Publicly Accessible Penn Dissertations

2018

Essays On Human Capital And Altruism

Amanda Chuan
University of Pennsylvania, chuan.amanda@gmail.com

Essays On Human Capital And Altruism

Abstract

This dissertation contains three self-contained chapters on human capital and altruism.

The first two chapters explore why women used to lag behind but now exceed men in college enrollment. Chapter 1 shows that examining occupations that require only a high school degree ("non-college" occupations) can help resolve two puzzles. First, why do women attend college at greater rates than men today, when men work more and earn more than women? I document that non-college occupations for men are both more plentiful and higher paying than those for women. Next, I link the occupational inequality in the non-college labor market to the gap in college enrollment, by employing two empirical exercises to show that non-college jobs dramatically affect college-going decisions. Using employment changes in the oil and gas industry, I demonstrate that increases in men's non-college job opportunities lead male high school graduates to forego college enrollment. Using the automation of the office, I demonstrate that declines in the non-college employment opportunities of women lead female college enrollment to grow over time. Thus, women's lower non-college job prospects contribute to their higher college enrollment. This leads to the second puzzle: why did women initially attend college at lower rates than men, when women have always had worse non-college job prospects than men? I develop a theoretical model to demonstrate that both the importance and availability of non-college occupations for women contributed to women's initially low enrollment, as well as to the growth in female enrollment over time, such that women eventually overtook men in college-going.

Chapter 1 argues that gender differences in occupations, particularly in the non-college labor market, lead women to choose to attend college at greater rates than men. In Chapter 2, I explore one key mechanism behind the severe occupational segregation in the non-college labor market. Using data from the National Longitudinal Study of Youth (1979), I show that there exist large differences in skill profiles between men and women. In particular, "gender-based skill" for men tends to represent mechanical skill, while "gender-based skill" for women tends to represent numerical and coding ability. Using a Roy model adapted from Rosen and Willis (1979), I show that "gender-based skill" for men commands a return in the non-college labor market and therefore increases the opportunity cost of college attendance. "Gender-based skill" for women, on the other hand, does not appear to increase women's non-college earnings. Finally, I find that these skill differences significantly impact the likelihood of enrolling in college through their effect on wages. By increasing the value of the outside option to attending college for men, gender-based skill contributes to the greater college enrollment rate of women.

Chapter 3, joint with Judd Kessler and Katherine Milkman, explores altruism in a unique field context. We examine how reciprocity, an important motivation behind altruism, changes over time using a large quasi-experiment in the field. Specifically, we analyze administrative data from a university hospital system. The data include information about over 18,000 donation requests made by the hospital system via mail to a set of its former patients in the four months following their first hospital visit. We exploit quasi-experimental variation in the timing of solicitation mailings relative to patient hospital visits and find that an extra 30-day delay between the provision of medical care and a donation solicitation decreases the likelihood of a donation by 30%. Our findings have important implications for models of economic behavior, which currently fail to incorporate reciprocity's sensitivity to time. The fact that reciprocal behavior decays rapidly as time passes also suggests the importance of capitalizing quickly on opportunities to benefit from a quid pro quo.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Applied Economics

First Advisor
Iwan Barankay

Keywords
altruism, college enrollment, gender, human capital, occupational sorting, reciprocity

Subject Categories
Labor Economics | Public Policy | Social and Behavioral Sciences

ESSAYS ON HUMAN CAPITAL AND ALTRUISM

Amanda Chuan

A DISSERTATION

in

Applied Economics

For the Graduate Group in Managerial Science and Applied Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2018

Supervisor of Dissertation

Iwan Barankay, Associate Professor of Management and Business Economics and Public Policy

Graduate Group Chairperson

Catherine Schrand, Celia Z. Moh Professor, Professor of Accounting

Dissertation Committee

Iwan Barankay, Associate Professor of Management and Business Economics & Public Policy

Judd Kessler, Assistant Professor of Business Economics & Public Policy

Corinne Low, Assistant Professor of Business Economics & Public Policy

Katherine Milkman, Evan C. Thompson Endowed Term Chair for Excellence in Teaching,
Associate Professor of Operations, Information and Decisions

Dedicated to my grandmother,

who gave me the world.

ACKNOWLEDGEMENT

I am deeply grateful to Iwan Barankay, Judd Kessler, Corinne Low, Katherine Milkman, and Petra Todd for their encouragement, guidance, and support over the years. They have become wonderful role models, as both researchers and human beings. I will forever appreciate the time they spent mentoring and teaching me. I am indebted to Alex Rees-Jones for his mentorship, thoughtfulness, and friendship. His kindness in spending countless hours chatting and reading over my paper helped me survive a crucial time in graduate school. I am grateful to Eduardo Azevedo for always taking the time to help me with my research and for his exceptionally sage career advice. I thank Clayton Featherstone for making this experience possible by interviewing me for Wharton's doctoral program, and for all the time he spent helping me with the theory section of Chapter 1. Finally, I will always treasure Anya Samek's life advice and life-long friendship. Working for her as an undergraduate research assistant was one of the best decisions of my life.

I appreciate the helpful feedback of many, on a wide variety of work. I thank Kerwin Charles, Gilles Duranton, Joseph Gyourko, Robert Jensen, Ben Keys, John List, Olivia Mitchell, Katja Seim, Todd Sinai, Jeremy Tobacman, Maisy Wong, Doug Webber, H2D2 Research workshop participants, WSAWBA conference participants, the Annual Behavioral Economics & Health Symposium, the Behavioral Decision Research in Management Conference, the Science of Philanthropy Conference, the Southern Economic Association Meetings, and Applied Economics student seminar participants at Wharton. I am indebted to Hunt Allcott and Daniel Keniston for graciously providing the data on oil and gas production used in Chapter 1. I am also grateful for the anonymous partner hospital system that provided the data used in Chapter 3. I gratefully acknowledge financial support provided by the Mack and Ackoff Fellowships.

My friends and colleagues made graduate school not only bearable, but also enjoyable. First-year classes would not have been the same without Amy Bond, Ryan Fackler, Mallick Hossain, Nitin Krishnan, Irina Pimenova, Paul Sangrey, and Hanna Wang. In addition, I thank Matthew Davis, Emma Boswell Dean, Alexa DeTogne, Jin Soo Han, Benjamin Hyman, Karthik Nagarajan, Jenny Palmer, Florian Rundhammer, David Schindler, Peichun Wang, Lauren Verity, Paula Wu, Karen Ye, Weilong Zhang, and Xingtan Zhang for the commiseration, the encouragement, and the good times.

Words cannot express how grateful I am to Ryan Durkin for being my source of strength and for making every challenge surmountable. He is the best partner in crime one can hope for, and by far the best thing that has happened to me. I thank my parents for encouraging my doctoral studies, and my brother for keeping things light. Most of all, I thank my grandparents, who sacrificed so much so that my brother and I could achieve our dreams.

ABSTRACT

ESSAYS ON HUMAN CAPITAL AND ALTRUISM

Amanda Chuan

Iwan Barankay

This dissertation contains three self-contained chapters on human capital and altruism.

The first two chapters explore why women used to lag behind but now exceed men in college enrollment. Chapter 1 shows that examining occupations that require only a high school degree ("non-college" occupations) can help resolve two puzzles. First, why do women attend college at greater rates than men today, when men work more and earn more than women? I document that non-college occupations for men are both more plentiful and higher paying than those for women. Next, I link the occupational inequality in the non-college labor market to the gap in college enrollment, by employing two empirical exercises to show that non-college jobs dramatically affect college-going decisions. Using employment changes in the oil and gas industry, I demonstrate that increases in men's non-college job opportunities lead male high school graduates to forego college enrollment. Using the automation of the office, I demonstrate that declines in the non-college employment opportunities of women lead female college enrollment to grow over time. Thus, women's lower non-college job prospects contribute to their higher college enrollment. This leads to the second puzzle: why did women initially attend college at lower rates than men, when women have always had worse non-college job prospects than men? I develop a theoretical model to demonstrate that both the importance and availability of non-college occupations for women contributed to women's initially low enrollment, as well as to the growth in female enrollment over time, such that women eventually overtook men in college-going.

Chapter 1 argues that gender differences in occupations, particularly in the non-college labor market, lead women to choose to attend college at greater rates than men. In Chapter 2, I explore one key mechanism behind the severe occupational segregation in the non-college labor market. Using data from the National Longitudinal Study of Youth (1979), I show that there exist large differences in skill profiles between men and women. In particular, "gender-based skill" for men tends to represent mechanical skill, while "gender-based skill" for women tends to represent numerical and coding ability. Using a Roy model adapted from Rosen and Willis (1979), I show that "gender-based skill" for men commands a return in the non-college labor market and therefore increases the opportunity cost of college attendance. "Gender-based skill" for women, on the other hand, does not appear to increase women's non-college earnings. Finally, I find that these skill differences significantly impact the likelihood of enrolling in college through their effect on wages. By increasing the value of the outside option to attending college for men, gender-based skill contributes to the greater college enrollment rate of women.

Chapter 3, joint with Judd Kessler and Katherine Milkman, explores altruism in a unique field context. We examine how reciprocity, an important motivation behind altruism, changes over time using a large quasi-experiment in the field. Specifically, we analyze administrative data from a university hospital system. The data include information about over 18,000 donation requests made by the hospital system via mail to a set of its former patients in the four months following their first hospital visit. We exploit quasi-experimental variation in the timing of solicitation mailings relative to patient hospital visits and find that an extra 30-day delay between the provision of medical care and a donation solicitation decreases the likelihood of a donation by 30%. Our findings have important implications for models of economic behavior, which currently fail to incorporate reciprocity's sensitivity to time. The fact that reciprocal behavior decays rapidly as time passes also suggests the importance of capitalizing quickly on opportunities to benefit from a quid pro quo.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER 1 : Non-College Occupations and the Gender Gap in College Enrollment

1.1 Introduction

Women are enrolling in college at greater rates than men, despite the fact that men have higher median earnings and higher labor force participation than women. This apparent contradiction has perplexed economists for decades.[1] I observe that for a high school graduate considering whether or not to attend college, the choice set appears dramatically different depending on gender. Men with only high school diplomas have viable, plentiful, and lucrative career prospects, especially given the plethora of blue-collar and trade occupations that pay highly based on physical strength, mechanical ability, or the willingness to face risky situations.[2] In 2015, jobs traditionally filled by men paid median incomes of $52,000 (truck driver), $53,000 (electrician), or $60,000 (police officer).[3] In contrast, the jobs typically held by women with only high school degrees are much lower paying. For example, jobs traditionally filled by women paid median incomes of $20,000 (cashier), $22,000 (housekeeper), and $24,000 (hairdresser).[4] If these occupational differences are broadly representative of the job prospects of men and women without a college degree, women may naturally respond by enrolling in college at greater rates than men.

The imbalance in occupations among workers with only high school degrees (hereafter, "non-college" workers) is an under-explored and overlooked reason for the greater college enrollment of women observed today. Moreover, this occupational gap contributed to the trends in the college gender gap over time, wherein women used to lag behind but now exceed men in college-going. This insight adds to the discussion on human capital investments by pointing out that: (1) women's supposed "over-investment" in college is not an over-investment at all, given the few alternative

[1] See Dougherty, 2005; Buchman and DiPrete, 2005; Goldin, Katz, and Kuziemko, 2006; Becker, Hubbard, and Murphy, 2010.

[2] Men have been shown to possess greater physical strength, mechanical ability, and tolerance for risk than women (see Miller et al., 1993; Eckel and Grossman, 2002; Blakemore et al., 2009; Croson and Gneezy, 2009).

[3] Bureau of Labor Statistics, 2014.

[4] Ibid.

options women have; and, similarly, (2) men's comparative "under-investment" in college may not only arise from their greater barriers to human capital investment,[5] but also their more lucrative outside options when making the college-going decision.

This paper proceeds in two parts. The first part argues that women's bleak outside options make it natural for them to exceed men in college-going. In Section 1.2, I document descriptive evidence that women with high school diplomas appear to face dramatic disadvantages in the labor market compared to their male counterparts. In Sections 1.3 and 1.4, I use two empirical exercises to show that these disadvantages directly contribute to the gender gap in college enrollment. In both exercises, I show that when the non-college occupations of one gender are disproportionately affected, there is a large gender difference in the college enrollment response, and therefore a significant change in the gap in college enrollment. Together, these results imply that the non-college labor market plays a large role in explaining why women attend college at greater rates than men today.

The second part of the paper addresses a related puzzle in the literature — why women first lagged behind and then exceeded men in college-going, when their non-college job prospects have always been worse than men's. In Section 1.4, I present evidence suggesting that women's non-college employment opportunities dramatically declined over time, while men's non-college job options remained plentiful by comparison. In Section 1.5, I situate this dynamic in a theoretical model to explain how declining non-college job options for women and increasing female labor force participation complemented each other in contributing to the growth in female enrollment over time, such that female enrollment eventually surpassed male enrollment. Finally, I use the model to estimate the extent to which the change in college enrollment from 1970 to 2010 can be attributed to changes in non-college job options.

In particular, Section 1.2 documents stylized facts regarding the large disparity in non-college occupations facing male and female high school graduates. Using decennial census microdata, I document a "missing quadrant" of high paying non-college occupations for women. The majority of

[5] Prior research has shown that men tend to be more impulsive, more myopic, and less risk averse than women, which may contribute to the lower high school graduation rates among men relative to women (see Bertrand and Pan, 2013; Becker, Hubbard, and Murphy 2010; Goldin, Katz, and Kuziemko 2006).

non-college occupations are male-dominated, while the few non-college occupations that employ women tend to exhibit low median earnings. I calculate the observed premium to college-going for men and women by constructing a weighted median of annual earnings, using the proportion of workers in each occupation as weights. I find that this premium is consistently higher for women than men by at least 30 log points from 1950 to 2010. Non-college women appear to face even larger disadvantages when it comes to careers, as opposed to just jobs. Over the life cycle, non-college men earn roughly the same as college women by age, but non-college women make far less, experience little earnings growth over their work lives, and are less likely to work in occupations that offer benefits. Overall, the job prospects of male high school graduates appear much more plentiful, higher paying, and more likely to be careers than the prospects of female high school graduates.

Does the imbalance in the non-college labor market translate to the gap in college enrollment? If so, do changes in non-college jobs shift enrollment rates for women, men, or both? Sections 1.3 and 1.4 address these questions for men and women, respectively. Both sections show that shocks to specific occupations and industries change the non-college job prospects of women relative to men, and correspondingly change the college enrollment gap.

Section 1.3 uses employment changes in the oil and gas industry to demonstrate that increases in the non-college employment opportunities of men in this industry lead men to forego attending college. Jobs in the oil and gas industry (e.g., oil field worker or driller) are dominated by men, and employment changes in this industry have a larger impact on male employment than female employment. Using oil and gas production data from Allcott and Keniston (2018), I find that natural variation in oil and gas reserves predicts the capacity of different counties to increase or decrease employment for oil and gas workers. Exploiting this variation, I estimate that an additional 1 percentage point increase in oil and gas employment leads to an additional 2-4 percentage point reduction in college enrollment among male high school graduates. This estimate is economically and significantly greater than the estimated response of female college enrollment, which is effectively zero.

Section 1.4 demonstrates that automation led to dramatic declines in the non-college employment opportunities of young women, which led female college enrollment to grow over time. I build on the routine-biased technical change literature, which reports that automation displaced routine-intensive occupations and drastically changed the structure of the non-college labor market (see Autor, Levy, and Murnane, 2003). I present new evidence that routine-intensive occupations employed over 60% of the young non-college female work force in 1970, and demonstrate that women's non-college jobs were especially vulnerable to the displacing effect of automation. Guided by this finding, I then use a shift-share instrument that predicts exposure to automation to isolate the causal effect on college enrollment. I demonstrate that an additional percentage point decline in routine-intensive jobs led to a 0.7 percentage point increase in the female college enrollment rate, which was significantly greater than the effect on male enrollment. This empirical exercise illustrates that like men, women respond dramatically to their non-college employment opportunities, suggesting that the anemic non-college prospects women face today contribute to their greater college enrollment.

Finally, Section 1.5 situates these findings in a theoretical model to simultaneously explain two puzzles: 1) why women attend college at greater rates than men now, even though men have earned more and worked more than women for most of history;[6] and 2) why women historically lagged behind men in college-going when their observed college premium was always higher than men's. The model illustrates that men's higher earnings and greater labor force attachment explain why male college enrollment shot up quickly and leveled off quickly. In contrast, the labor force participation of married women was initially low but grew substantially starting in the 1970s, making labor market outcomes more important for women *just as automation began to displace the bulk of their non-college job options*. The decline in women's non-college job prospects and the growth in female labor force participation were complementary in enabling women to realize their larger premium from schooling relative to men and propelling female college enrollment to surpass male college enrollment. A back-of-the-envelope calculation estimates that changes in non-college jobs account for 15% of the growth in female college enrollment and 1-12% of the change in male college enrollment between 1970 and 2010.

[6]A long literature on the gender gap in wages has shown that earnings for men tend to be higher than earnings for women, and that male labor force participation has been greater than female labor force participation (see Blau and Kahn, 2017 for a review).

This paper addresses an old but open question, but takes a distinct approach from most of the related literature. Rather than discuss the ability of women to outperform men academically (see Buchmann and Diprete, 2005; Jacob, 2002; Goldin, Katz, and Kuziemko, 2006; Becker, Hubbard, and Murphy 2010; Bertrand and Pan, 2013), or explore marriage market returns to attending college (see Chiappori, Iyigun, and Weiss, 2009; Chiappori, Salanie, and Weiss, 2015; Chiappori, Costas Dias, Meghir, 2016; Bronson, 2015; Zhang, 2016; Low, 2017), I focus on labor market returns. The majority of the literature on labor market returns and the college gender gap focuses on college jobs and uses structural models, Oaxaca decompositions, or panel data with the hope of isolating causal relationships (see Jacob, 2002; Dougherty, 2005; Charles and Luoh, 2003; Olivieri, 2014). In contrast, my paper uses exogenous variation in labor demand to test the hypothesis that the superior non-college job options of men lead to greater demand for college degrees among women. I show that women's enrollment rates increase when their non-college employment opportunities become scarce, and thus that their deteriorating non-college job options drove their college enrollment to grow and surpass that of men. I show that men's enrollment rates decline when their non-college labor market outcomes improve, and thus that their comparatively more plentiful non-college job options led a larger proportion of men than women to rationally forego attending college.

I make four contributions to the literature. To my knowledge, this paper is the first to connect gender differences in non-college job prospects to 1) the greater demand for a college degree observed today and 2) the trajectory of the college gender gap over time. The (few) other papers in this vein had other objectives, and therefore either do not show that changing non-college job opportunities lead to gender gaps in college enrollment (Charles, Hurst, and Notowidigdo, forthcoming), or do not show that individuals qualified to attend college actively forego college enrollment in the presence of more attractive outside options (Cascio and Narayan, 2015).[7]

Second, I leverage the task-based approach to measure occupational skill demands (Autor, Levy,

[7] Cascio and Narayan (2015) find that fracking increased high school drop-out rates among boys, but the focus of their paper is not to address gender differences in the *choice* to attend college. The mechanism for their findings may operate along dimensions other than choice. For example, if part-time jobs working in the oil and gas industry become more available for boys, boys may find it harder to balance a job with high school coursework, and therefore fail to complete high school even if they wished to graduate and attend college. In contrast, my paper finds that even among individuals qualified to attend college, men choose to forego college given an increase in oil and gas employment in their area.

and Murnane, 2003; Autor and Dorn, 2013), which provides more granular measures of the labor market returns to skill profiles than the conventional approach of examining wage gaps (see Goldin and Katz, 2010). Using this approach reveals that the returns to skills performed by non-college women declined relative to the skills performed by non-college men. I thus provide empirical facts that invite revisions of prior models, which overlook the role of declining non-college jobs for women in increasing the college premium for women (Welch, 2000; Rendall, 2010; Huang, 2013).

Third, I contribute to the literature on routine biased technical change. I demonstrate that automation propelled women to enter college at greater rates than before, by displacing their non-college employment opportunities. In contrast to the prior literature, which has mostly focused on how automation led to job market polarization (Autor, Levy, and Murnane 2003; Goos, Manning, and Salomans, 2009; Autor and Dorn, 2013; Goos, Manning and Salomans, 2014), I show that automation also affected the human capital investment decisions of women in irreversible ways.

Fourth, I present a simple model that resolves two contradictions. The first contradiction is that women attend college at greater rates than men, yet men have greater earnings and stronger labor force attachment (see Dougherty, 2005). The second contradiction is why men used to attend college at greater rates than women when outside options have always been worse for women.[8] My model demonstrates that men's greater earnings and labor force participation led them to attend college at higher rates than women at first, but that women's growing labor force participation allowed them to realize their greater labor market returns, which pushed women to eventually surpass men in college-going.

My results have direct implications for policy and future research. Policymakers have become increasingly concerned that men are lagging behind women in educational attainment (Rosin, 2010). Several countries have already implemented interventions intended to help men catch up, such as hiring more male teachers to serve as role models for boys, and tailoring class curricula to appeal to

[8] Becker, Hubbard, and Murphy (2010) identify a related mystery. For them, the true contradiction was why men surpassed women in college-going at first when a greater proportion of women were academically prepared to attend college relative to men.

boys (Rosin, 2010; The Economist, 2015).[9] The results of my paper suggest that these actions may be misguided. If men attend college at lower rates because they possess better outside options, then the gap in college enrollment may not be as inefficient as it seems, and interventions to minimize this gap may be ineffective at best and destructive at worst. Indeed, recent evidence from Carrell and Sacerdote (2013) indicates that interventions to encourage college-going have not shown much promise for men, and in their survey evidence, men cite larger expected earnings with only a high school degree as one key reason for choosing to not attend college. The aforementioned policy measures could even decrease welfare, for example if male teachers were hired at the expense of more qualified female teachers or if classroom curricula were changed to interest boys but ended up alienating girls. This paper suggests that before we devote public resources to eliminating educational differences between men and women, we should first re-examine why these differences exist in the first place, in order to determine the best role of policy in addressing the college gender gap.

1.2 Stylized Facts

To motivate the role of the non-college labor market in the college gender gap, this section presents a set of stylized facts regarding the gender disparity in non-college jobs using raw data from the 2010 American Community Survey. The evidence presented in this section is merely descriptive, and does not purport to isolate the causal effect of the non-college labor market on college enrollment rates. However, patterns in the raw data strongly suggest that gender-based sorting into occupations, particularly among non-college workers, contribute to the greater college enrollment of women over men.

Within the non-college labor market, men and women sort into different occupations at different rates, and the earnings of "traditionally female" occupations tend to be far lower than the earnings of "traditionally male" occupations. Based on these differences alone, the observed college premium (defined as the difference between median log college wages and median log non-college wages) is

[9] For example, Britain recently began a campaign to make reading more appealing to boys (Sommers, 2013).

dramatically greater for women than men. Women's apparent disadvantages in the non-college labor market take shape not only in the form of lower observed median earnings, but also worse observed career prospects in terms of lifetime earnings, earnings growth, and access to employment benefits. The greater college enrollment rate of women may be a natural result of these stark imbalances in observed non-college prospects between men and women.

Stylized Fact 1. *In the non-college labor market, there exists a "missing quadrant" of high paying jobs occupied by women.*

Figure 1.2 depicts the median annual earnings percentile and worker gender composition for each non-college occupation in 2010.[10] Each data point is an occupation as defined by the 1990 Census Bureau occupational classification scheme. To capture labor market returns for individuals most likely to consider the college-going decision, I restrict the data to only 18-30 year olds.

The figure makes two important points. First, the majority of non-college occupations are male-dominated. In fact, almost 65% of all non-college occupations employ 20% or fewer women. Many of these occupations are trade or blue-collar occupations, which either paid highly for work that demanded physical strength or mechanical ability, or paid highly for work that was unpleasant (see Chapter 2). For example, male-dominated occupations like miner, machinist, and truck driver report median annual earnings that fall between the 40th and the 80th percentile of median earnings for all occupations in 2010 (see table 1.1).[11] Second, "traditionally male" occupations tend to pay more than "traditionally female" occupations. The occupations that employ a non-trivial share of women (over 30%) have significantly lower median annual earnings than occupations that consist of over 80% men. As shown in table 1.1, common jobs among non-college women include cashier, cosmetologist, or housekeeper, where annual median earnings fell below the 10th percentile of median earnings for all occupations.

[10] I define "non-college occupations" as occupations where over 50% of workers have never enrolled in college.

[11] Chapter 2 presents some evidence that men tend to exhibit greater physical strength, mechanical ability, and risk-taking behavior than women, characteristics which command a wage premium in the non-college labor market. Additionally, employer discrimination may make it especially difficult for women to hold blue-collar occupations (see Hsieh et al., 2017). Whatever the reasons may be, the vast majority of non-college occupations employed very few women, which appears to contribute to the imbalance in non-college earnings between men and women.

These two points indicate that there exists a "missing quadrant" of high paying jobs held by women. There exist both low and high paying jobs for men, but women without college degrees only occupy low paying jobs. Figure 1.3 shows that there is a mirroring "missing quadrant" of low paying *college* jobs held by *men*. This second missing quadrant is to be expected, since no men would enter college to earn a low wage if there existed high paying alternatives which did not require a college degree. Together, figures 1.2 and 1.3 demonstrate that men typically sort into high paying occupations in the non-college market, whereas women do not. This sorting may in turn influence the composition of men and women who elect to attend college.

The evidence indicates that gender differences in the allocation of workers to occupations lead non-college women to earn less than non-college men. The occupational gender differences in the non-college labor market, which are more severe than those in the college labor market, create a greater gap between college and non-college earnings for women than for men.[12]

Stylized Fact 2. *Women have a higher observed college premium than men.*

Figure 1.4 explores this point in greater detail. The observed college premium in earnings for 18-30 year old workers is much higher for women than for men for all decades from 1950 to 2010. This difference was approximately 30 log points in 1950, rose to 50 log points by 1970 and 1980 right before women began to surpass men in college-going, and diminished to a little less than 40 log points by 2010 when the gap in college enrollment began to finally stop growing.[13] Appendix figure A.1 breaks down this difference by plotting the weighted median log wages by sex and education type, which reveals that the greater observed college premium of women is driven primarily by their

[12] Note that only legal occupations are shown. If illegal non-college occupations pay highly for women, then it could be the case that women have valuable alternatives to college-going that are not represented by figure 1.2. However, the estimated market for illegal work is quite small in the United States, especially in comparison to transition or developing countries (Fleming et al., 2000). Employment opportunities in illegal activities for women, such as prostitution, would therefore be correspondingly scarce. Many forms of illegal work for women are also quite dangerous and impose serious health risks (Gertler et al., 2005; Levitt and Venkatesh, 2007).

Even when taking into account the market for illegal work, women without college degrees face a disadvantage compared to their male counterparts. For women without college degrees, high-paying work can be obtained through entering an occupation that is male-dominated, entering a risky illegal occupation, or earning a college degree. Men, on the other hand, can obtain high-paying jobs without resorting to illegal market activity or obtaining a college degree.

[13] This analysis is complementary to the results shown in Charles and Luoh (2003), which finds a higher college earnings premium for women than men using observed log median earnings instead of log median earnings weighted by occupation.

lower non-college median log earnings. Within the college labor market, the gender difference in median log earnings is much smaller, since gender-based segregation across occupations is not as pronounced as it is among non-college occupations.

Overall, the evidence suggests that sorting across occupations creates larger gender differences in observed earnings among non-college workers than college workers. This sorting may stem from employer gender discrimination, which may limit women's opportunities in certain non-college occupations, or from employee preferences regarding work, which may result in a lower proportion of women willing to work in certain non-college occupations relative to men. Obtaining a college degree might therefore enable women to escape some of the observed inequalities entrenched in the non-college labor market through entering the (less unequal) college labor market.

Stylized Fact 3. *Among non-college workers, women's career characteristics appear worse than men's. Non-college occupations that employ women tend to have lower earnings growth, are less likely to offer retirement pensions, and are slightly less likely to offer health insurance.*

Attending college may change the worker's ability to pursue a *career*, as opposed to just a job. Based on the raw data, the non-college market appears more favorable to the career pursuits of men than women. I show that "traditionally male" non-college occupations enable their workers to support a family and remain committed to the same occupation in the long-term. In particular, "traditionally male" non-college occupations exhibit earnings growth and the provision of benefits, such as retirement pensions and employer-sponsored health insurance. "Traditionally female" non-college occupations, on the other hand, have little earnings growth, and are substantially less likely to provide retirement pensions. The data suggest that for the majority of women, obtaining a college degree is a pre-requisite for a rewarding career, while men can excel in their career without a college degree.

To approximate how earnings grow with age over an individual's work life, I use the National Longitudinal Study of Youth 1979 cohort and focus on the subsample of men and women with at least a high school diploma. I then split individuals by gender and college degree status to determine how hourly wage rates differ between non-college and college workers.

Figure 1.5 presents the median log hourly wage rate by age for workers between the ages of 25 and 55. Non-college women's career prospects appear to fare worse than non-college men's. In particular, the figure demonstrates that 1) the median earnings of non-college women are far lower at each age level than the median earnings for other occupations; and 2) the median earnings for non-college men are approximately equivalent to the median earnings of college women at each year of age. Although the evidence is purely descriptive and selection into working or college-going presents challenges to causal inference, Figure 1.5 provides motivating evidence that the non-college earnings gap between men and women may propagate throughout the work life and lead to large disparities in the value of a college degree for women relative to men.

Careers tend to exhibit not only earnings growth but also the provision of benefits, such as retirement pensions and health insurance. The last two columns of table 1.1 summarize information about benefits taken from the 2010 Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC).[14] "Traditionally female" non-college occupations are far less likely to have access to retirement pensions with their work, and are slightly less likely to be included in an employer group health plan. For example, among "traditionally male" occupations like truck driver, miner, and machinist, 46-62% of workers reported that their job offered retirement pensions, compared to only 11-36% of workers in female-dominated occupations like cashier, cosmetologist, or housekeeper. Among these occupations, over 95% of workers in "traditionally male" occupations reported being included in an employer group health plan, compared to less than 92% for workers in female-dominated occupations.

The descriptive evidence presented in this section establishes basic facts regarding the relationship between the non-college labor market and the gender gap in college enrollment. Several factors

[14]The American Community Survey (ACS) is large enough to estimate reliable summary statistics regarding work and earnings within occupations. Its measures regarding retirement income and health insurance, however, are too general for the purposes of this paper. Its retirement income questions ask about whether the respondent has income from retirement, survivorship, or disability benefits broadly. Its health insurance questions ask if the respondent is on employer-sponsored health insurance but does not ask about the policyholder, who can be any member in the respondent's family. In contrast, the CPS-ASEC Supplement asks individuals whether they have retirement income as a result of their employment, separate from survivorship payments, disability benefits, Social Security income, Veteran's administration payments or other forms of income. The CPS-ASEC also asks individuals if they are the policyholder for their employer-sponsored health insurance.

make it difficult to determine the causal effect of these non-college occupational gaps on the college gender gap. For instance, if higher ability individuals select into attending college, the observed college premium would be an inaccurate measure of the actual value of a college degree for the marginal man or woman. In addition, if women with low earnings potential select out of labor force participation, observed occupational sorting and earnings may incorrectly reflect the true difference in earnings potential between men and women. Furthermore, changes in the college gender gap could in turn affect the non-college occupation gap between men and women – for example, an exogenous increase in women's college enrollment relative to men's may mechanically decrease the labor share of "traditionally female" non-college occupations relative to "traditionally male" non-college occupations.

To isolate the role of the non-college labor market on the greater college enrollment of women over men, the next section employs two empirical exercises. These empirical exercises construct plausibly exogenous shifts in employment opportunities in various industries and occupations, allowing me to explore the college-going responses of men and women separately.

1.3 Male College Enrollment and the Oil and Gas Industry

Are non-college jobs important in influencing college enrollment rates? Access may be a limiting factor which determines who goes to college and who does not. College is expensive, time-consuming, difficult, and localized to certain areas. Lack of access is still a large public policy concern, as shown by the plethora of studies on expanding financial access to college (see Hoxby and Turner, 2015; Hill et al., 2005), expanding colleges to remote areas (see Garza and Eller, 1998), and providing students with the skills to succeed in college (see Bragg et al., 2006). If differential access to a college degree plays a large role in the college-going decision, then ability and means may explain much of the variation in college enrollment rates among high school graduates. Under such a model, changes in non-college employment may do comparatively little to shift college enrollment rates.

Therefore, the first question to address is whether changes in non-college jobs empirically lead to significant shifts in college enrollment, and whether men and women are differentially affected. I leverage the descriptive evidence in the previous section, which shows the large degree of gender segregation in the non-college labor market. This section uses employment in the oil and gas industry, a male-dominated field, to isolate the causal effect of male non-college employment on college-going.

Oil and gas production has substantial effects on local labor markets (see Bartik et al., 2017; Feyrer, Mansur, and Sacerdote, 2016; Allcott and Keniston, 2018; Cascio and Narayan, 2015), particularly for non-college work. For example, in 2006 breakthroughs in hydraulic fracturing and horizontal drilling enabled unprecedented quantities of oil and gas production in North Dakota (NPR, 2011; Brown, 2013). Oil production catapulted from 40 million barrels to 150 million barrels within the span of five years from 2006 to 2011, which created sudden and enormous changes in the labor market returns to work in the oil and gas industry.[15] By some estimates, the oil boom created 35,000 new jobs in 2011, which is enormous for a state with a population of 670,000 (McChesney, 2011). Unemployment in North Dakota fell to 3.3% in 2012, the lowest in the entire United States. Wages for non-college work also saw drastic growth: average salaries for oilfield workers rose to \$70,000-\$100,000, and truckers routinely made \$70,000-\$80,000 a year (Gold, 2015).

The example of North Dakota illustrates the ramifications of oil and gas production on the labor market. To explore whether oil and gas employment influenced the demand for a college education across the entire United States over last few decades, I use fluctuations in oil and gas production from the contiguous United States from 1970 to 2010.

Upticks in oil and gas production increase the employment demand for not only workers directly involved in oil and gas production (e.g., oil-well drillers, miners, drillers of earth), but also other workers in related fields. Truck drivers, shippers, material handlers, material movers, and haulers are required to transport oil to refineries; welders, electricians, mechanics, installation technicians,

[15]This information is obtained from oil production data provided by Allcott and Keniston (2018), which is described in detail later.

and millwrights are required to build and maintain the equipment required to facilitate production; structural metal workers, construction workers, concrete pourers, and foremen are required to build residential and commercial properties. My analysis considers occupations directly employed in the oil and gas industry, as well as "related" industries where employment demand is positively correlated with oil and gas employment.

Work in the oil and gas industry is especially dangerous and requires intensive physical labor. The industry is considered one of the most dangerous in America, and the workplace death rate in North Dakota had grown to five times the national average since the oil boom began (Berzon, 2015). It is perhaps for these reasons that employment opportunities in the oil and gas industry have historically attracted overwhelmingly male, blue-collar workers (Eligon, 2013). Figure 1.6 graphs the composition of workers in the oil and gas industry by sex and education group. Among workers with at least a high school diploma, men comprise the majority of the workforce in the oil and gas industry, while college and non-college women each constituted less than 10% of the entire workforce. Male high school graduates comprised of 50-70% of the workforce in occupations with high labor shares in the oil and gas industry, such as truck, delivery, or tractor driver, laborers outside construction, or miners.

To identify a causal channel between non-college labor market outcomes and college enrollment, I employ an instrumental variable strategy that exploits the fact that oil and gas production depends on the geology of the earth. There is a great deal of geographic heterogeneity in natural oil and gas reserves, which influences the sites of active oil and gas production. When demand for oil and natural gas is high, areas rich in natural reserves are able to dramatically increase employment, as demonstrated by the example of the North Dakota boom. However, areas poor in natural reserves show little change in employment over time. I also exploit time-series variation in domestic oil and gas employment and changes in international oil prices.

Using two instruments based on the geological variation in natural oil and gas reserves, national employment share in the oil and gas industry, and international import costs for crude oil, I find that a 1 percentage point increase in men's part-time non-college employment opportunities decreases male college enrollment by 2-4 percentage points. Among part-time college enrollees, the male college enrollment response is significantly greater than the female college enrollment response. This effect is strongest for individuals closest to the margin of college-going, and persists even after accounting for migration.

1.3.1 Data and Summary Statistics

Data on education, occupation, earnings, work, and demographic characteristics come from the Annual Social and Economic Supplement of the Current Population Surveys (CPS-ASEC), which are conducted every year jointly by the Bureau of Labor Statistics and the U.S. Census Bureau, and provided by the Integrated Public Use Microdata Series (Flood et al., 2015). The CPS-ASEC contains rich information regarding the occupations and industries in which each respondent worked, as well as detailed information regarding their earnings, hours and weeks worked, employment history, and schooling. Moreover, the CPS-ASEC contains rich data of migration patterns, which is especially useful when employing analysis that exploits spatial and time trends across labor markets.[16]

The main outcome variable used to measure college enrollment is *schlcoll*, the proportion of 16-24 year olds who report that they are *currently* enrolled in college full-time or part-time. To exclude students who may not have graduated from high school at the time of data collection, I restrict this sample to 18-24 year olds. There are two main advantages to using this variable as opposed to the educational attainment variables *educ* or *higrade*, which are the variables traditionally used in the education literature (see Autor and Acemoglu, 2011). First, by examining the proportion of students *currently* in college, I can measure instantaneous responses in the education decision to changing labor market conditions. This allows me to better hone in on the time window of interest, and decreases the likelihood that changes in college-going stem from events prior to the change in oil and gas employment that is of interest. Second, the variable distinguishes between full-time and part-time enrollees. I can therefore investigate whether changes in non-college employment opportunities have differential effects on different subgroups of the population. If individuals choose

[16]For more detail regarding the samples used in the analysis, see Data Appendix A.3.

to discontinue their education in the face of better non-college labor market conditions, we would expect the marginal college-goers, i.e. part-time college enrollees, to exhibit greater responses to changes in oil and gas employment opportunities. Indeed, my results show that the effect of oil and gas employment on college enrollment is most pronounced among male part-time college enrollees.

County-level data on natural reserves and oil and gas production were graciously provided by Hunt Allcott and Daniel Keniston. Allcott and Keniston (2018) compile a unique data set of resource endowments at the county level in the contiguous United States from 1962-2012 using information from DrillingInfo (a market research company), the United States Energy Information Administration (EIA), and local reports and geological surveys. I only use data for the years 1970-2010, since much of the data prior to 1970 is missing. Allcott and Keniston (2018) calculate the natural oil and gas reserve endowment per square area using the equation

$$r_c = \frac{\sum_{t=1960}^{T} \text{Production}_{ct} + \text{Proven Reserves}_{ct} + \text{Undiscovered Reserves}_{ct}}{\text{Area}_c}$$

Production_{ct} represents the production of oil or gas in year t in county c; $\text{Proven Reserves}_{ct}$ represent the reserves that oil and gas producers know to exist with relative certainty; $\text{Undiscovered Reserves}_{ct}$ are resources which oil and gas producers believe to exist due to the type of geological formations found in the earth, but have not yet determined to exist with certainty. The variable r_c represents the total amount of oil and gas reserves believed to ever exist beneath the earth in county c; it is invariant to oil and gas production from year to year.

I examine the effect of employment in the oil and gas industry, as well as employment in the oil, gas, and "related" industries. I classify workers as being employed in the oil and gas industry if they worked in oil and gas extraction, petroleum refining, petroleum production, mining, trucking, or warehousing and storage. For "related" industries, I add workers who were not explicitly employed in the aforementioned categories but had skills that were transferable to the work commonly performed in the oil and gas industry, such as construction workers, material handlers, geologists, miners, excavation operators, drillers of earth, operators of machinery, and petroleum engineers. In the results, I separately display my regressions for employment in the oil and gas industry and in oil, gas, and "related" industries. As expected, the results are larger for the sample of oil and gas workers, whose employment and education decisions are most directly impacted, than the sample of oil, gas, and "related" workers.

To establish baseline evidence that the oil and gas industry is especially relevant for men without college degrees, appendix table A.1 calculates the growth in employment share by gender and college status following national growth in oil and gas employment. I use two periods of time that experienced marked increases in national oil and gas employment: 1970-1980 and 2000-2010. The table demonstrates that the change in employment share is largest for non-college men by an order of magnitude in oil, gas, and "related" industries. In contrast, college men, college women, and non-college women experienced very little change in employment share. Table A.1 provides further support for the evidence in figure 1.6 that changes in oil and gas employment affect the non-college labor prospects of men the most.

My last data set comprises of the import prices of crude oil from foreign countries obtained from the U.S. Energy Information Administration (EIA). I use the price series of the landed costs of imported crude oil from 1973 (the first available year) to 2010.[17] These prices capture specific forms of variation in the cost of importing foreign oil, which influences the demand for domestic oil and gas production. The next section discusses this variation in greater detail.

1.3.2 Instrumental Variable Strategy

Using the resource endowment measure r_c, Allcott and Keniston (2018) construct a shift-share instrument that interacts county-level resource endowments with time-varying national employment in the oil and gas industry. I use a leave-one-out version of their instrument in my estimation procedure, but my analysis aggregates resource endowments to the state level. I compute the first

[17]Landed costs are the per-barrel price of oil, which include purchase, transportation, and insurance costs incurred from the purchase point to the point of discharge. Landed costs do not include costs incurred at the point of discharge, such as import tariffs or wharfage charges (EIA, 2018).

instrumental variable, the "employment instrument":

$$r_s E_{-s,t}$$

where $E_{-s,t}$ represents national employment in the oil and gas industry in year t and all states except for s, and $r_s = \sum_{c \in s} r_c$ represents the natural resource endowment in state s.

The first specification uses this instrumental variable, which I call the "employment instrument". My instrumental variable strategy makes two assumptions. First, it assumes that the geological composition of the earth affects oil and gas employment demand. Prior studies on the energy industry have found ample evidence for this causal channel (see Bartik et al., 2017; Feyrer, Mansur, and Sacerdote, 2016; Allcott and Keniston, 2018; Cascio and Narayan, 2015). Indeed, changes in oil and gas employment exhibit greater changes over time in states with above-median oil and gas natural resources ("high-resource" states) than states with below-median oil and gas natural resources ("low-resource" states). Figure 1.7 graphs the labor share of workers in the oil and gas industry by high- and low-resource state.[18] There exists a great deal of fluctuation in male employment in high-resource states, but male employment in low-resource states remains relatively constant. Female employment in both high- and low-resource states also remains constant over time, since the labor share of employment in oil and gas was very low (less than 1%) for women. The figure illustrates that states with rich natural resources are able to expand or diminish employment in the oil and gas industry, while states with relatively poor natural resources do not. The variation in natural resources influences the labor market outcomes of men far more than women, since jobs in the oil and gas industry comprise an extremely low share of female employment.

Second, the strategy assumes that the geological composition of the earth *only* affects changes in educational attainment through its effect on oil and gas employment opportunities. It is unlikely for

[18] States with above median natural resource endowments are Alabama, Arkansas, California, Colorado, Florida, Illinois, Kansas, Kentucky, Louisiana, Michigan, Mississippi, Montana, North Dakota, New Mexico, Ohio, Oklahoma, Texas, Utah, West Virginia, and Wyoming. States with below median natural resource endowments are Arizona, Connecticut, Delaware, Georgia, Iowa, Idaho, Indiana, Massachusetts, Maryland, Maine, Minnesota, Missouri, North Carolina, Nebraska, New Hampshire, New Jersey, Nevada, New York, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Virginia, Vermont, Washington, and Wisconsin.

educational attainment to directly affect the composition of natural oil and gas reserves below the ground, but omitted variables correlated with educational attainment may also be correlated with the geology of the earth. To investigate, I compare the observable characteristics in states with high resource endowments to states with low resource endowments for each year from 1970 to 2010. The results are summarized in appendix tables A.2-A.6.[19] Overall, resource endowments do not appear to determine significant differences across states: female college enrollment, male college enrollment, the proportion of women in a state, the proportion of blacks in a state, and the proportion by age bin do not differ systematically or significantly by the state's level of natural resources. In a few of the years, the proportion of individuals by different age bins are significantly different between high- and low-resource states – for example, the proportion of individuals between the ages of 18 to 25 differs significantly between high- and low-resource states in 2000, but for all other years, this relationship is insignificant. In all regressions, I include state fixed effects to control for any time-invariant characteristics correlated with education and employment.

The leave-one-out variable for employment $E_{-s,t}$ captures time-series variation in total domestic employment in the oil, gas, and "related" industries for all states except for the state of interest, s. Oil and gas employment in all other states is positively correlated with employment in state s, since oil and gas employment expands when demand for domestic oil and gas is high. But because actual employment in state s in year t is excluded, the instrument by construction nets out contemporaneous local labor market shocks that may influence both employment and college enrollment. Note that even if shocks are correlated across states and $E_{-s,t}$ is not exogenous to college enrollment rates in state s, the exclusion restriction for the instrument is satisfied as long as natural resources for oil and gas production do not depend on college enrollment rates (Goldsmith-Pinkham et al., 2018).

Overall, the intuition behind the employment instrument is that when national employment in the oil and gas industry rises, states with richer natural resource endowments can take advantage of their greater capacity for production by increasing oil and gas employment relative to states with poorer natural resource endowments. The effect of the geology of the earth on the demand increase in oil

[19] Only the years 1970, 1980, 1990, 2000, and 2010 are shown for brevity, but all other years are available upon request.

and gas workers should be uncorrelated with other factors that influence college enrollment. For example, during a rise in national oil and gas production, employment opportunities in oil, gas, and related industries will dramatically increase in North Dakota, a state rich in oil and gas reserves, but stay constant in South Carolina, a state with no known oil and gas reserves. This variation is useful in assessing the change in the proportion of current college enrollees as a result of expanding oil and gas employment.

In Specification 1, I regress employment state s in year t on the employment instrument, a vector of state-level controls, and state fixed effects. The controls include percent female, percent black, and percent by ten-year age bin.

$$E_{st} = \alpha_0 + \alpha_1 r_s E_{-s,t} + \alpha_2 X_{st} + \theta_s + u_{st} \tag{1.3.1}$$

In a second specification, I add a second instrumental variable that interacts the resource endowment variable with foreign oil prices. This “price instrument” is computed as

$$r_s p_t$$

where p_t is the average price of imported crude oil in year t. As before, $r_s = \sum_{c \in s} r_c$ represents the natural resource endowment in state s.

One feature of using international oil prices is that landed import costs of foreign crude oil imports, which depends on the supply of oil from other countries and the demand for oil worldwide, should influence labor demand for domestic oil and gas production. Moreover, supply and demand factors in the U.S. oil and gas market should play a small role in affecting international oil prices.[20] In robustness checks, I use other price series for imported crude oil, namely the price of oil from OPEC countries and non-OPEC countries (Specifications 3 and 4, respectively). I find very similar

[20]Note again that the instrumental variable strategy does not require that *international oil prices* be completely exogenous to U.S. oil and gas employment. Rather, the exclusion restriction only requires that the resource endowment variable r_s be unaffected by U.S. oil and gas employment (Goldsmith-Pinkham et al., 2018).

results in all regressions.

In the first stage for specifications 2-4, I regress employment state s in year t on the employment instrument and the price instrument, a vector of state-level controls, and state fixed effects. The controls include percent female, percent black, and percent by ten-year age bin.

$$E_{st} = \alpha_0 + \alpha_1 r_s E_{-s,t} + \alpha_2 r_s p_t + \alpha_3 X_{st} + \theta_s + u_{st} \tag{1.3.2}$$

From the first stage, I obtain the linear prediction in employment demand for the oil and gas industry, $\widetilde{E}_{st}$. Under the assumptions stated above, $\widetilde{E}_{st}$ should be exogenous to state-specific characteristics that would be correlated with both college enrollment and employment in the oil and gas industry. Using the results from the first stage, I then estimate the effect of changes in employment demand on Y_{st} : the male college enrollment rate, the female college enrollment rate, and the college gender gap (the male college enrollment rate - the female college enrollment rate). The second stage regression for specifications 1-4 is

$$Y_{st} = \beta_0 + \beta_1 \widetilde{E}_{st} + \beta_2 X_{st} + \theta_s + \varepsilon_{st} \tag{1.3.3}$$

The identification assumption in the instrumental variable specification would be violated if increasing employment demand changed the composition of workers in a state by attracting migrants. Any negative relationship between oil and gas employment opportunities and college enrollment rates may be caused by a net influx of non-college migrants, as opposed to existing residents choosing to forego attending college due to a rise in non-college employment opportunities. I therefore run additional regressions using subsamples of only individuals who did not migrate across states in the last year or who did not move for work purposes. The results are robust to these alternative specifications.

1.3.3 Results

All regressions are conducted at the state-year level. All regressions control for demographic characteristics at the state level (proportion female, proportion black, proportion by 10-year age bin, oil production, gas production), state fixed effects, and year fixed effects. Regressions are clustered at the state level and robust against heteroskedastic error terms.

Ordinary Least Squares

To examine baseline relationships between college enrollment and employment in the oil and gas industry, I run an ordinary least squares regression. Table 1.2 summarizes the coefficient estimates for employment in the oil and gas industry (Panel A) and for employment in the oil, gas, and related industries (Panel B). I separately examine the correlation in enrollment for full-time male enrollees (column 1), part-time male enrollees (column 2), full-time female enrollees (column 3), and part-time female enrollees (column 4). Overall, employment and college enrollment do not appear to be significantly correlated. The one exception is the significantly negative correlation of -0.48 $(p < 0.05)$ between male full-time college enrollment and employment in oil, gas, and related industries.

The estimates in table 1.2 alone cannot be used to make causal statements regarding non-college employment and education. For example, ordinary least squares cannot account for reverse causality: the proportion of individuals who choose to enroll in college may affect labor supply in the oil and gas industry. Additionally, there may be omitted variables that influence both education and employment. For instance, areas with high oil and gas employment may also be more rural, and more rural areas tend to have lower college enrollment rates. To isolate the effect of employment on education, I use a series of instrumental variable approaches. The next sections report the results of these approaches.

First Stage Results

Specifications 1 and 2 estimate the main results of the model. Specification 1 uses only the employment instrument (equation 1.3.1), while Specification 2 uses both employment and price instruments (equation 1.3.2). Both specifications produce similar estimates, despite using difference sources of variation to estimate the causal effect of interest. Specification 1 solely uses time-series variation in oil and gas employment in all states except for the state of interest. Specification 2, on the other hand, includes time-series variation in the foreign cost of importing crude oil, which has been shown to affect domestic oil and gas employment (see Hamilton, 2004).

Table 1.3 summarizes the first stage regressions. The upper panel presents the results of estimating Specification 1, while the lower panel presents the results of estimating Specification 2. The instruments have strong and significant positive correlations with both oil and gas employment (column 1) and oil, gas, and related employment (column 2). Under Specification 1, I estimate that a marginal 1 percentage point increase in the employment instrument leads to an additional 2 percentage point increase in oil and gas employment ($p < 0.01$). When including employment in related industries, this estimate increases to about 3 percentage points ($p < 0.01$). Under Specification 2, the point estimates on the employment instrument decreases, although not significantly. An additional 1 percentage point increase in the employment instrument increases employment in the oil and gas industry by about 1.4 percentage points and employment in oil, gas, and related industries by about 2.6 percentage points. The price instrument is economically significant and positively predicts employment, suggesting that domestic employment in oil and gas increases when the cost of foreign imports is high. All specifications pass the Anderson-Rubin test for weak instruments.

Figure 1.8 presents the results of the first stage predictions on actual employment. The left panel graphs the average labor share across the 48 contiguous states for oil and gas employment, while the right panel graphs the average labor share for oil, gas, and related employment. The solid line represents actual labor share. The long dashed line represents the first stage prediction from Specification 1, and the short dashed line represents the first stage prediction from Specification 2.[21]

[21] Year dummies are not included in the first stage prediction, since discrepancies between the actual and predicted

The first stage predictions appear to fit actual average labor share quite well after 1980 for both oil and gas employment *and* oil, gas, and related employment. Moreover, the first stage predictions do not depend on the choice of instruments: there is little discrepancy in the predictions between Specifications 1 and 2 when these predictions are averaged across states. In the results presented below, I nevertheless show the estimates from both Specifications 1 and 2, since average labor share masks the heterogeneity in labor share predictions across states. The difference in predictions for labor share, $\widetilde{E}_{st}$, may still differ between Specifications 1 and 2 from state to state.

Second Stage Results

Using both Specifications 1 and 2, I then estimate the second stage regression represented by equation 1.3.3. The results for oil and gas employment are presented in table 1.4, while the results for oil, gas, and related employment are presented in table 1.5. In both tables, the top panel presents Specification 1, which only uses the employment instrument, and the bottom panel presents Specification 2, which uses both the employment instrument and the price instrument. I separately examine the impact of employment on male full-time enrollment (column 1), male part-time enrollment (column 2), female full-time enrollment (column 3), and female part-time enrollment (column 4).

Overall, employment appears to have no effect on full-time enrollment for men or women. However, as depicted in Table 1.4, employment in the oil and gas industry has a substantial and significant negative impact on part-time college enrollment among men. A marginal 1 percentage point increase in employment leads to a decline in part-time male college enrollment by almost 4 percentage points in both Specifications 1 and 2 ($p < 0.01$). For female part-time enrollment, the coefficient on employment is marginally significant ($p < 0.10$) in Specification 1 but insignificant in Specification 2.

When examining the effect of employment in oil, gas, and related industries (Table 1.5), the results are qualitatively similar but smaller in magnitude, as expected. Because the sample now includes

values load on year dummies. This would lead to perfect predictions of actual mean labor share after 1980 or so.

workers who are less directly impacted by changes in the availability of oil and gas job opportunities, one would expect the effect on college enrollment decisions to be less pronounced. Employment in oil, gas, and related industries appears to have no significant impact on full-time enrollment for men or women, but a substantial and significant negative impact on part-time college enrollment for men. Increasing the labor share in oil, gas, and related industries by 1 percentage point leads to a 2 percentage point decline in the proportion of 18-24 year old men enrolled in college part-time. Similar to Table 1.4, the fourth column of Table 1.5 shows that employment has a marginally significant negative impact on female part-time enrollment under Specification 1 but not Specification 2.

Overall, the results lend support to the story that non-college employment opportunities shift college enrollment decisions. Such a mechanism would shift people at the margin of college-going, who are likely to be those who enroll in college part-time. In both tables 1.4 and 1.5, we find that among men, part-time college enrollees are significantly affected by changing employment opportunities but full-time college enrollees are not. Furthermore, the group most affected by the change in employment opportunities (in this case, young men) appears to have significantly stronger responses in their current college enrollment rates. The negative coefficient on enrollment for part-time male enrollees is significantly larger than that for part-time female enrollees in all specifications, for both oil and gas employment (Table 1.4) and for oil, gas, and related employment (Table 1.5). While the coefficient for part-time male enrollment is significant, large, and robust to alternative specifications, the coefficient on part-time female enrollment is marginally significant at best, and often insignificant. The results indicate that changes in oil and gas employment elicit a significantly stronger response among men than women when it comes to foregoing a college education.

1.3.4 Robustness

I perform a series of robustness checks in order to evaluate the strength of the results reported in Tables 1.4 and 1.5. First, the results may be driven by compositional effects: low-skill migrant workers could relocate to areas with booming oil and gas economies, which would mechanically create a negative correlation between oil and gas employment and college enrollment status. I therefore take advantage of the CPS's rich data on migration patterns and replicate my main results using subsamples of the worker population. Second, the results may be sensitive to the choice of international oil prices. Instead of the average oil prices used in the main analysis, I use two additional price series: oil prices from OPEC countries and oil prices from non-OPEC countries.[22]

Migration

The CPS contains rich information regarding migration patterns and reasons for moving. To determine if my main results are driven by the influx of low-skilled workers into areas of high oil and gas production, I use the CPS's migration data to restrict my analysis sample further. I restrict my first sample to workers who did not report moving for work purposes. My second sample includes only workers who reported having not moved across states in the past year.

My main results hold among workers who did not move for work purposes, as shown by Tables A.7-A.9. Table A.7 replicates the first stage results, table A.8 replicates the second stage results with oil and gas employment, and table A.9 replicates the second stage results with oil, gas, and related employment. The point estimates for the first stage regressions using Specifications 1 and 2 are nearly identical to those estimated using the full analysis sample, and once again all regressions pass the Anderson-Rubin test for weak instruments. The second stage results are also extremely similar to those obtained using the full analysis sample: there is no significant effect on full-time college enrollment for men or women, but a significant and large negative effect on male college enrollment (coefficients are around -3.6, $p < 0.01$). Among workers who did not move for work purposes, the coefficients on female part-time enrollment are all insignificantly different from 0. Again, male part-time college enrollment has a significantly stronger negative response than female part-time college enrollment.

Among workers who reported not having moved across states in the past year, the main results also

[22] OPEC stands for the Organization of Petroleum Exporting Countries. OPEC countries consist of Algeria, Angola, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, Qatar, United Arab Emirates, and Venezuela.

remain robust. Table A.10 replicates the first stage results. Although Specification 1, which only uses the employment instrument, produces almost identical results as the main analysis sample, the inclusion of the price instrument in Specification 2 leads to a weak first stage in the regression of oil and gas employment on the instruments (column 1, F-statistic$<$ 10). Specification 2 passes the weak instrument test in the regression of oil, gas, and related employment on the instruments (column 2, F-statistic $= 11.850$).

In spite of the weak first stage in Specification 2, Table A.11 shows that the effect of oil and gas employment on college enrollment among non-migrants is extremely similar to the effect for the main analysis sample. Again, oil and gas employment appears to have no significant effect on full-time college enrollees (although the coefficient for male college full-time enrollment is marginally significant in Specification 2, $p < 0.10$). The effect of oil and gas employment on female part-time enrollment becomes entirely insignificant. The effect for male part-time enrollees is on the order of 4 percentage points for each additional 1 percentage point increase in oil and gas employment share $(p < 0.01)$. Table A.12 demonstrates that coefficient estimates on oil, gas, and related employment among non-migrants is extremely similar to the main analysis sample. While labor share has no effect on full-time enrollment for men, or enrollment for women, there is a significant and sizable effect on part-time male enrollment rates.

Prices

The first stage predictions for employment in the oil and gas industry, $\widetilde{E}_{st}$, may be sensitive to the choice of prices for imported crude oil. I therefore substitute average prices with the import price from OPEC countries (Specification 3) and from non-OPEC countries (Specification 4). Overall, I find very similar estimates in both the first stage results and the second stage results. Table A.13 presents the first stage results of regressing employment share on instruments. Compared to using average prices, using OPEC and non-OPEC prices barely changes the coefficient estimates on the employment IV and the price IV. In all cases, the first stage regressions pass the Anderson-Rubin weak instruments test. Table A.14 replicates the two-stage least squares regression of college enrollment on oil and gas employment, while table A.15 replicates the regression of college enrollment on oil, gas, and related employment. The results are extremely similar across specifications. Employment share has a substantial and significantly negative impact on male part-time college enrollment, but no systematic significant effect on male full-time enrollment or female enrollment. As before, the coefficient estimates are consistently larger when considering the impact of oil and gas employment than oil, gas, and related employment, perhaps because oil and gas workers are most directly impacted by changes in oil and gas job opportunities and would therefore be more responsive in their college enrollment decisions.

1.4 Female College Enrollment and Automation

Section 1.3 presents evidence that men's college-going decisions are extremely responsive to changes in non-college employment opportunities. Does this same effect hold for women? It may be the case that women attend college for different reasons than men (e.g., attending college increases the likelihood of marrying a high earning spouse), so shifts in non-college employment opportunities may do little to shift college enrollment rates for women. This is important in determining how important non-college jobs are in contributing to the gender gap in college enrollment: do non-college jobs only affect the college gender gap by limiting the proportion of men who select into college-going? Or do non-college employment opportunities contribute to the growth in college enrollment for women as well?

I investigate this question by using the case of automation. Examining the correlation between college enrollment and non-college job opportunities alone is insufficient to isolate causal effects of non-college employment on college enrollment, since areas with high proportions of female college-goers will mechanically have lower shares of female workers in non-college jobs. Instead, I use an instrument for predicted automation exposure to show that a decline in non-college jobs for women, brought about by the automation of the office, leads to an increase in female college enrollment.

Automation led to dramatic changes in labor market (see Autor, Levy, and Murnane, 2003; Spitz-

Oener, 2006; Goos, Manning, and Salomans, 2009; Goos, Manning, and Salomans, 2014; Autor and Dorn, 2013; Autor and Acemoglu, 2011; Jaimovich and Siu, 2012; Cortes et al., 2014; Cortes et al., 2016), particularly for women (Black and Spitz-Oener, 2010; Autor and Wasserman, 2013; Beaudry and Lewis, 2014). I show that the continuous automation of the office decreased women's non-college job prospects and induced them to enter college at greater rates. This analysis complements the results from Section 1.3 by demonstrating that like male enrollment, female enrollment responds to changes in their non-college opportunities. Combining this result with the stylized facts in section 1.2 implies that the anemic options for women in today's non-college labor market are a key reason behind the greater proportion of women than men on college campuses today.

A secondary finding in this section is that automation led to historical growth in female college enrollment over time. Jobs that were displaced by automation, such as secretarial work, clerical work, telephone operators, and typists, employed the majority of non-college working women in 1970. From 1970 to 2010, the labor share of secretaries declined by 30%, while the labor share of typists declined by 86%. These large changes in key occupations for non-college female labor transformed the labor market, such that the labor market alternatives to college-going for women became increasingly scarce over time.

The adoption of automated systems by firms was an ongoing process throughout the 20th and 21st century. Automation significantly changed the content of jobs, by changing the marginal productivity of machines relative to that of human labor at certain tasks. To measure this change, the literature on automation focuses on the "routine", "manual", and "abstract" content of tasks performed in each occupation (see Autor and Dorn, 2013). "Routine" tasks are defined to be codifiable tasks that can be executed following an explicit set of rules. Technological development increasingly made it easier to write computer programs to execute these tasks, which had previously been performed by human labor. "Manual" tasks are defined as tasks required to be performed in person, such as physical tasks or service tasks. Finally, "abstract" tasks require more mental energy and involve more complex processes that could not be directly programmed, such as problem solving, management, and complex communication.[23] Prior work argues that automation directly substituted for routine jobs and complemented abstract and manual jobs.[24]

The other significant effect of automation, which has been overlooked and under-explored, is the disproportionate impact of automation on the occupations of women (Autor and Wasserman, 2013; Black and Spitz-Oener, 2010). Routine-intensive occupations were overwhelmingly dominated by female workers. In fact, I present new evidence that routine-intensive occupations employed over 60% of the high school graduate work force among women between the ages of 18 and 30. Moreover, "abstract"-intensive occupations tended to require a college degree, while occupations that were relatively "routine"- or "manual"-intensive did not. Thus, by displacing routine-intensive jobs but complementing abstract-intensive jobs, automation could have changed the labor market returns to attending college, and this change may have been stronger for women than for men. To my knowledge, this paper is the first to show that the decline in routine jobs significantly increased women's college enrollment. Thus, automation directly changed the college gender gap over time, by helping drive women's enrollment to grow and eventually surpass men's enrollment.

This empirical exercise, combined with the results from Section 1.3, reveals that non-college employment opportunities have dramatic effects on the college enrollment rates of both men and women. Due to gender differences in the distribution of workers to occupations, shocks to certain occupations can change the gender disparity in the non-college labor market, and therefore the enrollment rate of women relative to men. Putting these findings together, it would then be natural for women's worse non-college job prospects to generate greater demand for a college degree among women relative to men.

[23] Research has shown that "abstract" tasks are becoming increasingly automated, but that this is a more recent phenomenon that began after the 1990s (Frey and Osborne, 2017; Hershbein and Kahn, 2016).

[24] Prior work has demonstrated that computers and routine tasks functioned as substitutes in production while computers and abstract tasks were complements (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002). Computers increased the marginal productivity of abstract tasks and labor demand for workers with abstract skills (Brynjolfsson and Hitt 2000; Bresnahan et al., 2002; Spitz-Oener 2008; Autor, Levy, and Murnane, 2002). Abstract tasks typically had larger educational requirements of workers, and the onset of computerization increased these educational requirements (Spitz-Oener, 2006; Brynjolfsson and Hitt, 2000; Autor, Levy, and Murnane, 2002).

1.4.1 Data

The analysis in this section utilizes the census microdata for all decades in 1950-2000 and American Community Survey (ACS) data for each year from 2001 to 2010. Both the census microdata and the ACS data are collected by the U.S. Census Bureau and provided by the Integrated Public Use Microdata Series (IPUMS; Ruggles et al., 2017). The census and ACS data are the largest publicly available data sets, making them some of the only data appropriate for occupation-level analyses of employment and wage trends at disaggregated levels of geography. The census data for 1950, 1960, and 1970 include 1% of the population. The census data for 1980, 1990, and 2000 include 5% of the population. The American Community Survey data include around 0.4% of the population for the years 2001-2004 and 1% of the population for the years 2005-2010. For the analysis in this section, I use either the sample of all men and women or the sample of 18-30 year old men and women. The data provide information on college enrollment, work characteristics, and demographic variables.

To measure how automation changed the demand for skill profiles over time, I use pre-existing occupational measures and the task-based approach for measuring the impact of automation that is typically used in the literature (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos, Manning, Salomans, 2014), following the suggestion in Autor (2013) that researchers re-use, recycle, and re-apply “off-the-shelf” measures of occupational skill requirements so that findings can be assessed under common metrics. In particular, I use the data set on work content compiled by Autor and Dorn (2013). Autor and Dorn (2013) uses the Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET) to construct measures of routine, manual, or abstract task content for each occupation.

The primary measure of occupational task content in my analysis is the composite measure of routine task intensity (RTI), which represents the relative routine-intensity of an occupation. It is constructed by Autor and Dorn (2013) using the routine-, manual-, and abstract-task measures for each occupation k:

$$\mathrm{RTI}_k = \ln(\mathrm{routine}_k) - \ln(\mathrm{manual}_k) - \ln(\mathrm{abstract}_k) \tag{1.4.1}$$

Occupations with high levels of the variable $\mathrm{routine}_k$ relative to the variables manual_k and $\mathrm{abstract}_k$ score high on RTI_k, while occupations with low levels of the variable $\mathrm{routine}_k$ relative to the other two task measure variables score low on RTI_k.

1.4.2 Descriptive Evidence

The descriptive evidence presented here serves two objectives. First, it demonstrates that young women's non-college employment opportunities were especially vulnerable to displacement by automation, relative to young women's college employment opportunities and young men's (college and non-college) employment opportunities. Second, it illustrates the variation that drives the identification of the instrumental variable approach.

I start by evaluating a well-known result in the routine-biased technical change literature: the routine task intensity of occupations declined over time because automation displaced routine-intensive jobs (Autor and Dorn, 2013; Autor, Levy, and Murnane, 2003; Goos, Manning, and Salomans, 2014). Figure 1.9 graphs the average routine task intensity (RTI) in the labor force for 18-30 year old workers separately for men and women. A comparison between men and women reveals that the RTI content of women's jobs was much higher than the RTI content of men's jobs for all years in the data period, indicating that a greater proportion of the female labor force was employed in highly routine occupations relative to the male labor force. In 1950, average RTI was almost 0.8 standard deviations higher for women than for men.

Most importantly, figure 1.9 shows that the RTI of women's jobs plummeted from 1970 on, while the RTI of men's jobs stayed relatively steady at 0.2 standard deviations below the average. Thus, the documented decline in routine-intensity discussed in the prior literature appears to only exist for young women; for young men, RTI stayed relatively level. The evidence indicates that women's jobs drove the decline in routine task intensity among young workers. Increased automation, and the subsequent decline in the routine content of human labor, appears to have displaced women's job prospects by more than men's job prospects.

Appendix figure A.2 decomposes the change in RTI into its three component parts: the routine intensity measure, the manual intensity measure, and the abstract intensity measure. The raw data show that the decline in RTI for women is driven entirely by the decline in the routine intensity measure.[25] These trends are consistent with the evidence in appendix table A.16, which summarizes correlations between routine and abstract work for college and non-college female workers from 1950 to 2000. For women, the strong positive correlation between not attending college and working in routine-intensive jobs dissipates over the decades, while the positive correlation between attending college and working in abstract-intensive jobs becomes stronger and larger.

Figure 1.9 suggest that women's jobs experienced declines in routine-intensive task content while men's jobs did not. Did the automation of the office displace some jobs more than others in way that affected women more than men? Figure 1.10 shows that this appears to be the case. The top panel demonstrates a precipitous decline in high-RTI occupations since 1970, while the labor share of low-RTI occupations increased.[26] In the middle panel, I separately plot the labor share of high- and low-RTI occupations and find that labor share for women in high-RTI occupations declined, whereas the labor share for men in high-RTI occupations did not. Women in high-RTI occupations peaked at a little over 25 percent of the labor force in 1970, before declining precipitously to about 20 percent of the labor force in 2000. In contrast, women in low-RTI occupations, and men in high- and low-RTI occupations did not experience declines in labor share. In fact, their labor share actually rose slightly during this period.

The natural next question is: did automation affect the college-going margin for women? The bot-

[25] Abstract intensity increased by the same extent for both men's and women's jobs, while manual intensity remained relatively constant during this time.

[26] To accord with measures commonly used in the literature, I define high-RTI occupations as occupations in the top third of RTI in 1980, and low-RTI occupations as occupations in the bottom third of RTI in 1980 (see Autor and Dorn, 2013). Because that the graph only depicts the labor share for occupations at the top and bottom third of RTI, the labor shares do not sum to one in any year.

tom panel of figure 1.10 breaks down the change in labor share for college and non-college women by high- and low-RTI occupations. The employment share of high-RTI non-college women peaked at 14 percentage points before dropping almost 60% by 2000. For non-college women in low-RTI occupations, labor share remained steady, and for college women, the labor share increased during this period. These trends suggest that the displacement of jobs by automation documented by the prior literature disproportionately impacted the non-college job prospects of women. Simultaneously, the labor share of college women in both high- and low-RTI occupations increased. The results point to an asymmetrical effect of automation on labor market prospects, where the occupations that employed a large share of the non-college female workforce declined in labor share but the occupations that employed college women did not.

Finally, automation fundamentally changed the labor structure of non-college occupations. Figure 1.11 graphs the density of occupations by proportion of female workers in each occupation. The left panel displays the density for "non-college" occupations, in which the majority of workers had only high school degrees, while the right panel displays the density for "college" occupations, in which the majority of workers had college degrees. There were striking changes in gender composition among college and non-college occupations from 1970 to 2010. In 1970, the majority of non-college occupations were male-dominated (less than 30% women), some non-college occupations were female-dominated (at least 70% women), and very few occupations were "gender-equitable" (30-70% women). The female-dominated occupations that form the mass at the right of the 1970 non-college occupation distribution were all highly routine-intensive occupations: stenography, typist, secretary, telephone operator, etc. In contrast, college occupations were overwhelmingly male-dominated.

Over time, as automation displaced routine-intensive jobs, the mass at the right of the non-college occupation distribution declined and eventually disappeared. By 2010, almost all non-college occupations were male-dominated, and the non-college labor market became a relatively inhospitable place for women. In contrast, the number of female-dominated or gender-equitable college occupations rose. The descriptive evidence suggests that in the 1970s, women had job options in the non-college market but relatively few job options in the college market. Over time, their non-college job prospects declined while college occupations became more accessible. By 2010, the reverse is true. Very few non-college jobs were accessible to women, and the occupations that employed women had significantly lower wages, as shown by figure 1.2. On the other hand, women's access to the college labor market dramatically expanded, since college occupations that used to be traditionally male are now gender-equitable or even female-dominated.

1.4.3 Identification

To instrument for the decline of routine-intensive employment opportunities, I follow the approach of Autor and Dorn (2013) and construct a modified shift-share instrument that predicts the employment share of routine-intensive occupations in a local labor market. The logic behind this instrument is that local labor markets with higher 1950 shares of routine-intensive employment ("routine employment share") experienced greater automation than local labor markets with low 1950 shares of routine-intensive employment. The instrument is constructed as follows:

$$\widehat{\text{RSH}}_c = \sum_{i=1}^{I} E_{i,c,1950}\text{RSH}_{i,-c,1950} \tag{1.4.2}$$

where a local labor market is a commuting zone, indexed by c. $E_{i,c,1950}$ represents the employment share of industry i in commuting zone c in 1950. $RSH_{i,-c,1950}$ represents the share of routine occupations in industry i in all states except the state with commuting zone c.

In the first stage regression, I interact the shift-share instrument with a matrix of year dummies to nonparametrically predict the effect of the instrument on the actual labor share of routine-intensive employment in future years. The idea behind the identification strategy is that local labor markets with high baseline shares of industries that experienced a large amount of automation later on will experience larger displacement of women's non-college labor market opportunities later on. The instrument relies on the assumption that high 1950 shares of industries that automated later on should influence employment opportunities in future years, but not directly influence college enrollment rates in future years.

The first stage regression is

$$\text{RSH}_{ct} = \alpha_0 + \alpha_1 \widehat{\text{RSH}}_{c,1950} \times \mathbf{1}(\text{year} = t) + \alpha_2 X_{ct} + \phi_t + \theta_c + e_{ct} \tag{1.4.3}$$

where c indexes local labor market, t indexes the year, X_{ct} is a vector of controls for local labor market c at year t, ϕ_t is a vector of year dummies, and θ_c is a vector of fixed effects for local labor markets. I use the estimates from the first stage regression to predict variation in actual routine share employment for each year t, denoted by $\widetilde{RSH}_{ct}$.

The second stage regression is

$$Y_{ct} = \beta_0 + \beta_1 \widetilde{RSH}_{ct} + \beta_2 X_{ct} + \phi_t + \theta_c + \varepsilon_{ct} \tag{1.4.4}$$

The IV regression estimates the effect of declining employment opportunities in routine-intensive industries on the female college enrollment rate, the male enrollment rate, and the college gender gap (defined as the male college enrollment rate less the female college enrollment rate).

The first stage regression obtains the variation in actual routine employment share due to the industry composition of a local labor market in the base year of 1950, weighted by the national routine employment share of each industry in 1950. The measure is compiled from industry characteristics in 1950, which pre-date the changes in automation that occurred starting in the 1970s. The instrument should therefore net out any post-1950 correlations between employment opportunities and college enrollment, as long as these relationships are independent of 1950 industry composition. Moreover, since the instrument takes the average routine share of employment per industry for all states except the one that contains the commuting zone of interest, it nets out local labor market shocks that influence educational outcomes along dimensions other than changes in the employment share of routine-intensive occupations.

The exclusion restriction specifies that industry composition in a base year influences college enrollment decisions in a future year only through changing non-college occupations in that future year. This instrument leverages the argument in Autor and Dorn (2013) that labor markets with large baseline shares of industries high in routine-intensive work were the ones with greater demand for automation. Since automation displaced routine-intensive work, the instrument should predict future declines in job market opportunities for workers in routine-intensive occupations. My first-stage results, presented in table 1.6, are consistent with this argument. The correlation between the actual employment share of routine-intensive occupations and the instrumental variable is negative for all years starting in 1970, when routine-intensive employment shares first began declining. The correlation grows strictly more negative with each successive decade, which is also consistent with the story that the growth of automated processes in the workplace lead to persistent contractions in employment demand among routine-intensive occupations.[27]

There are a number of alternative explanations that lead to a violation of this exclusion restriction. First, one might argue that increased automation in different labor markets could have made it easier to attend school through decreasing the costs of finishing high school or expanding the resources of post-secondary institutions. For this alternative hypothesis to explain my findings, automation would have had to affect men and women differentially, since I find a significantly larger increase in female enrollment relative to the insignificant effect on male enrollment. This appears unlikely.

Another alternative hypothesis is that high 1950 levels of routine-intensive employment are correlated with omitted characteristics that influence both non-college employment and schooling choices. For example, local labor markets with social norms that were conducive to women work-

[27] First stage regressions were also conducted using median wages in routine-intensive occupations (not shown). Autor and Dorn (2013) do not find that automation uniformly decreased wages in the way that it did with employment. My findings are similar. When the instrument is interacted with year dummies, the resulting coefficients do not appear to be significantly negative and decreasing. The first stage regressions show that wages do not experience monotonic declines in labor markets with high predicted 1950 routine share employment, which violates a necessary condition of the LATE theorem for IV estimation (Angrist and Pischke, 2009). Because the instrument is a better predictor of employment opportunities in routine-intensive occupations, the analysis focuses on the relationship between employment opportunities in routine-intensive occupations and college enrollment.

ing may have had higher 1950 routine employment shares. These social norms could then have encouraged more women to attend college twenty years later. Here, it is important to note that my identifying variation draws from *predicted* routine employment shares, not actual routine employment shares. The variation in my specification arises from the industry composition in a local labor market in 1950. In other words, local labor markets with high 1950 shares of the industries that happened to automate faster later on were the markets that had high college enrollment among women (but not men) later on. By constructing predicted routine employment share using a shift-share approach, the instrumental variable strategy nets out the confounding effects of actual initial market conditions, as well as unobservable characteristics correlated with actual initial market conditions.

1.4.4 Results

I find that declining routine-intensive occupations, which employed the majority of the non-college female workforce among young workers, increased the college enrollment rate significantly more for women than for men. The main instrumental variable regression results are reported in table 1.7 for the sample of 18-25 year olds. Table 1.8 reproduces the regression for the larger sample of 18-30 year olds. For both tables, the first two columns report the results for women, the second two columns report the results for men, and the last two columns report the results with the gender gap (male enrollment minus female enrollment) as the dependent variable. All regressions include fixed effects for commuting zone, year, and region. The even-numbered columns also include commuting-zone level controls for total population, proportion of women, proportion of blacks, proportion of Hispanics, proportion by ten-year age bin.

Table 1.7 reports the main regression estimates, where the outcome variable is the proportion of 18-25 year olds who have ever enrolled in college. Decreasing the share of routine-intensive occupations by an additional percentage point leads the female enrollment rate among 18-25 year olds to increase by 0.50 percentage points ($p < 0.05$), as shown in column (1). In contrast, the effect on male enrollment, shown in column (3), is very close to zero (point estimate of -0.04) and statistically insignificant. The coefficient estimates are both economically and statistically significantly greater for women than for men. Column (5) shows that the net impact on the college gender gap (male enrollment less female enrollment) is a decline of 0.46 percentage points ($p < 0.01$). Columns (2), (4), and (6) add demographic controls at the commuting zone level, which allow for variation in enrollment rates due to the demographic composition of individuals within the commuting zone. I find that in all cases, the point estimates do not significantly change after the inclusion of demographic controls. Column (2) shows that the effect size increases directionally, such that an additional percentage point decline in the labor share of routine-intensive occupations increases female enrollment by 0.74 percentage points ($p < 0.01$). Column (4) show that the effect on male enrollment remains insignificant. Again, the estimated effect on female enrollment is economically and statistically significantly greater for women than for men. Finally, the net impact on the college gender gap, shown in column (6), is a decline of 0.54 percentage points.

Table 1.8 expands the sample to the proportion of 18-30 year olds who have ever enrolled in college. Since the sample now includes individuals who are further from the margin of college-going, the point estimates noticeably decline. As shown by column (1), decreasing the share of routine-intensive occupations by an additional percentage point leads to an increase in female enrollment by 0.35 percentage points. In contrast, column (3) shows that the effect of routine occupations on male enrollment is much smaller and insignificant. Column (5), which presents the results on the college gender gap (male enrollment less female enrollment), shows that the corresponding effect is a 0.18 decline in the college gender gap. As with the sample of 18-25 year olds, I find that the point estimates do not significantly change after including demographic controls. Column (2) shows that adding demographic controls directionally magnifies the effect of routine-intensive occupations, such that the estimated effect of an additional percentage point decline in routine-intensive labor share on female enrollment is now 0.48 percentage points. The effect on male enrollment, shown in column (4), remains insignificant. The net effect on the college gender gap is a 0.25 percentage point decline, shown in column (6).

1.5 Explaining Time Trends in the Reverse College Gender Gap: Theoretical Model

So far, the paper makes the case that women's worse non-college job prospects contribute in major ways to their greater college enrollment rate. But women's non-college prospects have always been worse than men's, so why have women not always exceeded men in college-going? The literature on the college gender gap has identified two symmetric puzzles: first, why did women attend college at greater rates than men after 1980, when men have always worked more and earned more than women?[28] Second, why did men attend college at greater rates than women before 1980, when women have always had a higher observed college premium than men?[29] This section presents a theoretical model that reconciles both of these contradictions.

The theoretical framework demonstrates that non-college jobs played a growing role in women's college-going decisions, and that this contributed to the growth and eventual dominance of women in college classrooms. Since this paper focuses on the role of labor market returns, the model purposefully abstracts from other factors that have already been shown to contribute to the college gender gap, such as abilities (see Becker, Hubbard, and Murphy, 2010; Jacob, 2002; Bertrand and Pan, 2013; Goldin, Katz, and Kuziemko, 2006), marriage market outcomes (see Chiappori, Iyigun, and Weiss, 2009; Chiappori, Costa Dias, and Meghir, 2015; Chiappori, Salanie, and Weiss, 2015; Bronson, 2015; Zhang, 2016; Low, 2017), or gender differences in preferences (see Niederle and Vesterlund, 2010), by treating these factors as equal between men and women. The model assumes three key differences between men and women: expected wage rates, time available for labor, and exposure to fertility risk.[30] Within the model, these three differences are sufficient to explain why men exceeded women in college-going at first while women exceeded men in college-going later on. In addition, one natural implication of this model is that the greater enrollment rate of women

[28] For literature that identifies this question, see DiPrete and Buchmann 2008; Jacob 2002; Becker, Hubbard, and Murphy 2010; Goldin, Katz, and Kuziemko 2006

[29] Becker, Hubbard, and Murphy (2010) and Goldin, Katz, and Kuziemko (2006) have identified men's initially greater enrollment rate to be the major puzzle in the literature.

[30] Fertility risk has been identified as one key reason why women used to have lower labor force participation and lower educational attainment than men (see Goldin and Katz, 2003; Bailey, 2006; Low, 2017; Gershoni and Low, 2017).

leads to the lower college wage rates for women compared to men. In other words, the gender wage gap among college workers is a direct result of the gender gap in college enrollment.

1.5.1 Model Setup

Individuals live for two periods. In each period, they have quasilinear utility over consumption c_t and leisure ℓ_t, as well as a fixed amount of housework that must be completed. Individuals maximize their utility by choosing how to allocate their remaining time net of housework.

In period 0, individuals must decide whether to attend college. The decision to attend college is denoted $s \in \{0,1\}$, where $s = 0$ represents the choice to not attend college and $s = 1$ represents the choice to attend college. Individuals make the decision to attend college based on their decisions regarding expected utility in periods 1 and 2.

In periods 1 and 2, individuals must choose how to allocate their time net of housework. Housework requirements are represented by H_t in period $t \in \{1,2\}$. The household efficiency parameter is given by α. Completing housework amount H_t takes $\frac{H_t}{\alpha}$ units of time. Individuals' time net of housework is therefore represented by $T - \frac{H_t}{\alpha}$, which I abbreviate to T_t to simplify notation.

In period 1, all individuals are single. They must allocate their time net of housework $T_1 = T - \frac{H_1}{\alpha}$ between college s, labor x_1, and leisure ℓ_1. If they work in period 1, they will receive expected wage rate $\underline{w}$. College enrollees must pay the costs of attending college, which consist of monetary costs d and idiosyncratic non-monetary costs ε, where ε is drawn from the distribution $G(\varepsilon)$.[31] In addition, attending college requires z units of time, where $z = 1$ is sufficient to obtain a college degree. As I will discuss in detail later, individuals face an unplanned pregnancy with probability q and expect to complete only $z < 1$ of their college requirements.

In period 2, all individuals marry. Individuals allocate their time net of housework $T_2 = T - \frac{H_2}{\alpha}$ between labor x_2 and leisure ℓ_2. Importantly, couples can pool their time to complete the household

[31] Following the formulation of Becker, Hubbard, and Murphy (2010), ε can be considered an ability cost. High-ability individuals have low non-monetary costs of college, while low-ability individuals have high non-monetary costs of college.

production required by the family. Their expected wage rate in period 2 is determined by whether a college degree was earned at the end of period 1, as denoted by sz, where $w(sz) \in \{\underline{w}, \overline{w}\}$. Individuals who do not earn a college degree by the end of period 1 ($sz < 1$) receive wage rate $\underline{w}$, and individuals who receive a college degree by the end of period 1 ($sz = 1$) receive wage rate $\overline{w}$, with $\overline{w} > \underline{w}$.

In period 2, the maximization problem is given by[32]

$$\begin{aligned} V_2(s,z) &= \max_{c_2,\ell_2} c_2 + \ln(\ell_2) \\ \text{subject to } & w(sz)[\underbrace{T_2 - \ell_2}_{x_2}] = c_2 \end{aligned} \tag{1.5.1}$$

In period 1, the maximization problem is given by

$$\begin{aligned} V_1(s,z) &= \max_{c_1,\ell_1} c_1 + \ln(\ell_1) - \varepsilon s + \beta V_2(s,z) \\ \text{subject to } & \underline{w}[\underbrace{T_1 - \ell_1}_{x_1} - sz] = c_1 + dsz \end{aligned} \tag{1.5.2}$$

In period 0, the utility maximization problem is given by

$$\max_s \mathbb{E}V_1(s,z) = \max_s \ (1-q)V_1(s, z=1) + qV_1(s, z<1) \tag{1.5.3}$$

1.5.2 Gender

Denote women by the subscript f and men by the subscript m. Men and women differ in three key ways. First, I assume that men have a higher expected wage rate than women to represent the empirical fact that men sort into higher paying occupations relative to women. Here, expected wage rates can be considered the sum of earnings in each occupation weighted by the probability of filling an occupation. A decline in non-college employment opportunities would be represented as

[32]The main results of the model are generalizable to the case where utility with respect to leisure follows a function v, where v is quasiconcave, twice differentiable, and homogeneous of a degree between 0 and 1.

a decline in the expected wage rate. In this formulation, men have higher wage rates than women within education groups. Following the data, I assume $\overline{w}_m > \overline{w}_f$ and $\underline{w}_m > \underline{w}_f$. The gender disparity among workers without a college degree is larger than the gender disparity among college graduates: $\overline{w}_f - \underline{w}_f > \overline{w}_m - \underline{w}_m$.

Second, men and women have potentially different time net of housework to allocate to labor x_t, leisure ℓ_t, and schooling s. In period 1, single men and women without children have the same amount of housework they must complete, given by H_1. Men and women will have an equal amount of time net of housework $T_1 = T - \frac{H_1}{\alpha}$ to allocate to labor, leisure, and schooling. In period 2, men and women marry and pool their time to complete the housework needed for the family. The time devoted to housework will differ between men and women, because married couples can specialize. The higher wage rate of men implies lower opportunity costs for women to engage in housework, assuming that both are equally efficient at it and that the marginal productivity of time in housework is constant. The comparative advantage of men in market work leads women to spend more time completing housework needed by the family, following Becker's theory of household specialization (Becker 1981, 1985).[33] Let $T_{2i} = T - \frac{H_{2i}}{\alpha}$ represent the time net of housework in period 2, with $H_{2i} = H_{2f}$ for wives, $H_{2i} = H_{2m}$ for husbands, and $H_{2f} > H_1 > H_{2m}$. To remain consistent with observed trends, the model assumes married men will always work. In other words, men's time net of housework $T_{2m} = T - \frac{H_{2m}}{\alpha}$ is high enough that it is always optimal for married men to work.

Lastly, women face fertility risk but men do not ($q_m = 0$). With probability $q_f > 0$, women will have an unplanned pregnancy in period 1 while single. Having an unplanned pregnancy introduces the expectation that female college enrollees will leave school without fulfilling the time requirements necessary to earn a college degree. In the state where women do not have an unplanned pregnancy in period 1, $z = 1$. In the state where women have an unplanned pregnancy in period 1, $z < 1$. They would then receive expected wages $\underline{w}_f$ instead of $\overline{w}_f$ in period 2. All women know the probability of an unplanned pregnancy q_f prior to making their decision to attend college in period 0. They know

[33] An alternative formulation which achieves the same result is to assume a comparative advantage in housework for women, which leads men to specialize in market work and explains their higher expected wage rates (Becker, 1985; Galor and Weil, 1996).

whether or not they have an unplanned pregnancy once period 1 starts, *after* their college-going decision is made but *before* their labor or leisure decisions in each period are made.

The discount factor for period 2 utility, β, may also differ between men and women. However, the crucial differences explored in the model are the three key differences described above. I therefore assume β is the same between men and women.

The timeline for the model can be summarized briefly as:

Period 0: Individual chooses $s \in \{0,1\}$. Then, z is realized.

Period 1: Individual chooses leisure ℓ_1, and in doing so chooses labor $x_1 = T_1 - \ell_1$.

Period 2: Depending on choice of s and realization of z, individual receives wage $w(sz)$. Individual chooses $\ell_2(sz)$ and labor $x_2(sz) = T_2 - \ell_2(sz)$.

1.5.3 When is enrollment higher for men than women? When is enrollment higher for women than men?

Based on equations (1.5.1)-(1.5.3) and the three key differences between men and women, the schooling decisions for men and women can be derived. I assume that single men and women have sufficient time for leisure and schooling in period 1 ($T_1 > \frac{1}{\underline{w}_m} + 1, T_1 > \frac{1}{\underline{w}_f} + 1$). The time assumption for single men guarantees that married men will always work in period 2 ($T_{2m} > \frac{1}{\underline{w}_m}$).[34] However, married women may not necessarily work in period 2. The schooling decision s_i for gender i is given by

$$s_i = \mathbf{1}\left[\gamma_i > \varepsilon\right] \tag{1.5.4}$$

[34] $T_{2m} > T_1$ and $T_1 > \frac{1}{\underline{w}_m} + 1$ imply that $T_{2m} > \frac{1}{\underline{w}_m}$.

The threshold college-going value γ_i differs by gender i. For men,

$$\gamma_m = \beta[T_{2m}(\overline{w}_m - \underline{w}_m) - \ln(\overline{w}_m/\underline{w}_m)] - \underline{w}_m - d \tag{1.5.5}$$

For women,

$$\gamma_f = \begin{cases} -[1-\breve{q}_f](\underline{w}_f + d) \\ \text{if wives do not work } (T_{2f} \leq \frac{1}{\overline{w}_f}) \\ \\ \beta(1-q_f)A_f - [1-\breve{q}_f](\underline{w}_f + d) \\ \text{if only female college graduates work } (\frac{1}{\overline{w}_f} < T_{2f} \leq \frac{1}{\underline{w}_f}) \\ \\ \beta(1-q_f)\left[T_{2f}(\overline{w}_f - \underline{w}_f) - \ln\left(\overline{w}_f/\underline{w}_f\right)\right] - [1-\breve{q}_f](\underline{w}_f + d) \\ \text{if all wives work } (\frac{1}{\underline{w}_f} < T_{2f}) \end{cases}$$

where $\breve{q}_f = q_f(1-z)$ and $A_f = \overline{w}_f(T_{2f} - \frac{1}{\overline{w}_f}) - \ln(\overline{w}_f T_{2f})$.

The schooling rule s_i states that individuals choose to attend college if and only if their future discounted earnings gain in period 2 exceeds their future discounted loss in utility from less leisure in period 2,[35] their foregone earnings from attending college in period 1, and the total (monetary and non-monetary) college costs in period 1.

Theory Appendix A.2 lists further derivations, details, and analysis. The three key points are summarized as follows.

First, men's higher earnings and higher labor force participation make their college-going decisions

[35] Recall that obtaining a college degree lowers the optimal leisure amount from $\frac{1}{\underline{w}}$ to $\frac{1}{\overline{w}}$.

strictly more responsive to labor market returns than the college-going decisions of women (see Proposition A.2.3 and A.2.4 in the Theory Appendix A.2). Since labor market returns for men were high, male enrollment shot up quickly and leveled off quickly. In contrast, female enrollment grew gradually but steadily over time. Initially, women's college-going decisions were not very responsive to their labor market returns, for many potential reasons. The model focuses on two reasons that have been identified by the literature: housework responsibilities kept most married women out of the labor force prior to the 1980s, and the risk that an unanticipated pregnancy would prevent women from finishing educational investments created uncertainty in whether women could capitalize on their labor market returns. Increased access to contraceptive technologies and advances in household production efficiency increased the responsiveness of women's college-going decisions to labor market returns over time (see Figure A.3, Equation A.2.23, and Equation A.2.24 in Appendix A.2).

Second, the model delivers closed form solutions regarding whether and how much women will work, based on their expected wage rates and the time they have available after housework. Expected non-college wage rates directly figure into women's college-going decisions even when married women do not work in period 2, since non-college wage rates represent the opportunity cost of college attendance when women are single in period 1. In contrast, expected college wage rates only play a role in women's college-going decisions when it is optimal for female college graduates to work when married in period 2. Consequently, women derive labor market benefits from earning a college degree only when female college graduates become efficient enough at housework to have time for market work (see Propositions A.2.3 and A.2.4 in the Theory Appendix A.2).

Third, fertility risk mediates the slope of the growth in female enrollment, in that declines in fertility risk increase the responsiveness of women's college enrollment decisions to their labor market returns. When fertility risk q_f is above $1-\frac{\overline{w}_m-\underline{w}_m}{\overline{w}_f-\underline{w}_f}$, female enrollment will always be below male enrollment. When fertility risk declines below $1-\frac{\overline{w}_m-\underline{w}_m}{\overline{w}_f-\underline{w}_f}$, it becomes possible for female enrollment to surpass male enrollment.[36]

[36]Setting the slopes of the college enrollment threshold for men and women equal, we have

$$\beta(1-q_f)[\overline{w}_f-\underline{w}_f]=\beta[\overline{w}_m-\underline{w}_m]$$

Figure 1.12 delivers the final result of the model. The left panel summarizes the role of increasing housework efficiency and declining fertility risk on how wage rates affect women's college-going. The x-axis is $T_{2i} = T - \frac{H_{2i}}{\alpha}$, time net of housework for gender i in period 2. The figure depicts how γ_i, the threshold college-going value for gender i, changes as T_{2i} increases.

The effect of increasing household efficiency is represented by an increase in α, which increases the time net of housework for women, T_{2f}. The female college-going threshold γ_f grows as T_{2f} increases, represented by right-ward movement along the x-axis. This growth stems entirely from the result that increasing T_{2f} increases the strength of the college-going response to wage rates. This growth is discontinuous, depending on the relationship between time net of housework T_{2f} and wage rates $(\underline{w}_f, \overline{w}_f)$. When $T_{2f} < \frac{1}{\overline{w}_f}$, it is not optimal for married women to work in period 2. They will attend college if and only if $\varepsilon < -[1-\check{q}_f](\underline{w}_f + d)$. A marginal increase in α will do nothing to increase the college-going threshold γ_f along this interval. On the other hand, if α is sufficiently high such that $T_{2f} \in (\frac{1}{\overline{w}_f}, \frac{1}{\underline{w}_f})$, then only married women with college degrees will work in period 2. A marginal increase in α increases the threshold γ_f by $\beta(1-q_f)\frac{H_{2f}}{\alpha^2}[\overline{w}_f - \frac{1}{T_{2f}}]$, which is positive due to the assumption that $T_{2f} > \frac{1}{\overline{w}_f}$. Lastly, if $T_{2f} > \frac{1}{\underline{w}_f}$, it is optimal for all married women to work. The slope of γ_f is the largest in this region – a marginal increase in α increases the threshold γ_f by $\beta(1-q_f)\frac{H_{2f}}{\alpha^2}[\overline{w}_f - \underline{w}_f]$.

The figure also graphs male enrollment, γ_m which grows as rising household production efficiency α increases the time net of housework for men T_{2m} (represented by a right-ward shift along the same x-axis).

The effect of declining fertility is represented by the shift from $\gamma_f(\widetilde{q}_f)$ to $\gamma_f(\widehat{q}_f)$, where $\widetilde{q}_f > 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f} > \widehat{q}_f$. Again, $1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ is the threshold below which it is possible for female enrollment to surpass male enrollment. For this reason $\gamma_f(\widehat{q}_f)$ crosses γ_m, but $\gamma_f(\widetilde{q}_f)$ never crosses γ_m.

Proposition 1 summarizes the conditions which create gender differences in college enrollment.

Proposition (Proposition 1)**.** *Let T_{2f} denote time net of housework for women and q_f denote the*

Solving for q_f, we obtain that the slope of the female enrollment threshold exceeds that of the male enrollment threshold if and only if $q_f < 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$.

probability that a woman will experience an unanticipated pregnancy in period 1. Let T_{2m} *denote the time net of housework for men. If* $q_f < 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$*, then there exists* $\widehat{T}$ *where* $\gamma_f(q_f, \widehat{T}) \geq \gamma_m(\widehat{T})$*.*

Then $\forall T_{2f} \in (\widehat{T}_{2f}, \widehat{T}_{2m})$*,*

$$\gamma_f(q_f, T_{2f}) > \gamma_m(\widehat{T}_{2m})$$

Women will exceed men in college enrollment.

For $T_{2f} < \widehat{T}_{2f}$ *when* $q_f < 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ *or for* $T_{2f} < T_{2m}$ *when* $q_f \geq 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$

$$\gamma_f(q_f, T_{2f}) < \gamma_m(\widehat{T}_{2m})$$

Men will exceed women in college enrollment.

Proof. See theory appendix A.2.

Proposition 1 demonstrates that necessary conditions for women to exceed men in college enrollment are that fertility risk q_f must fall below $1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ and that housework time must fall to a point where it is optimal for college women to work (in other words, household production efficiency parameter α must be high enough that time net of housework $T_{2f} = T - \frac{H_{2f}}{\alpha}$ must exceed $\frac{1}{\overline{w}_f}$). Once these two conditions are met, it is possible for women to take advantage of their higher labor market returns. Because $\overline{w}_f - \underline{w}_f > \overline{w}_m - \underline{w}_m$, the slope of female enrollment γ_f exceeds the slope of male enrollment γ_m. As long as housework time and fertility risk for women is sufficiently low, female college-going will be higher than male college-going even if women have less time for work and lower wage rates than men.

The right panel of figure 1.12 illustrates the change in female college-going threshold γ_f given a decline in the female non-college wage rate $\underline{w}_f$. The figure shows that a decline in the non-college wage rate of women makes it possible for women to surpass men in college enrollment at a lower level of household production efficiency than before. Consider a decline in $\underline{w}_f$ to $\underline{\underline{w}}_f$, which shifts γ_f up and shifts the vertical axis $\frac{1}{\underline{w}_f}$ further to the right, increasing the slope of γ_f.

This change is represented by the shift from $\gamma_f(\underline{w}_f)$ to $\gamma_f(\underline{\underline{w}}_f)$. As before, there exists $\widehat{T}$ such that $\gamma_f(\underline{w}_f, \widehat{T}) = \gamma_m(\widehat{T})$. Pick an arbitrary $\widehat{T}_{2m} > \widehat{T}$ and define $\widehat{T}_{2f}$ and $\underline{\underline{\widehat{T}}}_{2f}$ such that $\gamma_m(\widehat{T}_{2m}) = \gamma_f(\underline{w}_f, \widehat{T}_{2f}) = \gamma_f(\underline{\underline{w}}_f, \underline{\underline{\widehat{T}}}_{2f})$. It can be shown that $\underline{\underline{\widehat{T}}}_{2f} < \widehat{T}_{2f}$.[37]

This result is significant because it shows that declines in non-college wage rates for women complement increasing housework efficiency and decreasing fertility risk in enabling female enrollment to grow and overtake male enrollment. A decline in non-college wage rates enable female college enrollment to exceed male college enrollment at lower levels of household efficiency and higher levels of fertility risk. Declining employment opportunities in the non-college market therefore help explain not only why women overtook men in college enrollment, but also why the overtaking occurred as early as the 1980s, when female labor force participation was still quite low at 50%.

1.5.4 Estimating the impact of non-college jobs on aggregate trends

To show that non-college occupations played an important role in the evolution of the college gender gap, I conduct a back-of-the-envelope calculation to determine how much of the aggregate change in college enrollment can be explained by changes in non-college employment for men and women. Table 1.9 shows the change in non-college employment for men and women. It is important to note that these changes arise from both supply and demand effects. Supply-driven declines in non-college employment may arise, for example, from workers obtaining college degrees at higher rates for reasons unrelated to employment changes, non-college workers choosing to leave the labor force, or influxes of non-college workers from foreign countries. Demand-driven changes in non-college employment, on the other hand, stem from changes in employer demand for non-college workers. To estimate changes in college enrollment that stem from demand-driven changes in non-college jobs, I perform a simple variance decomposition which utilizes the relationship between the ordinary least squares estimator and the two-stage least squares estimator to back out the proportion of an aggregate change that can be attributable to demand changes (Autor, Dorn, and Hanson, 2013). Using the point estimates from Sections 1.3 and 1.4, my back-of-the-envelope calculations show that

[37] See appendix A.2 for a formal proof.

non-college jobs explain about 15% of the change in female enrollment and 1-12% of the change in male enrollment from 1970 to 2010.

Next, I use the model results to estimate the counterfactual college gender gap based on changes in non-college jobs alone by holding all other factors that influence college enrollment fixed at 2010 levels. I use the derivative of the schooling rule in the model to obtain a closed form expression of how college enrollment responds to non-college employment:

$$\left[\frac{\partial(\text{college enrollment})}{\partial(\text{non-college employment})}\right]_t = \beta(\text{time spent at work}_t) - \text{time spent at school} \tag{1.5.6}$$

The equation produces a measure of the responsiveness of female college-going to non-college employment. This responsiveness depends on the amount of time worked in the labor market. Historically, female enrollment was low – in 1970, only 30% of married women participated in the labor market at all – making the responsiveness of female college-going to non-college employment low. If married women had always worked as much as they did in 2010, they would have been far more responsive to their non-college labor market conditions. How would the trajectory of female college enrollment have changed in this case?

I perform a back-of-the-envelope counterfactual calibration exercise where I multiply the first term in equation (1.5.6) with the ratio of the time spent at work in 2010 over the time spent at work in a prior year t. This provides a rough approximation of how responsive female college-going would have been if women always worked as much as they did in 2010. I then take information from the American Time Use Survey, the American's Use of Time Survey, and the Time Use in Economic and Social Accounts Study to obtain measures of time spent in school and time spent at work for women (Aguiar and Hurst, 2007; Sayer, 2014).

Figure 1.13 presents the counterfactual estimation of college enrollment for men and women, where changes in college enrollment arise solely from changes in non-college jobs. If women had always worked as much as they did in 2010, they would have been much more responsive to their non-college job prospects. Based on the counterfactual estimation, their relatively anemic options in the non-college labor market would have pushed their college enrollment to exceed the college enrollment of men for all years in the estimation exercise. In other words, if women had always worked in the labor market as much as they have in recent years, they would have never lagged behind men in college enrollment. This back-of-the-envelope exercise provides suggestive evidence that the low hours women used to work were a key reason behind why women did not attend college at higher rates than men before 1980.

1.6 Conclusion

The greater college enrollment of women over men has been a long-standing open question. While most of the literature has focused on how college-going decisions are driven by preparedness, marriage market concerns, social concerns, or labor market outcomes for college graduates, this paper provides new evidence that the labor market for high school graduates plays a key role in explaining this gender gap. I document the large gender disparity in non-college job options and demonstrate that these disparities create unequal demand in a college degree between men and women. I then construct a theoretical model to explain how the gender imbalance in non-college job options can rationalize the greater enrollment of men before the 1980s and the greater enrollment of women after the 1980s, despite the fact that women's observed college premium has been consistently higher than men's during this time.

This paper speaks to the importance of outside options in contributing to the large difference in human capital investments between men and women. My findings demonstrate that men may not be "under-investing" in education as much as it may at first seem. Much of the public debate on the college gender gap has focused on how myopia, poor behavior in school, and lack of interest in learning present barriers to men from optimally investing in their education (Economist, 2015). In contrast, I show that one key reason behind why men enroll in college at lower rates than women is because they have more attractive alternatives to attending college. Thus, even if everyone behaved rationally, men would still be expected to enroll in college at a lower rate than women.

In addition to explaining present conditions, this paper rationalizes trends in the college gender gap over time, which have puzzled social scientists for decades. I demonstrate that the increasing rate of automation disproportionately displaced the non-college job options of young women just as female labor force participation began to grow substantially, which in turn led female college enrollment to increase at rates higher than male college enrollment. At the same time, men's non-college job opportunities remained plentiful by comparison, leading a greater proportion of men than women to rationally forego attending college. The combination of these factors contributed to both the greater college enrollment of men prior to 1980 and the greater college enrollment of women after 1980.

The results presented here raise further questions that merit exploration. Since women have access to fewer lucrative options with only a high school degree, higher earnings are required to induce the marginal man to enter college relative to the marginal woman. Average wages for male college graduates will therefore be higher than average wages for female college graduates. The gender gap in college enrollment thus creates a persistent gender gap in earnings among college workers. The large steady gap in college enrollment between men and women may explain why the gender gap in wages has failed to close, despite efforts from governments and firms alike. To my knowledge, this paper is the first to reveal a tension between the gender gap in college enrollment and the gender gap in wages, wherein interventions to narrow the gender gap in wages will widen the gender gap in college-going, and interventions to narrow the gender gap in college enrollment will widen the gender gap in wages.

A second, related implication of this paper is that women are more likely than men to choose non-STEM fields among college enrollees. Since the opportunity cost of attending college is lower for women than men, women have greater freedom to major in a less lucrative field and still make the investment in attending college worthwhile. Recent work by Card and Payne (2017) support this prediction. They show that men are 13 percentage points more likely than women to major in a STEM field, and that 9 of these 13 percentage points can be attributed to the higher college enrollment rate of women.

Overall, highlighting the role of the non-college labor market in the college gender gap yields the insight that different outside options lead men and women to self-select into attending college at differential rates. The marginal college-going woman will differ from the marginal college-going man, and this creates persistent differences in the fields that men and women choose, the average wages of men and women across the population of college workers, and a variety of other employment outcomes.

A third implication of this paper is that greater study should be devoted to non-college jobs in order to determine the optimal role of policy in individuals' private education decisions. If men choose to forego valuable college investments due to high paying non-college job prospects, future research should focus on what these jobs are. Do they pay enough to support a family over a lifetime? Are they viable career paths? How do people who forego formal human capital investment to work in these jobs weather adverse labor market shocks in the future? In the next chapter, I take one step in this direction by estimating a structural Roy model to show that some men can indeed maximize lifetime earnings by foregoing a college degree. However, more work to investigate the non-college labor market is needed in order to determine the welfare consequences of foregoing a college degree.

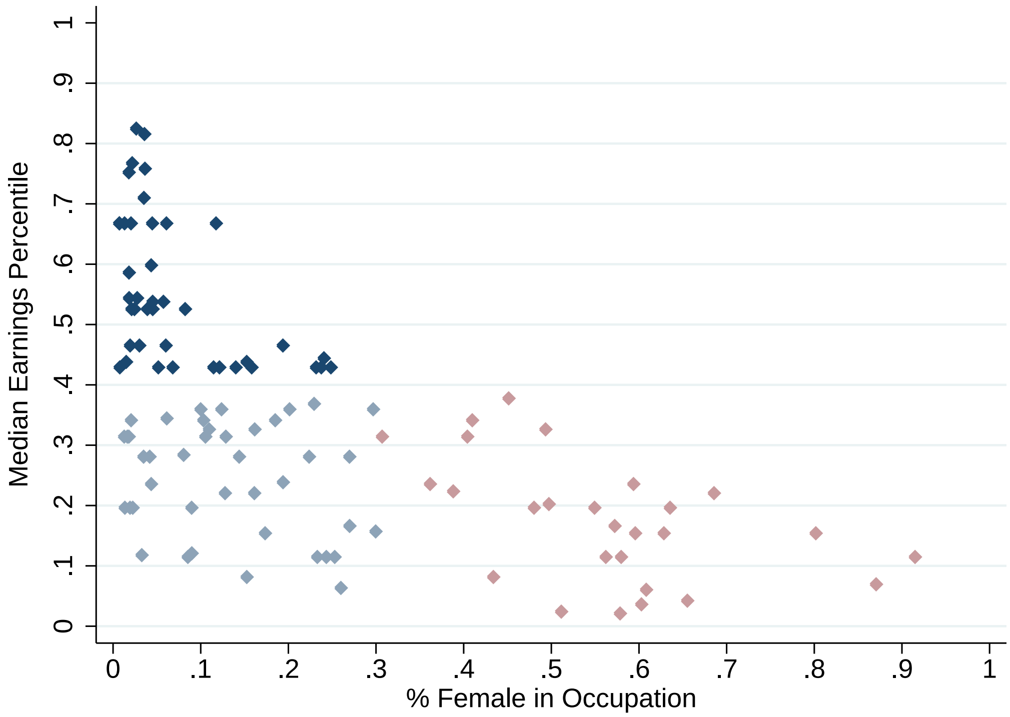
Figures

FIGURE 1.1
COLLEGE ENROLLMENT BY GENDER

Notes: Figure 1.1 shows the proportion of men and women between the ages of 18 and 30 who have ever enrolled in college. Before the 1980s, the proportion of men ever enrolled in college was greater than that of women. The gender gap in college enrollment closed when women's college enrollment rate converged to that of men. After the 1980s, the gender gap in college enrollment reversed when the college enrollment rate of women surpassed that of men. The male college enrollment rate has leveled off since the 1980s while the female college enrollment rate continued to increase from 1980 to 2010. The figure uses census microdata for each decade in 1950-2000 and American Community Survey (ACS) data for each year in 2001-2010.

FIGURE 1.2

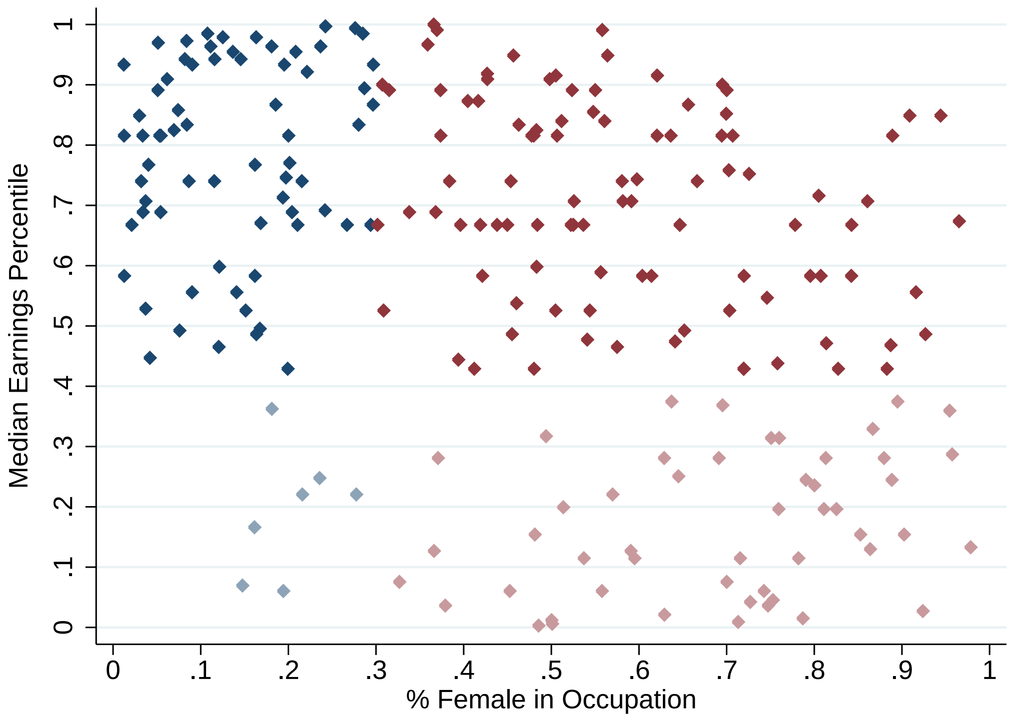
NON-COLLEGE OCCUPATIONS BY GENDER COMPOSITION AND PERCENTILE MEDIAN EARNINGS



Notes: The figure depicts a scatter plot of all non-college (at least 50% workers with only a high school degree) occupations by proportion of female workers and median earnings percentile. First, the majority of occupations (over 60%) are male-dominated, with 20% or fewer female workers. Second, occupations which employ a non-trivial fraction of women pay significantly lower median earnings than male-dominated occupations. The figure uses 2010 American Community Survey (ACS) data and the definition of occupation based on the 1990 Census Bureau occupational classification scheme. To focus on the non-college labor structure for young workers, only 18-30 year olds are included in the calculation of worker composition and median earnings percentile.

Figure 1.3

College Occupations by Gender Composition and Percentile Median Earnings



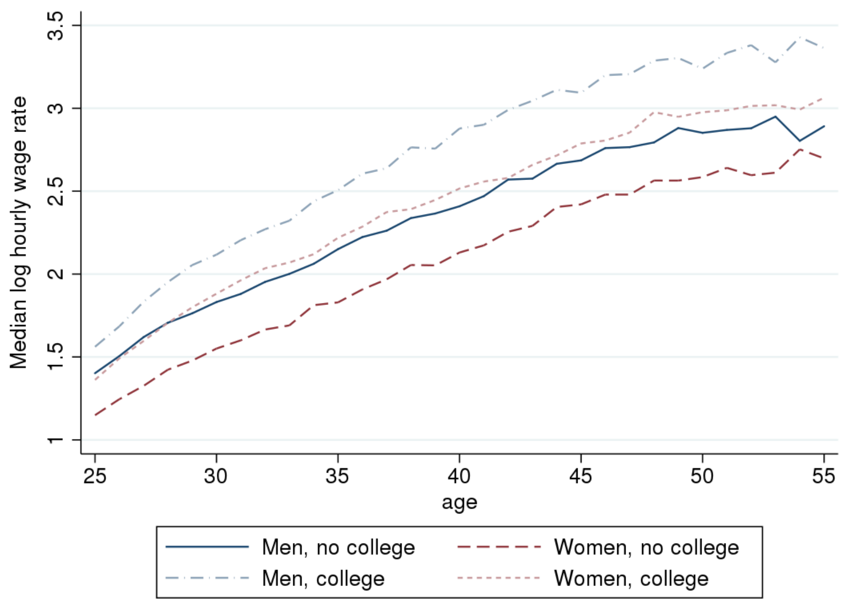
Notes: The figure depicts a scatter plot of all college (at least 50% workers who were college enrollees) occupations by proportion of female workers and median earnings percentile. The figure uses 2010 American Community Survey (ACS) data and the definition of occupation based on the 1990 Census Bureau occupational classification scheme. To focus on the non-college labor structure for young workers, only 18-30 year olds are included in the calculation of worker composition and median earnings percentile.

FIGURE 1.4

LOG WAGE GAP (WEIGHTED BY OCCUPATION) BETWEEN COLLEGE AND HIGH SCHOOL GRADUATES

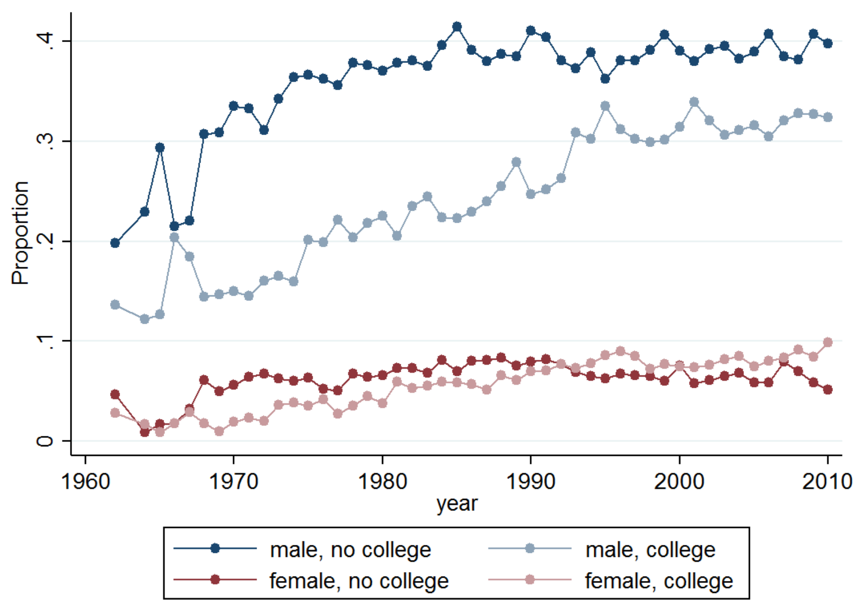
Notes: The figure depicts the observed college premium for men and women based on occupational differences alone. Median earnings are calculated by summing over the median earnings of each occupation, weighted by the share of each worker type employed in that occupation (where type is indexed by college enrollment status and sex). Figure 1.4 demonstrates that among 18-30 year olds, the difference in median wages between college graduates and high school graduates is consistently and substantially larger for women than for men.

FIGURE 1.5
MEDIAN ANNUAL EARNINGS BY AGE



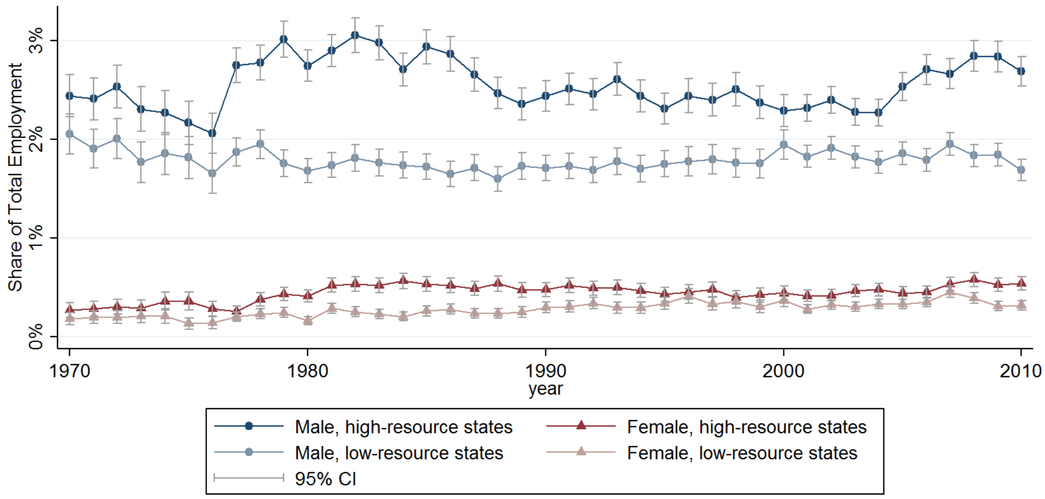
Notes: Figure 1.5 shows the median annual earnings among four occupation categories. All groups exhibit some growth in annual earnings over time, with college male occupations exhibiting the highest earnings at all ages, non-college male occupations making about as much as college female occupations, and non-college female occupations exhibiting the lowest earnings at all ages. The gender gap in annual wages and lifetime earnings is smaller among college occupations than non-college occupations. Women appear to face a larger earnings disadvantage in the non-college market than the college market. In addition, in contrast to the other groups, non-college female occupations exhibit almost no earnings growth over the working lives of their workers. This is consistent with the notion that non-college women tend to fill occupations that are not "careers", which typically exhibit some earnings growth with tenure.

FIGURE 1.6
OIL AND GAS EMPLOYMENT, WORKER COMPOSITION



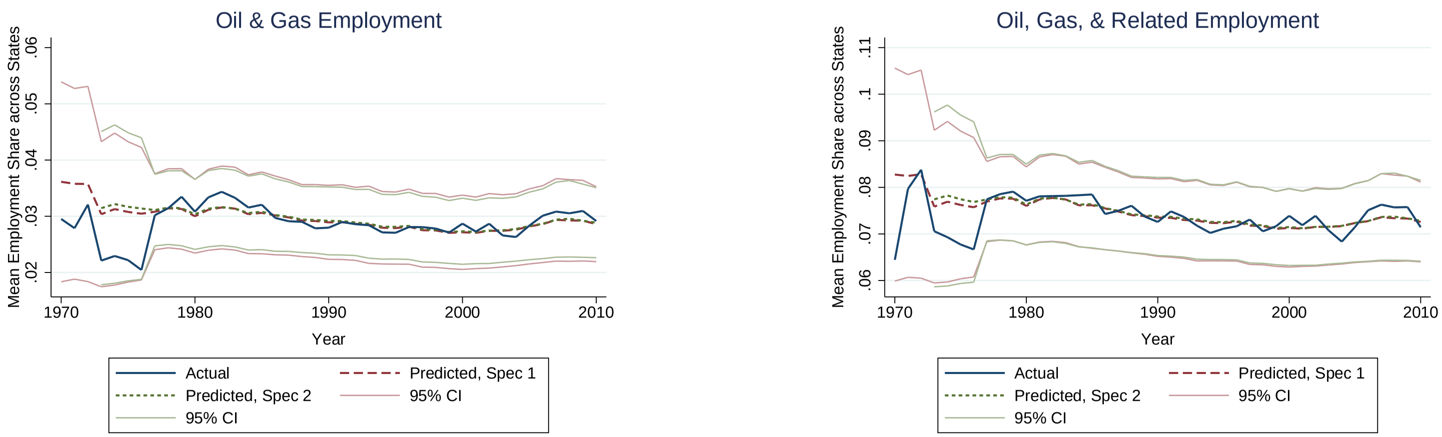
Notes: Figure 1.6 depicts the composition of workers by gender and education in the oil and gas industry. Male non-college workers comprise most of the workforce in the data period. College and non-college women make up less than 10% of the workforce each. The evidence suggests that male workers would be most affected by changes in the employment demand of the oil and gas industry, since they make up the overwhelming majority of workers in oil, gas, and related industries. This figure uses data from the CPS-ASEC for the years 1970-2010.

FIGURE 1.7
SHARE OF EMPLOYMENT IN OIL AND GAS INDUSTRY



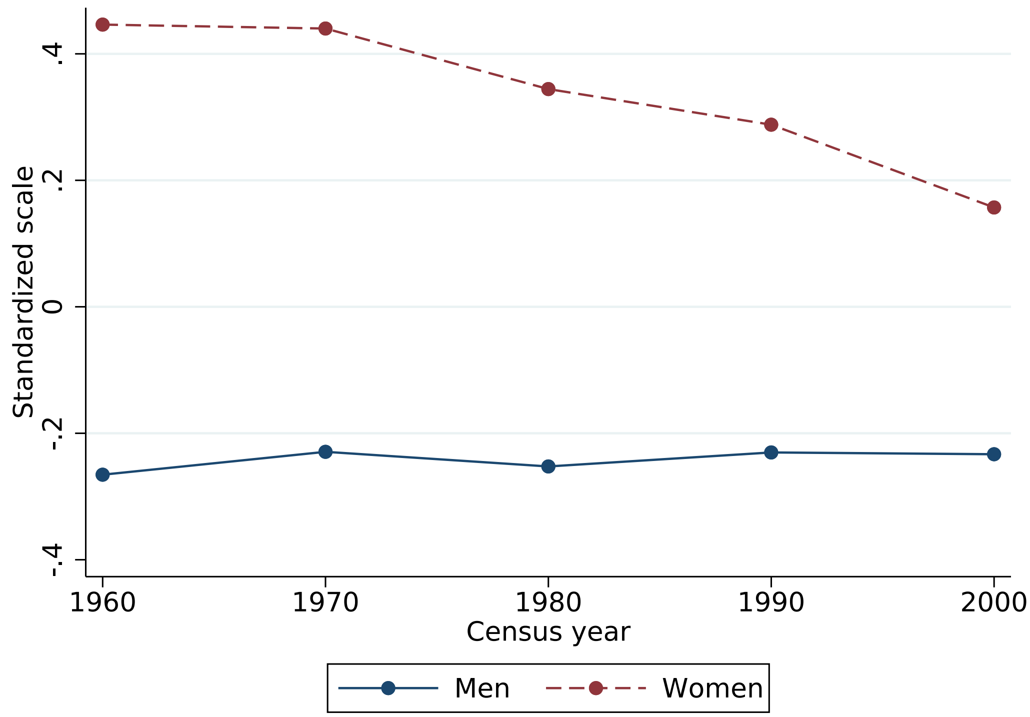
Notes: Figure 1.7 graphs the share of employment in the oil and gas industry by gender and whether the state is a high- or low-resource state. In both high- and low-resource states, employment of men in the oil and gas industry far exceed employment of women. Substantial employment fluctuations are only found among male employment in high-resource states. Employment of men in low-resource states, women in high-resource states, and women in low-resource states remains relatively constant despite booms and busts in the oil and gas industry during this period. The figure provides evidence that natural resources matter in determining employment in the oil and gas industry, and that these natural resources substantially determine the employment rates of men but have little effect on the employment rates of women.

FIGURE 1.8
FIRST STAGE PREDICTIONS



Notes: The figure shows the labor share in the oil and gas industry (left panel), and in the oil, gas, and related industries (right panel) averaged over the 48 contiguous states for each year. The solid line represents actual mean labor share. The long dashed line represents the predicted mean labor share from the first stage regression using Specification 1 (equation 1.3.1). The short dashed line represents the predicted mean labor share from the first stage regression using Specification 2 (equation 1.3.2). 95% Confidence Intervals are graphed for both predictions. Overall, there is little discrepancy between the two predictions. Both predictions appear to fit the actual mean employment share quite well for every year after 1980.

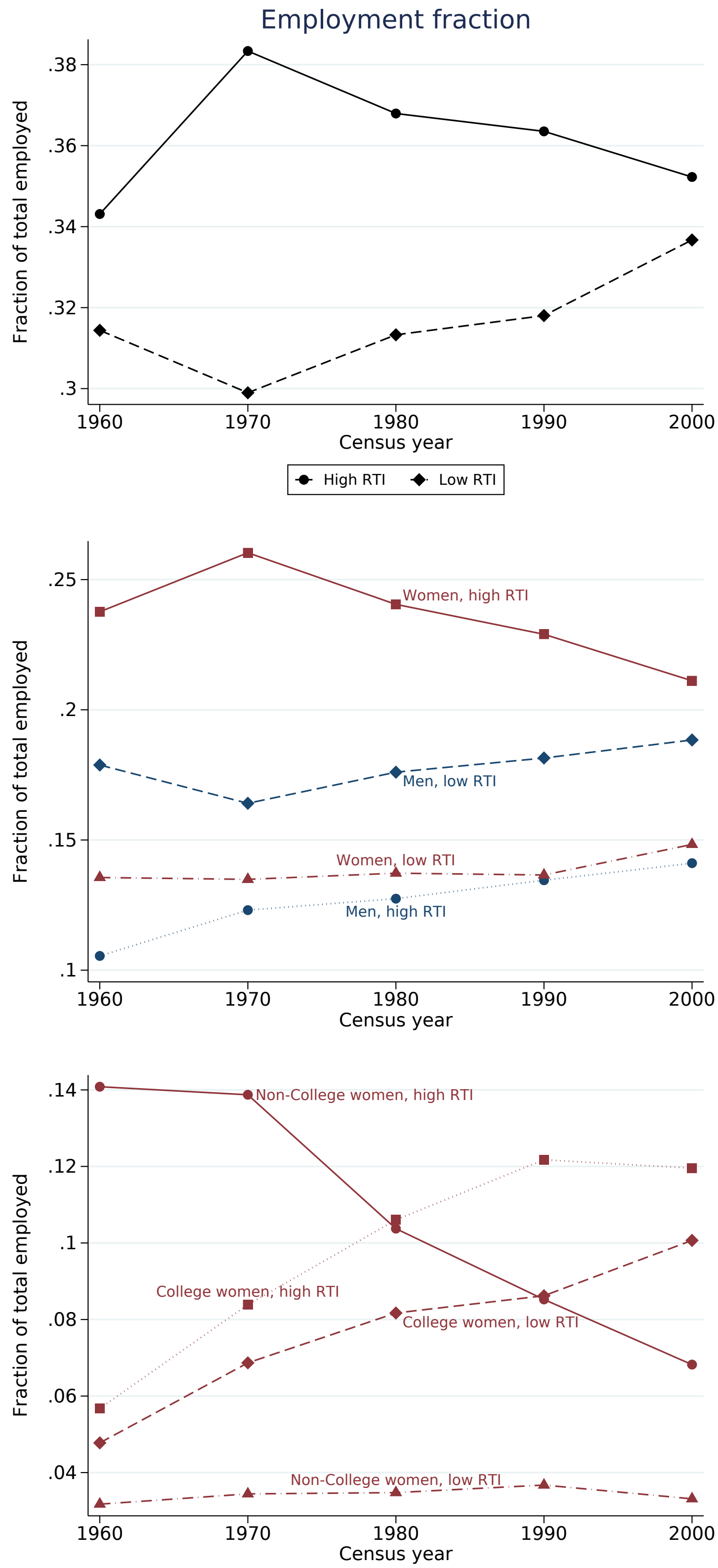
FIGURE 1.9
ROUTINE TASK INTENSITY (RTI) IN LABOR MARKET OVER TIME



Notes: Figure 1.9 depicts the measure for routine task intensity (RTI) in the labor force for young men (blue) and young women (red). This figure shows that the displacement of high-RTI jobs by automation fell on women but not men among young workers. The evidence suggests that the employment opportunities of women were most affected by the erosion of routine-intensive jobs. Data obtained from census microdata, ACS data, and the job characteristic measures constructed by Autor and Dorn (2013). Only individuals between the ages of 18 and 30 are included.

Figure 1.10

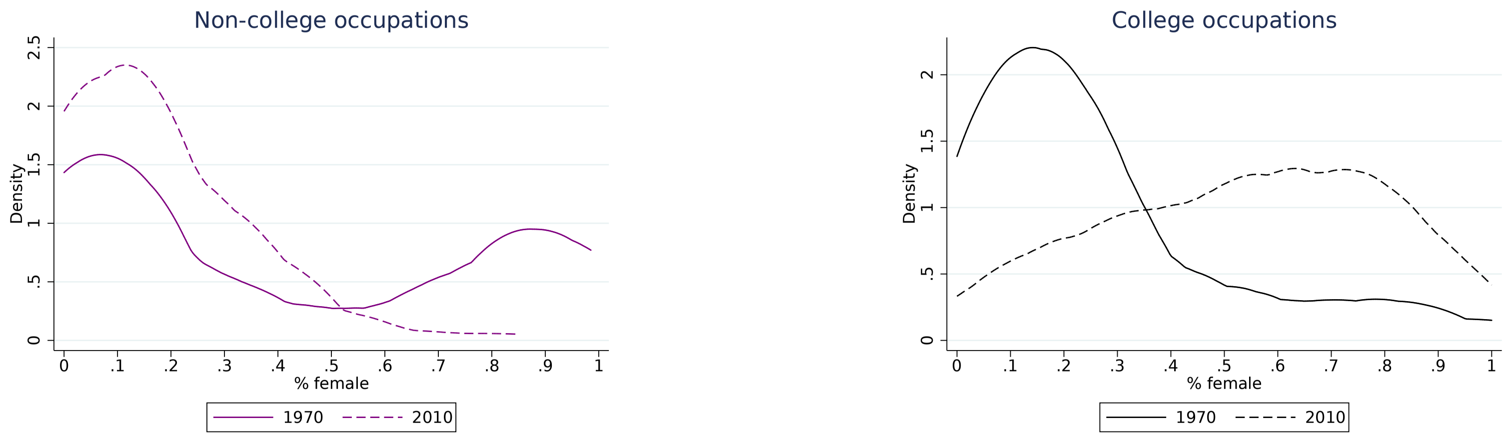
Employment Changes over Time, by Routine-Intensity of Job Tasks



Notes: Figure 1.10 graphs the proportion of employed workers by high (top third in 1950) and low (bottom third in 1950) routine task intensity (RTI), the measure of how routine the tasks in an occupation are. The top panel shows that beginning in 1970, the share of high-RTI occupations declined while the proportion of low-RTI occupations increased, consistent with the literature on the decline in routine-intensive tasks over time. The middle panel splits the relationship by gender. Importantly, the decline in highly routine occupations corresponds to a decline in the employment share for women but not men. For men, the employment share of high-RTI labor actually increased steadily during this period. Low-RTI labor share increased for both men and women. The bottom panel breaks down this relationship even further by education. The decline in routine-intensive employment is entirely driven by non-college women in high-RTI occupations. For all other groups, employment share did not decline. Female college workers gained employment share in both high- and low-RTI jobs. The fraction of non-college women in low-RTI occupations remained relatively unchanged during this period.

FIGURE 1.11

OCCUPATIONAL DISPERSION FOR COLLEGE AND NON-COLLEGE WORKERS

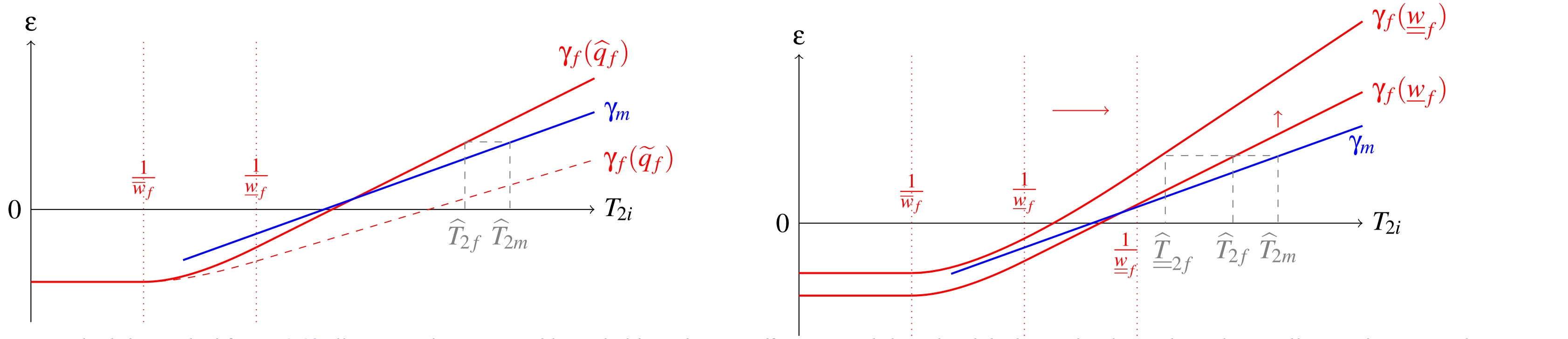


Notes: Figure 1.11 graphs the distribution of occupations by percent female for 1970 and 2010, for "non-college" occupations (left) and "college" occupations (right). "College" occupations are those with over 50% college workers; "non-college" occupations are those with over 50% non-college workers. 1950 is excluded since few occupations were comprised of over 50% college workers. Only individuals between the ages of 18 and 30 are included.

In 1970, over 60% of occupations employed at least 80% men among both college and non-college occupations, while a much smaller proportion of occupations were female-dominated, and very few occupations employed relatively equal amounts of men and women. The female-dominated occupations all concentrated among non-college occupations. Over time, non-college occupations continued to be segregated by gender, with few occupations that employed relatively equivalent amounts of men and women. However, the female-dominated non-college jobs declined in number, while college jobs became more gender-equitable. In other words, the jobs that used to employ non-college women declined, while the jobs that used to employ a majority of college men became accessible to college women.

FIGURE 1.12

THRESHOLD COLLEGE-GOING VALUES FOR MEN AND WOMEN



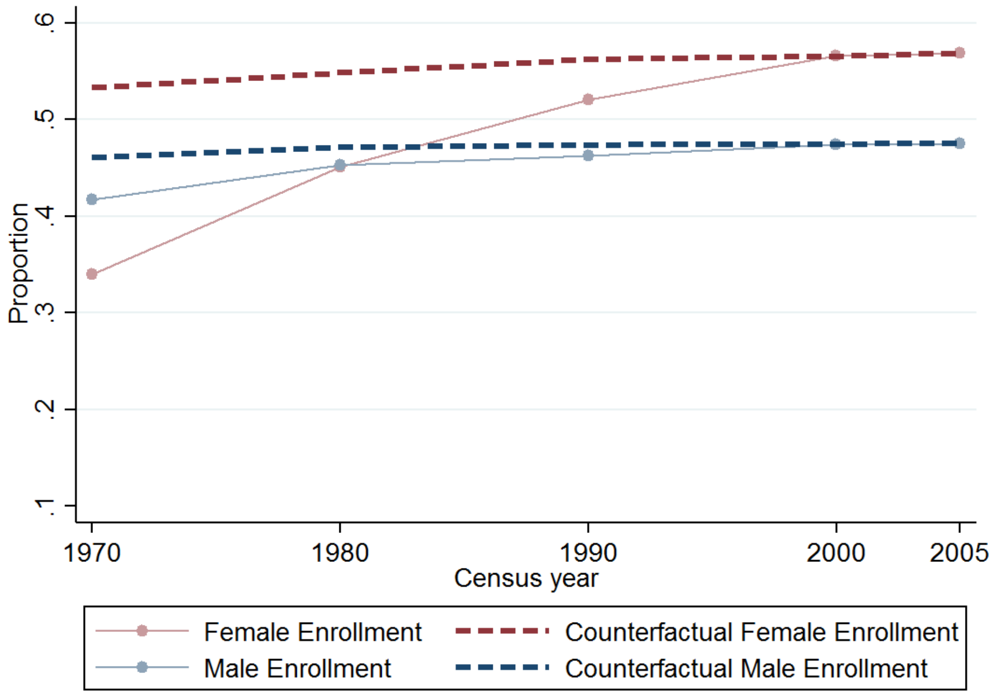
Notes: The left panel of figure 1.12 illustrates the impact of household production efficiency and the role of declining fertility risk on the enrollment of women relative to men. γ_m represents the growth in male enrollment as men's time net of housework increases, while γ_f represents the growth in female enrollment as women's time net of housework increases. As household production efficiency increases, the time needed to complete housework decreases and individuals have more time to work. The labor market returns to attending college therefore increase, which leads college enrollment to increase. Since women complete the housework required by the family, increasing household efficiency should increase women's enrollment by more than men's enrollment.

Secondly, the decline in fertility risk for women q_f is represented by a shift from $\gamma_f(\widetilde{q}_f)$ to $\gamma_f(\widehat{q}_f)$. The figure demonstrates that for high fertility risk $\widetilde{q}_f$, women can never surpass men in college enrollment, while for low fertility risk $\widehat{q}_f$, women can surpass men in college enrollment as long as household production is sufficiently efficient.

The right panel of figure A.3 demonstrates that declines in non-college wages complement household production efficiency and contraceptive technology in accelerating growth in female enrollment. A decline in non-college wage rates from $\underline{w}_f$ to $\underline{\underline{w}}_f$ shifts the γ_f function up and increases the slope of growth. The decline in non-college wage rates therefore makes it possible for women to surpass men in college-going at a higher level of fertility risk and lower level of household production efficiency than before.

Figure 1.13

Real and Counterfactual College Enrollment Rates



Notes: The bold, dashed lines represent the counterfactual college enrollment rates, where changes in college enrollment arise only from changes in the share of non-college jobs over time. The pale solid lines represent the true college enrollment rate. The graph demonstrates that if women had always worked as much as they did in 2010, women would have never lagged behind men in college enrollment.

Tables

TABLE 1.1

EXAMPLES OF NON-COLLEGE OCCUPATIONS, 2010

Occupation, 1990 basis	Percent of female workers	Earnings percentile	Work has pension plan	Employer-sponsored health insurance
Cashiers	71%	3%	36%	92%
Housekeepers and cleaners	82%	4%	24%	89%
Hairdressers and cosmetologists	88%	9%	11%	60%
Miners	3%	81%	62%	99%
Machinists	4%	60%	62%	97%
Truck, delivery, and tractor drivers	5%	41%	46%	95%

Notes: Table 1.1 lists examples of non-college occupations. The first three occupations (cashiers, housekeepers and cleaners, hairdressers and cosmetologists) are "traditionally female" occupations. The last three occupations (miners, machinists, and truck drivers) are "traditionally male" occupations. The "female" and "male" occupations differ greatly in terms of annual earnings and whether or not they provide benefits such as retirement pensions and health insurance. "Male" occupations pay between the 40th to the 80th percentile of median annual earnings among all occupations in 2010, while "female" occupations pay below the 10th percentile of median annual earnings. "Male" occupations are significantly more likely to offer a pension retirement plan for workers, and slightly more likely to offer employer-sponsored health insurance. The provision of these benefits indicate that "male" occupations are more likely to have the trappings of careers than "female" occupations. The proportion of female workers and earnings percentile data were obtained from the 2010 American Community Survey (ACS). The benefits data were obtained from the 2010 Annual Social and Economic Supplement of the Current Population Survey (CPS-ASEC). The American Community Survey provides reliable summary statistics regarding work and earnings within occupations. Its measures regarding retirement income and health insurance, however, are too general for the purposes of this paper. In contrast, the CPS-ASEC Supplement asks individuals whether they have retirement income as a result of their employment, separate from survivorship payments, disability benefits, Social Security income, Veterans administration payments or other forms of income. The CPS-ASEC also asks individuals if they are the policyholder for their employer-sponsored health insurance.

TABLE 1.2

OLS REGRESSION OF COLLEGE ENROLLMENT ON OIL & GAS EMPLOYMENT

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Panel A: Employment in Oil & Gas Industry			
Employment Share	-0.245	-0.076	-0.195	-0.134
	(0.346)	(0.123)	(0.309)	(0.149)
	Panel B: Employment in Oil, Gas, & Related Industry			
Employment Share	-0.477**	-0.012	-0.258	0.040
	(0.221)	(0.098)	(0.240)	(0.118)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Ordinary least squares regression of college enrollment on employment share. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Panel A displays the effect of employment share in only the oil & gas industry on college enrollment. Panel B displays the results of employment share in oil, gas, & related industries on college enrollment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 1.3
FIRST STAGE REGRESSION OF OIL & GAS EMPLOYMENT ON INSTRUMENTS

Main Analysis Sample

	Oil & Gas Employment (1)	Oil, Gas, & Related Employment (2)
	Specification 1: Employment IV $(r_s E_{-s,t})$	
Employment IV	2.087***	3.223***
	(0.804)	(1.028)
F-statistic	11.684	20.441
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*	
Employment IV	1.433*	2.614***
	(0.853)	(0.865)
Price IV	7.8e-05*	7.7e-05**
	(4.6e-05)	(3.6e-05)
F-statistic	10.860	11.580
Demographic controls	Yes	Yes
State FE	Yes	Yes
Observations	1782	1782

Notes: First stage regression of employment share on instruments. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. In all cases, the first stage regression passes the Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 1.4
2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL & GAS EMPLOYMENT

Main Analysis Sample

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil & Gas Employment	-1.777	-3.805***	-1.871	-1.414*
	(1.773)	(1.055)	(1.358)	(0.765)
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*			
Oil & Gas Employment	-1.806	-3.838***	-1.811	-1.095
	(1.334)	(1.089)	(1.431)	(0.698)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil & gas industry. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5

2SLS Regression of College Enrollment on Oil, Gas, & Related Employment

Main Analysis Sample

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil, Gas, & Related Employment	-1.101	-2.358***	-1.159	-0.876*
	(0.981)	(0.503)	(0.833)	(0.521)
	Specification 2: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs Average Prices			
Oil, Gas, & Related Employment	-0.990	-2.114***	-0.817	-0.369
	(0.709)	(0.436)	(0.808)	(0.444)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil, gas, & related industries. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 1.6

FIRST STAGE REGRESSION OF ROUTINE LABOR SHARE ON INSTRUMENTS

	Routine labor share (1)	Routine labor share (2)
predicted routine labor share * 1980	-0.123***	-0.132***
	(0.0232)	(0.0265)
predicted routine labor share * 1990	-0.336***	-0.356***
	(0.0272)	(0.0302)
predicted routine labor share * 2000	-0.493***	-0.460***
	(0.0267)	(0.0304)
Observations	2888	2888
F	193.8	127.1
Demo. ctrls		Yes
Commuting zone dummies	Yes	Yes
Year dummies	Yes	Yes

Notes: First stage regression of actual routine labor share on Bartik prediction of routine labor share (based on 1950 industry shares). Column (2) adds demographic controls for total population, proportion female, proportion black, proportion Hispanic, and proportion by ten-year age bin. Commuting zone and year dummies included. Regressions conducted at the commuting zone-year level. Standard errors clustered at the commuting zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.7

2SLS REGRESSION OF COLLEGE ENROLLMENT ON ROUTINE LABOR SHARE (18-25)

	% female enrollment (1)	% female enrollment (2)	% male enrollment (3)	% male enrollment (4)	college gender gap (5)	college gender gap (6)
Routine share employment	-0.502** (0.200)	-0.742*** (0.191)	-0.0423 (0.182)	-0.206 (0.175)	0.460*** (0.118)	0.536*** (0.148)
Observations	2888	2888	2888	2888	2888	2888
First Stage F-stat	193.8	127.1	193.8	127.1	193.8	127.1
RMSE	0.0554	0.0442	0.0572	0.0463	0.0348	0.0345
Demo. ctrls		Yes		Yes		Yes
Commuting zone dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Effect of declining routine-intensive employment on college enrollment among 18-25 year olds, using Bartik instrument for employment in high-routine occupations. Columns (2), (4), and (6) add demographic controls for total population, proportion female, proportion black, proportion Hispanic, and proportion by ten-year age bin. Commuting zone and year dummies included. Regressions conducted at the commuting zone-year level. Standard errors clustered at the commuting zone level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.8

2SLS REGRESSION OF COLLEGE ENROLLMENT ON ROUTINE LABOR SHARE (18-30)

	% female enrollment (1)	% female enrollment (2)	% male enrollment (3)	% male enrollment (4)	college gender gap (5)	college gender gap (6)
Routine share employment	-0.351** (0.164)	-0.476*** (0.158)	-0.172 (0.173)	-0.222 (0.168)	0.179** (0.0824)	0.254** (0.105)
Observations	2888	2888	2888	2888	2888	2888
First Stage F-stat	193.8	127.1	193.8	127.1	193.8	127.1
RMSE	0.0451	0.0355	0.0503	0.0400	0.0275	0.0270
Demo. ctrls		Yes		Yes		Yes
Commuting zone dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Effect of declining routine-intensive employment on college enrollment among 18-30 year olds, using Bartik instrument for employment in high-routine occupations. Columns (2), (4), and (6) add demographic controls for total population, proportion female, proportion black, proportion Hispanic, and proportion by ten-year age bin. Commuting zone and year dummies included. Regressions conducted at the commuting zone-year level. Standard errors clustered at the commuting zone level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9

Aggregate Changes in Non-College Employment

Year	Change in non-college jobs for women	Change in non-college jobs for men
1970-1980	-0.086	-0.086
1980-1990	-0.092	-0.075
1990-2000	-0.056	-0.028
2000-2005	-0.024	-0.017

Notes: The table presents the change in the labor share of non-college jobs for women and men. These tabulations are used to construct counterfactual college enrollment rates for men and women, depicted in figure 1.13.

CHAPTER 2 : Gender Differences in Skill Profiles, Wage Returns, and College Enrollment

2.1 Introduction

Chapter 1 targets occupational segregation as a key force behind the greater college enrollment rates of women relative to men today. Chapter 2 investigates one primary reason behind the gender segregation among non-college occupations and links it to gender differences in the returns to a college degree. Using detailed data on cognitive and non-cognitive skills from the National Longitudinal Study of Youth 1979, I employ principal component analysis to construct skill profiles for each individual. The data point to the existence of "gender-based skill", which differs between men and women. I then estimate a structural Roy model to compute the returns to different skills in the college and non-college labor markets. The model estimates reveal that gender-based skill commands high returns on non-college wages for men but not for women, since non-college occupations with high pay tend to value the gender-based skills of men. Overall, my findings suggest that gender-based skill complements non-college work for men and college work for women.

Using the National Longitudinal Study of Youth 1979 (NLSY79), I construct skill profiles separately for men and women using scores from the Armed Services Vocational Aptitude Battery (ASVAB). I find that in addition to cognitive skill, individuals possess another dimension of skill that varies by gender. For men, this gender-based skill loads heavily on the ASVAB tests designed to measure mechanical skill. For women, however, gender-based skill loads on the ASVAB tests designed to measure coding and numeracy. In a naive probit regression, I find that controlling for cognitive skill, men with higher measures of gender-based skill tend to be less likely to attend college. For women, on the other hand, gender-based skill does not significantly predict attending college.

I then use these skill profiles in a Roy model that separately identifies the impact of skills on initial wage rates and on the growth of wages over time, following the framework of Rosen and Willis

(1979). In the model, I use a Heckman selection correction procedure to correct for the tendency of higher-ability individuals to both attain more schooling and earn higher wages (Heckman, 1979). The model demonstrates that for men, gender-based skill leads to significantly greater wage growth over the life cycle in the *non-college labor market*, but not the college labor market. In contrast, for women, gender-based skill increases initial wages in only the college labor market. Finally, I use the model to estimate counterfactual college and non-college wages for each individual. I find that increases in non-college wages decrease college enrollment. Therefore, if men have higher non-college wages, they would be expected to rationally choose a lower level of college enrollment than women.

Overall, the results build a strong case that gender-based skill complements non-college labor for men. Additionally, they provide some evidence that gender-based skill complements college labor for women. I find that controlling for cognitive skills, higher gender-based skill predicts a lower probability of enrolling in college for men. The Roy model reveals one important channel behind this finding: gender-based skill commands a high non-college wage rate for men, which in turn increases the opportunity costs to attending college and decreases the earnings premium from a college degree. For women, gender-based skill increases college earnings in the same way that cognitive skill does. The results suggest that men face a trade-off between college and non-college earnings with respect to their skills. Having high gender-based skill is costly for men, in that it raises the value of their outside option. For women, no such trade-off exists: high gender-based skill operates in parallel with high cognitive skill by increasing future college wages.

This chapter contributes to existing knowledge by demonstrating that skill endowments create a comparative advantage in non-college work for men, such that it is natural for more women than men to choose to attend college. In the NLSY79 data, I demonstrate a stark gender difference with respect to certain skill profiles. Although cognitive and socio-emotional skills are approximately equivalent between men and women, men categorically score better on tests designed to measure mechanical ability. I present new evidence that this disparity has substantial implications for the college-going decision through affecting college and non-college wage rates. The results indicate that pre-existing differences between men and women make the greater college enrollment of women a more efficient outcome than it may at first appear. My empirical evidence provides further support for prior work on how the returns to brawn (physical ability) and brains (cognitive ability) impacts gender differences in employment and educational outcomes (see Welch, 2000; Rendall, 2017).

2.2 Data

This chapter uses data from the National Longitudinal Study of Youth 1979 (NLSY79), which is conducted by the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics, 2012). The study surveys a nationally representative sample of the same 12,686 individuals each year from 1979 to 1994 and every two years from 1996 to 2010. The NLSY79 is especially useful for examining the impact of skills on future occupational success, for two reasons. First, the NLSY79 contains rich longitudinal data for each year of work, which is critical for examining how skills influence the evolution of earnings over time. I use the longitudinal nature of the data to separately capture how skills influence initial wages and wage growth rates over the work life.[1]

Second, to explore the role of skill profiles in determining wage returns, I use the Armed Services Vocational Aptitude Battery (ASVAB) tests, which are taken by a little over 90% of the sample in 1981. ASVAB tests are designed and used by the military for enlistment screening and job assignment purposes (Prada and Urzua, 2014), and are widely used to measure cognitive and non-cognitive skill in the labor economics literature (see Neal and Johnson, 1996; Juhn et al., 2015; Lise and Postel-Vinay, 2016). Moreover, the NLSY79 routinely surveys respondents on socio-emotional skills, time preferences, and risk preferences, which have all been shown to be relevant in succeeding both at school and at work.

In particular, this chapter focuses on cognitive skill, "gender-based" skill, and socio-emotional skill.

[1]Individuals in the sample are born in the period 1955-1965. They are 14-22 when first surveyed by the NLSY79 in 1979 and 47-52 in 2012, the last year in the data.

Following the literature in labor economics (see Neal and Johnson, 1996; Juhn et al., 2015; Lise and Postel-Vinay, 2016), I measure cognitive skill using scores on the Armed Forces Qualification Test (AFQT), which is a combination of four ASVAB subtests: Arithmetic Reasoning, Mathematics Knowledge, Paragraph Comprehension, and Word Knowledge. Using principal component analysis on ASVAB scores, I determine that in addition to cognitive skill, there exists a second dimension of skill. Crucially, this second dimension differs for men and women. For men, this second skill loads on ASVAB subtests designed to test mechanical ability: Auto and Shop Information, Electronics Information, and Mechanical Comprehension. For women, this second skill loads on the Coding Speed and Numerical Operations subtests. Due to these stark gender differences, I call this second dimension of skill "gender-based" skill. Lastly, I use the Rotter Locus of Control and the Rosenberg Self-Esteem scales to measure socio-emotional ability (see Rotter, 1966; Rosenberg, 1965). The aim of this chapter is to demonstrate that, controlling for cognitive and socio-emotional skill, "gender-based skill" contributes to men's greater non-college wages and therefore their lower rate of college enrollment relative to women.

2.3 Wage Returns to Skill Profiles

Many occupations that do not require a college degree might still pay highly under the theory of compensating wage differentials (Smith, 1776; Rosen, 1986; Welch, 2000). For example, in trucking and transportation, construction, or law enforcement, employers value mechanical skill, physical strength, or risk-tolerance, among other attributes. Men face a comparative advantage in finding employment in such occupations, as shown by figure 1.2 and table 1.1 in Chapter 1. The evidence is consistent with prior work on gender differences in attributes and preferences. Experimental evidence has shown that women tend to be more risk-averse (Croson and Gneezy, 2009; Eckel and Grossman, 2008), which may contribute to the scarcity of women in risky occupations. Biological studies have demonstrated that in general, men are physically stronger than women (see Miller et al., 1993; Leyk et al., 2007), which likely contributes to the dominance of men in physically demanding occupations. This chapter argues that men appear to have higher mechanical skill than women, and that this mechanical skill presents costs to attending college for men by increasing expected non-college wages.[2]

To paint a baseline picture of the stark earnings differences between non-college men and women, table 2.1 lists the 18 highest-paying occupations that only require a high school diploma or equivalent (Bureau of Labor Statistics, 2014). Median salaries are obtained from the Bureau of Labor Statistics Occupational Outlook Handbook. I use 2010 census data to calculate the proportion of women employed in each occupation.[3] Women comprise less than 25% of the workforce in 11 of the 17 occupations for which 2010 census data exists.[4] The majority of male-dominated occupations involve work that requires risk, mechanical skill, and physical strength. For example, the Occupational Outlook Handbook reports that elevator installers and repairers "may suffer falls from ladders, burns due to electrical shocks, and muscle strains from lifting and carrying heavy equipment" (Bureau of Labor Statistics, 2014). Additionally, elevator installers and repairers are constantly exposed to hazardous substances. In a survey of work context, 94% of respondents reported being exposed to hazardous conditions "every day" and 80% reported being exposed to hazardous equipment "every day". Among the respondents, 99% reported exposure to high places "every day" (O-NET, 2015).

While table 2.1 mostly serves to present motivating examples, it is telling that the overwhelming majority of high paying non-college occupations employ very few women. The labor market rewards skills other than intelligence. If mechanical skill is one of these skills, and men possess greater endowments of mechanical skill than women, how might these ability differences influence the return to a college degree? The model in the next section explores these questions in greater detail.

[2] I remain agnostic as to why men may have higher mechanical skills than women. Perhaps biological differences lead to differences in mechanical skill. Perhaps more boys than girls grow up learning about cars or electronics, which enable them to perform better on tests that measure knowledge about automobiles, mechanics, and electronics. This chapter explores the ramifications of ability differences on future earnings independent of how they might have arisen.

[3] See data appendix A.3 for details.

[4] There is no 1990 occupational classification code for gaming manager in the 2010 American Community Survey data.

2.4 Model and Estimation Strategy

In this section, I investigate how gender differences in skill profiles contribute to differences in wages and college-going. I use principal component analysis to construct skill profiles, and find substantially different skill profiles between men and women. I then examine the impact of these skill profiles within a Roy model framework modified from Rosen and Willis (1979). The model allows for a direct comparison of whether different skill profiles garner different wage returns for male and female workers, since it enables the estimation of counterfactual wage rates for each individual in the data set. Finally, I examine whether gender differences in earnings over the life cycle contribute to gender differences in college-going.

2.4.1 Model of Wage Determination and the College-Going Decision

I extend the Rosen and Willis (1979) framework to incorporate a two-type ($\ell \in \{\text{male, female}\}$), multi-skill model of the college-going decision. As in Rosen and Willis (1979), wages evolve according to

$$w_{it}^{c,\ell} = \bar{w}_i^{c,\ell} \exp(g_i^{c,\ell} t) \tag{2.4.1}$$

where $\bar{w}_i$ is initial wage for individual i and g_i is growth rate of wages. Both initial wages and wage growth rates are indexed by $c \in \{0,1\}$, the decision to attend college, and ℓ, the gender of the individual.

Initial wages and wage growth rates are determined according a vector of skills for each individual. Specifically,

$$\ln \bar{w}_i^{1,\ell} = x_i \beta_{1,\ell} + u_{1i} \qquad \text{if } c = 1 \tag{2.4.2}$$

$$\ln \bar{w}_i^{0,\ell} = x_i \beta_{0,\ell} + u_{0i} \qquad \text{if } c = 0$$

$$g_i^{1,\ell} = x_i \gamma_{1,\ell} + u_{3i} \qquad \text{if } c = 1 \tag{2.4.3}$$

$$g_i^{0,\ell} = x_i \gamma_{0,\ell} + u_{2i} \qquad \text{if } c = 0$$

where u_1, u_2, u_3, u_4 are jointly normally distributed. Here, x_i includes skill profiles and a vector of demographic controls (age, race, family background, and location).

Individuals can choose to forego college and start work right away at $year_0^0$ for wage $w_{it}^{0,\ell}$ $(c = 0)$ or attend college and start their career at a later year, $year_0^1$, for wage $w_{it}^{1,\ell}$ $(c = 1)$. They make their decision based on whether college-going maximizes their lifetime earnings:

$$c = \mathbf{1}\{\ln V^{1,\ell} > \ln V^{0,\ell}\} \tag{2.4.4}$$

where life-time earnings follow the equation[5]

$$V^{c,\ell} = \int_{\text{year}_0^c}^{\infty} \bar{w}_i^{c,\ell} \exp(g_i^{c,\ell} t) \exp(-r_i t) dt \approx \frac{\bar{w}_i^{c,\ell}}{r_i - g_i^{c,\ell}} \exp(-r_i \text{year}_0^c) \tag{2.4.5}$$

Plugging equation (2.4.5) into equation (2.4.4) yields

$$c = \mathbf{1}\{\ln \bar{w}_i^{1,\ell} - \ln \bar{w}_i^{0,\ell} - \ln(r_i - g_i^{1,\ell}) + \ln(r_i - g_i^{0,\ell}) - r_i(\underbrace{year_0^1 - year_0^0}_{S}) > 0\} \tag{2.4.6}$$

Taylor approximating the non-linear terms around population terms $\bar{g}^1, \bar{g}^0, \bar{r}$ yields an equation that allows for separate identification of the effects of initial wages $\ln \bar{w}_i^{c,\ell}$ and wage growth rates $g_i^{c,\ell}$.

$$c = \mathbf{1}\{\alpha_0 + \alpha_1(\ln \bar{w}^{1,\ell} - \ln \bar{w}^{0,\ell}) + \underbrace{\alpha_2}_{\frac{1}{\bar{r} - \bar{g}^1}} g^{1,\ell} + \underbrace{\alpha_3}_{-\frac{1}{\bar{r} - \bar{g}^0}} g^{0,\ell} + \underbrace{\alpha_4}_{-[S - \frac{1}{r_i - \bar{g}_i^1} + \frac{1}{r_i - \bar{g}_i^0}]} r > 0\} \tag{2.4.7}$$

[5]Equation (2.4.5) integrates to infinity, which is unrealistic since individuals end their careers before then. This is merely an approximation, since the difference between ending a career at infinity and at 65 leads to negligible differences in the closed form solution.

The Taylor approximation also leads to sign predictions of the α values, which serve as an additional estimation check when the model is taken to the data. α_2 should be positive, α_3 should be negative, and α_4 should be negative as long as $S - year_0^1 - year_0^0$ is sufficiently large. The model estimates reflect these predictions.

Substituting equations (2.4.2) and (2.4.3) into equation (2.4.7) leads to the estimation equation

$$c = \mathbf{1}\{\alpha_0 + \alpha_1(X\beta_1 - X\beta_0) + \alpha_2 X\gamma_1 + \alpha_3 X\gamma_0 + \alpha_4 r > -\underbrace{(\alpha_1(u_1 - u_0) + \alpha_2 u_3 + \alpha_4 u_2)}_{\varepsilon}\} \tag{2.4.8}$$

Because u_1, u_2, u_3, u_4 are jointly normal, ε is normally distributed. With equation (2.4.8) alone, the parameters of interest α cannot be separately identified. Rather, equation (2.4.9) must be estimated in order to construct a control function that approximates the probability of an individual i attending college given $w_i = (x_i, r_i)$:

$$c = \mathbf{1}\{\alpha_0 + X(\alpha_1(\beta_1 - \beta_0) + \alpha_2\gamma_1 + \alpha_3\gamma_0) + \alpha_4 r > -\varepsilon\} = \mathbf{1}\{W\pi > -\varepsilon\} \tag{2.4.9}$$

The function $\hat{k}(X)$ constructed using estimates from equation (2.4.9) can then be used to control for selection into college. If certain characteristics directly affect both an individual's probability of attending college and his wages, the β coefficients would be biased. The control function approach addresses these concerns by including in the regression model a term that approximates an individual's probability of college attendance as a function of her underlying characteristics.

The wage regression equations are then

$$\ln w^{c,\ell} = X\beta_{c,\ell} + \sigma_w \hat{k}(X) + u_c \tag{2.4.10}$$

$$g^{c,l} = X\gamma_{c,\ell} + \sigma_g \hat{k}(X) + u_{c+2} \tag{2.4.11}$$

From equations (2.4.10) and (2.4.11), I obtain $\hat{\beta}_{c,\ell}$ and $\hat{\gamma}_{c,\ell}$. I then construct counterfactual wages terms for each individual i if he had gone to college and if he had not: $\widehat{\ln\overline{w}_i}^{0,\ell}$, $\widehat{\ln\overline{w}_i}^{1,\ell}$, $\widehat{g}_i^{0,\ell}$, and $\widehat{g}_i^{1,\ell}$. Finally, using these counterfactual wages terms, the model then estimates the coefficients of interest, α, which represent the effect of college and non-college wages on the college-going decision:

$$c = \mathbf{1}\{\alpha_0 + \alpha_1(\widehat{\ln\overline{w}}^{1,\ell} - \widehat{\ln\overline{w}}^{0,\ell}) + \alpha_2\widehat{g}^{1,\ell} + \alpha_3\widehat{g}^{0,\ell} + \alpha_4 r \tag{2.4.12}$$

The α_1 estimated from equation 2.4.12 represents the effect of the difference in log initial wages on the college-going decision; α_2 represents the effect of the college wage growth rate on the college-going decision; α_3 represents the effect of the non-college wage growth rate on the college-going decision. The next section reports the results from the model.

2.5 Results

2.5.1 Gender Differences in Skill Measures

I use principal component analysis to transform the scores of the ten ASVAB scores into aggregate skill measures. Figures 2.1 and 2.2 show the component loadings for men and women, respectively. Loadings for component 1 are displayed on the x-axis, while loadings for component 2 are displayed on the y-axis. Component 1 loadings are similar for men and women, and the loadings are high on all the ASVAB tests designed to measure intellectual skill (Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning, Mathematical Knowledge, Numerical Ability, and Coding Speed) (Prada and Urzua, 2014).

However, the principal component analysis reveals that one component alone is insufficient to explain the variation in ASVAB scores for men and women. There exists a secondary component, which loads heavily onto the three ASVAB tests designed to test mechanical skill (Automobile and Shop information, Electronics Information, and Mechanical Comprehension) *only for men*. For women, the secondary component loadings are on Coding Speed and Numerical Operations. The component 2 loadings provide evidence that men have greater endowments in mechanical skill relative to women. For women, variation in the mechanical ability test scores and intellectual ability test scores are captured by the same component, suggesting that performance on the mechanical ability tests is primarily explained by intellectual skill. For men, variation in mechanical ability test scores is captured by a component that is orthogonal to the component that captures variation in intellectual ability test scores.

The second component is important for explaining ability for both men and women, but represent different skills. For men, the second component represents mechanical skill. For women, the second component measures additional intellectual skill (that might differ slightly from the intellectual skill measured by the first component). Since the second component loads onto Numerical Operations and Coding Speed scores for women, it appears to represent some measure of technical intellectual ability. For simplicity, it is useful to think of the second component as a representative measure of "gender-based" skill, which represents mechanical skill for men and technical intellectual skill for women. The labor market may reward gender-based skill, in addition to the more traditional intellectual skill that has been the focus on most of the labor economics literature.[6] I explore this point in the Roy model.

Table 2.2 lists the (standardized) gender-based ability measure computed from the principal component analysis. Table 2.2 also lists the raw ASVAB scores of the three battery tests designed to test mechanical ability: Automobile and Shop Information, Electronics Information, and Mechanical Comprehension. In all three measures, men significantly outperform women independent of the college-going decision. This corroborates the principal component analysis result that men possess

[6] I use exploratory factor analysis as well, and obtain similar results. For women, the loadings for component 2 are on word knowledge instead of coding speed and numerical ability, but otherwise the results of the Roy model remain similar.

mechanical ability but that mechanical ability is difficult to detect in women, since figure 2.2 shows that performance on the three mechanical ability tests seems to be primarily explained by intellectual ability in women. For women, gender-based ability loads on *Coding Speed* and *Numerical Operations*. On average, scores for both subtests are higher for women than men within education categories, but the differences are negligible.

Table 2.2 also shows the average of Armed Forces Qualification Test (AFQT) scores, which has been commonly used in the economics of educational literature as a measure of intellectual ability (see Neal and Johnson, 1996). Individuals who attend college score significantly higher in the AFQT than individuals who do not attend, and this result holds for both men and women. The AFQT is calculated as a linear combination of the Paragraph Comprehension, Word Knowledge, Mathematical Knowledge, and Arithmetic Reasoning subtests in the ASVAB (ASVAB Fact Sheet).

Table 2.2 also lists socio-emotional ability, which is roughly similar between men and women. Socio-emotional skill is constructed as an arithmetic average of the Rotter Locus of Control scale and the Rosenberg Self-Esteem scale from the NLSY79 dataset (following Prada and Urzua, 2014; Heckman, Stixrud, and Urzua, 2006). The loadings of component 1 and component 2 are close to 0 on the socio-emotional measure for both men and women, while the loading for the third and last component (not shown) is close to 1 on the socio-emotional measure for both men and women. These results are consistent with the assumptions of orthogonality between socio-emotional skills and intellectual skills used in prior literature (see Prada and Urzua, 2014; Heckman, Stixrud, and Urzua, 2006). I control for socio-emotional ability in the model, since it has been shown to matter for educational attainment and for wage determination.

Finally, the table breaks down log hourly wages by gender and education. College-goers make more than those who only hold high school diplomas. Male college-goers make more than women college-goers, and male high school graduates make more than female high school graduates. As in the census data, the gender wage gap among non-college workers is higher than that among college workers. The model separates hourly wages into two components: log initial wage rate at the start of the career, and the growth rate of wages over the life cycle. Log initial wage rates are higher for college graduates than high school graduates, and higher for men than women within education categories. However, wage growth rates are similar at around 0.08 across the four categories.

2.5.2 Roy Model Results

Table 2.3 reports the probit of individual skill profiles (including gender-based ability, intellectual ability, and socio-emotional skill) on whether the individual attended college. It presents the estimates from equation (2.4.9). Only individuals with at least a high school diploma are included. Columns (1) and (2) display the coefficient estimates for men, while columns (3) and (4) display the coefficient estimates for women. Columns (1) and (3) use the raw ASVAB scores for mechanical ability (Automobile and Shop Information, Electronics Information, and Mechanical Comprehension), while Columns (2) and (4) use gender-based skill constructed from the principal component analysis. The regression controls for socio-emotional skill, risk aversion measures, time preferences, and a quadratic in AFQT as a measure of intellectual ability. Controls for geographic region, urban environment, height, race, age, and number of siblings are also included, since all of these measures have been shown to matter for college enrollment status.

Column (1) shows that for men, scoring high on the Automobile and Shop Information test or the Mechanical Comprehension test is negatively associated with the probability of attending college, holding intellectual ability constant. According to column (3), this effect does not hold true for women. There is a high degree of correlation between scores on each of the three mechanical ability ASVAB tests, which explains why the coefficient on Electronic Information is insignificant and why the coefficient on mechanical comprehension is only marginally significant. Appendix table B.1 uses each score alone as a proxy for mechanical ability. Each test score negatively predicts the probability of enrolling in college for men but has no effect on college enrollment for women.

Columns (2) and (4) then uses the measure of gender-based ability constructed from the principal component analysis. Holding intellectual abilities constant, a standard deviation increase in gender-based ability decreases the probability of attending college by 18 percentage points for men but does not affect the probability of attending college for women. Using the coefficient estimates in table 2.3, I construct a control function that estimates the probability that an individual chooses to attend college as a function of his underlying characteristics. This control function is included in the wage regressions.

Table 2.4 presents the regression of skill profiles on log initial wages for college-educated men (1), non-college men (2), college-educated women (3), and non-college women (4). It displays the estimates from equation (2.4.10). The regression includes individual demographics and the control function predicted from equation (2.4.9). AFQT is significant and positive on log initial wages for men, independent of college-going status. AFQT is insignificant for women, but gender-based skill is positive for women who attended college. For women, gender-based skill is comprised of a linear combination of Numerical Operations and Coding Speed. College-educated women who score high on either of these measures are more likely to earn greater initial wages, since high numerical or coding ability are likely to make them more attractive employees.[7]

Table 2.5 performs the regression of skill profiles on wage growth rates for college-educated men (1), non-college men (2), college-educated women (3), and non-college women (4). It displays the estimates from equation (2.4.11). Mechanical skill increases the rate of wage growth for non-college men but not college-educated men. This increase in wage growth rate more than compensates for the decrease in log initial wages that non-college men with high mechanical ability experience (as shown in table 2.4).[8] Together, tables 2.4 and 2.5 suggest that non-college men with high mechanical ability sort into occupations with low initial wages but high wage growth. This is empirically observed in the NLSY79 data.

The estimates presented in tables 2.4 and 2.5 are used to construct counterfactual wages, which are then used to estimate equation (2.4.12). For each individual, the model predicts the log initial wage

[7]In alternative specifications, I compose a "mechanical" skill measure for women by taking men's loadings on the ASVAB mechanical tests and combining them with women's corresponding scores. I compose this mechanical skill measure using both principal component analysis and exploratory factor analysis. This measure does not appear to influence wage returns for women in either case. The results of these specifications are available upon request.

[8]In simulations, the increased wage growth rate leads non-college men with high mechanical ability to enjoy substantially larger income over the life-cycle even at high discount rates, despite their lower initial wages.

if college was chosen and if college was not chosen, as well as the growth rate of wages if college was chosen and if college was not chosen. These wage terms are estimated separately for men and women. Constructing the counterfactual wage terms allows for identification of the α values in equation (2.4.12), which represent the effect of college and non-college wages over the life-cycle on the decision to attend college.

Table 2.6 presents the estimates from equation (2.4.12). I regress an indicator for college attendance on the difference in constructed log initial wages, the wage growth rate for conditional on attending college, the wage growth rate conditional on not attending college, and the annual discount rate. The estimates are in line with those from the original Rosen and Willis (1979) model, although they are more realistic. If the difference in log initial wages increases by 10%, men are 7.5 percentage points more likely to attend college and women are 14 percentage points more likely to attend college. A 1% increase in the college wage growth rate leads men to be 3.8 percentage points more likely to attend college and women to be 2.3 percentage points more likely to attend college. For the same increase in the wage growth rate from not attending college, men are 3.4 percentage points less likely to attend college and women are 3.8 percentage points less likely to attend college.

The estimates from the model may appear to be high at first, especially compared to the results presented in Part I. However, a 10% increase in initial wages would be quite large - the difference in median wages between college-educated men and non-college educated men is a 25% change. Therefore, a 10% increase in initial wages should generate large responses in the college-going decision for both men and women. A small increase in the wage growth rate has large ramifications for earnings over the life-cycle. An increase of 1% should also lead to large responses by men and women who take into account their lifetime wealth when making their decision to attend college.

2.5.3 Model Fit

To assess how well the model matches to actual wages over the work life, I plot estimated earnings and actual earnings against the number of years worked. Figure 2.3 presents median hourly earnings by gender and education status. Although the model systematically underestimates the level of earnings, it appears to predict *trends* in earnings quite well for individuals with fewer than ten years on the job. For more than ten years on the job, there is a large spike in actual earnings, which cannot be captured by the simple functional form assumption on wage evolution from Rosen and Willis (1979). The model also does not account for selection into years worked. One explanation for the spike in earnings is that people who work more than ten years at a job tend to have systematically higher earnings than people who work fewer than ten years at a job (potentially because people with lower earnings also tend to exhibit lower attachment to the labor force, are more likely to fall into unemployment, are more likely to choose to exit the labor force temporarily, etc.).

Overall, it appears that the model does a satisfactory job of examining changes in wages over time. A model which more flexibly incorporates wage evolution over the work life and accounts for selection into labor force participation may better match observed data, especially for workers who have worked in the labor market for more than ten years. However, adding features which incorporate differential attachment to the labor force will dramatically complicate the model, and the marginal benefit of better predictions for workers with greater than ten years of work tenure may not justify the cost of a significantly more complicated model.

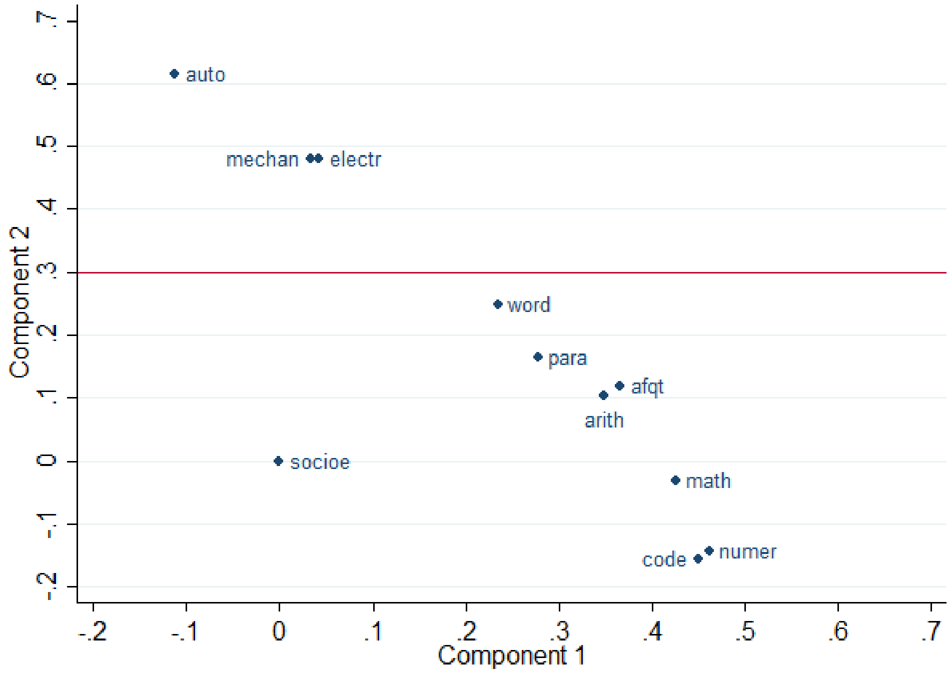
2.6 Conclusion

This paper explores a potential reason behind the extreme occupational sorting among men and women in the non-college labor market, as well as a mechanism that explains why men earn higher non-college wages. First, I use principal component analysis to show that men and women possess skills other than the intelligence measures traditionally used by the labor market literature. These "gender-based skills", which consist of mechanical skill in men and numerical ability in women, also matter in determining educational attainment and labor market outcomes.

I estimate a Roy model, modifying the framework of Rosen and Willis (1979), to examine how multidimensional skill profiles influence earnings and the college-going decision. The model specifies separate wage returns to different skills. I find that mechanical skill exists for men but is difficult to detect in women, and that the labor market rewards high mechanical skill in the form of higher non-college wages. The higher mechanical skill of men generate greater opportunity costs to attending college. In contrast, the skill profiles of women do not appear to present costs to attending college – if anything, numerical ability works alongside traditional intelligence to increase women's college wages. Thus, multidimensional skill profiles present trade-offs to men in terms of college and non-college earnings potential, but not women. *Ceteris paribus*, men with high mechanical skill are more likely to choose to forego attending college, contributing to the lower college enrollment of men relative to women.

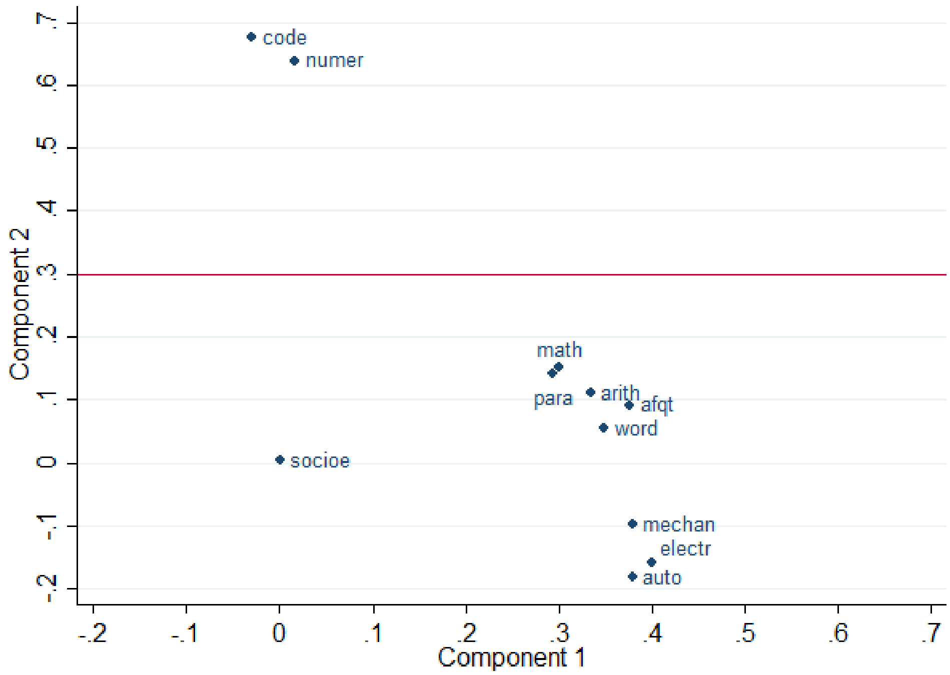
Figures

FIGURE 2.1
COMPONENT LOADINGS FOR ASVAB SCORES, MEN



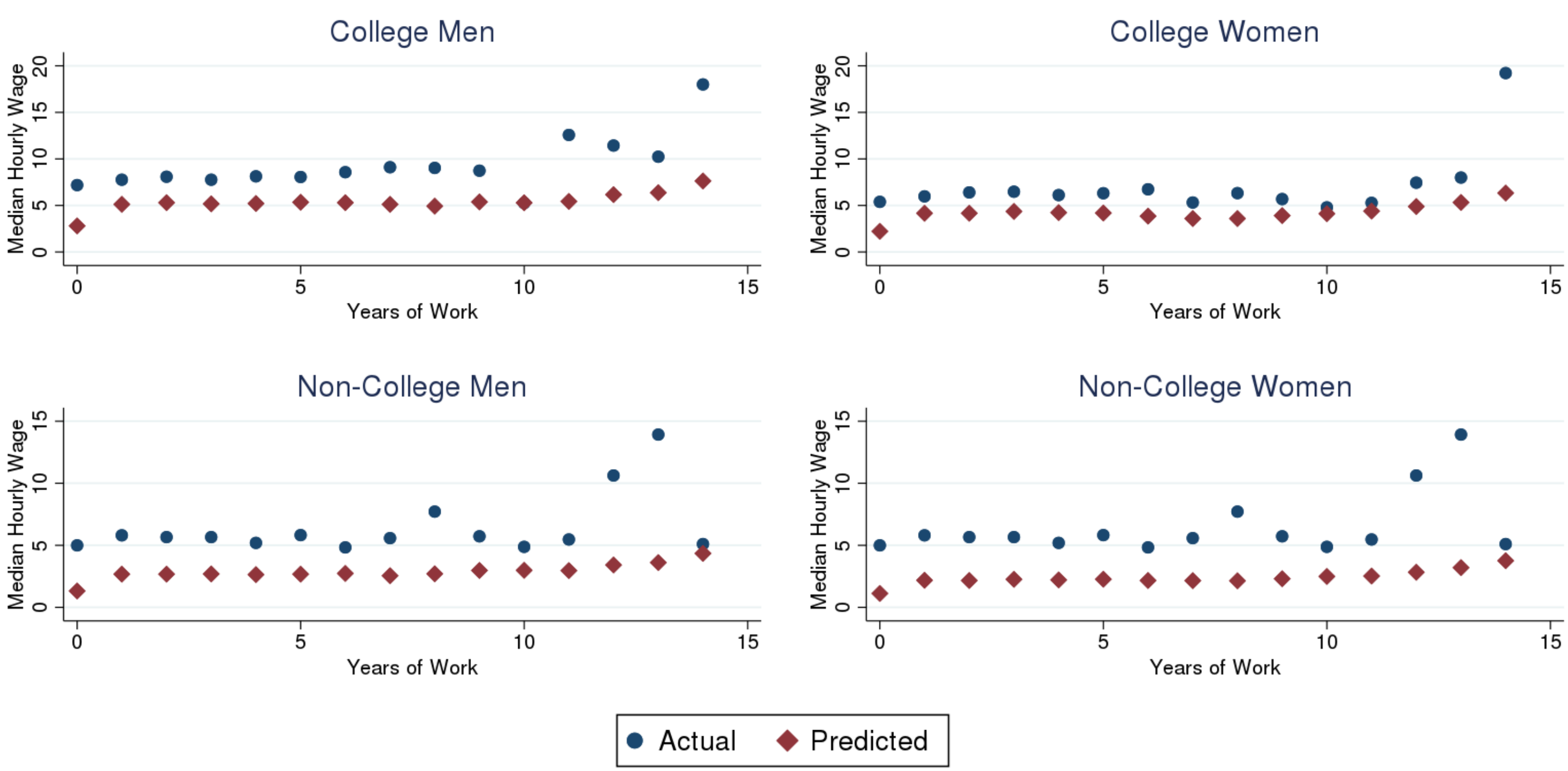
Notes: Principal component analysis was conducted on Armed Services Vocational Aptitude Battery (ASVAB) test scores for the NLSY79 sample. Figure 2.1 depicts the principal component loadings for men. Component 1 loads onto the ASVAB designed to measure intellectual ability (word knowledge, paragraph comprehension, arithmetic reasoning, mathematics knowledge, numerical operations, and coding speed). Component 2 loads onto the ASVAB tests designed to measure mechanical ability (automobile and shop information, electronics information, mechanical comprehension). The results indicate that in addition to intellectual ability (captured by component 1) men also possess mechanical ability (captured by component 2).

FIGURE 2.2
COMPONENT LOADINGS FOR ASVAB SCORES, WOMEN



Notes: Principal component analysis was conducted on Armed Services Vocational Aptitude Battery (ASVAB) test scores for the NLSY79 sample. Figure 2.2 depicts the principal component loadings for women. As with men, component 1 loads onto most of the test scores designed to measure intellectual ability. Component 1 loads onto the mechanical ability tests as well. The fact that the same component loads onto tests of both intellectual and mechanical ability for women suggests that women who perform well on mechanical ability tests do so because of their high intellectual skill. It is not possible to detect a mechanical ability component for women that is separate from intelligence. Component 2 loads onto coding and numerical ability for women, suggesting that technical intellectual ability may be an additional skill women possess.

FIGURE 2.3
MODEL PREDICTIONS



Notes: The figure plots median hourly wages by gender and education status. The circle markers represent actual wages, while the diamond markers represent predictions from the model. The model systematically underestimates the level of hourly earnings, but tracks the changes in earnings over work tenure quite well for people with less than ten years of work tenure. For workers with more than ten years of work tenure, there are large spikes in actual hourly earnings which cannot be accounted for in the model due to the model's simple functional form assumption on wage evolution over time.

Tables

TABLE 2.1
HIGHEST-PAYING OCCUPATIONS AVAILABLE TO HIGH SCHOOL GRADUATES

Occupation	2012 Median Pay	% female
Elevator installers and repairers	$75,000 or more	2.1
Transit and railroad police	$55,000 to $74,999	6.8
Police and sheriff's patrol officers	$55,000 to $74,999	20.8
Buyers and purchasing agents, farm products	$55,000 to $74,999	30.2
Postal service mail carriers	$55,000 to $74,999	36.0
Boilermakers	$55,000 to $74,999	1.7
Real estate brokers	$55,000 to $74,999	52.3
Purchasing agents, except wholesale, retail, and farm products	$55,000 to $74,999	53.4
Artists and related workers	$55,000 to $74,999	50.7
Claims adjusters, examiners, and investigators	$55,000 to $74,999	72.9
Electrical power-line installers and repairers	$55,000 to $74,999	3.3
Gaming managers	$55,000 to $74,999	-[9]
Power planet operators	$55,000 to $74,999	13.7
Farmers, ranchers, and other agricultural managers	$55,000 to $74,999	16.2
Power distributors and dispatchers	$55,000 to $74,999	13.7[10]
Commercial pilots	$55,000 to $74,999	9.5
Detectives and criminal investigators	$55,000 to $74,999	20.8[11]
Nuclear power reactor operators	$55,000 to $74,999	13.7[12]

Notes: Table 2.1 lists the highest paying occupations which do not require a college degree, the median salary in 2012, and the proportion of workers that are female in each occupation. Occupation titles and 2012 median salary information come from the Bureau of Labor Statistics Occupational Outlook Handbook (Bureau of Labor Statistics, 2014). The proportion of female workers per occupation come from the 2010 American Community Survey data (Ruggles et al., 2017).

[9] Occupation not in census data.
[10] Occupation not in census data. Proportion taken from power plant operator occupation.
[11] Police and detectives are classified together in the census data.
[12] Occupation not in census data. Proportion taken from power plant operator occupation.

TABLE 2.2
SUMMARY STATISTICS IN NLSY79 SAMPLE

	Male		Female	
	College	No College	College	No College
College	0.5152		0.5709	
	(0.4999)		(0.4950)	
Log hourly wages	2.074	1.819	1.844	1.516
	(0.5346)	(0.5224)	(0.5224)	(0.5389)
Log hourly wages: $lnw^{c,\ell}$	1.614	0.781	1.425	0.550
(at career start)	(0.629)	(0.505)	(0.630)	(0.541)
Wage growth rate: $g^{c,\ell}$	0.0848	0.0857	0.0706	0.0810
	(0.0572)	(0.0385)	(0.0636)	(0.0406)
Gender-based Skill	0.515	-0.562	0.352	-0.487
	(1.474)	(1.825)	(1.215)	(1.404)
Auto & Shop Score	55.66	52.84	45.46	42.42
	(8.592)	(10.46)	(6.658)	(6.51)
Electronics Score	55.96	49.93	47.86	43.23
	(8.50)	(9.914)	(7.995)	(7.845)
Mechanical Score	56.32	50.76	48.24	43.45
	(8.59)	(10.22)	(8.080)	(7.046)
Numerical Operations	52.60	45.54	53.72	48.46
	(8.087)	(10.23)	(7.729)	(9.662)
Coding Speed	50.86	44.34	53.70	50.09
	(8.549)	(8.953)	(8.728)	(9.588)
AFQT (standardized)	0.879	-0.145	0.647	-0.212
	(0.893)	(0.842)	(0.889)	(0.769)
Word Knowledge	53.73	45.73	52.79	45.84
	(7.147)	(10.05)	(7.682)	(9.642)
Paragraph Comprehension	53.41	44.99	53.70	47.43
	(7.588)	(10.58)	(7.650)	(9.934)
Arithmetic Reasoning	55.55	47.12	51.83	44.53
	(8.940)	(8.976)	(9.104)	(7.846)

Mathematics Knowledge	56.18	45.64	53.73	44.98
	(9.564)	(7.616)	(9.182)	(7.313)
Socio-emotional Skill	15.86	15.33	15.67	15.23
	(2.016)	(1.973)	(1.985)	(2.043)
Rotter Locus of Control Scale	8.023	8.766	8.222	8.945
	(2.362)	(2.349)	(2.364)	(2.332)
Rosenberg Self-Esteem Scale	24.89	23.15	23.84	22.89
	(4.243)	(4.255)	(4.266)	(4.564)
N	1171	1102	1425	1071

Notes: Summary statistics for college enrollment status, wages, and skill measures in NLSY79 analysis sample. "Gender-based skill" for men is comprised of a linear combination of scores on the Auto and Shop Information, Electronics Information, and Mechanical Comprehension tests in the Armed Services Vocational Aptitude Battery (ASVAB) subtests. "Gender-based skill" for women is a linear combination of scores on the Coding Speed and Numerical Operations ASVAB subtests. The Armed Forces Qualification Test (AFQT) score is a composite score traditionally used to measure cognitive ability (see Neal and Johnson, 1996). AFQT scores are derived from the Arithmetic Reasoning, Mathematics Knowledge, Paragraph Comprehension, and Word Knowledge ASVAB subtests. Socio-emotional skill is the average of scores on the Rotter locus of control scale and the Rosenberg self-esteem scale (Rotter, 1966; Rosenberg, 1965). This paper examines the impact of "gender-based skill", controlling for cognitive skill (as measured by AFQT) and socio-emotional skill, on wage rates and college-going. Standard deviations in parentheses.

TABLE 2.3
PROBIT REGRESSION OF COLLEGE ATTENDANCE ON SKILL PROFILES

	Male		Female	
	College	College	College	College
	(1)	(2)	(3)	(4)
gender-based skill		-0.183***		0.0199
		(0.0354)		(0.0298)
auto shop score	-0.0258***		-0.00241	
	(0.00583)		(0.00588)	
electronic score	0.00493		-0.00246	
	(0.00598)		(0.00537)	
mechanical score	-0.00990*		-0.00435	
	(0.00559)		(0.00543)	
$AFQT$	0.880***	0.957***	0.941***	0.871***
	(0.0645)	(0.0714)	(0.0613)	(0.0572)
$AFQT^2$	0.116***	0.112***	-0.0118	-0.00489
	(0.0371)	(0.0376)	(0.0392)	(0.0403)
socioemotional	0.104***	0.102***	0.0894***	0.0876***
	(0.0332)	(0.0331)	(0.0307)	(0.0309)
risk aversion	0.0437***	0.0438***	0.0260**	0.0253**
	(0.0128)	(0.0126)	(0.0119)	(0.0119)
annual discount rate	-0.722	-0.750	-0.391	-0.367
	(0.508)	(0.505)	(0.497)	(0.498)
Constant	1.349*	-0.132	1.504**	1.143**
	(0.733)	(0.689)	(0.600)	(0.540)
Demo. controls	YES	YES	YES	YES
Observations	2272	2272	2493	2493
Pseudo R^2	0.253	0.249	0.213	0.213

Notes: Probit regression of college enrollment status on skill profiles (equation 2.4.9). Regressions control for region of residence, whether residence is urban, height, age, race, and number of siblings. Coefficients on dummies for missing variables suppressed. Cross-sectional regression at year = 1990. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.4

HECKMAN SELECTION CORRECTED RESULTS FOR LOG INITIAL WAGES

	Male		Female	
	College	No College	College	No College
	(1)	(2)	(3)	(4)
gender-based skill	-0.0319	-0.0461*	0.0437**	0.0109
	(0.0296)	(0.0241)	(0.0175)	(0.0176)
$AFQT$	0.388***	0.232**	0.0670	-0.0116
	(0.144)	(0.101)	(0.117)	(0.102)
$AFQT^2$	0.00538	0.00870	-0.00837	0.0158
	(0.0273)	(0.0337)	(0.0248)	(0.0284)
socioemotional	0.0637***	0.0284	-0.00806	0.00984
	(0.0231)	(0.0198)	(0.0184)	(0.0181)
risk aversion	0.0378***	0.00538	-0.00510	0.00771
	(0.0103)	(0.00700)	(0.00719)	(0.00699)
Constant	2.051***	1.211***	3.672***	1.476***
	(0.666)	(0.341)	(0.300)	(0.418)
Demo. controls	YES	YES	YES	YES
Observations	1132	1087	1385	1036
R^2	0.154	0.078	0.211	0.112

Notes: Regression of initial wage rate on skill profiles using Heckman selection correction method (equation 2.4.10). Regressions control for region of residence, whether residence is urban, height, age, race, experience, and experience^2. Coefficients on dummies for missing variables suppressed. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.5
HECKMAN SELECTION CORRECTED RESULTS FOR WAGE GROWTH

	Male		Female	
	College	No College	College	No College
	(1)	(2)	(3)	(4)
gender-based skill	0.00257	0.00403**	-0.000650	0.00194
	(0.00272)	(0.00187)	(0.00249)	(0.00150)
$AFQT$	-0.00133	-0.0130	0.0115	0.00415
	(0.0124)	(0.00959)	(0.0106)	(0.00678)
$AFQT^2$	0.000127	-0.00663**	-0.000596	-0.00223
	(0.00269)	(0.00283)	(0.00250)	(0.00220)
socioemotional	-0.00401*	-0.000954	0.00175	-0.000440
	(0.00231)	(0.00143)	(0.00208)	(0.00158)
risk aversion	-0.000765	-0.000508	0.00129**	0.0000455
	(0.000798)	(0.000547)	(0.000519)	(0.000466)
Constant	0.101*	0.0880***	0.0265	0.107***
	(0.0529)	(0.0254)	(0.0320)	(0.0297)
Demo. controls	YES	YES	YES	YES
Observations	1118	1084	1368	1035
R^2	0.067	0.075	0.025	0.057

Notes: Regression of wage growth rate on skill profiles using Heckman selection correction method (equation 2.4.11). Regressions control for region of residence, whether residence is urban, height, age, race, experience, and experience^2. Coefficients on dummies for missing variables suppressed. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 2.6

REGRESSION ESTIMATES: EFFECT OF WAGES ON COLLEGE ENROLLMENT

	Male (1)	Female (2)
difference in initial wages	1.830***	3.495***
	(0.145)	(0.173)
wage growth rate, college	47.87***	28.57***
	(2.259)	(4.118)
wage growth rate, non-college	-42.93***	-47.64***
	(4.583)	(5.080)
annual discount rate	-1.261**	-0.0399
	(0.571)	(0.475)
Constant	-1.123***	-0.120
	(0.328)	(0.303)
Observations	2273	2496
Pseudo R^2	0.240	0.185

Notes: Regression of college enrollment status on counterfactual initial wage rates, wage growth rates, and discount rate (equation 2.4.12). Coefficients on dummies for missing variables suppressed. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CHAPTER 3 : A Field Study of Charitable Giving Reveals that Reciprocity Decays over Time

3.1 Introduction[1]

Reciprocity motivates a wide range of cooperative behaviors that are crucial to the functioning of modern society (Gachter and Herrmann, 2009). Reciprocity can involve rewarding kind actions or punishing unkind actions. In this paper, we focus on positive reciprocity, defined as any costly behaviors taken to reward a past action that was either kind or beneficial (Falk and Fischbacher, 2006; McCabe et al., 2003). We present the first evidence from a large-scale field study of a fundamental, and previously under-appreciated, feature of positive reciprocity: it decays over time. Our findings have important implications for long-term relationships between individuals as well as the relationships between individuals and organizations. In particular, if feelings of reciprocity diminish over time, interactions between parties may need to be temporally close in order to sustain strong reciprocal relationships. Our findings also provide guidance for governments and organizations interested in leveraging reciprocity to generate compliance or contributions. Policy makers and fundraisers may want to capitalize quickly on the reciprocal motives they induce in others.

Successful fundraising is critical to the survival of most not-for-profit organizations. We study positive reciprocity in a setting where individuals receive a service from a not-for-profit organization and subsequently have the option to reciprocate by making a charitable gift. Specifically, we study giving to a massive hospital system that provides patients with medical care and later solicits them for charitable contributions. We examine how patients' propensity to donate relates to the delay separating their first-ever visit to the hospital and their subsequent receipt of a donation solicitation. Many non-profit organizations that provide services depend on charitable contributions from those they have served, just like our partner hospital system. Schools, hospitals, religious organizations,

[1] This chapter is a postprint version of an article published in the Proceedings of the National Academy of Sciences. The article is under Creative Commons Attribution-NonCommercial-NoDerivatives license 4.0 (CC BY-NC-ND). Chuan, A., Kessler, J., Milkman, K., 2018. A Field Study of Charitable Giving Reveals that Reciprocity Decays over Time. Proceedings of the National Academy of Sciences. DOI: 10.1073/pnas.1708293115

humane societies, and disaster relief providers all deliver services to individuals and later solicit donations from them. Reciprocity may play a large role in the success of these donation solicitations (Meer, 2012). Hospitals alone, the focus of our paper, take in over $9.6 billion in donations each year in the United States (Rosin, 2014).

Past research in economics and psychology has shown that donation decisions are extremely sensitive to context effects (Andreoni and Payne, 2013). Nevertheless, standard theories of economic behavior do not allow the delay separating a service interaction from a donation solicitation to affect generosity, holding all else constant (e.g., the arrival of new information or an income shock). On the other hand, psychology research suggests that the timing of a solicitation relative to a recent interaction could indeed affect generosity. Past research on psychological reactance suggests that requesting a donation too quickly after a service interaction could be off-putting, as it might appear opportunistic and manipulative (Brehm, 1966; Clee and Wicklund, 1980). If this were the case, a longer delay separating a service interaction from a donation solicitation would be expected to increase generosity by reducing reactance. However, there are also reasons to believe that a longer delay separating a service interaction from a donation solicitation could decrease generosity. Memories decay rapidly over time (Schacter, 1999) , so if more time separates a service encounter from a donation solicitation, the gratitude and reciprocity produced by that encounter should be less vividly recalled. Likewise, to the extent that reciprocity is driven by gratitude – a transient, "hot" state – longer delays between a service interaction and a solicitation would be expected to reduce generosity (Loewenstein, 1996; Ritov, 2006; 12. Metcalfe and Mischel, 1999).

Past empirical research has been limited in its ability to isolate the effects of time delays on positive reciprocity, and studies exploring this topic have yielded mixed results. Some past experiments suggest that positive reciprocity completely dies out within a day (Gneezy and List, 2006; Bellemare and Shearer, 2009; Estevez-Sorenson, 2017; Sliwka and Werner, 2017). However, these studies could not disentangle decaying reciprocity from decaying energy, as they measured reciprocity by examining study participants' work output in response to a wage hike, and exhaustion is a powerful alternative explanation for the decay in output detected over time. Other wage experiments have shown that reciprocity stays constant over the course of several hours (Kube et al., 2012; Gilchrist et al., 2016), but these results could easily be due to the short follow-up periods studied. Finally, two wage experiments showed increases in reciprocity over the course of several hours (Kube et al., 2013; Ockenfels et al., 2016). However, these studies again measured reciprocity by examining worker output and the findings could well be the result of learning effects, whereby practice allows workers to improve their performance on a task over time.

Past psychology studies offer some support for the possibility that longer delays may decrease generosity. Using a laboratory experiment and hypothetical scenarios, Burger et al. (1997) showed that the likelihood of returning a small favor (e.g., the gift of a soda from a confederate, the loan of pizza money or help with class notes from a hypothetical acquaintance) decreases the longer the time delay between receiving the favor and an opportunity to reciprocate. Similarly, Flynn (2003) finds that in workplace surveys and a laboratory experiment, the recipients of favors report valuing them less when more time has elapsed since the favor. However, these intriguing studies relied on small samples, idiosyncratic stimuli, and often could not disentangle forgetting about a past favor from a decaying desire to reciprocate.

One field experiment by Becker et al. (2013) examined how the usefulness of a gift influenced the likelihood that its recipient will choose to reciprocate by completing a survey. Although the relationship between reciprocity and time was not the focus of this research, the authors present evidence that a gift encouraged reciprocal behavior six months later but not 18 months later. Importantly, the same individuals were asked to reciprocate twice, so the lack of reciprocity 18 months after the receipt of a gift may be due to the fact that those who reciprocated at six months did not feel the need to reciprocate again.

We build on these past findings with a field study that precisely explores how reciprocity decays over time periods ranging from several weeks to a few months. To investigate how reciprocity changes over time in the field, we partnered with a large university hospital system comprised of a network of eight hospitals. Using data from 82,231 outpatient hospital visits as well as 18,515 donation solicitations and responses to those solicitations, we exploit quasi-experimental variation in the delay separating the hospital system's solicitation mailings from patients' hospital visits to study how this delay affects giving. Specifically, the hospital system solicits donations by mailing solicitations to thousands of recent patients on the same date. Because the timing of patients' hospital visits is random with respect to the date of this mailing, we can examine how the delay separating a patient's recent hospital visit from the receipt of a solicitation affects donations. Our key finding is that an additional 30-day delay in requesting a donation shortly after the provision of medical care decreases the likelihood of a donation to the hospital system by over 30%.

Our paper makes several key contributions to our understanding of the relationship between reciprocity and time. First, we document the decay of reciprocity over time in a consequential field setting, rather than the laboratory. Second, we isolate a decay in reciprocity separately from a decay in social pressure. In our study, prospective donors receive a request to donate via a mailing that they open in the privacy of their own homes. Past studies of the sensitivity of reciprocity to time delays have always examined people's decisions to return a favor either during a face-to-face interaction, where the request to reciprocate was made by the individual who had already performed a favor for the subject (Burger et al., 1997), or when the potential beneficiary was in the same room (Neo et al., 2013; Oechssler et al., 2015; Grimm and Mengel, 2011). These designs not only prevented researchers from separating decays in reciprocity from decays in social pressure, but also introduced the possibility that study participants distorted their behavior because they were aware that they were participating in a research study (Burger et al., 1997; Flynn, 2003; Neo et al., 2013; ; Oechssler et al., 2015; Grimm and Mengel, 2011). Because the individuals we study were not aware that their behavior would be observed by researchers, our data is not subject to concerns about experimenter demand effects. Third, our paper isolates the effect of time delays on reciprocity, while many prior studies of gift exchange in the workplace are unable to disentangle the effect of reciprocity from the effects of exhaustion or learning (Gneezy and List, 2006; Bellemare and Shearer, 2009; Esteves-Sorenson, 2017; Sliwka and Werner, 2017; Kube et al., 2013; Ockenfels et al., 2015). Finally, our study benefits from an extremely large participant sample we are able to examine the behavior of a far larger population than past studies of reciprocity, which improves the precision of our estimates and allows us to detect statistically significant evidence of positive reciprocity where other studies were under-powered to do so (Oechssler, 2015).

To our knowledge, this is the first large-scale field study to explicitly explore the endurance of reciprocity over time. Our evidence that positive reciprocity decays dramatically over time informs economists' understanding of repeated, cooperative interactions and suggests the value of capitalizing quickly on opportunities to benefit from a quid pro quo. Our findings are important for practitioners who often choose to wait before soliciting donations from prospective donors after rendering them a service. This common practice of waiting to solicit could lead non-profit organizations to lose substantial fundraising revenue. Our findings indicate that the loss in fundraising revenue from waiting to solicit is quite large: a back-of-the-envelope calculation comparing our treatment effect to others in the literature suggests that avoiding an additional 30-day delay between providing a service and requesting a donation could improve donation rates by as much as offering a one-to-one matching donation (Karlan and List, 2007). In addition to improving our understanding of how to promote the provision of public goods, the findings we present have important implications for leading economic models of reciprocity, which currently fail to incorporate sensitivity to time (Cox et al., 2007).

3.2 Methods

Human Subjects Protections. Prior to the start of this project, the Institutional Review Board at the University of Pennsylvania reviewed and approved our study procedure. Since our project involved analysis of archival data, a waiver of informed consent was deemed appropriate by the IRB per Federal regulation HHS CFR 45.46.117(c)(2).

Data. We received donation solicitation data on adult outpatients who visited the hospital system between May 2013 and April 2015.[2] These data sets are de-identified and publicly available for

[2]The data the hospital system chose to share with us on charitable giving included all adult outpatients except those who: (a) had Medicaid as a form of insurance, (b) were behavioral health patients, (c) were younger than 40 years old and so were never mailed solicitations following the hospital system's solicitation protocols, (d) were patients of certain special medical care divisions (e.g., hospices), (e) had incomplete contact information, (f) were on the Do Not Solicit list,

download on our author websites. To explore the endurance of reciprocity over time, we focus on outpatients who were solicited for a donation by the hospital system's Annual Giving Department in our data window and for whom we have complete information about all hospital visits. This focus leads to two data restrictions. First, we restrict our analysis to patients whose first visit was within our data window, allowing us to observe their full visit history at any of the eight hospitals in the network. Second, we restrict our analysis to patients who were solicited in response to their first-ever visit to the hospital system,[3] which allows us to cleanly estimate how reciprocal giving is affected by the delay in the timing of a solicitation relative to that first visit. These sample restrictions leave us with a large pool of patients ($N_{\text{unique\_patients}} = 18,515$; $N_{\text{outpatient\_visits}} = 82,231$) who were each solicited for a donation by our partner hospital system. It is worth noting that our results replicate when we do not make these conservative restrictions and instead include the first observed solicitations by the hospital system to all patients in our dataset (this expands our sample to 149,817 patients, but we are forced to ignore all hospital visits before May 2013, which do not appear in our data; see Table C.1 in Appendix C.1).

Table 3.1, column 1 provides main summary statistics for our analysis sample. We report on the demographic characteristics of patients in our sample, the average number of visits patients made to the hospital system before receiving a donation solicitation, and the average number of hospital visits a patient made in the 132 days following her first visit,[4] as well as the percentage of patients who donate upon receiving a solicitation, and the average gift conditional on donation, which was $49.14. The full list of summary statistics is available in Table C.2, column 1 in Appendix C.1. Table C.2, columns 2 and 3 present balance regressions confirming that the time delay separating a patient's first hospital visit from her first solicitation is (as we will assume throughout our analyses) approximately random with respect to observable patient characteristics.

(g) were employees of the hospital system, or (h) visited a medical location that was not immediately identifiable as a medical care location within the hospital system.

[3]The hospital system relied on somewhat ad-hoc rules (based on patients' demographic characteristics) that varied from mailing to mailing to determine who would receive solicitations. However, we only study those who received mailings and include fixed effects for mailing date in all analyses, ensuring these selection criteria do not impact our causal estimates of the relationship between delay and reciprocity.

[4]132 days is the longest period separating a first hospital visit from an initial donation solicitation in our data sample. We use the number of visits a patient made within 132 days of her first visit as a control for a patient's sickliness in some of our analyses.

Econometric Model. Our empirical approach leverages the fact that while patients' first hospital visits occur continuously throughout the year, donation solicitation mailings from our partner hospital system are sent in batches on fixed dates. On these fixed dates, solicitation mailings are sent simultaneously to all patients whose first visit to the hospital system occurred at any time during a predetermined, preceding two-month visit window called a mailing cycle. The timing of these batch mailings is such that two patients whose first visits occurred up to 60 days apart, but whose first visits occurred during the same mailing cycle, would receive solicitations on the same date.

Table 3.2 shows the range of potential dates of a patient's first hospital visit within each mailing cycle, and the associated month and year in which solicitations were sent to patients. The dates associated with a mailing cycle always include two consecutive calendar months (e.g., the first mailing cycle in our data includes patient visits in May and June of 2013). The solicitation mailing date for a mailing cycle is generally a few weeks after the last recorded patient visit date associated with that cycle, as this gives the development office time to organize the relevant patient information and send out mailings.[5] We estimate our effects within mailing cycles. That is, we compare people whose first visit falls earlier in a specific mailing cycle to people whose first visit falls later in that same mailing cycle by including mailing cycle fixed effects in all of our regression analyses.[6] We take two complementary econometric approaches to estimating the effect of time delays on reciprocity.

Econometric approach # 1 - time delay between a patient's first visit and solicitation

Our first strategy is to examine the effect of the time delay between a patient's first hospital visit and

[5]There are some exceptions to this rule, but we avoid any confounds from these exceptions by estimating our effects within mailing cycles. Namely, if a particular mailing cycle is delayed, this will not bias our estimates since we will only compare patients from a delayed mailing cycle to each other when estimating the effect of a time delay on giving. For additional details, see Appendix C.1.

[6]Since the timing of the first patient visit relative to the end of a mailing cycle is presumably exogenous, we are able to use this variation to generate a causal estimate of the effect of the delay between service provision and solicitation on donation decisions. Patients would need to be strategically timing first visits to the hospital around unannounced and variable solicitation mailing cycle dates for this assumption to be violated. While it is possible for unobserved factors to influence both the timing of each patient's visit and the donation decision, this is unlikely. These factors would have to influence first visit timing *relative to the date of the solicitation mailing* and simultaneously influence the donation decision. This possibility appears to be ruled out by our tests of the balance of our sample across solicitation mailing delays, shown in columns 2 and 3 of Table C.2.

the mailing of a solicitation request on that patient's donation decision by estimating the following ordinary least squares (OLS) regression:

$$\text{Any\_Donation}_i = \beta_0 + \beta_1 \text{First\_Visit\_Delay}_i + \beta \text{Controls}_i + \varepsilon_i \tag{3.2.1}$$

where Any_Donation$_i$ equals 0 if individual i did not donate in our data set and 100 if individual i made a donation (so estimated coefficients can be interpreted in percentage points). First_Visit_Delay$_i$ is the delay between patient $i's$ first hospital visit and the date on which he or she was solicited by mail to donate, and $_1$ is the coefficient of interest. Controls$_i$ is a vector of controls. In all of our regressions, this vector of controls includes dummies for mailing cycle, to restrict comparison to patients within the same mailing cycle, as well as hospital and medical department dummies, since different types of individuals may visit different hospitals and medical departments.[7]

We test the robustness of all of our analyses to the addition of further control variables. One (uninteresting) way that the time delay separating a patient's first visit from a solicitation could affect her donation decision is by changing the number of subsequent visits to the hospital she has time to make before being solicited, since additional hospital visits may alter a patient's willingness to donate. Therefore, in some regressions, we add controls for the number of hospital visits a patient made between her first visit and the date when a donation solicitation was mailed. We include dummy variables for each possible number of visits before the solicitation to non-parametrically control for pre-solicitation hospital visits. When we add controls for the number of pre-solicitation visits, however, our analyses compare patients with the same number of visits spread out over different time durations (i.e., different time lags between first visit and solicitation), making it critical to also control for the sickliness of patients, since a patient who visits the hospital three times in one week is likely sicklier than a patient who visits three times in one month. In these regressions, we thus also control non-parametrically for the number of visits patients make within 132 days of their first hospital visit. The addition of these controls, along with indicators for the medical department a

[7] Our identification assumption is that a patient's first visit occurs on a random date within a mailing cycle *conditional* on the hospital and medical department that patient visits.

patient visited (previously mentioned), proxy for a patient's sickliness. Finally, we also add controls for all observable patient demographic characteristics deducible from data provided by the hospital system, which include gender, age (at date of solicitation), marital status, and state of residence.

As noted above, these empirical specifications rely on the assumption that the delay between a patient's first hospital visit and her first receipt of a solicitation from the hospital system is exogenous after including our vector of controls. Given that it would be nearly impossible for patients to time their hospital visits strategically around (unknown) future solicitation dates,[8] we are confident that this assumption is valid. Also noted above, consistent with this assumption, columns 2 and 3 of Table C.2 report the results of balance regressions, which show that the date of a patient's first visit within a mailing cycle is uncorrelated with observable patient characteristics with either set of controls in place.

Econometric approach # 2 - time delay between a patient's last visit and solicitation:

The large majority of patients in our sample (77.16%) make multiple hospital visits before they receive a solicitation triggered by their first visit. It could be argued that the delay following service provision most likely to impact reciprocity would be the delay separating a patient's last visit prior to solicitation and the receipt of a mailing. Thus, our second econometric approach to estimating the impact of a time delay on reciprocity investigates how a delay between a patient's last visit and the date of a solicitation mailing affects giving. This exercise is complicated by the fact that the timing of a patient's last visit is endogenous to her total number of hospital visits such that more frequent visitors are more likely to have a last visit closer to a solicitation date.

To take advantage of the fact that we expect the timing of a patient's first visit to be exogenous with respect to total hospital visits, conditional on our controls, our second empirical strategy relies on an instrumental variables approach (Angrist and Pischke, 2009), treating the timing of the first visit as an instrument for the timing of the last visit. We estimate our two-stage least squares instrumental variables regressions as shown in equations 3.2.2 and 3.2.3:

[8] Note that the solicitation schedule is set in advance and does not respond to the characteristics of recent hospital patients.

$$\text{Last\_Visit\_Delay}_i = \alpha_0 + \alpha_1 \text{First\_Visit\_Delay}_i + \alpha \text{Controls}_i + u_i \tag{3.2.2}$$

$$\text{Any\_Donation}_i = \gamma_0 + \gamma_1 \widetilde{\text{Last\_Visit\_Delay}}_i + \gamma \text{Controls}_i + \nu_i \tag{3.2.3}$$

As defined previously, Any_Donation_i equals 0 if individual i did not donate in our data set and 100 if individual i made a donation (so estimated coefficients can be interpreted in percentage points). $\text{Last\_Visit\_Delay}_i$ is the delay between patient i's last pre-solicitation hospital visit and the date of solicitation. Also, as defined previously, $\text{First\_Visit\_Delay}_i$ is the delay between patient i's first hospital visit and the date of solicitation and Controls_i is a vector of controls, which includes the same sets of variables included our previously described regressions. $\widetilde{\text{Last\_Visit\_Delay}}_i$ is the predicted delay between patient i's last pre-solicitation visit and the solicitation date, it is the exogenous component of $\text{Last\_Visit\_Delay}_i$ estimated from equation 3.2.2, and γ_1 is the coefficient of interest.

Note that interpreting γ_1 as the causal effect of $\text{Last\_Visit\_Delay}_i$ on Any_Donation_i requires both that the $\text{First\_Visit\_Delay}_i$ be exogenous conditional on our vector of controls (which we justify above) and that the only effect $\text{First\_Visit\_Delay}_i$ has on Any_Donation_i is through its influence on $\text{Last\_Visit\_Delay}_i$. This means that our second specification is valid only under the assumption that donation decisions are driven primarily by the last pre-solicitation visit to the hospital, and that earlier visits play a negligible role in the decision to donate. Under this assumption, our first specification can be viewed as the reduced form of our second specification.

3.3 Results

Donation rates decline as the time separating a patient's hospital visit and solicitation increases. This result holds in both of our empirical approaches described above. Figure 3.1 presents the raw correlation between the time delay separating a patient's (first or last) hospital visit from her receipt of a solicitation mailing and the likelihood a patient made a donation to our partner hospital system. It shows that the percentage of patients who donate decreases considerably (from almost 1.5% to 0.4%) as the time delay separating a visit from a solicitation increases. This decline over time holds for both the first and the last pre-solicitation hospital visit.

We observe the same relationship depicted in the raw data in Figure 3.1 in our regression analyses, reported in Table 3.3. Columns 1 and 2 of Table 3.3 report the coefficient estimates from our first regression specification in which we estimate the effect of the delay between a patient's first hospital visit and her first receipt of a donation solicitation on the likelihood of giving. In column 1, we only include our key controls: fixed effects for mailing cycle, hospital visited, and medical department visited. We find that increasing the delay separating a patient's first visit and her solicitation by 30 additional days decreases the probability that the patient will donate by 0.30 percentage points ($p < 0.05$). This effect represents a 36% decrease in the donation rate relative to the mean donation rate, across the whole sample, of 0.83 percentage points. In column 2, we add further controls to eliminate the possible impact of "extra" opportunities to visit the hospital pre-solicitation that may arise when patients' first visits come earlier in a mailing cycle. In particular, as described previously, we add non-parametric controls for the total number of visits a patient made to the hospital before a solicitation was mailed, non-parametric controls for the number of visits within a fixed window of 132 days following a patient's first hospital visit (a proxy for sickliness), and demographic controls. Our column 2 results remain extremely similar to those presented in column 1: increasing the lag time separating a patient's first visit from her first receipt of a solicitation by an additional 30 days decreases the probability of donation by 0.25 percentage points ($p < 0.05$), a 30% decrease relative to the average donation rate.

In columns 3 and 4 of Table 3.3, we present the results of our instrumental variable (IV) regressions. These regressions estimate the effect of the delay separating a patient's last hospital visit from the mailing of a donation solicitation on donation likelihood using the delay between a patient's first hospital visit and the date of the solicitation mailing as an instrument. As shown in Table 3.3, both F-statistics are above 3,000, demonstrating a strong first stage and avoiding any potential concerns about weak instruments (Angrist and Pischke, 2009). Column 3 of Table 3.3 includes the same controls as column 1 and estimates that an additional 30 days separating a patient's last hospital visit from the date of her first donation solicitation decreases the probability of a donation by 0.51 percentage points ($p < 0.05$), a 61% decrease from the average donation rate. Column 4 includes the same additional controls as column 2 and estimates a comparable 0.41 percentage point decrease in the probability of donation for an additional 30 days separating a patient's last visit and the date on which the hospital system sent her a donation solicitation ($p < 0.05$). As shown in our Appendix C.1 (Table C.3), these results are robust to including a wide range of different subsets of the full set of controls included in columns 2 and 4.[9]

We conducted a series of supplemental analyses detailed in Appendix C.1 to shed additional light on the psychological mechanism responsible for our findings. If gratitude is a hot state that decays over time driving reductions in reciprocity, we would expect reciprocity to decay more rapidly among patients with more severe ailments who have more reason to be grateful for their care. To measure ailment severity, we asked three physicians at our partner hospital system to independently rate each of the 11 medical departments that handled more than 1,000 outpatients in our data set. The physicians unanimously rated oncology, cardiology, and surgery as departments with the most severe cases. We thus classified patients who visited the oncology, cardiology, or surgery departments as "severe" and patients who only visited other rated departments as "not severe". We then reproduced our primary analyses (presented in Table 3.3) separately for "severe" patients and for not severe patients (presented in Table C.5). The results demonstrate that severe patients show significantly more pronounced decays in reciprocity over time than other patients ($p < 0.05$ in all Wald Tests). While these results suggest that those who were more grateful display more decay, consistent with the possibility that gratitude is a "hot" state that wanes quickly, we cannot rule out other explanations for the decay in reciprocity among patients with severe illnesses (e.g., income effects).[10]

[9]We also examine the effect of a time delay on the donation amount (in natural logs, with log donation amount equal to 0 for non-donors) in Table C.10 to determine if a time delay influences the amount donated. Consistent with our main result that a time delay in soliciting a donation decreases the proportion who give, we find that the unconditional donation amount decreases as the solicitation delay increases.

[10]For example, patients with more severe illnesses have to spend more money on treatment, leaving them less able to donate to the hospital over the duration of the treatment.

To bolster our interpretation that gratitude is central to our decay results, the Appendix C.1 provides three additional empirical exercises comparing the decay observed among patients who likely had better experiences with the hospital system to the decay observed among patients who likely had worse experiences with the hospital system. In particular, we proxy for better experiences with the hospital system using: 1) the likelihood of returning to the hospital system for additional outpatient care, 2) having visited a higher ranked hospital, and 3) having visited a higher ranked medical provider based on survey data collected by the hospital system. These three analyses all suggest that reciprocity decays faster (directionally, but not significantly) among patients whose experiences were better, consistent with gratitude playing a central role in driving our results.

3.4 Discussion

Past research indicates that reciprocity is a major driver of generosity (Andreoni and Payne, 2013; Gneezy and List, 2006). Thus, when an individual receives a service, she may feel inclined to behave reciprocally (e.g., perhaps by donating to the provider of the service in the form of a tip). In this paper, we provide field evidence that such reciprocity wanes over time. Currently, behavioral models of reciprocal motives do not incorporate time-sensitivity; instead, they implicitly assume that the willingness to reciprocate is constant (Cox et al., 2007). Some psychological theories suggest that soliciting reciprocity too soon (e.g., asking a beneficiary of a charitable organization to donate soon after receiving a service) could decrease reciprocity because the request may be viewed as opportunistic or manipulative (Brehm, 1966; Clee and Wicklund, 1980). Other theories leave open the possibility that reciprocity could decline over time due to either forgetfulness (Schacter, 1999) or the fleeting nature of visceral states that may contribute to it (e.g., gratitude; Loewenstein, 1996; Ritov, 2006; Metcalfe and Mischel, 1999; Burger et al., 1997; Flynn, 2003; Neo et al., 2013). Our findings inform both economic and psychological theories of reciprocity by providing field evidence that reciprocity declines precipitously over the course of a few months.

We study decays in reciprocity by examining patient decisions about giving to a university hospital system that has provided them with medical care. We show that reciprocity decreases as the delay between a visit to the hospital and a solicitation for a donation increases. An additional 30-day delay in requesting a donation after a patient's first hospital visit decreases the likelihood of a donation by 30% or more, while a 30-day added delay separating a patient's last hospital visit from a solicitation decreases donations by approximately 50%.

Our results significantly extend past research by cleanly isolating the relationship between reciprocity and time in a field setting. The rate of decay reported in our paper is roughly five times slower than that reported in Burger et al. (1997)'s study of favors, which finds that the tendency to return a small favor declines by 64% over one week. However, given that we study positive reciprocity towards a hospital system providing potentially life-saving treatment and Burger et al. (1997) explored positive reciprocity towards someone who provided a trivial favor (e.g., offering a stranger a soda), it is unsurprising that we find more persistent reciprocity. It is also likely that participants in Burger et al.'s studies simply forgot they had received a small gift two weeks prior, while the donation solicitation letters we studied ensured that participants recalled their interactions with the hospitals requesting reciprocal donations. In addition, the rate of decay in reciprocity we detect is roughly four times faster than the rate detected by in Becker et al. (2013). However, Becker et al. measure decay in reciprocal behavior by examining whether households agree to participate in a national survey both six and 18 months after receiving a gift, and therefore cannot isolate a decay in reciprocity from the possibility that households are unwilling to reciprocate twice for a single gift.

Our findings have immediate practical implications for charitable organizations. Organizations that provide a service or otherwise interact with potential donors may be able to dramatically increase donation rates and fundraising revenue by decreasing the delay between an interaction with a prospective donor and a donation request. Comparing our effect size estimates to those from past research suggests that for an organization like the one we studied that sends out solicitation requests every two months, changing to a schedule involving solicitation mailings every month could increase donation rates by as much as introducing a 1-to-1 donation match incentive.[11]

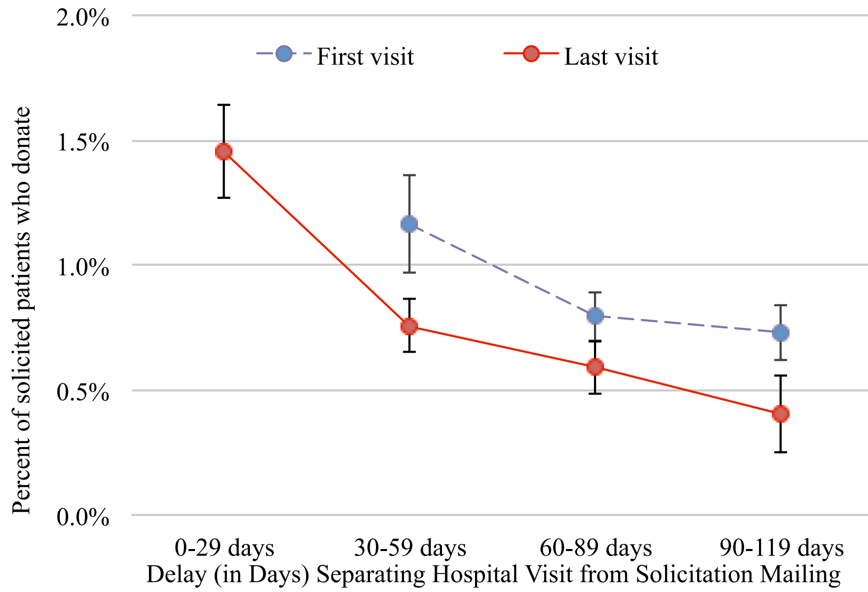
Finally, while our analysis focuses on charitable giving to a university hospital system, our results speak to contexts outside of charitable giving. Since reciprocity is important across a wide variety of contexts, our findings have implications for our understanding of myriad social interactions. For example, stores may increase long-term customer loyalty if they can decrease the time between a customer's initial purchase and her next visit. Partnerships may enjoy greater longevity and success if both parties engage in frequent contact early on in relationships. And after two people first meet, they may be more prone to collaborate toward a shared goal the sooner such an opportunity presents itself. To the extent that the time delays separating interactions can be controlled, it may be valuable for individuals and organizations to consider our findings regarding the time-sensitivity of reciprocity when scheduling such interactions.

[11]In our setting, we find that a 30-day decrease in delay increases donation rates by at least 0.3 percentage points. Estimates from previous experimental work have found a similar 0.3 percentage point increase in donation rates due to the introduction of a 1-to-1 match (see Karlan and List, 2007).

Figures

FIGURE 3.1

RAW RELATIONSHIP BETWEEN THE DELAY SEPARATING A HOSPITAL VISIT FROM A SOLICITATION AND A PATIENT'S DONATION LIKELIHOOD



Notes: This graph presents raw data. The x-axis shows the delay separating a patient's hospital visit and the date of the patient's first solicitation for a donation. The y-axis shows the percent of solicited patients who donated. The top dashed line corresponds to data on patients' first-ever hospital visits, while the bottom solid line corresponds to data on patients' last hospital visits (following their first-ever hospital visit) prior to being solicited.

Tables

TABLE 3.1

SUMMARY STATISTICS FOR MAIN ANALYSIS SAMPLE

Patient Demographics	
Age	Avg.= 64.19
	(S.D.= 11.45)
Female name	45.71%
Male name	46.14%
Gender of name unknown	8.15%
Hospital Visits	
# Hospital visits between 1st visit and solicitation	Avg.= 3.42
	(S.D.= 3.11)
# Hospital visits within 132 days of 1st visit	Avg.= 4.44
	(S.D.= 4.74)
Donations	
Percent Donate	0.83%
Donation$\vert$Donation > 0	Avg.= \$49.14
	(S.D.= 36.68)
Patients	18,515

Table 3.1 presents main summary statistics describing our study sample. Sample means are shown with standard deviations in parentheses. Several patients' age data was missing from our primary age data source (solicitation administrative data); for these patients, we imputed age from the date of birth in the administrative health data ($N = 3,695$). To protect patient privacy, imputed age was top-coded at 90 in the data. Gender was imputed from patients' first names using the mapping in Morton, Zettelmeyer, and Silva-Risso (2003).

TABLE 3.2
MAILING CYCLE DATES

Associated range of dates of patients' first visits	Associated solicitation mailing date
May 1 - Jun 30, 2013	July 2013
July 1 - Aug 31, 2013	September 2013
Sep 1 - Oct 31, 2013	December 2013
Nov 1 - Dec 31, 2013	January 2014
Jan 1 - Feb 28, 2014	March 2014
Mar 1 - Apr 30, 2014	July 2014
May 1 - Jun 30, 2014	July 2014
Jul 1 - Aug 31, 2014	September 2014
Sep 1 - Oct 31, 2014	December 2014
Nov 1 - Dec 31, 2014	February 2015
Jan 1 - Feb 28, 2015	March 2015
Mar 1 - Apr 30, 2015	May 2015

Table 3.2 describes the timing of mailing cycles and solicitation mailings. The first column reports the range of hospital visit dates associated with the mailing cycle. The second column reports the month and year in which the corresponding solicitation mailing was sent. For example, all patients who visited the hospital between July 1st, 2014 and August 31st, 2014 would have their solicitations sent on one day in September, 2014. The minimum delay between hospital visit and the solicitation mailing is 24 days. The maximum is 132 days. The median is 68 days, and the mean is 67.34 days (standard deviation 20.94 days).

TABLE 3.3
EFFECT OF TIME DELAY ON RECIPROCITY

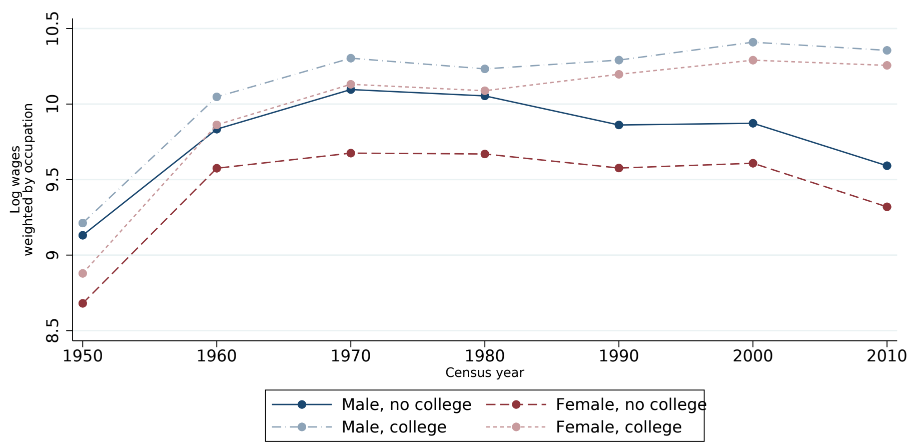
	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Delay (in days) between first visit and solicitation x 30	-0.298** (0.122)	-0.247** (0.125)		
Delay (in days) between last visit and solicitation x 30			-0.509** (0.208)	-0.407** (0.204)
R-squared	0.006	0.019	0.006	0.019
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
First Stage F-Statistic			3,092	6,757

Notes: Columns 1 and 2 report ordinary least squares (OLS) coefficient estimates from regressions predicting a patient's decision to donate with the time delay separating that patient's first hospital visit from the date when she was solicited. Columns 3 and 4 report coefficient estimates from instrumental variables analyses in which the delay between a patient's first hospital visit and the date of a solicitation mailing is used as an instrument for the delay between a patient's last pre-solicitation hospital visit and the date of a solicitation mailing. Columns 1 and 3 include "Key Controls": dummies for mailing cycle, hospital visited, and medical department visited. Columns 2 and 4 add "Additional Controls": dummies for a patient's total number of hospital visits before the solicitation mailings were sent, dummies for a patient's number of hospital visits within 132 days of her first hospital visit (a proxy for sickliness), and controls for gender, age, marital status, and state of residence. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.1 Chapter 1 Appendix: Tables and Figures

Figures

FIGURE A.1
LOG WAGE GAP (WEIGHTED BY OCCUPATION) BETWEEN COLLEGE AND HIGH SCHOOL GRADUATES



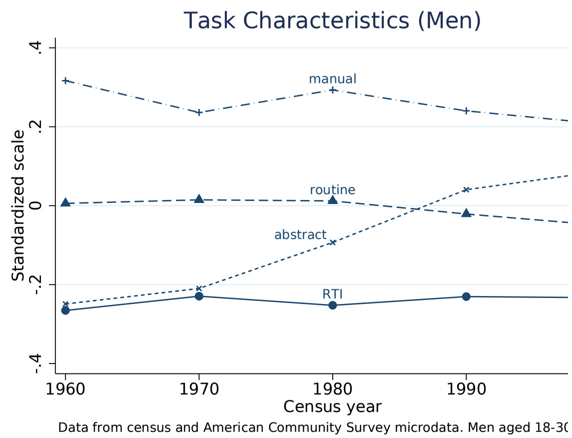
Notes: Figure A.1 depicts median earnings weighted by the labor share of each worker type in an occupation, where worker type is indexed by college status and sex. The explicit formula used to calculate weighted median earnings is

$$ln\ median\ earnings_{gender,college} = ln\left(\sum_{occ}\left[median(earnings_{occ})\frac{total\ workers\ in\ occ_{gender,college}}{total\ workers_{gender,college}}\right]\right)$$

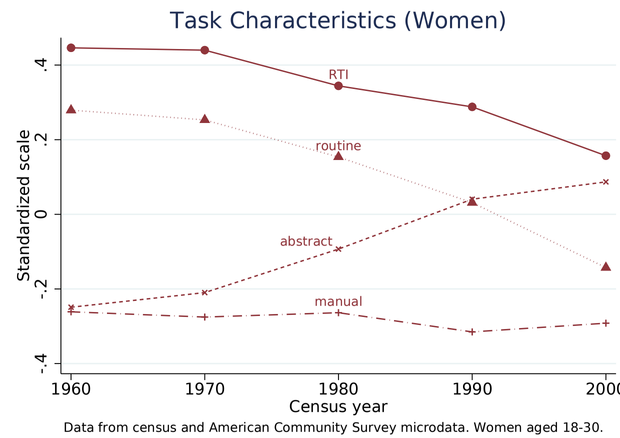
Any differences in median earnings between worker types stems entirely from distributional differences of worker types across occupations. The data come from the decennial census microdata from 1950 to 2000 and from the 2010 American Community Survey (ACS) data. To focus on the discrepancy among young workers, only 18-30 year olds are included.

FIGURE A.2
JOB CHARACTERISTICS OVER TIME

MEN



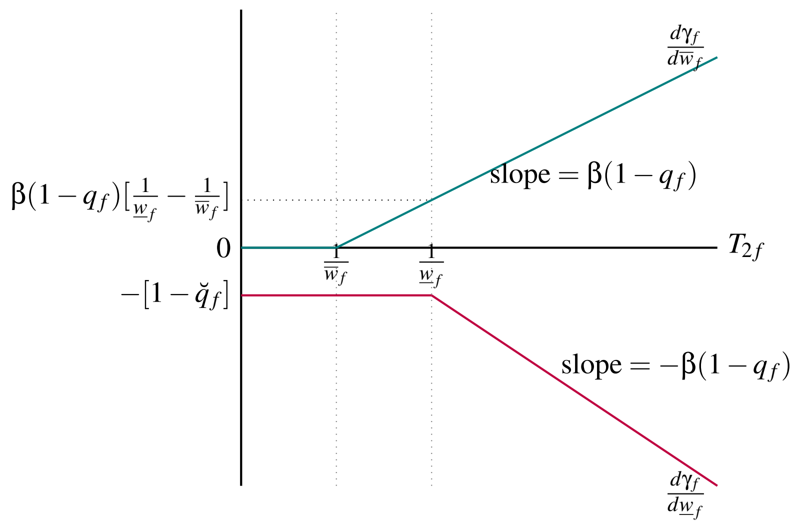
WOMEN



Notes: Figure A.2 depicts average routine-intensity, manual-intensity, abstract-intensity, and RTI (the composite measure) in the labor force for young men (left) and young women (right). This figure shows that the displacement of high-RTI jobs by automation fell on women but not men among young workers. The evidence suggests that the employment opportunities of women were most affected by the erosion of routine-intensive jobs. Data obtained from census microdata, ACS data, and the job characteristic measures constructed by Autor and Dorn (2013). Only individuals between the ages of 18 and 30 are included.

FIGURE A.3

EFFECT OF T_{2f} ON RELATIONSHIP BETWEEN WAGE RATES AND COLLEGE-GOING



Notes: The figure depicts the effect of increasing time net of housework, T_{2f}, on the responsiveness of women's college-going to their wage rates. The effect of college wage rates on women's college-going, $\frac{d\gamma_f}{d\overline{w}_f}$, is weakly positive, while the effect of non-college wage rates on women's college-going, $\frac{d\gamma_f}{d\underline{w}_f}$, is strictly negative. When $T_{2f} < \frac{1}{\overline{w}_f}$, married women do not work and only non-college wage rates influence the college-going decision, since they represent the opportunity costs to attending college in period 1 while single. When $T_{2f} \in [\frac{1}{\overline{w}_f}, \frac{1}{\underline{w}_f}]$, only married women with college degrees work, and $\frac{d\gamma_f}{d\overline{w}_f}$ increases with T_{2f}. Finally, when $T_{2f} > \frac{1}{\underline{w}_f}$, married women without college degrees also join the work force and $\frac{d\gamma_f}{d\underline{w}_f}$ becomes more negative with increasing T_{2f}.

Tables

TABLE A.1
EMPLOYMENT CHANGES IN OIL AND GAS INDUSTRY

	Oil and Gas Industry		Oil, Gas, and Related Industries	
	1970-1980	2000-2010	1970-1980	2000-2010
Non-college men	1.18%	0.42%	4.18%	1.65%
College men	0.73%	0.09%	0.81%	-0.63%
Non-college women	0.02%	-0.07%	0.29%	0.07%
College women	0.24%	0.13%	0.55%	-0.06%

Notes: Table A.1 shows the change in employment in the oil and gas industry or in the oil, gas, and related industries as a proportion of total employment for men and women based on college status. The table examines two decades in which national growth in oil and gas employment was large: 1970-1980 and 2000-2010. In both of of these periods, non-college men experienced much larger changes in employment share in the relevant industries than college men, college women, or non-college women. This provides further evidence that employment changes in these industries impact the non-college labor market returns of men.

TABLE A.2
SUMMARY STATISTICS BY STATE RESOURCE LEVEL, 1970

	Low-Resource	High-Resource	Difference
Female college enrollment	0.347	0.374	-0.0272
	(0.0173)	(0.0187)	(0.0256)
Male college enrollment	0.423	0.464	-0.0414
	(0.0277)	(0.0127)	(0.0331)
% female	0.518	0.513	0.00586
	(0.00205)	(0.00397)	(0.00421)
% black	0.111	0.122	-0.0111
	(0.0260)	(0.0275)	(0.0381)
% 18-25 years old	0.119	0.126	-0.00731
	(0.00295)	(0.00298)	(0.00425)
% 26-35 years old	0.125	0.118	0.00688
	(0.00343)	(0.00446)	(0.00553)
% 36-45 years old	0.120	0.110	0.00930**
	(0.00274)	(0.00297)	(0.00406)
% 46-55 years old	0.111	0.113	-0.00260
	(0.00395)	(0.00342)	(0.00538)
% 56-65 years old	0.0908	0.0925	-0.00175
	(0.00446)	(0.00574)	(0.00715)
% older than 65 years old	0.0864	0.0885	-0.00209
	(0.00508)	(0.00643)	(0.00807)
Observations	10	8	

Table A.2 reports the results of a t-test comparing the characteristics of high-resource states with the characteristics of low-resource states. Overall, there are few significant differences in observed composition between high- and low-resource states. The proportion of 36-45 year olds is significantly different ($p < 0.05$). These differences are insignificant for almost all other years. Standard errors in parentheses. Stars denote significant differences between high- and low-resource states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.3

SUMMARY STATISTICS BY STATE RESOURCE LEVEL, 1980

	Low-Resource	High-Resource	Difference
Female college enrollment	0.396	0.400	-0.00456
	(0.00999)	(0.0172)	(0.0187)
Male college enrollment	0.396	0.408	-0.0126
	(0.00878)	(0.0129)	(0.0151)
% female	0.514	0.513	0.000504
	(0.00181)	(0.00229)	(0.00289)
% black	0.0845	0.106	-0.0215
	(0.0156)	(0.0227)	(0.0266)
% 18-25 years old	0.150	0.148	0.00234
	(0.00210)	(0.00315)	(0.00364)
% 26-35 years old	0.157	0.157	0.0000911
	(0.00224)	(0.00386)	(0.00420)
% 36-45 years old	0.117	0.110	0.00706**
	(0.00202)	(0.00207)	(0.00296)
% 46-55 years old	0.103	0.0978	0.00543*
	(0.00207)	(0.00231)	(0.00314)
% 56-65 years old	0.0936	0.0907	0.00285
	(0.00166)	(0.00262)	(0.00296)
% older than 65 years old	0.0964	0.101	-0.00490
	(0.00255)	(0.00454)	(0.00487)
Observations	28	20	

Table A.3 reports the results of a t-test comparing the characteristics of high-resource states with the characteristics of low-resource states. Overall, there are few significant differences in observed composition between high- and low-resource states. The proportion of 36-45 year olds is significantly different ($p < 0.05$), and the proportion of 46-55 year olds is marginally significantly different ($p < 0.10$). Standard errors in parentheses. Stars denote significant differences between high- and low-resource states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.4
SUMMARY STATISTICS BY STATE RESOURCE LEVEL, 1990

	Low-Resource	High-Resource	Difference
Female college enrollment	0.479	0.479	-0.000114
	(0.0111)	(0.0195)	(0.0211)
Male college enrollment	0.456	0.428	0.0282
	(0.0111)	(0.0201)	(0.0214)
% female	0.520	0.528	-0.00748
	(0.00353)	(0.00528)	(0.00611)
% black	0.0846	0.102	-0.0174
	(0.0176)	(0.0258)	(0.0301)
% 18-25 years old	0.150	0.156	-0.00586
	(0.00370)	(0.00521)	(0.00621)
% 26-35 years old	0.223	0.227	-0.00413
	(0.00616)	(0.00812)	(0.0100)
% 36-45 years old	0.187	0.185	0.00238
	(0.00530)	(0.00496)	(0.00755)
% 46-55 years old	0.130	0.132	-0.00139
	(0.00387)	(0.00398)	(0.00569)
% 56-65 years old	0.113	0.108	0.00568
	(0.00418)	(0.00545)	(0.00675)
% older than 65 years old	0.145	0.137	0.00807
	(0.00570)	(0.00575)	(0.00832)
Observations	28	20	

Table A.4 reports the results of a t-test comparing the characteristics of high-resource states with the characteristics of low-resource states. Overall, there are no significant differences in observed demographic characteristics between high- and low-resource states. Standard errors in parentheses. Stars denote significant differences between high- and low-resource states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.5
SUMMARY STATISTICS BY STATE RESOURCE LEVEL, 2000

	Low-Resource	High-Resource	Difference
Female college enrollment	0.629	0.611	0.0181
	(0.0170)	(0.0207)	(0.0267)
Male college enrollment	0.569	0.576	-0.00701
	(0.0160)	(0.0175)	(0.0241)
% female	0.516	0.518	-0.00150
	(0.00388)	(0.00389)	(0.00565)
% black	0.0967	0.0991	-0.00236
	(0.0186)	(0.0203)	(0.0279)
% 18-25 years old	0.137	0.153	-0.0159**
	(0.00486)	(0.00492)	(0.00710)
% 26-35 years old	0.172	0.169	0.00290
	(0.00583)	(0.00803)	(0.00967)
% 36-45 years old	0.217	0.207	0.0101
	(0.00501)	(0.00760)	(0.00874)
% 46-55 years old	0.172	0.168	0.00388
	(0.00386)	(0.00436)	(0.00587)
% 56-65 years old	0.115	0.111	0.00375
	(0.00375)	(0.00571)	(0.00655)
% older than 65 years old	0.149	0.151	-0.00229
	(0.00552)	(0.00803)	(0.00941)
Observations	28	20	

Table A.5 reports the results of a t-test comparing the characteristics of high-resource states with the characteristics of low-resource states. Overall, there are few significant differences in observed demographic characteristics between high- and low-resource states. In 2000, the proportion of 18-25 year olds differs significantly between low- and high-resource states ($p < 0.05$). However, this difference is insignificant for all other years. Standard errors in parentheses. Stars denote significant differences between high- and low-resource states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.6
SUMMARY STATISTICS BY STATE RESOURCE LEVEL, 2010

	Low-Resource	High-Resource	Difference
Female college enrollment	0.659	0.641	0.0178
	(0.0118)	(0.0165)	(0.0197)
Male college enrollment	0.566	0.565	0.00101
	(0.0137)	(0.0169)	(0.0217)
% female	0.517	0.514	0.00285
	(0.00141)	(0.00202)	(0.00239)
% black	0.102	0.102	-0.000169
	(0.0175)	(0.0222)	(0.0279)
% 18-25 years old	0.141	0.143	-0.00209
	(0.00389)	(0.00497)	(0.00623)
% 26-35 years old	0.166	0.165	0.000610
	(0.00484)	(0.00655)	(0.00797)
% 36-45 years old	0.166	0.174	-0.00788
	(0.00325)	(0.00402)	(0.00514)
% 46-55 years old	0.188	0.178	0.0105
	(0.00428)	(0.00492)	(0.00655)
% 56-65 years old	0.152	0.148	0.00403
	(0.00442)	(0.00600)	(0.00728)
% older than 65 years old	0.152	0.156	-0.00404
	(0.00429)	(0.00778)	(0.00830)
Observations	28	20	

Table A.6 reports the results of a t-test comparing the characteristics of high-resource states with the characteristics of low-resource states. Overall, there are no significant differences in observed demographic characteristics between high- and low-resource states. Standard errors in parentheses. Stars denote significant differences between high- and low-resource states. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE A.7

FIRST STAGE REGRESSION OF OIL & GAS EMPLOYMENT ON INSTRUMENTS
(DID NOT MIGRATE FOR WORK PURPOSES)

	Oil & Gas Employment (1)	Oil, Gas, & Related Employment (2)
	Specification 1: Employment IV $(r_s E_{-s,t})$	
Employment IV	2.168***	3.218***
	(0.810)	(1.011)
F-statistic	12.277	21.891
	Specification 2: Employment $(r_s E_{-s,t})$ + *Price* $(r_s p_t)$ *IVs* *Average Prices*	
Employment IV	1.454*	2.546***
	(0.869)	(0.860)
Price IV	8.5e-05*	8.5e-05**
	(4.8e-05)	(3.5e-05)
F-statistic	11.041	12.224
Demographic controls	Yes	Yes
State FE	Yes	Yes
Observations	1782	1782

Notes: First stage regression of employment share on instruments. Sample of workers who did not report moving across states for work purposes. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. In all cases, the first stage regression passes the Anderson-Rubin test for weak instruments.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.8

2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL & GAS EMPLOYMENT
(DID NOT MIGRATE FOR WORK PURPOSES)

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil & Gas Employment	-1.616	-3.576***	-1.877	-1.153
	(1.786)	(1.006)	(1.348)	(0.766)
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*			
Oil & Gas Employment	-1.773	-3.668***	-1.861	-1.026
	(1.442)	(1.039)	(1.511)	(0.710)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil & gas industry. Sample of workers who did not report moving across states for work purposes. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.9

2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL, GAS, & RELATED EMPLOYMENT
(DID NOT MIGRATE FOR WORK PURPOSES)

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil, Gas, & Related Employment	-1.069	-2.366***	-1.242	-0.763
	(1.060)	(0.535)	(0.838)	(0.563)
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*			
Oil, Gas, & Related Employment	-1.045	-2.187***	-1.075	-0.362
	(0.812)	(0.482)	(0.823)	(0.507)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil, gas, & related industries. Sample of workers who did not report moving across states for work purposes. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.10

FIRST STAGE REGRESSION OF OIL & GAS EMPLOYMENT ON INSTRUMENTS
(DID NOT MIGRATE IN PAST YEAR)

	Oil & Gas Employment (1)	Oil, Gas, & Related Employment (2)
	Specification 1: Employment IV $(r_s E_{-s,t})$	
Employment IV	2.129***	3.239***
	(0.786)	(0.998)
F-statistic	11.258	22.388
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*	
Employment IV	1.344	2.515***
	(0.823)	(0.821)
Price IV	9.4e-05*	9.1e-05**
	(5.0e-05)	(3.9e-05)
F-statistic	9.891	11.850
Demographic controls	Yes	Yes
State FE	Yes	Yes
Observations	1782	1782

Notes: First stage regression of employment share on instruments. Sample of workers who reported not having moved across states in the past year. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. In all cases, the first stage regression passes the Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.11
2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL & GAS EMPLOYMENT
(DID NOT MIGRATE IN PAST YEAR)

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil & Gas Employment	-1.857	-3.721***	-2.035	-0.955
	(1.691)	(1.022)	(1.338)	(0.680)
	Specification 2: Employment $(r_s E_{-s,t})$ *+ Price* $(r_s p_t)$ *IVs Average Prices*			
Oil & Gas Employment	-2.143*	-3.893***	-1.890	-0.794
	(1.259)	(1.073)	(1.490)	(0.607)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil & gas industry. Sample of workers who reported not having moved across states in the past year. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.12

2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL, GAS, & RELATED EMPLOYMENT
(DID NOT MIGRATE IN PAST YEAR)

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_sE_{-s,t})$			
Oil, Gas, & Related Employment	-1.192	-2.388***	-1.307	-0.613
	(0.954)	(0.477)	(0.811)	(0.475)
	Specification 2: Employment $(r_sE_{-s,t})$ *+ Price* (r_sp_t) *IVs Average Prices*			
Oil, Gas, & Related Employment	-1.195*	-2.250***	-1.137	-0.198
	(0.720)	(0.448)	(0.792)	(0.413)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil, gas, & related industries. Sample of workers who reported not having moved across states in the past year. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specification 2 uses both the employment and the price instrument. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.13
FIRST STAGE REGRESSION OF EMPLOYMENT ON INSTRUMENTS
(ROBUSTNESS)

Main Analysis Sample

	Oil & Gas Employment (1)	Oil, Gas, & Related Employment (2)
	Specification 1: Employment IV $(r_s E_{-s,t})$	
Employment IV	2.087^{***}	3.223^{***}
	(0.804)	(1.028)
F-statistic	11.684	20.441
	Specification 2: Employment $(r_s E_{-s,t})$ + *Price* $(r_s p_t)$ *IVs Average Prices*	
Employment IV	1.433^{*}	2.614^{***}
	(0.853)	(0.865)
Price IV	7.8e-05*	7.7e-05**
	(4.6e-05)	(3.6e-05)
F-statistic	10.860	11.580
	Specification 3: Employment $(r_s E_{-s,t})$ + *Price* $(r_s p_t)$ *IVs OPEC Prices*	
Employment IV	1.432^{*}	2.603^{***}
	(0.851)	(0.863)
Price IV	7.5e-05*	7.5e-05**
	(4.4e-05)	(3.4e-05)
F-statistic	10.648	11.479
	Specification 4: Employment $(r_s E_{-s,t})$ + *Price* $(r_s p_t)$ *IVs Non-OPEC Prices*	
Employment IV	1.439^{*}	2.633^{***}
	(0.847)	(0.864)
Price IV	8.1e-05*	7.9e-05**
	(4.8e-05)	(3.7e-05)
F-statistic	11.038	11.653
Demographic controls	Yes	Yes
State FE	Yes	Yes
Observations	1782	1782

Notes: First stage regression of employment share on instruments. Regressions control for proportion female, pro-

portion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specifications 2, 3, and 4 use both the employment and the price instrument. In Specification 2, the price instrument is constructed from the average landed costs of crude oil. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from OPEC countries. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from non-OPEC countries. In all cases, the first stage regression passes the Anderson-Rubin test for weak instruments. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.14

2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL & GAS EMPLOYMENT (ROBUSTNESS)

Main Analysis Sample

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil & Gas Employment	-1.777	-3.805***	-1.871	-1.414*
	(1.773)	(1.055)	(1.358)	(0.765)
	Specification 2: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs Average Prices			
Oil & Gas Employment	-1.806	-3.838***	-1.811	-1.095
	(1.334)	(1.089)	(1.431)	(0.698)
	Specification 3: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs OPEC Prices			
Oil & Gas Employment	-1.892	-3.832***	-1.801	-1.086
	(1.282)	(1.087)	(1.425)	(0.698)
	Specification 4: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs Non-OPEC Prices			
Oil & Gas Employment	-1.728	-3.842***	-1.844	-1.115
	(1.382)	(1.091)	(1.439)	(0.700)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil & gas industry. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specifications 2, 3, and 4 use both the employment and the price instrument. In Specification 2, the price instrument is constructed from the average landed costs of crude oil. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from OPEC countries. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from non-OPEC countries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.15

2SLS REGRESSION OF COLLEGE ENROLLMENT ON OIL, GAS, & RELATED EMPLOYMENT (ROBUSTNESS)

Main Analysis Sample

	Male Enrollment		Female Enrollment	
	Full-time	Part-time	Full-time	Part-time
	(1)	(2)	(3)	(4)
	Specification 1: Employment IV $(r_s E_{-s,t})$			
Oil, Gas, & Related Employment	-1.101	-2.358***	-1.159	-0.876*
	(0.981)	(0.503)	(0.833)	(0.521)
	Specification 2: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs Average Prices			
Oil, Gas, & Related Employment	-0.990	-2.114***	-0.817	-0.369
	(0.709)	(0.436)	(0.808)	(0.444)
	Specification 3: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs OPEC Prices			
Oil, Gas, & Related Employment	-1.035	-2.122***	-0.834	-0.377
	(0.686)	(0.437)	(0.810)	(0.444)
	Specification 4: Employment $(r_s E_{-s,t})$ + Price $(r_s p_t)$ IVs Non-OPEC Prices			
Oil, Gas, & Related Employment	-0.949	-2.107***	-0.791	-0.364
	(0.728)	(0.435)	(0.806)	(0.446)
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	1248	1248	1248	1248

Notes: Second stage regression of college enrollment on employment share in the oil, gas, & related industries. Regressions control for proportion female, proportion black, proportion by ten-year age bin, year dummies, and state dummies. All regressions conducted at the state-year level. Standard errors clustered at state level. Specification 1 uses only the employment instrument. Specifications 2, 3, and 4 use both the employment and the price instrument. In Specification 2, the price instrument is constructed from the average landed costs of crude oil. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from OPEC countries. In Specification 3, the price instrument is constructed from the average landed costs of crude oil from non-OPEC countries. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.16

CORRELATIONS BETWEEN GENDER AND JOB CONTENT

Year	Corr(female no college, routine)	Corr(female college, abstract)
1950	0.142***	0.0433***
1970	0.133***	0.107***
1980	0.0775***	0.117***
1990	0.0341***	0.147***
2000	0.00420***	0.156***

Notes: The table presents pairwise correlations of worker type and task-intensity. Non-college women are significantly more likely to work in routine-intensive occupations, but this likelihood declines over time. College women are significantly more likely to work in abstract-intensive occupations, and this likelihood increases over time. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Chapter 1 Appendix: Theory

A.2.1 College-going decision for men

The assumption $T_1 > \frac{1}{\underline{w}_m} + 1$ guarantees that single men will have time for both leisure and schooling in period 1, and guarantees that married men will always work in period 2 ($T_{2m} > \frac{1}{\underline{w}_m}$).[1] The marginal returns to leisure are strictly decreasing while the marginal costs are constant, guaranteeing a unique solution to the utility maximization problem defined by equations (1.5.1), (1.5.2), and (1.5.3) for men.

Proposition (Proposition A.2.1)**.** *The schooling rule for men can be defined by a threshold value γ_m, such that men will attend college if and only if they draw non-monetary costs ε where $\varepsilon < \gamma_m$.*

$$s_m = \boldsymbol{1}\left[\gamma_m > \varepsilon\right] \tag{A.2.1}$$

where $\gamma_m = \beta\left[T_{2m}(\overline{w}_m - \underline{w}_m) - ln(\frac{\overline{w}_m}{\underline{w}_m})\right] - \underline{w}_m - d$

Proof. For men, the indirect utility from choosing to attend college is given by

$$V_1(s=1,z=1) = \beta\left[\overline{w}_m[T_{2m} - 1/\overline{w}_m] + \ln\left(1/\overline{w}_m\right)\right] + \underline{w}_m\left[T_1 - 1/\underline{w}_m - 1\right] - d - \varepsilon + \ln\left(1/\underline{w}_m\right) \tag{A.2.2}$$

The indirect utility from choosing to not attend college is given by

$$V_1(s=0,z=1) = \beta\left[\underline{w}_m\left[T_{2m} - 1/\underline{w}_m\right] + \ln\left(1/\underline{w}_m\right)\right] + \overline{w}_m\left[T_1 - 1/\underline{w}_m\right] + \ln\left(1/\underline{w}_m\right) \tag{A.2.3}$$

Men will attend college if and only if $V_1(s=1,z=1) - V_1(s=0,z=1) > 0$. Taking the difference between (A.2.2) and (A.2.3), we have

$$V_1(s=1,z=1) - V_1(s=0,z=1) = \beta\left[T_{2m}(\overline{w}_m - \underline{w}_m) - \ln\left(\overline{w}_m/\underline{w}_m\right)\right] - \underline{w}_m - d - \varepsilon \tag{A.2.4}$$

The schooling rule is therefore defined as

$$s_m = \mathbf{1}\left[\beta\left[T_{2m}(\overline{w}_m - \underline{w}_m) - \ln\left(\overline{w}_m/\underline{w}_m\right)\right] - \underline{w}_m - d > \varepsilon\right] \tag{A.2.5}$$

[1]Since $T_{2m} > T_1$ by assumption, then $T_{2m} > T_1 > \frac{1}{\underline{w}_m} + 1 > \frac{1}{\underline{w}_m}$.

$\square$

Equation (A.2.1) demonstrates that men choose to attend college if and only if their future discounted additional earnings in period 2 exceeds the future discounted loss in utility from less leisure in period 2, their foregone earnings from attending college in period 1, and the total (monetary and non-monetary) college costs in period 1.

A.2.2 College-going decision for women

The focus of this model is the change in labor force participation of married women over time, so for ease of exposition I assume that single women with and without children have time for both leisure and schooling in period 1 ($T_1 > \frac{1}{\underline{w}_f} + 1$). Married women may or may not work in period 2. If they do work, female college graduates will work strictly more than women without college degrees.[2]

Proposition (Proposition A.2.2)**.** *The college enrollment rule for women is given by the threshold value γ_f, such that women will attend college if and only if they draw non-monetary costs ε where $\varepsilon < \gamma_f$. Threshold value γ_f takes on different values depending on whether or not it is optimal for married women to work.*

$$s_f = \boldsymbol{1}\left[\gamma_f > \varepsilon\right] \tag{A.2.6}$$

where

$$\gamma_f = \begin{cases} -[1-q_f(1-z)](\underline{w}_f + d) \\ \textit{if wives do not work } (T_{2f} \leq \frac{1}{\overline{w}_f}) \\ \\ \beta(1-q_f)\left[\overline{w}_f T_{2f} - 1 - ln(\overline{w}_f T_{2f})\right] - [1-q_f(1-z)](\underline{w}_f + d) \\ \textit{if only female college graduates work } (\frac{1}{\overline{w}_f} < T_{2f} \leq \frac{1}{\underline{w}_f}) \\ \\ \beta(1-q_f)\left[T_{2f}(\overline{w}_f - \underline{w}_f) - ln\left(\overline{w}_f/\underline{w}_f\right)\right] - [1-q_f(1-z)](\underline{w}_f + d) \\ \textit{if all wives work } (\frac{1}{\underline{w}_f} < T_{2f}) \end{cases}$$

Proof. For women, the indirect utility from attending college depends on whether or not it is optimal for them to work when married in period 2.

Case 1: It is not optimal for married women to work in period 2 ($T_{2f} \leq \frac{1}{\overline{w}_f}$). The indirect utility from choosing to attend college is

[2] This stems from the assumption that utility is quasilinear in consumption and that women with college degrees earn higher wage rates than those without: $\overline{w}_f > \underline{w}_f$.

$$\mathbb{E}V(1,z) = (1-q_f)\Big[\underline{w}_f(T_1 - 1/\underline{w}_f - 1) - d - \varepsilon + \ln\big(1/\underline{w}_f\big) + \beta\ln\big(T_{2f}\big)\Big] + \\ q_f\Big[\underline{w}_f(T_1 - 1/\underline{w}_f - z) - dz - \varepsilon + \ln\big(1/\underline{w}_f\big) + \beta\ln\big(T_{2f}\big)\Big] \quad \text{(A.2.7)}$$

The indirect utility from choosing to not attend college is

$$\mathbb{E}V(0,z) = \underline{w}_f(T_1 - 1/\underline{w}_f) + \ln\big(1/\underline{w}_f\big) + \beta\ln\big(T_{2f}\big) \quad \text{(A.2.8)}$$

Subtracting A.2.8 from A.2.7, provides the schooling rule:

$$s_f = \mathbf{1}\Bigg[\mathbb{E}V(1,z) - \mathbb{E}V(0,z) > 0\Bigg] = \Bigg[-[1-q_f(1-z)][\underline{w}_f + d] - \varepsilon > 0\Bigg] \quad \text{(A.2.9)}$$

Case 2: It is only optimal for married women with college degrees to work in period 2 ($\frac{1}{\overline{w}_f} \leq T_{2f} < \frac{1}{\underline{w}_f}$). The indirect utility from choosing to attend college is

$$\mathbb{E}V(1,z) = (1-q_f)\Big[\underline{w}_f(T_1 - 1/\underline{w}_f - 1) - d - \varepsilon + \ln\big(1/\underline{w}_f\big) + \beta\big[\overline{w}_f(T_{2f} - 1/\overline{w}_f) + \ln\big(1/\overline{w}_f\big)\big]\Big] + \\ q_f\Big[\underline{w}_f(T_1 - 1/\underline{w}_f - z) - dz - \varepsilon + \ln\big(1/\underline{w}_f\big) + \beta\ln(T_{2f})\Big] \quad \text{(A.2.10)}$$

The indirect utility from choosing to not attend college is

$$\mathbb{E}V(0,z) = \underline{w}_f(T_1 - 1/\underline{w}_f) + \ln\big(1/\underline{w}_f\big) + \beta\ln(T_{2f}) \quad \text{(A.2.11)}$$

The difference in indirect utilities obtained from subtracting A.2.11 from A.2.10 is given by

$$s_f = \mathbf{1}\Bigg[\mathbb{E}V(1,z) - \mathbb{E}V(0,z) > 0\Bigg] = \\ \Bigg[\beta(1-q_f)\big[\overline{w}_f(T_{2f} - 1/\overline{w}_f) - \ln\big(\overline{w}_f T_{2f}\big)\big] - [1-q_f(1-z)][\underline{w}_f + d] - \varepsilon > 0\Bigg] \quad \text{(A.2.12)}$$

Case 3: It is optimal for married women to work in period 2 ($T_{2f} > \frac{1}{\underline{w}_f}$). The indirect utility from choosing to attend college is given by

$$\mathbb{E}V(1,z) = (1-q_f)\Big[\underline{w}_f(T_1 - {}^1\!/\!_{\underline{w}_f} - 1) - d - \varepsilon + \ln\big({}^1\!/\!_{\underline{w}_f}\big) + \beta\big[\overline{w}_f(T_{2f} - {}^1\!/\!_{\overline{w}_f}) + \ln\big({}^1\!/\!_{\overline{w}_f}\big)\big] +$$
$$q_f\Big[\underline{w}_f(T_1 - {}^1\!/\!_{\underline{w}_f} - z) - dz - \varepsilon + \ln\big({}^1\!/\!_{\underline{w}_f}\big) + \beta\big[\underline{w}_f(T_{2f} - {}^1\!/\!_{\underline{w}_f}) + \ln\big({}^1\!/\!_{\underline{w}_f}\big)\big]\Big] \quad \text{(A.2.13)}$$

The indirect utility from choosing to not attend college is given by

$$\mathbb{E}V(0,z) = \underline{w}_f(T_1 - {}^1\!/\!_{\underline{w}_f}) + \ln\big({}^1\!/\!_{\underline{w}_f}\big) + \beta\big[\underline{w}_f(T_{2f} - {}^1\!/\!_{\underline{w}_f}) + \ln\big({}^1\!/\!_{\underline{w}_f}\big)\big] \quad \text{(A.2.14)}$$

The difference in indirect utilities obtained from subtracting A.2.14 from A.2.13 yields

$$s_f = \mathbf{1}\Bigg[\mathbb{E}V(1,z) - \mathbb{E}V(0,z) > 0\Bigg] =$$
$$\Bigg[\beta(1-q_f)\Big[T_{2f}(\overline{w}_f - \underline{w}_f) - \ln\big({}^{\overline{w}_f}\!/\!_{\underline{w}_f}\big)\Big] - [1 - q_f(1-z)][\underline{w}_f + d] - \varepsilon > 0\Bigg] \quad \text{(A.2.15)}$$

□

Based on Proposition A.2.2, the schooling rule for women will always depend on women's non-college wage rates, even if they will not work in period 2. However, women's schooling rule does not depend on college wage rates if it is not optimal for female college graduates to work.

A.2.3 Effect of wage rates on college-going

Men choose to attend college if and only if they draw non-monetary costs $\varepsilon \sim G(\varepsilon)$ below γ_m, and women choose to attend college if and only if they draw $\varepsilon \sim G(\varepsilon)$ below γ_f. Proposition A.2.3 summarizes how these threshold values change given changes in non-college wage rates.

Proposition (Proposition A.2.3)**.** *The effect of non-college wage rates in decreasing college-going is strictly larger in magnitude for men than women.*

$$0 > \frac{d\gamma_f}{d\underline{w}_f} > \frac{d\gamma_m}{d\underline{w}_m} \quad \text{(A.2.16)}$$

Proof. Taking the derivative of the threshold college-going value for men, γ_m, with respect to men's non-college wage rates, $\underline{w}_m$, we have

$$\frac{d\gamma_m}{d\underline{w}_m} = -\beta \underbrace{\left[T_{2m} - \frac{1}{\underline{w}_m}\right]}_{x^*_{2m}(sz<1)} - 1 \tag{A.2.17}$$

The first term in equation A.2.17 shows that a marginal decline in the non-college wage rate for men increases the college-going threshold by the optimal labor amount, weighted by the discount factor for period 2 utility. The second term in equation A.2.17 shows that a marginal decline in the non-college wage rate increases the college-going threshold by decreasing the marginal opportunity cost of schooling in period 1.

Taking the derivative of the threshold college-going value for women γ_f with respect to women's non-college wage rates, $\underline{w}_f$, we have

$$\frac{d\gamma_f}{d\underline{w}_f} = \begin{cases} -[1 - q_f(1-z)] & \text{if } T_{2f} \leq \frac{1}{\underline{w}_f} \\ -\beta(1-q_f)\underbrace{\left[T_{2f} - \frac{1}{\underline{w}_f}\right]}_{x^*_{2f}(sz<1)} - [1 - q_f(1-z)] & \text{if } T_{2f} > \frac{1}{\underline{w}_f} \end{cases} \tag{A.2.18}$$

For women, a marginal decline in the non-college wage rate increases the college-going threshold by the expected optimal labor amount weighted by the discount factor β, provided that women's time net of housework exceeds their optimal leisure amount and that they have time left over to work ($T_{2f} > \frac{1}{\underline{w}_f}$). A marginal decline in the non-college wage rate also increases the college-going threshold by decreasing the expected marginal opportunity cost of schooling in period 1.

Optimal time spent at work $x^*_2 = T_2 - \frac{1}{\underline{w}}$ is increasing in wage rates $\underline{w}$, so $\underline{w}_f < \underline{w}_m$ and $T_{2m} > T_{2f}$ implies that $x^*_{2f} < x^*_{2m}$. Moreover, $(1 - q_f) < 1$ and $1 - q_f(1-z) < 1$. Therefore, each term in equation (A.2.18) is smaller in magnitude than each term in equation (A.2.17) and

$$\frac{d\gamma_f}{d\underline{w}_f} < \frac{d\gamma_m}{d\underline{w}_m} < 0 \tag{A.2.19}$$

□

The effect of non-college wages in decreasing college-going rates is stronger for men than women, for three reasons. First, women's non-college wage rates are lower than men's, which decreases the amount of labor time women optimally *choose* to supply. Second, married women's time net of housework is less than married men's, which leaves them with less time they *can* convert to labor. Third, the probability of an unplanned pregnancy decreases the likelihood that women who attend college will earn a college degree, which decreases the period 2 expected earnings gain from attending college. The effect of any increase in non-college wage rates on college-going is smaller given this lower expected earnings gain. On an additional interesting side note, the risk of leaving school having only finished partway *decreases* the period 1 cost of college for women, by decreasing the earnings women expect to forego while in school.

On the other hand, the effect of *college* wage rates on college-going is positive, strictly for men and weakly for women. There are two results to highlight. First, men's college-going decision is more responsive to their college wage rates than women's. Second, women's college wage rates have no effect on women's college-going if female college graduates do not work in period 2, but women's non-college wage rates always have a negative effect on women's college-going (even if they do not work in period 2). These results are formalized in proposition A.2.4.

Proposition (Proposition A.2.4)**.** *The effect of college wage rates in increasing college-going is strictly larger in magnitude for men than women.*

$$\frac{d\gamma_m}{d\overline{w}_m} > \frac{d\gamma_f}{d\overline{w}_f} \geq 0 \tag{A.2.20}$$

where the last relationship holds with equality if married female college graduates do not work ($T_{2f} \leq \frac{1}{\overline{w}_f}$).

Proof. Taking the derivative of the threshold college-going value for men, γ_m, with respect to men's college wage rates, $\overline{w}_m$, we have

$$\frac{d\gamma_m}{d\overline{w}_m} = \beta[\underbrace{T_{2m} - 1/\overline{w}_m}_{x^*_{2m}(sz=1)}] > 0 \tag{A.2.21}$$

For men, a marginal increase in the college wage rate increases the college-going threshold by the optimal labor amount, weighted by the discount factor for period 2 utility.

Taking the derivative of the threshold college-going value for women, γ_f, with respect to women's college wage rates, $\overline{w}_f$, we have

$$\frac{d\gamma_f}{d\overline{w}_f} = \begin{cases} 0 & \text{if } T_{2f} \leq \frac{1}{\overline{w}_f} \\ \beta(1-q_f)\big[\underbrace{T_{2f} - \frac{1}{\overline{w}_f}}_{x^*_{2f}(sz=1)}\big] & \text{if } T_{2f} > \frac{1}{\overline{w}_f} \end{cases} \tag{A.2.22}$$

For women, a marginal increase in the college wage rate increases the college-going threshold by the expected optimal labor amount weighted by the discount factor for period 2 utility, provided that it is optimal to work when married in period 2. If it is not optimal for married women to work, changes in the college wage rate have no effect on the college-going threshold.

Since it is assumed that $T_{2m} > 1/\overline{w}_m$, the amount of time men spend at work is always positive. Therefore, the effect of college wage rates on the college-going threshold γ_m for men is strictly positive. If it is optimal for women with college degrees to work ($T_{2f} > 1/\overline{w}_f$), the effect of their college wage rates on their college-going threshold γ_f is also positive. However, because 1) $\overline{w}_f < \overline{w}_m$

and optimal time spent at work is increasing in wage rates, and because 2) women have less time net of household production than men do ($T_{2f} < T_{2m}$), women will spend strictly less time at work than men: $x^*_{2f}(sz=1) = T_{2f} - {}^1\!/\overline{w}_f < T_{2m} - {}^1\!/\overline{w}_m = x^*_{2m}(sz=1)$. The responsiveness of college-going to college wage rates will therefore be higher for men than women.

If it is not optimal for married women with college degrees to work ($T_{2f} \leq \frac{1}{\overline{w}_f}$), then the effect of college wage rates $\overline{w}_f$ on γ_f is 0. □

A.2.4 Roles of increasing household production efficiency and declining fertility risk

Increasing household production efficiency

Increases in the efficiency of household production α decrease the time needed for housework and increase the time individuals allocate to labor and leisure. This analysis focuses on the effect of a rise in α on the time women have to allocate to labor and leisure, T_{2f}. The results for the time men can allocate to labor and leisure, T_{2m}, are similar.

Figure A.3 illustrates how the effect of wage rates on college-going changes as T_{2f} increases. For values of T_{2f} below $\frac{1}{\overline{w}_f}$, wives do not work in period 2. Only non-college wage rates influence enrollment, since women must still forego earnings in order to attend school in period 1 even if they did not expect to work in period 2. As T_{2f} increases past $\frac{1}{\overline{w}_f}$, it becomes optimal for only wives with college degrees to work. The effect of college wage rates on female enrollment grows discontinuously from 0 to $\beta(1-q_f)[T_{2f} - \frac{1}{\overline{w}_f}]$, since women now experience an expected earnings gain in period 2 from obtaining a college degree. As T_{2f} increases past $\frac{1}{\underline{w}_f}$, it becomes optimal for wives without college degrees to join wives with college degrees in the workforce. The negative effect of non-college wages on female enrollment jumps from $-[1-q_f(1-z)]$ to $-\beta(1-q_f)[T_{2f} - \frac{1}{\underline{w}_f}] - [1-q_f(1-z)]$. If women expect to work even without a college degree, pursuing a college degree now entails sacrificing their non-college earnings, so the effect of non-college wage rates is stronger than the case where women don't expect to earn anything if they did not attend college.

Declining fertility risk

I will next examine how changes in the probability of an unplanned pregnancy, q_f, influences the response of female enrollment to changes in college and non-college wage rates. Taking the derivatives of $\frac{d\gamma_f}{d\underline{w}_f}$ and $\frac{d\gamma_f}{d\overline{w}_f}$ with respect to q_f, we have

$$\frac{d^2\gamma_f}{d\underline{w}_f dq_f} = \beta \max[T_{2f} - \frac{1}{\underline{w}_f}, 0] + 1 - z \text{ where } z < 1 \tag{A.2.23}$$

$$\frac{d^2\gamma_f}{d\overline{w}_f dq_f} = -\beta \max[T_{2f} - \frac{1}{\overline{w}_f}, 0] \tag{A.2.24}$$

As access to contraceptive technologies expanded, the probability of an unplanned pregnancy, q_f, declined. Equations (A.2.23) and (A.2.24) show that this increased the role of expected wage rates in the college-going decisions of women. First, declining fertility risk increased the probability that women who enrolled in college would actually obtain a college degree. Consequently, the expected earnings gain to attending college rose. Any changes in wage rates would have a larger effect on the expected earnings gain to attending college, as shown by both equations (A.2.23) and (A.2.24). Second, women expected to spend more time in college since they had a lower probability of dropping out. Any changes in non-college wage rates would then have a larger effect in changing the total foregone earnings of college enrollment, as shown by the second term in equation (A.2.23).

As contraceptive technologies decreased the probability of unplanned pregnancies, college and non-college wage rates became increasingly important in the college-going decision of women. First, declining fertility risk increased the expected earnings gain from attending college, because women had higher expectations that they would complete college and receive wage rate $\overline{w}_f$ in period 2. A decline in non-college wage rates or an increase in college wage rates would therefore have a larger impact in increasing the expected period 2 earnings gains of attending college, as shown by equations (A.2.23) and (A.2.24). Second, the lower likelihood of leaving school partway means women expected to spend more time in college. Any declines in non-college wage rates had a larger impact in decreasing the earnings women must forego to attend college, as shown by equation (A.2.23).[3]

A.2.5 When is enrollment higher for men than women? When is enrollment higher for women than men?

Figure 1.12 delivers the final result of the model. The left panel summarizes the role of increasing housework efficiency and declining fertility risk on how wage rates affect women's college-going. The x-axis is $T_{2i} = T - \frac{H_{2i}}{\alpha}$, time net of housework for gender i. The figure depicts how γ_i, the threshold college-going value for gender i, changes as T_{2i} increases.

The effect of increasing household efficiency on how female college-going responds to wage rates is represented by increasing time net of housework for women, $T_{2i} = T_{2f}$. Female college-going threshold γ_f grows as T_{2f} increases, represented by right-ward movement along the x-axis. This growth stems entirely from the result that increasing T_{2f} increases the strength of the college-going response to wage rates. This growth is discontinuous, depending on the relationship between time net of housework T_{2f} and wage rates $(\underline{w}_f, \overline{w}_f)$. When $T_{2f} < \frac{1}{\overline{w}_f}$, it is not optimal for married women to work in period 2. They will attend college if and only if $\varepsilon < -[1 - q_f(1-z)](\underline{w}_f + d)$. A marginal increase in α will do nothing to increase the college-going threshold γ_f along this interval. On the other hand, if α is sufficiently high such that $T_{2f} \in (\frac{1}{\overline{w}_f}, \frac{1}{\underline{w}_f})$, then only married women with college degrees will work in period 2. A marginal increase in α increases the threshold γ_f by $\beta(1-q_f)\frac{H_{2f}}{\alpha^2}[\overline{w}_f - \frac{1}{T_{2f}}]$, which is positive due to the assumption that $T_{2f} > \frac{1}{\overline{w}_f}$. Lastly, if $T_{2f} > \frac{1}{\underline{w}_f}$, it

[3] In addition, equation (A.2.23) demonstrates that fertility risk influences the effect of non-college wage rates whether or not women work ($\frac{d^2\gamma_f}{d\underline{w}_f dq_f} > 0$), while equation (A.2.24) demonstrates that fertility risk only influences the effect of college wage rates when women with college degrees work ($\frac{d^2\gamma_f}{d\overline{w}_f dq_f} < 0$ if and only if $T_{2f} > \frac{1}{\overline{w}_f}$).

is optimal for all married women to work. The slope of γ_f is the largest in this region – a marginal increase in α increases the threshold γ_f by $\beta(1-q_f)\frac{H_{2f}}{\alpha^2}[\overline{w}_f - \underline{w}_f]$.

The figure also graphs male enrollment, γ_m which grows as time net of housework for men $T_{2i} = T_{2m}$ increases (represented by a right-ward shift along the same x-axis).

The effect of declining fertility is represented by the shift from $\gamma_f(\widetilde{q}_f)$ to $\gamma_f(\widehat{q}_f)$, where $\widetilde{q}_f > 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f} > \widehat{q}_f$. Again, $1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ is the threshold below which it is possible for female enrollment to surpass male enrollment. For this reason $\gamma_f(\widehat{q}_f)$ crosses γ_m, but $\gamma_f(\widetilde{q}_f)$ never crosses γ_m.

Proposition A.2.5, which is the same as Proposition 1 in the main text, summarizes the conditions which create gender differences in college enrollment.

Proposition (Proposition A.2.5)**.** *Let T_{2f} denote time net of housework for women and q_f denote the probability that a woman will experience an unanticipated pregnancy in period 1. Let T_{2m} denote the time net of housework for men. If $q_f < 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$, then there exists $\widehat{T}$ where $\gamma_f(q_f, \widehat{T}) \geq \gamma_m(\widehat{T})$.*

Then $\forall T_{2f} \in (\widehat{T}_{2f}, \widehat{T}_{2m})$,

$$\gamma_f(q_f, T_{2f}) > \gamma_m(\widehat{T}_{2m})$$

Women will exceed men in college enrollment.

For $T_{2f} < \widehat{T}_{2f}$ when $q_f < 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ or for $T_{2f} < T_{2m}$ when $q_f \geq 1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$

$$\gamma_f(q_f, T_{2f}) < \gamma_m(\widehat{T}_{2m})$$

Men will exceed women in college enrollment.

Proof. The slope of γ_m is $\beta[\overline{w}_m - \underline{w}_m]$. For $T_{2f} > \frac{1}{\underline{w}_f}$, the slope of γ_f is $\beta(1-q_f)[\overline{w}_f - \underline{w}_f]$. Because $\overline{w}_f - \underline{w}_f > \overline{w}_m - \underline{w}_m$, there exists a $q_f \in (0,1)$ such that $\beta(1-q_f)[\overline{w}_f - \underline{w}_f]$ exceeds $\beta[\overline{w}_m - \underline{w}_m]$. For a sufficiently large value of $\widehat{T}$, $\gamma_f(\widehat{T}) \geq \gamma_m(\widehat{T})$. For any arbitrary $\widehat{T}_{2m}$ above $\widehat{T}$, $\gamma_f(q_f, \widehat{T}_{2m}) > \gamma_m(\widehat{T}_{2m})$ (as depicted by figure 1.12). Since both γ_m and γ_f are continuous with constant slope, there exists $\widehat{T}_{2f} < \widehat{T}_{2m}$ such that $\gamma_f(q_f, \widehat{T}_{2f}) = \gamma_m(\widehat{T}_{2m})$. For all $T_{2f} \in (\widehat{T}_{2f}, \widehat{T}_{2m})$, $\gamma_f(q_f, T_{2f}) > \gamma_m(\widehat{T}_{2m})$. In other words, there exists an interval $(\widehat{T}_{2f}, \widehat{T}_{2m})$ such that for all values of time net of housework for women T_{2f} within this interval, the college-going threshold for women γ_f will exceed the college-going threshold for men γ_m at $\widehat{T}_{2m}$. □

Proposition A.2.5 demonstrates that necessary conditions for women to exceed men in college enrollment are that fertility risk q_f must fall below $1 - \frac{\overline{w}_m - \underline{w}_m}{\overline{w}_f - \underline{w}_f}$ and that housework must fall to a point where it is optimal for college women to work (in other words, time net of housework T_{2f} must exceed $\frac{1}{\overline{w}_f}$). Once these two conditions are met, it is possible for women to take advantage of their higher labor market returns. Because $\overline{w}_f - \underline{w}_f > \overline{w}_m - \underline{w}_m$, the slope of female enrollment γ_f exceeds the slope of male enrollment γ_m. As long as housework time for women is sufficiently low, female college-going will be higher than male college-going even if women have less time for work and lower wage rates than men.

The right panel of figure 1.12 represents the change in female college-going threshold γ_f given a decline in the female non-college wage rate $\underline{w}_f$. Consider a decline in $\underline{w}_f$ to $\underline{\underline{w}}_f$, which pushes the y-intercept up and shifts the vertical axis $\frac{1}{\underline{w}_f}$ further to the right, increasing the slope of γ_f. This change is represented by the shift from $\gamma_f(\underline{w}_f)$ to $\gamma_f(\underline{\underline{w}}_f)$. For any $\widehat{T}_{2m}$, define $\widehat{T}_{2f}$ and $\underline{\underline{\widehat{T}}}_{2f}$ to be such that $\gamma_m(\widehat{T}_{2m}) = \gamma_f(\underline{w}_f, \widehat{T}_{2f}) = \gamma_f(\underline{\underline{w}}_f, \underline{\underline{\widehat{T}}}_{2f})$. Claim 1 shows that $\underline{\underline{\widehat{T}}}_{2f} < \widehat{T}_{2f}$.

Claim 1. $\underline{\underline{\widehat{T}}}_{2f} < \widehat{T}_{2f}$.

Proof. Choose any $\widehat{T}_{2m} > \widehat{T}$, where $\widehat{T}$ is defined such that $\gamma_m(\widehat{T}) \leq \gamma_f(\underline{w}_f, \widehat{T})$.

Denote $g_1(T_{2i}) = \gamma_f(\underline{w}_f, T_{2i}) - \gamma_m(\widehat{T}_{2m})$ and denote $g_2(T_{2i}) = \gamma_f(\underline{\underline{w}}_f, T_{2i}) - \gamma_m(\widehat{T}_{2m})$. Since $\gamma_f(\underline{\underline{w}}_f, T_{2i}) > \gamma_f(\underline{w}_f, T_{2i})\ \forall T_{2i}$, $g_2(T_{2i}) > g_1(T_{2i})\ \forall T_{2i}$. Both $g_1(T_{2i})$ and $g_2(T_{2i})$ are strictly increasing but initially negative. Therefore, $g_2(T_{2i})$ intersects the y-axis at a lower level of T_{2i} than $g_1(T_{2i})$.
Let $\widehat{T}_{2f}, \underline{\underline{\widehat{T}}}_{2f}$ be such that $g_1(\widehat{T}_{2f}) = 0$ and $g_2(\underline{\underline{\widehat{T}}}_{2f}) = 0$. Then $\underline{\underline{\widehat{T}}}_{2f} < \widehat{T}_{2f}$. $\square$

This result is significant because it shows that declines in non-college wage rates for women complement increasing housework efficiency and decreasing fertility risk in enabling female enrollment to grow and overtake male enrollment. A decline in non-college wage rates enable female college enrollment to exceed male college enrollment at lower levels of household efficiency and higher levels of fertility risk. Declining employment opportunities in the non-college market therefore help explain not only why women overtook men in college enrollment, but also why the overtaking occurred as early as the 1980s, when household efficiency and declining fertility risk had shown significant advancements but had not yet reached current levels.

A.2.6 Extension: Gender Wage Gap

Figure 1.12 reveals that women are willing to accept lower college wage rates than men to enter the college market, due to the large imbalance in non-college wage rates between men and women. The difference between college and non-college wage rates is greater for women ($\overline{w}_f - \underline{w}_f > \overline{w}_m - \underline{w}_m$) and this is sufficient to entice a greater proportion of women to choose to attend college than men, even though college wage rates are higher for men than women ($\overline{w}_m > \overline{w}_f$). The empirical disparity in non-college job prospects, documented in Section 1.2, may therefore explain why the gender wage gap in college occupations has been so persistent. Since women have access to fewer lucrative options in the non-college labor market, they are willing to enter the college market for lower pay relative to men, and therefore men continue to enjoy greater college earnings than women on average.

One implication of this argument is that external measures to narrow the gender gap in wages will widen the gender gap in college enrollment. Policy interventions to make women's college earnings equal to that of men will lead female college enrollment, γ_f, to increase relative to male college enrollment, γ_m. For symmetric reasons, external measures to narrow the gender gap in college enrollment will widen the gap in wages. The model suggests that gender differences in the non-college labor market link the gender gap in college enrollment with the gender gap in college earnings.

Current policies aimed at leveling one inequality may exacerbate the other, since prior research has overlooked the role of the non-college market in contributing to both.

A.3 Chapter 1 Appendix: Data

A.3.1 Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) Data

In Sections 1.2 and 1.3, I use data from the Annual Social and Economic Supplement of the Current Population Surveys (CPS-ASEC), which is jointly conducted by the U.S. Census Bureau and the Bureau of Labor Studies and provided by the Integrated Public Use Microdata Series (IPUMS; Flood et al., 2015). I use the sample of 16-64 year olds from the years 1970-2010, although for many measures I restrict the sample to just 18-25 year olds or 18-30 year olds. In most of the analysis, I restrict the sample to full-time (at least 35 hours worked per week), full-year (at least 40 weeks worked per year) workers using the definitions employed by Acemoglu and Autor (2011).

The main outcome variable used to measure college enrollment is SCHLCOLL, the proportion of 16-24 year olds who report that they are *currently* enrolled in college full-time or part-time. To exclude students who may not have graduated from high school at the time of data collection, I restrict this sample to 18-24 year olds. Individuals who did not report an education level are excluded from the analysis.

Workers are coded potentially affected by the oil and gas industry if they belong to the following industries: petroleum and coal production, mining (including oil and gas extraction), trucking services, warehousing and storage. Workers are coded as potentially affected by the oil, gas, and related industries if they belonged to any of the aforementioned industries or were employed in the following occupations: construction inspectors; inspectors and compliance officers; metallurgical and materials engineers; petroleum, mining, and geological engineers; chemical engineers; electrical engineers; industrial engineers; mechanical engineers; geologists; drillers of earth, construction trades (not elsewhere classified); extractive occupations (drillers of oil wells, explosives workers, miners, other mining occupations); supervisors of motor vehicle transportation; truck, delivery, and tractor drivers; transport equipment operatives; material moving equipment operators; helpers, constructive, and extractive occupations.

Annual earnings data is obtained from the income from INCWAGE, the pre-tax income from wages and salary variable. Earnings are top-coded at the 95th percentile of reported earnings and bottom-coded at the 1st percentile of reported earnings. All annual earnings are inflated to 2008 dollars. Only workers who reported being in the labor force, whether employed or unemployed, are included.

All regressions using CPS-ASEC data are conducted at the state-year level. Microdata are aggregated up to the state level using person-level weights for CPS supplement data. For the subsample analysis of non-migrants in Section 1.3, I only include workers who reported living in the same house, moving within the county, or moving to a different county in the same state. I exclude workers who reported moving between states or moving abroad. I also exclude workers who did not respond to the migration questions. Workers are classified as moving for work if they report that they moved: for a new job or transfer, to look for work or lost a job, for an easier commute, or for other job-related reasons.

A.3.2 Census and American Community Survey (ACS) Microdata

In Sections 1.2 and 1.4, I use the decennial census microdata from 1950 to 2000 and the annual American Community Survey (ACS) microdata from 2001-2010, which are both conducted by the U.S. Census Bureau and provided by the Integrated Public Use Microdata Series (IPUMS, Ruggles et al., 2017). I use the sample of 16-64 year olds, but for some analyses I restrict the sample to just 18-25 year olds or 18-30 year olds. In most of the analysis, I restrict the sample to full-time (at least 35 hours worked per week), full-year (at least 40 weeks worked per year) workers using the definitions employed by Acemoglu and Autor (2011).

The college enrollment variable is constructed using the harmonized EDUCD variable. Individuals are coded as having ever enrolled in college if they report having at least some college education. Individuals are coded as having never enrolled in college if their highest reported level of educational attainment was a high school diploma or equivalent. Individuals who did not report an education level were excluded from the analysis.

Annual earnings data is obtained from the variable INCWAGE, the pre-tax individual income from wages and salary. Annual earnings are only computed for workers who report working for wages or salary. Individuals who report being self-employed or an unpaid family worker, and individuals who report working no weeks in the previous year, are excluded. Annual earnings are topcoded at the pre-determined Census topcode levels, which vary from year to year. Annual earnings are bottom coded as the 1st percentile of reported earnings for each year. All earnings are inflated to 2008 dollars.

The census and ACS data are merged to the occupational task intensity data compiled by Autor and Dorn (2013) using the OCC1990 variable, which is harmonized across all years. The Routine Task Intensity (RTI) measure is the primary measure I use to determine how "routine-intensive" an occupation is. An occupation is classified as highly routine-intensive occupation if its RTI measure scores in the top third of all RTI. Out of 330 total occupations, 113 occupations fit this criterion.

All regressions are conducted at the commuting zone-year level. The census and ACS data are merged to corresponding commuting zones using the crosswalks provided by Autor and Dorn (2013). Demographic characteristics, occupations, education, earnings, and work variables are aggregated up to the commuting zone level using person-level weights.

B.1 Chapter 2 Appendix: Tables and Figures

Tables

TABLE B.1
PROBIT REGRESSION OF COLLEGE ATTENDANCE ON SKILL PROFILES - SUBTEST SCORES

	Male			Female		
	College	College	College	College	College	College
	(1)	(2)	(3)	(4)	(5)	(6)
auto shop score	-0.0285***			-0.00424		
	(0.00474)			(0.00557)		
electronic score		-0.0135***			-0.00375	
		(0.00512)			(0.00516)	
mechanical score			-0.0216***			-0.00533
			(0.00472)			(0.00517)
AFQT	0.859***	0.791***	0.851***	0.909***	0.915***	0.922***
	(0.0557)	(0.0592)	(0.0580)	(0.0522)	(0.0564)	(0.0553)
socioemotional	0.102***	0.0994***	0.104***	0.0900***	0.0897***	0.0884***
	(0.0332)	(0.0331)	(0.0332)	(0.0308)	(0.0307)	(0.0308)
risk aversion	0.0431***	0.0435***	0.0449***	0.0256**	0.0257**	0.0258**
	(0.0127)	(0.0126)	(0.0126)	(0.0118)	(0.0118)	(0.0119)
Demo. controls	YES	YES	YES	YES	YES	YES
Constant	1.191*	0.771	1.205*	1.306**	1.284**	1.397**
	(0.708)	(0.715)	(0.722)	(0.564)	(0.560)	(0.580)
Observations	2272	2272	2272	2493	2493	2493
Pseudo R^2	0.252	0.241	0.246	0.213	0.213	0.213

Notes: Probit regression of college enrollment status on ASVAB subtest scores for Auto & Shop Information, Electronics Information, or Mechanical Comprehension (modified version of equation 2.4.9). Regressions control for region of residence, height, age, and race. Coefficients on dummies for missing variables suppressed. Cross-sectional regression at year = 1990. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1 Chapter 3 Appendix: Tables

C.1.1 Additional Data Details

As mentioned in the main text, our partner hospital system typically sends solicitation mailings to patients a few weeks after the end of a mailing cycle. There are some exceptions to this rule: patients whose first visit occurred in September or October were solicited in December in an attempt by the hospital system to leverage potentially higher giving rates during the holiday season. Patients whose first visit occurred in March or April of 2014 were not solicited until July 2014, about six weeks later than usual, due to idiosyncratic logistical issues arising from the centralization of patient information into a new data warehouse.

C.1.2 Additional Methods and Results

Analysis by Severity of Illness

In additional analyses, we repeat each of the two empirical approaches described in the main text, but we split patients based on a proxy for the severity of their medical condition. To measure the severity of patients' ailments, we asked three physicians at our partner hospital system to independently rate each of the 11 medical departments that handled more than 1,000 outpatients in our data set. Physicians were asked to rate departments on a scale from 1 (lowest severity) to 7 (highest severity). Inter-rater agreement was strong (Cronbachs alpha = 0.88 across the ratings). The physicians unanimously rated oncology, cardiology, and surgery to be the medical departments that handled the most severe cases. We classified the 6,257 patients who visited the oncology, cardiology, and surgery departments as "severe", and we classified the 8,495 patients who did not visit these departments but visited other rated departments as "not severe". 3,763 patients only visited small (unclassified) departments and were dropped from these secondary analyses. Table C.4 provides summary statistics describing these subsamples of our data and Table C.5 presents the regression results separately for "severe" and "not severe" patients.

Table C.4 shows how "severe" and "not severe" patients compare to one another and the full sample along observable demographic characteristics. Table C.5 displays the same analyses presented in Table 3.3 separately for "severe" patients (Panel A) and for "not severe" patients (Panel B). The coefficient estimates demonstrate that decay in reciprocity over time is particularly large among patients with "severe" ailments: a 30-day delay between visiting the hospital and receiving a solicitation decreases the donation rate by at least 0.7 percentage points ($p < 0.01$ in all cases). In contrast, the decay over time in reciprocity is insignificant among "not severe" patients. Wald tests, presented in the bottom row of table C.3, show that the decline in giving over time is significantly steeper among "severe" patients than among "not severe" patients ($p < 0.05$ in all cases).

Analysis by Patient Experience

To assess whether positive reciprocity is driving our results, we separately explore the behavior of patients who likely had more positive experiences with the hospital system and patients who likely had less positive experiences. We take three approaches, which all provide suggestive evidence that patients who are more satisfied with their experiences, and thus are more likely to exhibit positive reciprocity, display directionally larger decay.

First, we separately examine outpatients who (a) choose to return vs. (b) choose not to return to our hospital system within a set window after their initial visit (132 days, the longest period of time between an initial visit and the corresponding solicitation mailing date). Outpatients who choose to return to the hospital system are likely more satisfied on average with their experience than outpatients who do not. If decays in reciprocity over time are driven by gratitude, and not salience or forgetfulness, time-dependent positive reciprocity should be observed for more satisfied patients (i.e., repeat visitors). The results are summarized in Table C.6. (Note that we only look at first visits in this analysis, since for patients who only visit the hospital system once, the first visit and last visit are the same.) We indeed find that the decay in giving that we observe overall is primarily driven by patients who make multiple visits to the hospital system. For patients who did not make repeat visits to the hospital system, the decay is directionally smaller in magnitude and insignificant.

Second, we use the data on hospital ratings from the Center for Medicare and Medicaid Services (CMS) website as a proxy for patient satisfaction.[1] Only large hospitals receive a rating, and the three hospitals in our dataset with ratings include 14,504 of the 18,515 total patients in the analysis sample (about 78% of our data). As Table C.7 shows, we find that patient giving statistically significantly declines over time for the two hospitals with 4-star rating. This decline is directionally smaller in magnitude and insignificant for the hospital with a lower, 3-star rating.

Third, we construct measures of medical provider quality using patient experience survey data from Press Ganey. We then investigate how the decay differs according to whether a patient visited a provider with above-median scores or a provider with below-median scores. We consider the provider associated with the first visit when analyzing the effect of the timing of the first visit and the provider associated with the last visit when analyzing the effect of the timing of the last visit. We obtained average responses to 47 questions from Press Ganey surveys of patients about a variety of topics and use factor analysis to identify the questions that are correlated with each other. There are two factors that meet the Kaiser criterion, whose eigenvalues are greater than or equal to unity (Yeomans and Golder, 1982). Factor 1 loads on the following sections of the survey: quality of care provider, personal issues like cleanliness and sensitivity to needs, overall experience, quality of medical care given by care provider. Factor 2 loads on the following sections of the survey: ease of accessing care, quality of the waiting areas, quality of the nursing staff, and quality of the receptionists and clerks. We investigate Factor 1 in Table C.8 and Factor 2 in Table C.9. Patients whose first visit is with providers who scored above the median on the second factor have directionally larger decays than patients who visited providers who scored below the median on the

[1] These data are publicly provided by the Centers for Medicare and Medicaid Services (CMS), and are a common measure of hospital quality (see Werner et al., 2011). https://www.cms.gov/medicare/quality-initiatives-patient-assessment-instruments/hospitalqualityinits/hospitalcompare.html.

second factor. The difference in decay between above-median and below-median providers on the second factor gets directionally larger when considering the last visit. In contrast, we find that the first factor is not very predictive of decay.

These analyses provide additional evidence suggesting that patients with more positive experiences (i.e., those who chose to return to the hospital system for further care after a presumably positive first interaction, those who visited a higher rated hospital, and those who visited higher rated providers) generally showed directionally larger declines in giving over time, relative to patients with less pleasant experiences. While power limitations make it quite difficult for us to find statistically significant differences in the rate of decay across groups based on these measures, the magnitudes of decay all trend in line with our predictions and provide suggestive evidence that we are observing a decay in positive reciprocity over time.

Tables

TABLE C.1
EFFECT OF TIME DELAY ON RECIPROCITY

Outpatients first solicited in Mar 2013 - Apr 2015

	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Delay (in days) between first visit and solicitation x 30	-0.0921**	-0.112**		
	(0.0395)	(0.0399)		
Delay (in days) between last visit and solicitation x 30			-0.209**	-0.200**
			(0.0898)	(0.0708)
Observations	149,817	149,817	149,817	149,817
R-squared	0.002	0.007	0.003	0.007
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
First Stage F-Statistic			12,980	31,602

Notes: This table reproduces Table 3.3 in the main text with a larger sample of outpatients. We use all outpatients who were solicited for a donation for the first time during March 2013 - April 2015 and ignore all of their visits to the hospital system before March 2013, which do not appear in our data. Compared to our main analysis sample, this sample includes outpatients who had visited the hospital system before the visit that triggered a solicitation. Baseline giving in this larger sample is 0.61%. Columns 1 and 2 report ordinary least squares (OLS) coefficient estimates from a regression of the delay between a patient's first hospital visit and the date of a solicitation mailing on donation rates. Columns 3 and 4 report coefficient estimates from instrumental variables analyses in which the delay between a patient's first hospital visit and the date of a solicitation mailing is used as an instrument for the delay between a patient's last pre-solicitation hospital visit and the date of a solicitation mailing. Columns 1 and 3 include "Key Controls": dummies for mailing cycle, hospital visited, and medical department visited. Columns 2 and 4 add "Additional Controls": dummies for a patient's total number of hospital visits before the solicitation mailings were sent, dummies for a patient's number of hospital visits within 132 days of her first hospital visit, and controls for gender, age, marital status, and state of residence. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.2
SUMMARY STATISTICS AND REGRESSIONS TESTING DEMOGRAPHIC BALANCE ACROSS SOLICITATION DELAYS

	Summary Statistics	Regressions Predicting Timing of First Visit	
	(1)	(2)	(3)
Patient Demographics			
Age	Avg.= 64.19	0.0189	0.0185
	(S.D.= 11.45)	(0.0123)	(0.0120)
Single	18.50%		
Married	64.09%	-0.0381	-0.177
		(0.326)	(0.318)
Divorced	5.87%	-0.304	-0.340
		(0.575)	(0.560)
Separated	0.60%	-0.403	-0.130
		(1.560)	(1.533)
Widowed	8.21%	-0.0525	-0.0395
		(0.543)	(0.530)
Marital Status Unknown	2.73%		
In-State Resident	57.87%	-12.76	-10.44
		(12.50)	(10.54)
Female name	45.71%	-0.525	-0.452
		(0.460)	(0.447)
Male name	46.14%	-0.0809	-0.0223
		(0.460)	(0.447)
Gender of name unknown	8.15%		
Hospital Visits			
# Hospital visits between 1st visit and solicitation	Avg.= 3.42		
	(S.D.= 3.11)		
# Hospital visits within 132 days of 1st visit	Avg.= 4.44		
	(S.D.= 4.74)		
Donations			
Percent Donate	0.83%		
Donate$\|$Donate > 0	Avg.= $49.14		
	(S.D.= 36.68)		
Patients	18,515	18,515	18,515
R-squared		0.048	0.104
Key Controls		YES	YES
State Dummies		YES	YES
# Hospital visits between first visit and solicitation			YES
# Hospital visits within 132 days of first visit			YES

F statistic	1.010	1.041
p-value	0.455	0.391

Notes: Column 1 presents summary statistics describing our study sample. Sample means are shown with standard deviations in parentheses. Several patients' age data was missing from our primary age data source (solicitation administrative data); for these patients, we imputed age from the date of birth in the administrative health data ($N = 3,695$). To protect patient privacy, imputed age was top-coded at 90 in the data. Gender was imputed from patients' first names using the mapping in Morton, Zettelmeyer, and Silva-Risso (2003). Columns 2 and 3 present ordinary least squares (OLS) regressions of the timing of a first patient visit on demographic variables with standard errors shown in parentheses. Specifically, we regress the time delay separating a patient's first hospital visit from the date of their first solicitation on the patient's age when solicited, marital status (single is the omitted category), imputed gender based on first names (gender of name unknown is the omitted category), and state of residence. We perform a joint F-test on these demographic characteristics and report the F-statistic and p-value in the bottom two rows. Column 2 includes the control variables included in all of our later regressions (mailing cycle, hospital, and medical department visited). Column 3 adds additional controls (dummies for number of hospital visits between the first patient visit and the solicitation mailing, dummies for number of hospital visits within 132 days of first visit). The F-tests presented here show that patient demographics do not jointly predict the time delay separating a patient's first hospital visit from her receipt of a solicitation, suggesting that this time delay is uncorrelated with other factors that might influence donation decisions (as we assume throughout our analyses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.3

DELAY BETWEEN HOSPITAL VISIT AND SOLICITATION, ROBUSTNESS CHECKS

	% Donate	% Donate	% Donate	% Donate	% Donate
	(1)	(2)	(3)	(4)	(5)
Delay (in days) between first	-0.184*	-0.298**	-0.301**	-0.274**	-0.247**
visit and solicitation x 30	(0.0973)	(0.122)	(0.123)	(0.126)	(0.125)
Delay (in days) between last	-0.330*	-0.509**	-0.477**	-0.452**	-0.407**
visit and solicitation x 30	(0.174)	(0.208)	(0.195)	(0.207)	(0.204)
Observations	18,515	18,515	18,515	18,515	18,515
# Hospital visits between first visit and solicitation			YES	YES	YES
# Hospital visits within 132 days of first visit				YES	YES
Demographic Controls					YES

Notes: Estimated effects of the delay between a hospital visit and a solicitation on donation rates. The first row represents the estimated effect of a solicitation delay since the first hospital visit using ordinary least squares regressions. The second row represents the estimated effect of a solicitation delay since the last hospital visit using instrumental variables regressions. Column 1 includes no controls. Column 2 controls for hospital visited, mailing cycle of patient visit, and medical department visited (replicating column 1 of Table 3.3 in the main text). Column 3 adds control dummies for number of hospital visits before the solicitation mailings were sent. Column 4 adds controls for the patients number of hospital visits within 132 days of first hospital visit. Finally, column 5 adds controls for patient gender, age, marital status, and state of residence (replicating column 2 of Table 3.3 in the main text). Standard errors are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.4
SUMMARY STATISTICS BY PATIENT SEVERITY

	Full Sample	Severe	Not Severe
Patient Demographics			
Age	Avg.= 64.19 (S.D.= 11.45)	Avg.= 65.29 (S.D.= 11.45)	Avg.= 63.50 (S.D.= 11.37)
Single	18.50%	17.07%	18.08%
Married	64.09%	64.65%	65.45%
Divorced	5.87%	5.61%	5.74%
Separated	0.60%	0.67%	0.55%
Widowed	8.21%	9.16%	7.30%
Marital Status Unknown	2.73%	2.84%	2.87%
In-State Resident	57.87%	51.29%	62.47%
Female Name	45.71%	44.94%	45.18%
Male Name	46.14%	48.22%	46.40%
Gender of Name Unknown	8.15%	6.84%	8.42%
Hospital Visits			
# Hospital visits between 1st visit and solicitation	Avg.= 3.42 (S.D.= 3.11)	Avg.= 4.60 (S.D.= 3.66)	Avg.= 2.84 (S.D.= 2.11)
# Hospital visits within 132 days of 1st visit	Avg.= 4.44 (S.D.= 4.74)	Avg.= 6.00 (S.D.= 5.74)	Avg.= 3.71 (S.D.= 3.54)
Donations			
Percent Donate	0.83%	1.29%	0.62%
Donate$\|$Donate > 0	Avg.= \$49.14 (S.D.= 36.68)	Avg.= \$48.64 (S.D.= 36.10)	Avg.= \$47.30 (S.D.= 32.09)
Patients	18,515	6,257	8,495

Notes: Sample means are shown for each population with standard deviations in parentheses. The first column shows summary statistics for the full analysis sample. The second column shows summary statistics for patients who visited a medical department classified as handling severe ailments (oncology, surgery, or cardiology). The third column shows summary statistics for patients who only visited other departments that were classified in our analysis (primary care, dermatology, ear nose and throat, gastroenterology, orthopedics, radiology, neurology, and urology). The remaining 3,763 patients only visited small or unclassified departments and were excluded from our secondary analyses examining ailment severity as a moderator of our main effect. Several patients' age data was missing from our primary age data source (solicitation administrative data); for these patients, we imputed age from the date of birth in the administrative health data ($N = 3,695$). To protect patient privacy, imputed age was top-coded at 90 in the data. Gender was imputed from patients' first names using the mapping in Morton, Zettelmeyer, and Silva-Risso (2003).

TABLE C.5

ESTIMATING THE EFFECT OF A TIME DELAY ON RECIPROCITY FOR PATIENTS WITH SEVERE AILMENTS VS. OTHERS

	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Panel A: Medical departments classified as handling severe ailments (oncology, surgery, cardiology), $N = 6,257$				
Delay (in days) between first visit and solicitation x 30	-0.735***	-0.781***		
	(0.264)	(0.274)		
Delay (in days) between last visit and solicitation x 30			-1.420***	-1.420***
			(0.511)	(0.491)
R-squared	0.004	0.032	0.000	0.027
First Stage F-Statistic			774	1,757
Panel B: Other medical departments, $N = 8,495$				
Delay (in days) between first visit and solicitation x 30	-0.0223	0.115		
	(0.158)	(0.157)		
Delay (in days) between last visit and solicitation x 30			-0.0402	0.185
			(0.285)	(0.251)
R-squared	0.004	0.018	0.004	0.017
First Stage F-Statistic			1,212	3,255
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
Wald Test p-value: Severe vs. Other	0.021	0.005	0.013	0.004

Notes: Panel A presents the results of the same set of regressions presented in Table 3.3 for patients visiting medical departments that handle particularly severe ailments as rated by physicians at our partner hospital system. Panel B presents the results for patients visiting only departments that handle less severe ailments. Columns 1 and 2 report ordinary least squares (OLS) coefficient estimates from a regression of the delay between a patient's first hospital visit and the date of a solicitation mailing on donation rates. Columns 3 and 4 report coefficient estimates from instrumental variables analyses in which the delay between a patient's first hospital visit and the date of a solicitation mailing is used as an instrument for the delay between a patient's last pre-solicitation hospital visit and the date of a solicitation mailing.

Columns 1 and 3 include "Key Controls": dummies for mailing cycle, hospital visited, and medical department visited. Columns 2 and 4 add "Additional Controls": dummies for a patient's total number of hospital visits before the solicitation mailings were sent, dummies for a patient's number of hospital visits within 132 days of her first hospital visit, and controls for gender, age, marital status, and state of residence. Medical departments classified as severe are: cancer, cardiology, and surgery. Medical departments that were not classified as severe include: primary care, dermatology, ear nose and throat, gastroenterology, orthopedics, radiology, neurology, and urology. The p-values from Wald tests comparing the effect of a delay between patients with severe vs. other ailments is reported in the bottom row. Standard errors are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.6

DONATION BEHAVIOR FOR PATIENTS WITH ONE VERSUS REPEAT PATIENT VISITS

	% Donate (1)	% Donate (2)
Panel A: Patients with multiple visits in 132 days, $N = 14,898$		
Delay (in days) between first visit and solicitation x 30	-0.377***	-0.300**
	(0.139)	(0.142)
R-squared	0.007	0.023
Panel B: Patients with only one visit in 132 days, $N = 3,617$		
Delay (in days) between first visit and solicitation x 30	-0.0573	-0.0708
	(0.249)	(0.252)
R-squared	0.011	0.029
Key Controls	YES	YES
Additional Controls		YES
Wald Test p-value: One Visit vs. Multiple Visits	0.263	0.429

Notes: The regressions reproduce the main regressions in table 3.3, using patients who chose to return to hospital system more than once in 132 days (Panel A) and using only the subsample of patients who visited the hospital system once in 132 days (Panel B). 132 days is the largest window of time between a patient's first hospital visit and the solicitation mailing in the analysis sample.

Column 1 controls for mailing cycle, hospital, and medical department. Column 2 additionally controls for the number of hospital visits between the first visit and the solicitation date, the number of hospital visits within 132 days, and demographic controls. The last row displays the p-value of a Wald test comparing the coefficient estimates for patients who visited the hospital system once compared to patients who visited the hospital system more than once (Panel A compared to Panel B). Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.7

DONATION BEHAVIOR BY HOSPITAL RATING

	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Panel A: Hospitals with 4-star ratings ($N = 12,079$)				
Delay (in days) between first visit and solicitation x 30	-0.362**	-0.295*		
	(0.160)	(0.165)		
Delay (in days) between last visit and solicitation x 30			-0.635**	-0.511*
			(0.281)	(0.285)
R-squared	0.007	0.026	0.006	-0.001
First Stage F-Statistic			1,859	3,796
Panel B: Hospital with 3-star rating ($N = 2,425$)				
Delay (in days) between first visit and solicitation x 30	-0.174	-0.138		
	(0.258)	(0.269)		
Delay (in days) between last visit and solicitation x 30			-0.269	-0.209
			(0.397)	(0.400)
R-squared	0.013	0.037	0.002	0.001
First Stage F-Statistic			576	1,054
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
Wald Test p-value: 4-star vs. 3-star	0.536	0.620	0.450	0.533

Notes: The regressions reproduce the main regressions in table 3.3 using the three largest hospitals in the hospital system, which are the only hospitals large enough to have official patient experience ratings in the CMS Hospital Compare data. We compare the two hospitals with a 4-star rating (Panel A) to the one hospital with a 3-star rating (Panel B). Patients who visited hospitals with high ratings are likely to have more positive patient experiences on average than patients who visited hospitals with lower ratings.
Columns 1 and 3 control for mailing cycle, hospital, and medical department. Columns 2 and 4 additionally control for the number of hospital visits between the first visit and the solicitation date, the number of hospital visits within 132 days, and demographic controls. The last row displays the p-value of a Wald test comparing the coefficient estimates for patients of the 4-star hospitals to patients of the 3-star hospital (Panel A compared to Panel B). Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.8

DONATION BEHAVIOR BY MEDICAL PROVIDER RATING (FACTOR 1)

	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Panel A: Above median				
Delay (in days) between first visit and solicitation x 30	-0.523*	-0.366		
	(0.268)	(0.276)		
Delay (in days) between last visit and solicitation x 30			-1.235**	-0.800
			(0.563)	(0.512)
Patients	4,745	4,745	4,908	4,908
R-squared	0.016	0.047	0.011	0.000
First Stage F-Statistic			551.3	1,358
Panel B: Below median				
Delay (in days) between first visit and solicitation x 30	-0.570**	-0.529**		
	(0.235)	(0.237)		
Delay (in days) between last visit and solicitation x 30			-0.571	-0.434
			(0.356)	(0.337)
Patients	4,724	4,724	4,934	4,934
R-squared	0.016	0.084	-0.004	-0.001
First Stage F-Statistic			749.4	1,737
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
Wald Test p-value: Above vs. Below Median	0.895	0.655	0.318	0.550

Notes: The regressions reproduce the main regressions in table 3.3, using patients who visit medical providers who score above the median in Factor 1 (Panel A) and patients who visit medical providers who score below the median in Factor 1 (Panel B). Factor 1 is a variable computed from exploratory factor analysis of Press Ganey Patient Experience Survey data. Factor 1 loads on the following sections in the Press Ganey survey: quality of care provider, personal issues like cleanliness and sensitivity to needs, overall experience, quality of medical care given by care provider.

Columns 1 and 3 control for mailing cycle, hospital, and medical department. Columns 2 and 4 additionally control for the number of hospital visits between the first visit and the solicitation date, the number of hospital visits within 132 days, and demographic controls. The last row displays the p-value of a Wald test comparing the coefficient estimates for patients who visited a provider who scored above the median in Factor 1 and patients who visited a provider who scored below the median in Factor 1. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.9

DONATION BEHAVIOR BY MEDICAL PROVIDER RATING (FACTOR 2)

	% Donate (1)	% Donate (2)	% Donate (3)	% Donate (4)
Panel A: Above median				
Delay (in days) between first visit and solicitation x 30	-0.713***	-0.710***		
	(0.270)	(0.266)		
Delay (in days) between last visit and solicitation x 30			-1.152**	-1.057***
			(0.451)	(0.409)
Patients	4,718	4,718	4,910	4,910
R-squared	0.015	0.051	0.004	-0.001
First Stage F-Statistic			700.9	1,661
Panel B: Below median				
Delay (in days) between first visit and solicitation x 30	-0.364	-0.156		
	(0.228)	(0.238)		
Delay (in days) between last visit and solicitation x 30			-0.659	-0.0971
			(0.467)	(0.441)
Patients	4,751	4,751	4,932	4,932
R-squared	0.013	0.087	-0.001	0.000
First Stage F-Statistic			604	1,417
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
Wald Test p-value: Above vs. Below Median	0.323	0.121	0.448	0.111

Notes: The regressions reproduce the main regressions in table 3.3, using patients who visit medical providers who score above the median in Factor 2 (Panel A) and patients who visit medical providers who score below the median in Factor 2 (Panel B). Factor 2 is a variable computed from exploratory factor analysis of Press Ganey Patient Experience Survey data. Factor 2 loads on the following sections in the Press Ganey survey: ease of accessing care, quality of waiting areas, quality of the nurse, and quality of the clerks and receptionists.

Columns 1 and 3 control for mailing cycle, hospital, and medical department. Columns 2 and 4 additionally control for the number of hospital visits between the first visit and the solicitation date, the number of hospital visits within 132 days, and demographic controls. The last row displays the p-value of a Wald test comparing the coefficient estimates for patients who visited a provider who scored above the median in Factor 2 and patients who visited a provider who scored below the median in Factor 2. Standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE C.10
EFFECT OF TIME DELAY ON LOG DONATION AMOUNT

	Log (Donation) in \$ + 1) (1)	Log (Donation) in \$ + 1) (2)	Log (Donation) in \$ + 1) (3)	Log (Donation) in \$ + 1) (4)
Delay (in days) between first visit and solicitation x 30	-0.011** (0.0046)	-0.0090* (0.0048)		
Delay (in days) between last visit and solicitation x 30			-0.019** (0.0079)	-0.015* (0.0078)
Observations	18,515	18,515	18,515	18,515
R-squared	0.006	0.021	0.006	0.021
Key Controls	YES	YES	YES	YES
Additional Controls		YES		YES
First Stage F-Statistic			3,092	6,757

Notes: Columns 1 and 2 report ordinary least squares (OLS) coefficient estimates from a regression of the delay between a patient's first hospital visit and the date of a solicitation mailing on the logged donation received (set to 0 for non-donors). Columns 3 and 4 report coefficient estimates from instrumental variables analyses in which the delay between a patient's first hospital visit and the date of a solicitation mailing is used as an instrument for the delay between a patient's last pre-solicitation hospital visit and the date of a solicitation mailing. Columns 1 and 3 include "Key Controls": dummies for mailing cycle, hospital visited, and medical department visited. Columns 2 and 4 add "Additional Controls": dummies for a patient's total number of hospital visits before the solicitation mailings were sent, dummies for a patient's number of hospital visits within 132 days of her first hospital visit, and controls for gender, age, marital status, and state of residence. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

BIBLIOGRAPHY

[1] Acemoglu, D., Autor, D., 2011. Skills, Tasks, and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, Vol. 4, Part B, edited by Orley Ashenfelter and David Card, 1043-1171. Amsterdam: Elsevier.

[2] Aguiar, M., Hurst, E., 2007. Measuring Trends in Leisure: The Allocation of Time over Five Decades. The Quarterly Journal of Economics 122(3), 969-1006.

[3] Allcott, H., Keniston, D., 2018. Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America. Review of Economic Studies, forthcoming.

[4] Andreoni, J., Payne, A., 2013. Charitable Giving. Handbook of Public Economics 5, 1-49.

[5] Angrist, J., Pischke, J., 2009. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, New Jersey: Princeton University Press.

[6] ASVAB Fact Sheet. http://official-asvab.com/docs/asvab_fact_sheet.pdf

[7] Autor, D., 2013. The "Task Approach" to Labor Markets: An Overview. NBER Working Paper 18711.

[8] Autor, D., Dorn, D., 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. American Economic Review 103(5), 1553-1597.

[9] Autor, D., Dorn, D., Hanson, G., 2013. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. American Economic Review 103(6), 2121-2168.

[10] Autor, D., Levy, F., Murnane, R., 2002. Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank. Industrial and Labor Relations Review 55(2), 432-447.

[11] Autor, D., Levy, F., Murnane, R., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics 118(4), 1279-1333.

[12] Autor, D., Wasserman, M., 2013. Wayward Sons: The Emerging Gender Gap in Labor Markets and Education. *Third Way, March 2013.*

[13] Bailey, M., 2006. More Power to the Pill: The Impact of Contraceptive Freedom on Women's Life Cycle Labor Supply. Quarterly Journal of Economics 121(1), 289-320.

[14] Bartik, A., Currie, J., Greenstone, M., Knittel, C., 2017. The Local Economic and Welfare Consequences of Hydraulic Fracturing. NBER Working Paper 23060.

[15] Beaudry, P., Lewis, E., 2014. Do Male-Female Wage Differentials Reflect Differences in the Return to Skill? Cross-City Evidence from 1980-2000. American Economic Journal: Applied Economics 6(2), 178-194.

[16] Becker, G., 1981. *A Treatise on the Family.* Cambridge, Massachusetts: Harvard University Press.

[17] Becker, G., 1985. Human Capital, Effort, and the Sexual Division of Labor. Journal of Labor Economics 3(1), S33-S58

[18] Becker, G., Hubbard, W., Murphy, K., 2010. Explaining the Worldwide Boom in the Higher Education of Women. Journal of Human Capital 4(3), 203-241.

[19] Becker, S., Messer, D., Wolter, S., 2013. A Gift is Not Always a Gift: Heterogeneity and Long-term Effects in a Gift Exchange Experiment. Economica 80(318), 345-371.

[20] Bellemare, C., Shearer, B., 2009. Gift giving and worker productivity: Evidence from a firm-level experiment. Games and Economic Behavior 67(1), 233-244.

[21] Bertrand, M., Pan, J., 2013. The Trouble with Boys: Social Influences and the Gender Gap in Disruptive Behavior. American Economic Journal: Applied Economics 5(1), 32-64.

[22] Berzon, A., 2015. Oil Deaths Rise as Bakken Boom Fades. The Wall Street Journal. March 12, 2015.

[23] Black, S., Spitz-Oener, A., 2010. Explaining Womens Success: Technological Change and the Skill Content of Womens Work. Review of Economics and Statistics 92(1), 187-194.

[24] Blakemore, J., Berenbaum, S., Liben, L., 2009. *Gender development.* New York: Psychology Press; 2009.

[25] Blau, F., Kahn, L., 2017. The Gender Wage Gap: Extent, Trends, and Explanations. Journal of Economic Literature 55(3), 789-865.

[26] Bragg, D.D., Kim, E., Barnett, E.A., 2006. Creating Access and Success: Academic Pathways Reaching Underserved Students. New Directions for Community Colleges 135, 5-19.

[27] Brehm J., 1966. *A Theory of Psychological Reactance.* Academic Press: Oxford.

[28] Bresnahan, T., Brynjolfsson, E., Hitt, L., 2002. Information Technology, Workplace Organization, and the demand for Skilled Labor: Firm-Level Evidence. Quarterly Journal of Economics 117(1), 339-376.

[29] Bronson, M., 2015. Degrees are Forever: Marriage, Educational Investment, and Lifecycle Labor Decisions of Men and Women.

[30] Brown, C., 2013. North Dakota Went Boom. The New York Times Magazine. Jan. 31, 2013.

[31] Brynjolfsson, E., Hitt, L., 2000. Beyond Computation: Information Technology, Organizational Transformation and Business Performance. Journal of Economic Perspectives 14(4), 23-48.

[32] Buchmann, C., DiPrete, T., 2006. The Growing Female Advantage in College Completion: The Role of Family Background and Academic Achievement. American Sociological Review 71(4), 515-541.

[33] Bureau of Labor Statistics, U.S. Department of Labor. National Longitudinal Survey of Youth 1979 cohort, 1979-2010 (rounds 1-24). Produced and distributed by the Center for Human Resource Research, The Ohio State University. Columbus, OH: 2012.

[34] Bureau of Labor Statistics, U.S. Department of Labor (2014). *Occupational Outlook Handbook, 2014-15 Edition.*

[35] Burger, J., Horita, M., Kinoshita, L., Roberts, K., Vera, C., 1997. Effects on Time on the Norm of Reciprocity. Basic and Applied Social Psychology 19(1),91-100.

[36] Card, D., Payne, A., 2017. High School Choices and the Gender Gap in STEM. NBER Working Paper 23769.

[37] Carrell, S., Sacerdote, B., 2017. Why Do College-Going Interventions Work? American Economic Journal: Applied Economics 9(3), 124-151.

[38] Cascio, E., Narayan, A., 2015. Who Needs a Fracking Education? The Educational Response to Low-Skill Biased Technological Change. NBER Working Paper 21359.

[39] Charles, K., Hurst, E., Notowidigdo, M., 2016. Housing Booms, Labor Market Opportunities, and College Attendance. American Economic Review, forthcoming.

[40] Charles, K., Luoh, M., 2003. Gender Differences in Completed Schooling. The Review of Economics and Statistics 85(3), 559-577.

[41] Chiappori, P., Costas Dias, M., Meghir, C., 2016. The Marriage Market, Labor Supply and Education Choice.

[42] Chiappori, P., Iyigun, M., Weiss, Y., 2009. Investment in Schooling and the Marriage Market. The American Economic Review 99(5), 1689-1713.

[43] Chiappori, P., Salanie, B., Weiss, Y., 2015. Partner Choice and the Marital College Premium: Analyzing Marriage Patterns Over Several Decades.

[44] Chuan, A., 2018. Gender Differences in Skill Profiles, Wage Returns, and College Enrollment.

[45] Clee, M., Wicklund, R., 1980. Consumer behavior and psychological reactance. Journal of Consumer Research 6(4), 389-405.

[46] Cortes, G., Jaimovich, N., Nekarda, C., Siu, H., 2014. The Micro and Macro of Disappearing Routine Jobs: A Flows Approach. NBER Working Paper 20307.

[47] Cortes, G., Jaimovich, N., Siu, H., 2016. Disappearing Routine Jobs: Who, How, and Why? NBER Working Paper 22918.

[48] Cox, J., Friedman, D., Gjerstad, S., 2007. A tractable model of reciprocity and fairness. Games and Economic Behavior 59, 17-45.

[49] Croson, R., Gneezy, U., 2009. Gender differences in preferences. Journal of Economic Literature 47(2), 1-27.

[50] Diprete, T., Buchmann, C., 2006. Gender-Specific Trends in the Value of Education and the Emerging Gender Gap in College Completion. Demography 43(1), 1-24.

[51] Dougherty, C., 2005. Why Are the Returns to Schooling Higher for Women than for Men? The Journal of Human Resources 40(4), 969-988.

[52] Eckel, C., Grossman, P., 2002. Sex and risk: experimental evidence. In: Plott, C., Smith, V., (Eds.), *Handbook of Experimental Economics Results, vol. 1*. Elsevier, New York.

[53] Economist, 2015. Manhood. May 23, 2015.

[54] U.S. Energy Information Administration (EIA). 2018, March 19. *Petroleum & Other Liquids: Definitions, Sources and Explanatory Notes*. Retrieved from https://www.eia.gov/dnav/pet/TblDefs/pet_pri_land1_tbldef2.asp.

[55] Eligon, J., 2013. An Oil Town Where Men Are Many, and Women Are Hounded. The New York Times. Jan. 15, 2013.

[56] Esteves-Sorenson C., 2017. Gift Exchange in the Workplace: Addressing the Conflicting Evidence with a Careful Test. Management Science.

[57] Falk, A., Fischbacher, U., 2006. A Theory of Reciprocity. Games and Economic Behavior 54(2), 293-315.

[58] Feyrer, J., Mansur, E., Sacerdote, B., 2017. Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution. American Economic Review 107(4), 1313-1334.

[59] Fleming, M., Roman, J., Farrell, G., 2000. The Shadow Economy. Journal of International Affairs 53(2), 387-409.

[60] Flood, S., King, M., Ruggles, S., Warren, J., 2017. Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset]. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D030.V5.0.

[61] Flynn, F., 2003. What have you done for me lately? Temporal adjustments to favor evaluations. Organizational Behavior and Human Decision Processes 91(1), 38-50.

[62] Frey, C., Osborne, M., 2017. The future of employment: How susceptible are jobs to computerisation? Technological Forecasting & Social Change 114, 254-280.

[63] Gachter, S., Herrmann, B., 2009. Reciprocity, culture and human cooperation: previous insights and a new cross-cultural experiment. Philosophical Transactions of the Royal Society B: Biological Sciences 364(1518), 791-806.

[64] Galor, O., Weil, D., 1996. The Gender Gap, Fertility, and Growth. American Economic Review 86(3), 374-387.

[65] Garza, H., Eller, R.D., 1998. The Role of Rural Community Colleges in Expanding Access and Economic Development. New Directions for Community Colleges 103, 31-41.

[66] Gershoni, N., Low, C., 2017. The Impact of Extended Reproductive Time Horizons: Evidence from Israel's Expansion of Access to IVF.

[67] Gertler, P., Shah, M., Bertozzi, S., 2005. Risky Business: The Market for Unprotected Commercial Sex. Journal of Political Economy 113(3), 518-550.

[68] Gilchrist, D., Luca, M., Malhotra, D., 2016. When $3+1>4$: Gift structure and reciprocity in the field. Management Science 62(9), 2639-2650.

[69] Gneezy, U., List, J., 2006. Putting Behavioral Economics to Work: Testing for Gift Exchange in Labor Markets using Field Experiments. Econometrica 74(5), 1365-1384.

[70] Gold, R., 2015. Crude-Oil Price Collapse Takes Toll on Williston. March 12, 2015.

[71] Goldin, C., Katz, L., 2002. The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions. Journal of Political Economy 110(4), 730-770.

[72] Goldin, C., Katz, L., 2010. *The Race between Education and Technology.* Harvard University Press: Cambridge, Massachusetts.

[73] Goldin, C., Katz, L., Kuziemko, I., 2006. The Homecoming of American College Women: The Reversal of the College Gender Gap. Journal of Economic Perspectives 20(4), 133-156.

[74] Goldsmith-Pinkham, P., Sorkin, I., Swift, H., 2018. Bartik Instruments: What, When, Why, and How. NBER Working Paper 24408.

[75] Goos, M., Manning, A., Salomons, A., 2009. Job Polarization in Europe. American Economic Review: Papers & Proceedings 99(2), 58-63.

[76] Goos, M., Manning, A., Salomans, A., 2014. Explaining Job Polarization: Routine-Biased Technical Change and Offshoring. American Economic Review 104(8), 2509-2526.

[77] Grimm, V., Mengel, F., 2011. Let me sleep on it: Delay reduces rejection rates in ultimatum games. Economics Letters 111, 113-115.

[78] Hamilton, J., 2004. Historical Oil Shocks. NBER Working Paper 16790.

[79] Heckman, J., 1979. Sample Selection Bias as a Specification Error. Econometrica 47(1), 153-161.

[80] Heckman, J., Stixrud, J., Urzua, S., 2006. The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. Journal of Labor Economics 24(3), 411-482.

[81] Hershbein, B., Kahn, L., 2016. Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings.

[82] Hill, C.B., Winston, G.C., and Boyd, S.A., 2005. Affordability: Family Incomes and Net Prices at Highly Selective Private Colleges and Universities. Journal of Human Resources 40(4), 769-790.

[83] Hoxby, C.M., Turner, S., 2015. What High-Achieving Low-Income Students Know about College. American Economic Review: Papers & Proceedings 105(5): 514-517.

[84] Hsieh, C., Hurst, E., Jones, C., Klenow, P., 2016. The Allocation of Talent and U.S. Economic Growth.

[85] Huang, L., 2013. A Revolution in Education: Determinants of the Gender Gap Reversal.

[86] Jacob, B., 2002. Where the boys aren't: non-cognitive skills, returns to school, and the gender gap in higher education. Economics of Education Review 21, 589-598.

[87] Jaimovich, N., Siu, H., 2012. The Trend is the Cycle: Job Polarization and Jobless Recoveries. NBER Working Paper 18334.

[88] Juhn, C., Rubinstein, Y., Zuppann, C., 2015. The Quantity-Quality Trade-off and the Formation of Cognitive and Non-Cognitive Skills. NBER Working Paper 21824.

[89] Kube, S., Marechal, M., Puppea, C., 2012. The currency of reciprocity: Gift exchange in the workplace. The American Economic Review 102(4), 1644-1662.

[90] Kube S., Marechal M., Puppe, C., 2013. Do wage cuts damage work morale? Evidence from a natural field experiment. Journal of the European Economic Association 11(4), 853-870.

[91] Karlan D., List J., 2007. Does Price Matter in Charitable Giving? Evidence from a Large-Scale Natural Experiment. American Economic Review 97(5), 1774-1793.

[92] Levitt, S., Venkatesh, S., 2007. An Empirical Analysis of Street-Level Prostitution.

[93] Leyk, D., Gorges, W., Ridder, D., Wunderlich, M., Ruther, T., Sievert, A., Essfeld, D., 2007. Hand-grip strength of young men, women and highly trained female athletes. European Journal of Applied Physiology 99, 415-421.

[94] Lise, J., Postel-Vinay, F., 2016. Multidimensional Skills, Sorting, and Human Capital Accumulation.

[95] Loewenstein, G., 1996. Out of control: Visceral influences on behavior. Organizational Behavior and Human Decision Processes 65(3), 272-292.

[96] Low, C., 2017. A “Reproductive Capital” Model of Marriage Market Matching.

[97] Metcalfe, J., Mischel, W., 1999. A Hot/Cool-System Analysis of Delay of Gratification: Dynamics of Willpower. Psychological Review 106(1), 3-19.

[98] McCabe, K., Rigdon, M., Smith, V., 2003. Positive reciprocity and intentions in trust games. Journal of Economic Behavior & Organization 52(2), 267-275.

[99] McChesney, J., 2011. Oil Boom Puts Strain on North Dakota Towns. NPR. December 2, 2011.

[100] Meer, J., 2012. Does Generosity Beget Generosity? Alumni Giving and Undergraduate Financial Aid. Economics of Education Review 31(6):890-907.

[101] Miller, A., MacDougall, J., Tarnopolsky, M., Sale, D., 1993. Gender differences in strength and muscle fiber characteristics. European Journal of Applied Physiology and Occupational Physiology 66(3), 254-262.

[102] Morton, F., Zettelmeyer, F., Silva-Risso, J., 2003. Consumer Information and Discrimination: Does the Internet Affect the Pricing of New cars to Women and Minorities? Quantitative Marketing and Economics 1(1), 65-92.

[103] Neal, D., Johnson, W., 1996. The Role of Premarket Factors in Black-White Wage Differences. Journal of Political Economy 104(5), 869-895.

[104] Neo, W., Yu, M., Weber, R., Gonzalez, C., 2013. The effects of time delay in reciprocity games. Journal of Economic Psychology 34, 20-35.

[105] National Public Radio, 2011. New Boom Reshapes Oil World, Rocks North Dakota. Sept. 25, 2011.

[106] Niederle, M., Vesterlund, L., 2010. Explaining the Gender Gap in Math Test Scores: The Role of Competition. Journal of Economic Perspectives 24(2), 129-144.

[107] Ockenfels, A., Sliwka, D., Werner, P., 2015. Timing of kindness - Evidence from a field experiment. Journal of Economic Behavior & Organization 111, 79-87.

[108] Oechssler, J., Roider, A., Schmitz, P., 2015. Cooling Off in Negotiations: Does it Work? Journal of Institutional and Theoretical Economics 171, 565-588.

[109] Olivieri, E., 2014. Occupational Choice and the College Gender Gap.

[110] O*Net, 2015. Retrieved from http://www.onetonline.org. Accessed July 7, 2015.

[111] Prada, M., Urzua, S., 2014. One Size Does Not Fit All: Multiple Dimensions of Ability, College Attendance, and Wages. NBER Working Paper 20752.

[112] Rendall, M., 2017. Brain versus Brawn: Realization of Women's Comparative Advantage.

[113] Ritov, I., 2006. The Effect of Time on Pleasure with Chosen Outcomes. Journal of Behavioral Decision Making 19, 177-190.

[114] Rosin, H., 2010. The End of Men. The Atlantic, July/August 2010 Issue.

[115] Rosen, S., 1986. The Theory of Equalizing Differences, in *Handbook of Labor Economics,* ed. by Orley Ashenfelter and Richard Layard. Amsterdam: North Holland, pp. 641-692.

[116] Rosen, S., Willis, R., 1979. Education and Self-Selection. Journal of Political Economy 87(5), S7-S36.

[117] Rosin, T., 2014. Nonprofit hospitals received more than $9.6B in donations in 2014. Becker's Healthcare.

[118] Rosenberg, M., 1965. *Society and the adolescent self-image.* Princeton, NJ: Princeton University Press.

[119] Rotter, J., 1966. Generalized expectancies for internal versus external control of reinforcement. Psychological Monographs: General & Applied. 80(1), 128.

[120] Ruggles, S., Genadek, K., Goeken, R., Grover, J., Sobek, M., 2017. Integrated Public Use Microdata Series: Version 7.0 [dataset]. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D010.V7.0.

[121] Sayer, L., 2014. "Trends in Women's and Men's Time Use, 1965-2012: Back to the Future?" in *Gender and Couple Relationships*, edited by Susan M. McHale, Valerie King, Jennifer Van Hook, & Alan Booth. Pennsylvania State University National Symposium on Family Issues (NSFI) book series, Springer.

[122] Schacter, D. (1999) The seven sins of memory: Insights from psychology and cognitive neuroscience. American Psychologist 54(3), 182.

[123] Sliwka, D., Werner, P., 2017. Wage Increases and the Dynamics of Reciprocity. Journal of Labor Economics 35(2), 299-344.

[124] Smith, A., 1776. *An Inquiry into the Nature and Causes of the Wealth of Nations.* London: W. Strahan and T. Cadell.

[125] Sommers, C., 2013, October 28. What Schools Can Do to Help Boys Succeed. *Time.* Retrieved from http://ideas.time.com/2013/10/28/what-schools-can-do-to-help-boys-succeed

[126] Spitz-Oener, A., 2006. Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. Journal of Labor Economics 24(2), 235-269.

[127] Spitz-Oener, A., 2008. The Returns to Pencil Use Revisited. Industrial and Labor Relations Review 61(4), 502-517.

[128] Welch, F., 2000. Growth in Women's Relative Wages and in Inequality among Men: One Phenomenon or Two? American Economic Review 90(2), 444-449.

[129] Werner, R., Kolstad, J., Stuart, E., Polsky, D., 2011. The Effect Of Pay-For-Performance in Hospitals: Lessons for Quality Improvement. Health Affairs 30(4), 690-698.

[130] Yeomans, K., Golder, P., 1982. The Guttman-Kaiser Criterion as a Predictor of the Number of Common Factors. Journal of the Royal Statistical Society 31(3), 221-229.

[131] Zhang, H., 2017. A Marriage-Market Perspective of the College Gender Gap.