, and area of law. *** p< 0.01, ** p< 0.05, * p< 0.1

The Cronbach's alpha for everyone is 0.777, for males is 0.785, and is 0.767 for females, all above our threshold of 0.70.

Table B.6: Robustness checks

Robustness tests	**Male**	**Female**	**Everyone**
Determinant of correlation matrix	0.001	0.001	0.001
Bartlett test of sphericity (p-value)	0.000	0.000	0.000
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.739	0.745	0.754
Cronbach's alpha	0.785	0.767	0.777

Table B.8: Gender difference in fertility timing with yulized factors

	Early parenthood			**Late parenthood**		
Predicted intensity level		High	Low		High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.0805***	-0.153***	-0.0513*	0.0562**	0.118**	0.0360
	(0.0246)	(0.0569)	(0.0276)	(0.0249)	(0.0579)	(0.0276)
Observations	2,087	2,087	2,087	2,087	2,087	2,087
Controls for:						
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Ability proxies	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income and spousal employment	Yes	Yes	Yes	Yes	Yes	Yes
Yulized factor scores	Yes	Yes	Yes	Yes	Yes	Yes

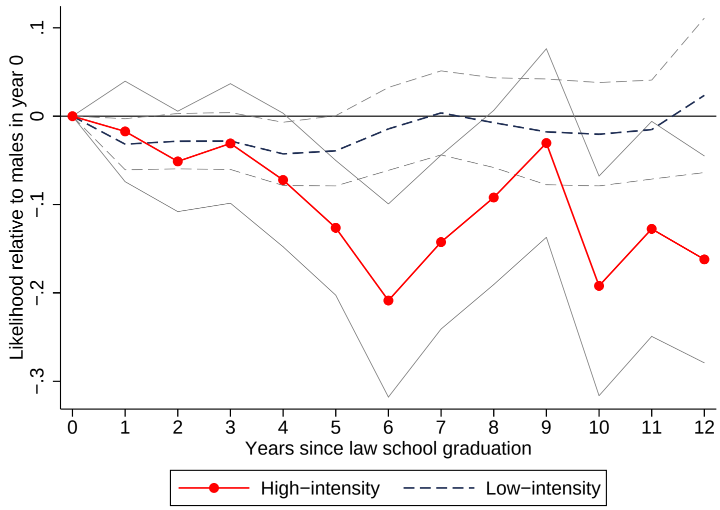
Notes: Demographic characteristics include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, initial number of job offers, and bar exam attempts. Job characteristics include initial firm's size, initial hours worked, and area of law. Yulized factors are constructed from residuals of the regression of survey questions against female, race/ethnicity, marital status, number of children, undergraduate and law school GPAs, participation in general law review, judicial clerkships, number of job offers, number of bar exam attempts, licensed status, debt, and intention to practice. *** p< 0.01, ** p< 0.05, * p< 0.1

Table B.9: Gender difference in fertility timing with survey questions

	Early parenthood			**Late parenthood**		
Predicted intensity level		High	Low		High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.0894***	-0.162***	-0.0623**	0.0664***	0.135**	0.0481*
	(0.0249)	(0.0584)	(0.0269)	(0.0252)	(0.0591)	(0.0267)
Observations	2,087	2,087	2,087	2,087	2,087	2,087
Controls for:						
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Ability proxies	Yes	Yes	Yes	Yes	Yes	Yes
Job characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Income and spousal employment	Yes	Yes	Yes	Yes	Yes	Yes
Why sector	Yes	Yes	Yes	Yes	Yes	Yes
Why law	Yes	Yes	Yes	Yes	Yes	Yes
Why job	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Demographic characteristics include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, initial number of job offers, and bar exam attempts. Job characteristics include initial firm's size, initial hours worked, and area of law. *** p< 0.01, ** p< 0.05, * p< 0.1

Figure B.3: Gender difference in fertility timing by predicted intensity level using work-life balance



Source: AJD restricted data.
Notes: Distributions are plotted for all full-time workers in private law firms with 30+ lawyers and with positive values.

Table B.10: Predictive power of predicted intensity measure

	(1)	(2)	(3)	(4)
Predicted intensity (standard deviations)	0.112***	0.111***	0.101***	0.0801***
	(0.0121)	(0.0123)	(0.0120)	(0.0141)
Avg. likelihood		0.17		
Observations	1,780	1,780	1,780	1,780
Controls for:				
Demographic characteristics		Yes	Yes	Yes
Ability proxies			Yes	Yes
Job characteristics				Yes

Notes: Demographic characteristics include race and ethnicity, age, law school graduation date, geographic location at time of initial survey, and initial marital status. Ability proxies include undergraduate and law school GPAs, U.S. News' 2003 law school ranking, participation in general law review, judicial clerkships, initial number of job offers, and bar exam attempts. Job characteristics include initial firm's size, initial hours worked, and area of law. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

Table B.11: Estimating structural break in parent-share growth

Outcome: Change in share of parents			
Post-JD year index	**Estimates**	**R2**	**Ajd. R2**
1	0.132**	0.9618	0.9482
	(0.0568)		
2	0.0163	0.9472	0.9283
	(0.0673)		
3	-0.0273	0.9476	0.9289
	(0.0638)		
4	-0.0901	0.9555	0.9396
	(0.0554)		
5	-0.0753	0.9531	0.9364
	(0.0554)		
6	0.130**	0.9645	0.9518
	(0.0495)		
7	-0.0559	0.9498	0.9319
	(0.0625)		
8	0.0159	0.9472	0.9283
	(0.0673)		
9	0.0792	0.9523	0.9352
	(0.0635)		
10	0.104*	0.9567	0.9412
	(0.0584)		

Source: AJD restricted data.

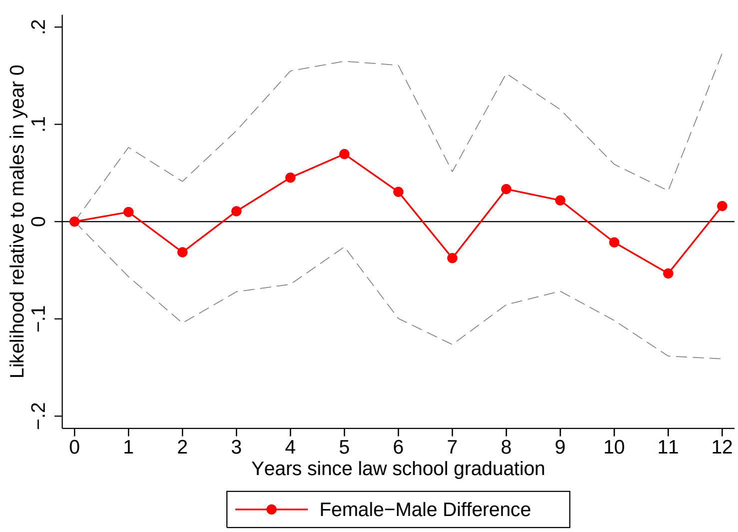
Notes: N = 20. Regression sample runs from 4 years before JD to 15 years after JD. Estimates are β_1 from the following regression model: $D_t = \beta_0 + \beta_1 \cdot \mathbb{1}\{T = t\} + \tau + \varepsilon_t$ where t denotes number of years relative to the year of law school graduation, D_t is the change in share of parents from $t-1$ to t, and τ is a quartic time trend. *** p< 0.01, ** p< 0.05, * p< 0.1

Table B.12: Gender difference in parenthood-timing with alternative threshold

	Early parenthood			Late parenthood		
Predicted intensity level		High	Low		High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Female-male difference	-0.0671***	-0.0514	-0.0627**	0.0866***	0.126**	0.0670**
	(0.0232)	(0.0555)	(0.0260)	(0.0239)	(0.0555)	(0.0267)
Avg. male likelihood	0.35	0.34	0.27	0.55	0.51	0.66
Avg. female likelihood	0.25	0.25	0.21	0.67	0.70	0.71
Observations	2,087	2,087		2,087	2,087	
Baseline controls	Yes	Yes		Yes	Yes	

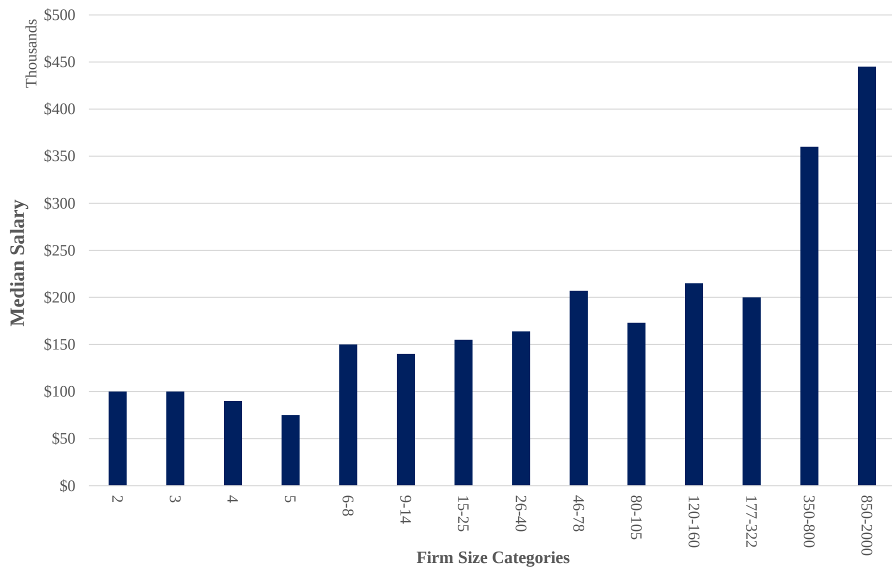
Source: AJD restricted data.
Notes: Early parenthood is defined as having one's first child within the first 5 years after law school. Late parenthood is defined as having one's first child at least 7 years after law school. See notes in Table 2.4 for description of baseline controls. *** p< 0.01, ** p< 0.05, * p< 0.1

Figure B.4: Gender difference in exit likelihood from high-stress firms



Source: AJD restricted data.
Notes: This figure plots the gender difference in hazard of exiting a high-stress firm. High-stress firms are defined as firms with at least 350 lawyers. This threshold was found by comparing the median equity-partner's salary by firm-size (see Table B.5 below).

Figure B.5: Equity partner's median salary by firm-size



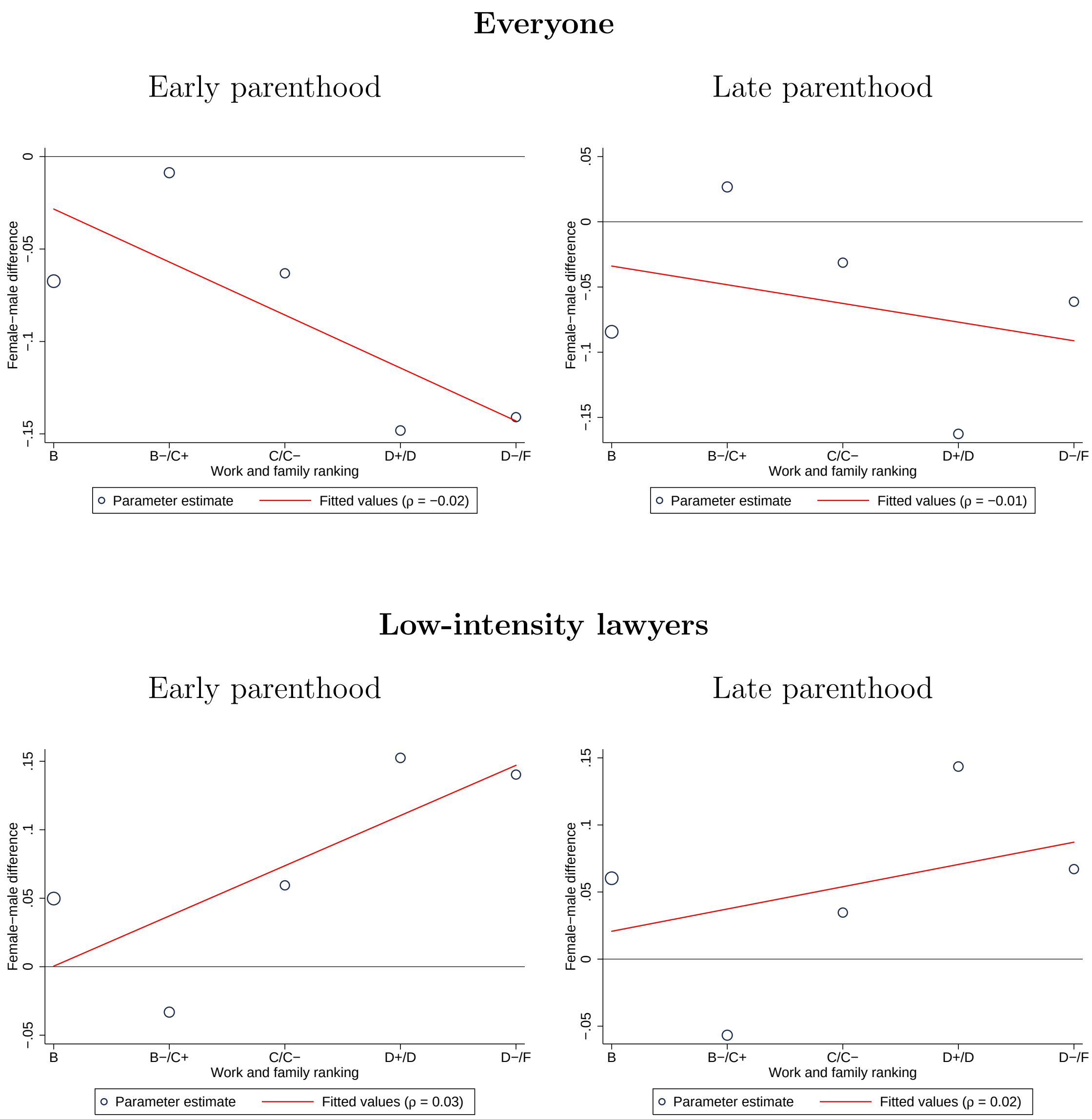
Source: AJD restricted data.
Notes: Firm-size categories were clasffied into 15 quantiles.

Table B.13: Geographic regions by work family conditions

Geographic region	**Grade**
New York City, DC, Los Angeles, San Francisco	B
New Jersey, Oregon	B-
Minneapolis, Oklahoma	C+
Atlanta, Connecticut	C
St. Louis, Boston	C-
Chicago, Houston	D+
Tennessee	D
Florida	D-
Indiana, Utah	F

Source: Institute for Women's Policy Research's *Status of Women* 2015 report.
Notes: State grades for work and family conditions consider paid leave legislation, elder and dependent care, child care, and the gender gap in parents' labor force participation rates.

Figure B.6: Gender fertility difference by work and family conditions in geographic region



Source: AJD restricted data, Institute for Women's Policy Research's *Status of Women* 2015 report.
Notes: State grades for work and family conditions are taken from the Institute for Women's Policy Research's *Status of Women* 2015 report. Work and family conditions consider paid leave legislation, elder and dependent care, child care, and the gender gap in parents' labor force participation rates. Size of circles represent the census region's population. Fitted values are weighted by population size.

Table B.14: Census regions by white-collar male sexism index

Census region	**Sexism index**
E. South Central (Tennessee)	-0.019
S. Atlantic (DC, Atlanta, Florida)	-0.027
W. South Central (Houston, Oklahoma)	-0.032
Mountain (Utah)	-0.06
Middle Atlantic (New York City, New Jersey)	-0.083
Pacific (Los Angeles, San Francisco, Oregon)	-0.117
W. North Central (Minneapolis)	-0.125
E. North Central (Chicago, Indiana, St. Louis)	-0.162
New England (Boston, Connecticut)	-0.241

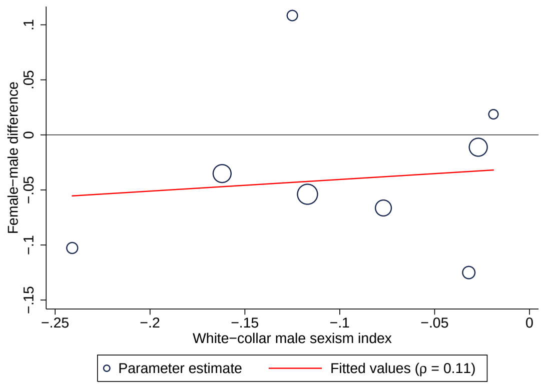
Source: Pan (2015), Table 5.

Notes: Sexism index is constructed using white-collar male responses from the 1977-1998 GSS data. Positive values depict more sexist attitudes.

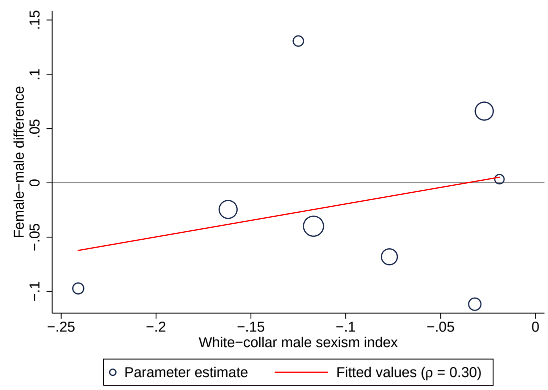
Figure B.7: Gender fertility difference by level of gender norms in Census region

Everyone

Early parenthood

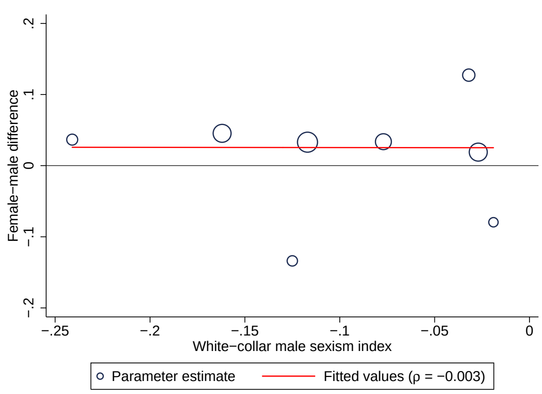


Late parenthood

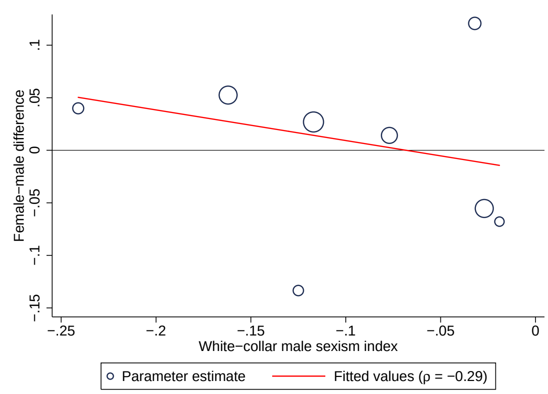


Low-intensity lawyers

Early parenthood



Late parenthood



Source: AJD restricted data, Pan (2015).
Notes: White-collar male sexism index is constructed from the GSS survey and is taken from Pan (2015). Size of circles represent the census region's population. Fitted values are weighted by population size.

APPENDIX C

HOUSING BOOMS, BUSTS, AND THE ADDED WORKER EFFECT (WITH DAN A. BLACK AND KERWIN CHARLES)

C.1 Estimating structural break

CHN use quarterly house price data between 2000Q1 and 2005Q4 to estimate the structural break in each MSA:

$$P_k^H(t) = \omega_k + \tau_k \cdot t + \lambda_k \cdot (t - t_k^*) \cdot \mathbb{1}\{t > t_k^*\} + \upsilon_{kt} \tag{C.1}$$

where $P_k^H(t)$ is the log local housing price in MSA k in quarter t, t_k^* is the date of the structural break in the MSA's time series (restricted to be between 2000Q1 and 2005Q1), τ_k is an MSA-specific linear time trend before the structural break, and λ_k is the size of the MSA-specific structural break. λ_k captures the extent to which the growth rate of the MSA's quarterly house price series changes at the break. We search for the location of the break, t_k^*, that maximizes that R^2 of the regression.

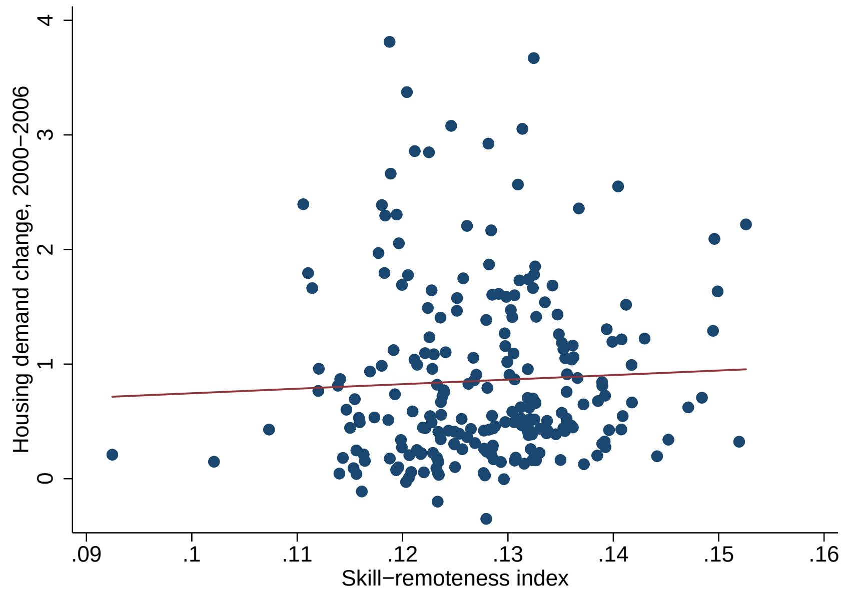
Table C.1: List of MSAs by Tercile of Construction Skill-Remoteness Index

MSA name	**Tercile**	**MSA name, continued**	**Tercile**	**MSA name, continued**	**Tercile**
Elkhart-Goshen, IN	1	Benton Harbor, MI	1	Fort Walton Beach, FL	2
Hickory-Morganton, NC	1	Kenosha, WI	1	Salt Lake City-Ogden, UT	2
Fort Smith, AR/OK	1	St. Cloud, MN	1	Eugene-Springfield, OR	2
Naples, FL	1	Stockton, CA	1	Milwaukee, WI	2
Las Vegas, NV	1	Louisville, KY/IN	1	Tacoma, WA	2
Lakeland-Winterhaven, FL	1	St. Joseph, MO	1	Savannah, GA	2
Joplin, MO	1	Kalamazoo-Portage, MI	1	Brownsville-Harlingen-San Benito, TX	2
York, PA	1	Greeley, CO	1	Columbus, GA/AL	2
Fayetteville-Springdale, AR	1	Albany, GA	1	Flint, MI	2
Jackson, TN	1	Canton, OH	1	Altoona, PA	2
Lancaster, PA	1	Grand Junction, CO	1	Fort Collins-Loveland, CO	2
Greenville-Spartenburg-Anderson, SC	1	Janesville-Beloit, WI	1	Dayton-Springfield, OH	2
Racine, WI	1	Vineland-Milville-Bridgetown, NJ	1	Bremerton, WA	2
Wausau, WI	1	Bakersfield, CA	1	Kokomo, IN	2
Grand Rapids, MI	1	Lafayette, LA	1	Cleveland, OH	2
State College, PA	1	Springfield, MO	1	South Bend-Mishawaka, IN	2
Appleton-Oshkosh-Neenah, WI	1	Medford, OR	1	Augusta-Aiken, GA/SC	2
Rocky Mount, NC	1	Scranton-Wilkes-Barre, PA	1	Glens Falls, NY	2
Jacksonville, NC	1	Longview-Marshall, TX	1	Phoenix, AZ	2
Chattanooga, TN/GA	1	Green Bay, WI	1	Knoxville, TN	2
Fort Wayne, IN	1	Billings, MT	1	Tulsa, OK	2
Mansfield, OH	1	Toledo, OH/MI	1	Fort Pierce, FL	2
Decatur, AL	1	Greenville, NC	1	Gadsden, AL	2
Lynchburg, VA	1	Dothan, AL	1	Miami-Hialeah, FL	2
Lake Charles, LA	1	Lafayette-W. Lafayette, IN	1	Peoria, IL	2
Ocala, FL	1	Indianapolis, IN	1	Buffalo-Niagara Falls, NY	2
Reading, PA	1	Erie, PA	1	Baton Rouge, LA	2
Yuma, AZ	1	Jamestown-Dunkirk, NY	1	Cincinnati-Hamilton, OH/KY/IN	2
Daytona Beach, FL	1	Akron, OH	1	Nashville, TN	2
Fort Myers-Cape Coral, FL	1	Sarasota, FL	1	Providence-Fall River-Pawtucket, MA/RI	2
Rockford, IL	1	Beaumont-Port Arthur-Orange, TX	2	Monroe, LA	2
Merced, CA	1	Biloxi-Gulfport, MS	2	Detroit, MI	2
Evansville, IN/KY	1	Mobile, AL	2	Allentown-Bethlehem-Easton, PA/NJ	2
Visalia-Tulare-Porterville, CA	1	Waterloo-Cedar Falls, IA	2	New Orleans, LA	2
Myrtle Beach, SC	1	Asheville, NC	2	Norfolk-VA Beach–Newport News, VA	2
Sumter, SC	1	Roanoke, VA	2	Orlando, FL	2
Youngstown-Warren, OH/PA	1	Alexandria, LA	2	Portland, ME	2
Sharon, PA	1	Davenport, IA - Rock Island-Moline, IL	2	Duluth-Superior, MN/WI	2
Hagerstown, MD	1	Fresno, CA	2	Utica-Rome, NY	2
Greensboro-Winston Salem-High Point, NC	1	Charlotte-Gastonia-Rock Hill, NC/SC	2	Tampa-St. Petersburg-Clearwater, FL	2
Riverside-San Bernardino, CA	1	Wichita, KS	2	Tucson, AZ	2
Johnson City-Kingsport–Bristol, TN/VA	1	Johnstown, PA	2	Tyler, TX	2
Lima, OH	1	Memphis, TN/AR/MS	2	Santa Rosa-Petaluma, CA	2
Reno, NV	1	Dover, DE	2	Little Rock-N. Little Rock, AR	2
Sioux City, IA/NE	1	Atlantic City, NJ	2	Los Angeles-Long Beach, CA	2
Modesto, CA	1	Lexington-Fayette, KY	2	Charleston-N. Charleston, SC	2
Salinas-Sea Side-Monterey, CA	1	Sioux Falls, SD	2	Lincoln, NE	2
Saginaw-Bay City-Midland, MI	1	Decatur, IL	2	Goldsboro, NC	2
Terre Haute, IN	1	Ventura-Oxnard-Simi Valley, CA	2	Redding, CA	2

MSA name	Tercile	MSA name, continued	Tercile	MSA name, continued	Tercile
San Luis Obispo-Atascad-P Robles, CA	2	Pittsburgh, PA	3	Denver-Boulder, CO	3
Oklahoma City, OK	2	Kansas City, MO/KS	3	San Francisco-Oakland-Vallejo, CA	3
Abilene, TX	2	Richmond-Petersburg, VA	3	Hartford-Bristol-Middleton- New Britain, CT	3
Wichita Falls, TX	2	Houston-Brazoria, TX	3	Provo-Orem, UT	3
Flagstaff, AZ/UT	2	Harrisburg-Lebanon–Carlisle, PA	3	Portland, OR/WA	3
Rochester, NY	2	Amarillo, TX	3	Fayetteville, NC	3
Birmingham, AL	2	Santa Barbara-Santa Maria-Lompoc, CA	3	Seattle-Everett, WA	3
McAllen-Edinburg-Pharr-Mission, TX	2	Atlanta, GA	3	Lansing-E. Lansing, MI	3
Salem, OR	2	Wilmington, DE/NJ/MD	3	Philadelphia, PA/NJ	3
Spokane, WA	2	San Diego, CA	3	Columbia, SC	3
LaCrosse, WI	3	Cedar Rapids, IA	3	Auburn-Opekika, AL	3
Newburgh-Middletown, NY	3	Topeka, KS	3	Charlottesville, VA	3
Montgomery, AL	3	Pensacola, FL	3	Huntsville, AL	3
Macon-Warner Robins, GA	3	Des Moines, IA	3	Albany-Schenectady-Troy, NY	3
Syracuse, NY	3	Barnstable-Yarmouth, MA	3	Iowa City, IA	3
Chicago, IL	3	Colorado Springs, CO	3	Baltimore, MD	3
Omaha, NE/IA	3	Springfield-Holyoke-Chicopee, MA	3	New York, NY-Northeastern NJ	3
Richland-Kennewick-Pasco, WA	3	Kankakee, IL	3	Champaign-Urbana-Rantoul, IL	3
Ann Arbor, MI	3	Minneapolis-St. Paul, MN	3	Santa Fe, NM	3
San Antonio, TX	3	Lubbock, TX	3	Raleigh-Durham, NC	3
Fort Lauderdale-Hollywood-Pompano Beach, FL	3	Albuquerque, NM	3	Austin, TX	3
Yuba City, CA	3	Kileen-Temple, TX	3	San Jose, CA	3
West Palm Beach-Boca Raton-Delray Beach, FL	3	Columbia, MO	3	Boston, MA/NH	3
Corpus Christi, TX	3	Boise City, ID	3	Olympia, WA	3
Columbus, OH	3	Jackson, MS	3	Gainesville, FL	3
Melbourne-Titusville-Cocoa-Palm Bay, FL	3	Santa Cruz, CA	3	Trenton, NJ	3
St. Louis, MO/IL	3	New Haven-Meriden, CT	3	Bryan-College Station, TX	3
Binghamton, NY	3	Chico, CA	3	Washington, DC/MD/VA	3
Dallas-Fort Worth, TX	3	Madison, WI	3		
Fargo-Morehead, ND/MN	3	Bloomington-Normal, IL	3		

Source: Construction skill-remoteness from 2000 CPS data and 2000 OES data.

Figure C.1: Correlation of housing demand change versus construction skill-remoteness



Source: Local housing demand data is from FHFA and the Census Building Permits Survey. Construction skill-remoteness from 2000 CPS data and 2000 OES data.
Notes: The red line is the fitted line between 2000-2006 housing demand change and the 2000 construction skill-remoteness index. The slope is 0.046.