THREE ESSAYS ON HUMAN CAPITAL AND LABOR SUPPLY

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Economics – Doctor of Philosophy

2021

ABSTRACT

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This dissertation contains three chapters that study individuals' willingness to work, factors that influence their human capital development, and the interaction between their human capital investment decisions and labor supply.

Chapter one examines how college students choose their credit hour enrollment, labor supply, and borrowing, paying particular attention to the role of wages, financial resources and beliefs. To formalize these relationships, I construct a dynamic structural model where students choose their credit hours, work hours, and borrowing to maximize lifetime utility. I collect data from two sources to estimate the model: (1) a unique survey of Michigan State undergraduates eliciting their employment history, family financial support, beliefs about the returns to studying and beliefs about earning a high GPA, and (2) administrative data from the University. Estimates of the model suggest that students' credit hour decision is inelastic with respect to changes in financial aid, tuition, beliefs, or wages. Students' labor supply and borrowing decisions are responsive to changes in wages, and for a subset of students, changes in beliefs. I also conduct two counterfactual simulations, increasing the minimum wage and making college tuition free, and evaluate how these policy changes affect student decisions and outcomes.

The second chapter studies the relationship between the gender composition of a student's peers and two of their non-cognitive factors: sense of belonging and self-worth. Using data from Add Health and exploiting idiosyncratic variation in the share of female peers across grades within schools, I find positive but small effects of a higher share of female peers for male students. I do not find statistically significant effects for female students, but I can rule out large positive effects.

The third chapter, jointly written with Todd Elder and Steven J. Haider, estimates how the wage elasticity of labor supply has changed for single and married men and women over the last two

decades. The wage elasticity of labor supply is arguably one of the most fundamental parameters in economics, but despite the central role of this parameter, few studies have examined how it has evolved past the early 2000s. We find robust evidence that the labor supply elasticities for all four demographic groups have increased modestly. For women, this finding is a substantial departure from earlier evidence. We also contribute to the literature on the robustness of discrete choice labor supply models by estimating elasticities under a variety of assumptions and specifications. Our estimated trends are remarkably similar across specifications.

ACKNOWLEDGMENTS

This dissertation is the result of much guidance and support from my advisors, colleagues, and friends. I would like to specifically acknowledge the contributions of the following individuals for their role in helping this dissertation come to completion:

My dissertation chair, Steven Haider, who mentored me as a scientist and instructor, challenged me to be the best I could be, and always made time to meet with me and discuss my research. Steven was also a consistent advocate for me and my career, seeking opportunities for me to grow as a researcher and helping me secure funding for my work.

My dissertation committee members, Scott Imberman, Michael Conlin, and Kris Renn, and other faculty in the Economics Department at MSU, including Jeffrey Wooldridge, Todd Elder, and Justin Kirkpatrick, who generously gave their time to review drafts of individual chapters, provide extensive feedback, and help me become a more adept researcher.

My classmates, Dylan Brewer, Riley Acton, and Luke Watson, who never hesitated to help me think through a challenging research question, share MATLAB and Stata code, sit in my practice presentations, and read drafts of my work.

Administrators and staff at MSU, including Mark Largent, Karen Clark, Dean Valenti, Justin Bruner, and Jim Murphy, who volunteered their time and resources to help me design and distribute the Student Enrollment and Employment Survey and utilize university administrative records.

My parents, Don and Joni Orr, who raised me to have the curiosity and persistence necessary to pursue a doctorate and made significant sacrifices so I could receive a great education.

My family, Ed and Elyse Streit, Fred and Marla Meldrum, and Ginger and Sheridan Rampaul, who never hesitated to give me good company and a place to stay when I wanted a break.

My friends, both old and new, who kept me sane and in good spirits: Matt and Meredith Bateman, Kat Davis, Rachel Rosenberg, Matt Harding, Dylan and Amanda Brewer, Riley, Luke, Alyssa Harben, Gabrielle Pepin, Bryce VanderBerg, Hannah Gabriel, and Nick Rowe.

Most importantly, my wife Miriam, who celebrated all my accomplishments as if they were

her own, was patient and understanding when I worked long nights, taught me the ins and outs of post-secondary financial aid regulations and procedures, and made countless sacrifices so I could pursue this goal.

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CHAPTER 1

CLOCKING INTO WORK AND OUT OF CLASS: COLLEGE STUDENT ENROLLMENT, LABOR SUPPLY, AND BORROWING DECISIONS

1.1 Introduction

Post-secondary education yields significant returns in the labor market (Oreopoulos and Petronijevic 2013; Carneiro et al. 2011; Hussey and Swinton 2011). Nevertheless, there are many factors that prevent a college enrollee from realizing the full return of a college degree. A third of students who begin college will leave without earning a bachelor's degree, thus incurring the direct financial and opportunity costs of college without the return to graduating (Shapiro et al. 2019). Even among students that eventually complete their degree, their college's quality (Black and Smith 2006), major field of study (Altonji et al. 2012), cumulative grade point average upon graduation (Hershbein 2019), cumulative credit hours (Arteaga 2018), net cost of attendance, level of student loans, and time-to-degree (Dannenberg and Mugglestone 2017) can all alter the value of their investment. Recent research also highlights the non-monetary returns to attending college, which can be diminished if students lack the leisure time to take advantage of their college's amenities (Jacob et al. 2018; Gong et al. 2019).

Many of the benefits and costs to college are intrinsically linked to the student's enrollment intensity, time allocation and financing decisions. The more classes a student takes, the quicker she can complete her degree, reducing the direct costs of tuition, the opportunity costs of foregone wages, and the likelihood that an unexpected life event necessitates her departure from college (Belfield et al. 2016; Attewell and Monaghan 2016). However, unless the student increases her total time spent on schoolwork to maintain a similar level of effort across those additional classes, her grades can suffer, increasing the likelihood of failing a course, delaying her time to graduation, and adversely affecting prospective employers' perceptions of her ability. Spending more time on schoolwork carries a cost as well, reducing the time available for work and time available for leisure. These complex tradeoffs make it difficult to understand students' behavior or predict the effects of policies designed to improve student welfare, like reducing the cost of tuition or increasing students' wages.

This chapter studies how students navigate these tradeoffs to maximize their lifetime utility, paying particular attention to the role of financial resources and individuals beliefs. Unfortunately, information on resources, such as family financial support, and beliefs, such as expected returns to studying, are not readily available in administrative data. To measure such factors, I developed a survey that elicits students' employment history, wages, family financial support, and subjective expectations on study hours, the returns to studying and returns to graduating with a high GPA. After distributing my survey to a random sample of undergraduates at Michigan State University, I obtained administrative records from the University's Office of the Registrar and Office of Financial Aid containing students' course history at MSU, financial aid eligibility by term, and borrowing history.

To analyze the data, I construct a dynamic model of student behavior. Students choose their credit hour enrollment, labor supply, studying, and borrowing to maximize their lifetime utility subject to time and consumption budget constraints. The model incorporates important features of the college decision-making environment, including students facing borrowing constraints, receiving financial support from their family, earning grades for their classes, and having individual-specific beliefs about the returns to studying and returns to graduating with a high GPA. The dynamics of the model also capture two important intertemporal tradeoffs. The choices of a student in one period affects her behavior in future in-school periods (e.g., if a student takes a small number of credit hours early in her tenure at college, she will need to make up for it with more credit hours later). Additionally, students' choices in college affect their future earnings and debt obligations post-college.

The structural model allows me to estimate students' preferences over in-school consumption, leisure, grades, future earnings, and cumulative debt. I then derive individual-specific elasticities for credit hour enrollment, labor supply, and borrowing with respect to changes in financial aid, tuition, beliefs, and wages. I find that students' credit hour enrollment is largely unresponsive to changes in these variables. The labor supply decision, on the other hand, is much more responsive with an average wage elasticity of 0.29 in the fall and spring semesters. This is similar to the wage elasticity for working-age married women in the United States (McClelland and Mok 2012). Labor supply is also responsive to beliefs about the returns to studying and returns to graduating with a high GPA, specifically among students who expect they would substitute their work time for more study time. Students' borrowing choices are most responsive to changes in financial aid and the university's tuition rate.

With the model estimates in hand, I simulate the effects of two policies which increase the affordability of college but alter students' incentives in very different ways: an increase in the minimum wage to \$15 per hour and making in-state tuition free for current students. An increase in the minimum wage increases work hours by 0.75 hours a week in the fall and spring and by 1.14 hours a week in the summer. To a lesser extent students decrease their borrowing, and I do not find any significant changes in credit hours or expected GPA. Free in-state tuition increases credit hours by 0.09 hours in the fall and spring, which is not a large enough change to appreciably decrease time-to-degree. While there are only minimal changes in work hours, average borrowing decreases by \$2,107 per year. As with the increase in minimum wage, making in-state tuition free does not significantly change expected GPA.

This chapter makes several contributions. It develops an estimable model that emphasizes the credit hour decision and relationship between credits, grades, and future earnings. This is one of the first papers to propose such a structural model of the credit hour decision beyond the part-time and full-time margins. This paper also contributes to the literature by estimating labor supply elasticities specifically for college students. I pay particular attention to the unique financial resources and constraints students face and explicitly model the additional cost of labor on expected grades and credit accumulation. Finally, this paper adds to the growing literature on dynamic discrete choice estimation that incorporates subjective expectations, and it is the first to do so with expectations of the GPA returns to studying and labor market returns to graduating with a high GPA.

The standard approach to estimating dynamic models requires estimating laws of motion of state variables from panel data, assuming heterogeneity in the process is fully captured by observable characteristics of individuals, and imposing individuals' expectations of the future match the predicted laws of motion (Aguirregabiria and Mira 2010). Eliciting subjective expectations allows one to directly incorporate heterogeneity in beliefs. Furthermore, subjective expectations are required to separately identify the role of preferences from beliefs, an important distinction for this research (Manski 1993).

The chapter proceeds as follows. In Section 2, I summarize the existing literature on college student credit hour enrollment intensity and labor supply. In Section 3, I introduce my data and describe the sample. Section 4 details the structural model and my estimation procedure. Section 5 presents the estimated auxiliary model parameters, utility parameters, elasticities, and results from counterfactual simulations. Section 6 concludes.

1.2 Related literature

1.2.1 Credit hour enrollment

The vast majority of research on college student credit hour enrollment uses reduced form methods to estimate how changes in financial aid affect student outcomes. For example, several recent papers exploit discontinuities in students' eligibility for need-based aid and find small or null effects on credit hours (Angrist et al. 2020; Denning et al. 2019; Denning and Jones 2019; Denning 2019). When effects are present, they seem to be explained by changes in labor supply. Most of this evidence is based on students from lower income households who qualify or are close to qualifying for need-based aid, so it is unclear how students from more affluent households might respond to changes in aid.

Another potential determinant of credit hour enrollment is the price per credit hour. In one of the few studies on the topic, Hemelt and Stange (2016) find that students who face no marginal cost to credit hours above the full-time minimum are seven percentage points more likely to enroll in one to three credit hours above the full-time minimum, but they are also six percentage points more likely to withdraw from a class during the semester, leading to no significant increase in credit attainment. This suggests that students are willing to experiment with taking more classes when the monetary cost of doing so is low, but other factors make it difficult to persist with heavier schedules.

While it appears that students' credit hour decision on the intensive margin is not significantly affected by their financial resources, there is evidence that students respond to direct financial incentives to take more classes. These incentives come in the form of state or institutional aid where students are required to complete 30 credit hours per year to renew their aid eligibility. Miller et al. (2011) and Scott-Clayton (2011) both find significant increases in the probability that students take 15 credit hours a semester when offered financial aid with a credit hour requirement. Even small monetary incentives can induce this behavior as Miller et al. (2011) find in a study evaluating a grant of only $1,000 per year.

1.2.2 Labor supply

Student labor supply has increased over the last half-century, mostly among students at four-year colleges, on both the extensive and intensive margins (Bound et al. 2012; Scott-Clayton 2012). Currently, 42% of full-time undergraduates work during the fall semester, up from 33% in the 1970s.[1] Students work an average of 25 hours per week across the year. These changes in labor are not inconsequential. The literature frequently finds that student labor supply decreases study time, education enrollment, educational attainment, and to a lesser extent, grades. See the recent literature review by Neyt et al. (2019) for more details.

Despite the frequency and ramifications of student employment, there is very little research on wage elasticities for college students; in fact, many researchers that estimate labor supply elasticities remove students from their sample to focus exclusively on prime-age workers. For examples, see literature reviews by Bargain and Peichl (2016) and McClelland and Mok (2012). Elasticities

[1] Current results based on the author's own calculations using the October Education Supplement of the CPS for 2017 and 2018. These rates are similar to those reported by Scott-Clayton 2012, which end in 2009.

for students may differ from elasticities for non-students due to the added costs of working while in school (e.g., fewer credit hours, lower grades) and the added need for money to pay for tuition.

Studies on the effects of increased financial aid provide estimates of the relationship between non-labor income and labor supply. Exploiting a discontinuity in financial aid eligibility based on age, Denning (2019) estimates that a \$1,452 increase in financial aid per year leads to a \$511 reduction in labor market earnings per year. Broton et al. (2016) use random assignment of the Wisconsin Scholars Grant, an award of \$3,500 a year, and find work hours decrease by 1.69 hour per week, which is 14.35% of the mean. Studying an even larger grant, DesJardins et al. (2010) estimate that receiving the \$8,000 per year Gates Millennium Scholar award reduces labor supply by 4.2 to 4.3 hours per week. Not surprisingly, larger grants appear to reduce labor supply by more than smaller grants.

1.2.3 Structural models of enrollment and employment

Much of the literature on human capital investment and labor supply treats schooling and labor as mutually exclusive actions (e.g., Arcidiacono 2004; Keane and Wolpin 1997; Altonji 1993). When models allow individuals to work and enroll in school simultaneously, they typically do not allow individuals to choose the intensity of their schooling (Joensen 2009; Ehrenberg and Sherman 1987). There are a few notable exceptions where researchers have modeled both the extensive and intensive schooling and labor supply decisions. Gayle (2006) provides a finite-horizon model where young adults (14 to 21 year olds) choose their schooling (enrollment and intensity), leisure, and labor supply. Gayle documents inequalities in labor supply, intensity of schooling, and grade progression by race. He then simulates the effect of a lump-sum transfer conditional on not working and finds minimal effects on labor supply or grade progression. Keane and Wolpin (2001) provide a finite-horizon model where agents choose school attendance, work participation, and borrowing. School attendance is restricted to no attendance, part-time, or full-time. Keane and Wolpin pay particular attention to the role of family financial support and borrowing constraints; they conclude that family financial support is a significant determinant of part-time or full-time attendance, but relaxing borrowing constraints only affects labor supply and consumption, not attendance.

1.3 Data

For this chapter I use data from the Student Enrollment and Employment Survey (SEES), a survey I developed and distributed to a random sample of undergraduates at Michigan State University in the spring of 2019. I also obtained administrative records from the Office of the Registrar and Office of Financial Aid at the University for the SEES respondents, providing a detailed picture of students' decisions and financial resources. Together, the data contain students' credit hour, labor supply, and borrowing histories for their entire enrollment at MSU. In addition, they contain students' wages (expected wages for non-workers), cost of attendance, loan eligibility, grants and scholarships, living situation, rent, and family financial support for education and living expenses. The data also contain students' expected study hours conditional on credit hour and work schedules, beliefs about the returns to studying on GPA, and beliefs about the returns to graduating with a high GPA on future labor market earnings.

This section describes the sampling frame and presents summary statistics for particular variables of interest. A full text of the survey is available online.

1.3.1 Sampling frame and survey distribution

Michigan State University is a large, public research university in the United States.[2] All MSU undergraduate students who were 18 years old or older, were not on an athletic scholarship, and had an expected graduation date of December 2019 or later were eligible to receive the SEES. The Office of the Registrar provided me with 6,000 randomly selected email addresses from this sampling frame, and I emailed an invitation to take the survey to these students on March 12, 2019. Students were told the survey would take between 15 and 35 minutes to complete, and they

[2] Appendix table A.4.1 contains summary statistics for the MSU undergraduate population and population of undergraduate students at other public four-year-degree-granting institutions.

would receive a $10 Amazon Gift Card upon completion. After two reminder emails, I closed the survey on April 23, 2019 with 1,665 partial and complete responses. I restrict my analytic sample to continuously enrolled domestic first-time-in-college students who successfully completed the survey.[3] After these restrictions, I am left with 985 students and 2,943 student-period pairs (1,964 fall and spring and 979 summer).

Table A.1.1 presents summary statistics for the analytic sample and survey recipients. The sample of respondents is more likely to be female, white (non-Hispanic) or Asian, in-state, and in the honors college than the broader sample of domestic first-time-in-college students who received the survey invitation.

1.3.2 Observed credit hour enrollment and financing choices

The Office of the Registrar provided students' credit hour enrollment by term. Table A.1.2 presents the proportion of students who enrolled in varying credit hour amounts. In the fall and spring, almost half of students enrolled in 27 to 29 credits, and 95% of students enrolled in 24 to 32 credit hours. In the summer, 62% of students did not enroll in any credits, and among students who did enroll, 40% took three to five credits and 42% took six to eight credits. Notably, many students may not be enrolled in enough credits to graduate within four years of starting at MSU. Without any transfer credits, the typical student needs to complete at least 120 credit hours to graduate, or 30 credits per year over four years. As shown in the last column of Table A.1.2, 46% of students enroll in fewer than 30 credits across the entire year.

[3] I limit the sample to domestic first-time-in-college students, as international students (54) face additional restrictions on their employment and borrowing and transfer students have unobserved credit enrollment and borrowing histories from their prior institutions (296). I further restrict the sample to students who were continuously enrolled at least part-time at MSU for the fall and spring semesters, as students who temporarily "stop-out" (55) may do so for reasons that are outside of the scope of this research, like serious illness, family emergencies, or having a child. I also exclude students who failed to reach the end of the survey (87), failed the attention check question (75), or skipped a question required to estimate the model (64). Finally, I exclude students who believe their grades will decrease as they increase their time on schoolwork (23) or believe their future wage will be lower after graduating with a 4.0 GPA as opposed to dropping out (26), as this strongly suggests that the student did not properly understand the questions.

The SEES asked students to identify semesters they worked a part-time or full-time job, and if they worked, how many hours they usually worked per week. Students were equally likely to work during the fall and spring or summer terms – 52% of students worked at least one hour per week in the fall and spring and 51% of students worked at least one hour per week in the summer – but they did not work the same number of hours across terms. Student workers worked an average of 12 hours per week in the fall and spring term, while workers worked an average of 33 hours per week in the summer term. As shown in Figure A.1.1, the modal number of hours worked per week in the fall and spring was ten, though eight and 15 hours were also common. In the summer, 40 hours per week was the modal choice by a large margin.

The Office of Financial Aid provided students' borrowing history by term. Each year, students receive a financial aid offer that includes their subsidized and unsubsidized loan offers (collectively, Stafford loans). Stafford loan limits are set by the federal government, ranging from $5,500 for dependent freshmen to $12,500 for independent juniors and seniors, and students cannot receive more in Stafford loans than their budget (expected cost of attendance minus non-loan financial aid) allows. In the fall and spring, 85% of students were eligible for Stafford loans, and 48% of students accepted at least some non-zero loan amount. In the summer, only 23% were eligible for Stafford loans, and only 9% borrowed some non-zero loan amount. This is not surprising – students must be enrolled in at least six credit hours to be eligible for Stafford loans.

Students do not need to accept the full Stafford loan offer, though in the fall and spring only 8% of borrowers accept less. If students want to borrow beyond their Stafford loan offer, they must apply for loans from private vendors. As with Stafford loans, students cannot take out more private student loans than their budget allows, though the credit hour requirement may be lower than the six credits required for Stafford loans. In the fall and spring, 17% of students accepted private loans, and in the summer, 3% of students accepted private loans. Figure A.1.2 presents the distribution of accepted student loan amounts.

1.3.3 Cost of attendance and financial need

A student's cost of attendance is the estimated amount of the money she will spend to attend the university for a year. There are four broad components of cost of attendance: tuition, books, fees, and living expenses. In my sample, the average fall-spring cost of attendance was $28,359 for an in-state student and $52,728 for an out-of-state student.[4] Students have two main sources of funding to cover their cost of attendance that does not require them to work or borrow: grants and family financial support.[5] In the fall and spring, the average in-state student received $6,076 in grants and $15,956 in family financial support, leaving $6,328 of unmet financial need. The average out-of-state received $16,608 in grants and $30,614 in family financial support, leaving only $5,505 of unmet financial need.

Averages hide significant heterogeneity across students as Figure A.1.3 shows. Each panel presents the average amount of grant aid and family financial support received by students in different quintiles of the unmet need distribution. For both in-state and out-of-state students, students in the bottom two quintiles received enough aid and support to cover their cost of attendance. At the other extreme, students in the highest quintile of unmet need required $21,364 (in-state) or $35,557 (out-of-state) of additional income or loans to cover their expected costs.

1.3.4 Subjective expectations

The SEES contains three sets of subjective expectations: students' beliefs of their time spent on schoolwork conditional on work and credit hour enrollment, their distribution of class grades conditional on schoolwork hours, and their distribution of post-school salaries conditional on GPA.

[4]For all years in my sample, MSU charged students tuition per credit hour attempted. Rates varied by the student's residence (i.e., in-state or out-of-state), independent status, college, and class level. An in-state first-year student, without any additional tuition modifiers, paid $14,640 for 30 credit hours; a similar out-of-state student paid $39,766. In addition to tuition, students purchase textbooks and other supplies which the University budgets at 7% of the base per-credit rate. Some students also paid program fees, ranging from $100 to $670 a semester depending on their college. Expected living expenses ranged from $11,122 to $14,320 and included room and board and smaller miscellaneous expenses.

[5]See Appendix Section A.3 for details on how the SEES measured family financial support.

To elicit beliefs about time spent on schoolwork, I showed students six work hour and credit hour schedules (e.g., working ten hours per week while enrolled in 15 credit hours) and asked them how many hours they expect to spend on schoolwork during a typical non-exam week. Students were instructed to include class attendance, completing assignments, and reviewing notes within "schoolwork", and they were given attention check questions to verify they understood what "time spent on schoolwork" should include. Appendix Figure A.4.1 contains an example of what students were given for one schedule, and Table A.1.3 presents the distribution of expected schoolwork hours for all six schedules.

At 12 credit hours and no work hours, the average student expects to spend 21.98 hours on schoolwork in a typical week. Students substitute schoolwork time for work time, as the average expected time on schoolwork decreases to 18.48 hours with 20 hours of work. Students also expect to spend less time on schoolwork per credit as they take more credits, as the average expected time on schoolwork increases from 21.98 hours (1.83 per credit) to 27.71 hours (1.54 per credit) when credits increase from 12 hours to 18 hours.

To elicit beliefs about the distribution of grades conditional on schoolwork, I followed the method proposed by Delavande and Rohwedder (2008). Students were shown a set of bins representing different outcomes – 0.0 (F), 1.0 to 1.5 (D), 2.0 to 2.5 (C), 3.0 to 3.5 (B), and 4.0 (A) – and asked to place ten balls across the bins where each ball represented the likelihood of observing the outcome.[6] This exercise was repeated for a series of scenarios: spending one hour on schoolwork per course per week, three hours on schoolwork, six hours on schoolwork, and nine hours on schoolwork.[7] Appendix Figure A.4.3 presents the average reported probability of earning each grade for each scenario. At only one hour of schoolwork, the average student believes they are

[6]Eliciting distributions with the balls-in-bins method has two advantages. First, the visual frequency representation can be understood by a respondent with limited formal education of probability (Delavande et al. 2011). Second, the balls-in-bins method always yields a valid probability distribution, as respondents cannot violate monotonicity of the cumulative distribution function or the bounding of probabilities between zero and one. A sample response is provided in Appendix Figure A.4.2.

[7]A typical course is three credit hours.

most likely going to earn a C grade. As time spent on schoolwork increases, so does the probability of earning higher grades. There is significant heterogeneity in these beliefs as Figure A.1.4 shows. The interquartile range of expected grades in a course with only one hour of schoolwork is 1.40 to 2.75, which spans a third of all available grades. The range of expected grades decreases as students spend more time on schoolwork, but there are still meaningful differences at nine hours of schoolwork; a quarter of students believe they will earn less than a 3.25, while a quarter believe they will earn a 4.0.

To elicit beliefs about the distribution of post-school salaries conditional on GPA, I again used the balls-in-bins method. The SEES asked students to consider five scenarios: failing to graduate, graduating with a cumulative GPA between 2.0 and 2.49, graduating with a cumulative GPA between 2.5 and 2.9, graduating with a cumulative GPA between 3.0 and 3.49, and graduating with a cumulative GPA between 3.5 and 4.0. Students were given six bins of possible full-time salaries: less than $40 thousand, $40 to $59 thousand, $60 to $79 thousand, $80 to $99 thousand, $100 to $119 thousand, and greater than $120 thousand. Appendix Figure A.4.4 presents the average reported probability of earning each salary for each GPA scenario. The majority of students believe they will earn less than $40 thousand a year if they left MSU without a degree. Students believe they are more likely to earn higher salaries as they increase their GPA. As with the distribution of grades, there is significant heterogeneity in these beliefs. Figure A.1.5 presents the distribution of expected salaries across students. The interquartile range of expected salaries without a degree is $26 to $44 thousand, and this spread only increases with graduating and receiving a higher GPA. With a 3.5 to 4.0 GPA upon graduation, a quarter of students expect to earn less than $70 thousand while a quarter believe they will earn more than $105 thousand.

1.4 Structural model

This section presents a dynamic structural model to formalize the relationship between a student's choices, financial resources, and beliefs. The student begins with her first year of college and chooses her credit hour enrollment, labor supply, and borrowing to maximize the present discounted value of her lifetime utility. She derives utility from consumption, leisure, and the grades she earns from her classes. Grades also affect her future salary upon leaving college. The student leaves college when she earns enough credits to graduate with a degree, reaches the maximum allowable time in college, or chooses to permanently exit.

1.4.1 Model structure

1.4.1.1 Decision periods

I take the college entrance decision as given and begin the individual's decision horizon at the start of her first year in college. Decision periods correspond with academic terms, with the fall and spring as period one, summer as period two, fall and spring of the next year as period three, etc.[8] Individual i remains in college until she graduates, chooses to leave without a degree, or reaches period T. Individual i graduates when her cumulative credit hours earned exceeds her graduation threshold $\bar{K}_i$ and her cumulative GPA exceeds a 2.0.[9] After leaving college, either voluntarily, due to graduation, or because she reached the maximum time permitted, individual i enters the full-time labor market. I model the full-time labor market as an absorbing state where the individual's remaining lifetime utility is a function of her post-school wage and cumulative debt.[10]

[8] I choose to combine the fall and spring to align with the actual decision periods of students at Michigan State University. Students enroll for their fall and spring classes at the same time and accept their loan offer for the two semesters together. They are allowed to change their spring classes and loans in the future, but I do not permit that here.

[9] I allow the graduation threshold to vary by individual for two reasons. First, some majors have higher credit requirements than others. Second, some students enter college with Advanced Placement, Dual-credit, or other transfer credits. The simplest way to account for these credits in the model is reducing the graduation threshold. Changing the initial value of the state variable for number of credits introduces error into the GPA calculation.

[10] By modeling the full-time labor market as an absorbing state, I do not permit individuals to leave college and return at a later time. Per the National Student Clearinghouse, only 13% of students re-enroll within five years of leaving school without a degree (Shapiro et al. 2019). At a university like MSU, where the six-year completion rate is near 80% (U.S. Department of Education 2020), it is unlikely that many students plan on temporarily leaving school and returning in the near future.

This simplification allows me to focus on the decisions made in college while still incorporating intertemporal tradeoffs that involve post-college outcomes.

1.4.1.2 Choices

Each period in school, individual i decides whether to continue in school or drop-out and enter the full-time labor market. If she chooses to continue in school, she makes three additional decisions: her labor supply h_{it}, credit hour enrollment k_{it}, and new student loans b_{it}. Individual i chooses her labor supply from the discrete set of 0 hours, 300 hours, and 600 hours which corresponds to 0, 10, and 20 hours per week in the fall and spring periods and 0, 20, and 40 hours per week in the summer periods.[11] Credit hour enrollment is also restricted to a discrete set. In the fall and spring, individual i can choose 26 credits, 30 credits, or 34 credits; in the summer, individual i can choose 0 credits, 3 credits, or 8 credits. In addition, she can choose not to borrow additional loans, borrow her Stafford loan offer, or borrow her maximum student loan eligibility. I denote the entire set of feasible choices in period t with A_t.[12]

1.4.1.3 State variables

Individual i enters each period with a set of state variables: cumulative credit hours earned K_{it}, cumulative grade point average G_{it}, cumulative debt B_{it}, and time-invariant characteristics X_i. I denote this collection of state variables with S_{it}. Individual i begins college with no credit hours,

[11] Discretization of the choice set simplifies the estimation procedure. It avoids the solving of first-order conditions, and it easily incorporates corner solutions (e.g., no work, no classes, and no or maximum borrowing). One drawback is the modeler must specify the number of feasible choices; however, previous work in the labor supply literature has found estimated utility parameters are robust to this decision (Löeffler et al. 2018).

[12] A_t depends on t to reflect that the credit hour choice set differs in the fall and spring from the summer.

GPA, or debt. State variables evolve according to the following laws of motion:

$$K_{i,t+1} = K_{it} + \sum_{k=1}^{k_{it}} 1[g_{ikt} > 0]$$

$$G_{i,t+1} = G_{it}\left(\frac{K_{it}}{K_{it}+k_{it}}\right) + \left(\frac{\sum_{k=1}^{k_{it}} g_{ikt}}{K_{it}+k_{it}}\right) \tag{1.1}$$

$$B_{i,t+1} = (1+r_t)(B_{it}+b_{it})$$

Cumulative credits earned is the number of credit hours where a passing grade (greater than 0.0) was earned for that credit. Cumulative GPA is the weighted average of the individual's previous cumulative GPA and newly earned grades.[13] I denote the grade earned for credit k by individual i in period t with g_{ikt}. Cumulative debt is equal to prior debt plus new borrowing, after interest accumulation.

1.4.1.4 Preferences

While enrolled in school, individual i has preferences over three payoff variables: consumption $c(a,S_{it})$, leisure $l(a,S_{it})$, and semester grade point average $g_{it} \equiv \frac{1}{k}\sum_k g_{ikt}$. I denote the end-of-period utility function that represents in-school preferences with $U_t^{sch}(c,l,g,\varepsilon)$. I assume that the individual's preferences can be separated into an observable component $u_t^{sch}(c,l,g)$ and unobservable (to the econometrician) choice-specific shock $\varepsilon_{it} \equiv \{\varepsilon_{ait} : a \in A_t\}$. The choice-specific preference shocks are independently distributed across choices, individuals, and time according to

[13] The weighted average formula for cumulative GPA is not correct for students that earned a 0.0 (failing) grade in a course, as credits that received a 0.0 do not contribute to K_{it}, but fewer than 4% of student-term pairs include a 0.0 grade, so this formula is correct for the vast majority of observations. A precise calculation requires tracking separately the number of credits attempted and the number of credits passed and using credits attempted in the weights. If this were the only shortcoming, the current formula would over-estimate cumulative GPA; however, students are allowed to retake a failed class and replace their 0.0 grade with a higher grade from a second attempt. I do not record when students do this. If I did track cumulative credits attempted separately and used it in place of K_{it}, I would not correctly replace 0.0 grades with their revised grade. In this regard, the current formula underestimates cumulative GPA. Considering both factors together, it is ambiguous whether the formula over- or under-estimates cumulative GPA, as the errors partially cancel each other out.

a type I extreme value distribution, and the preference shocks are revealed to the individual at the beginning of the period.

The utility from individual i choosing action a in period t is given by the below equation; for notational convenience I have suppressed the payoff function arguments and replaced them with subscripts to denote the individual, choice, and time period:

$$U_t^{sch}(c_{ait}, l_{ait}, g_{it}, \varepsilon_{ait}) = u_t^{sch}(c_{ait}, l_{ait}, g_{it}) + \varepsilon_{ait}. \tag{1.2}$$

Once the individual leaves school and enters the post-school labor market, she receives a single utility realization equal to the discounted present value of her lifetime utility in the labor market, $U_t^{post}(S_{it})$. This utility sum is a function of her wage and cumulative debt upon entry into the post-school labor market which jointly determine her "full income".[14] Finally, I use $U_t(a, S, \varepsilon)$ to denote individual i's utility when her entrance into the post-school labor market is unknown ex ante:

$$U_t(a_{it}, S_{it}, \varepsilon_{it}) = 1[\text{in-school}_{it}]U_t^{sch}(c_{ait}, l_{ait}, g_{it}, \varepsilon_{ait}) + 1[\text{post-school}_{it}]U_t^{post}(S_{it}). \tag{1.3}$$

1.4.1.5 Constraints

Individual i faces constraints on consumption, leisure, and borrowing. Her consumption is equal to her labor income, changes in debt, and family financial support less net (of grants) education expenses. Labor income is the product of an hourly wage w_i^{sch} and hours worked. Both family support $fam(\cdot)$ and net education expenses $edu_t(\cdot)$ can depend on individual i's choices and state variables.[15]

$$c_{it}(a_{it}, S_{it}) = w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}). \tag{1.4}$$

[14] Instead of modeling the individual's entire lifetime labor supply problem, I assume she can maximize her utility according to a two-stage budgeting model, and her lifetime value function is simply a function of her wage and debt (e.g., Blundell and Walker 1986).

[15] Net education expenses depend on credit hour enrollment, cumulative credit hours, and time-invariant student characteristics. Family financial support varies with choices and states through changes in net education expenses.

When an individual is still in school, her wage is a constant individual-specific part-time wage w_i^{sch}. Once out of school, her full-time wage w_i^{post} is drawn from the distribution $F_i^w(S_{it})$. This distribution is a function of her credit hours and GPA, and the distribution can vary across individuals even if they have identical credit hours and grades (e.g., via differences in productivity). Family support and net educational expenses are time-invariant functions and are known with certainty by the individual. I do not permit individuals to have negative consumption. Instead, I impose a consumption floor $\underline{c}$ such that any individual that would have consumption lower than $\underline{c}$ receives an external transfer that brings her consumption up to $\underline{c}$.

Individual i's leisure time is equal to her total time endowment L_t less study hours $study_i(a_{it})$ and work hours:

$$l_{it}(a_{it}, S_{it}) = L_t - study_i(a_{it}) - h_{it}. \tag{1.5}$$

I model study hours as a time-invariant and deterministic function of individual i's other choices, specifically, her labor supply and credit hour enrollment. This is a strong restriction – holding credit hours and labor supply fixed, the individual cannot trade leisure for additional study time.[16] To increase study time, she must change one of her work hours or credit hours. There is also non-negativity constraint on leisure – individuals cannot choose to study and work so much that their leisure is negative.

1.4.1.6 Grades

At the end of each period, individual i receives a grade g_{ikt} for each credit hour she was enrolled in. Grades enter the utility function directly and affect the evolution of state variables, and consequently, future earnings. Grades are random variables drawn from the distribution $F_i^g(study_i/k_{it})$.

[16]The purpose of this restriction is two-fold. First, modeling the study decision as an "outcome" as opposed to a choice avoids introducing a fourth dimension in the choice problem, significantly reducing the computational burden of estimation. Second, specifying this as a time-invariant and deterministic function of two other choices allows me to estimate study hours with data from the SEES. The alternative involves solving for study hours as a best response function of the state variables and other choices. Without a closed-form solution, I would need to solve for the best response for every individual, instantiation of states, choice bundle, and parameter iteration in the maximization routine.

This distribution is a function of individual i's study hours per credit hour, and she does not know what grades she will earn until the conclusion of the period. Thus, when she maximizes her lifetime utility, the uncertainty of what grade she will earn may affect her optimal decision. She may choose a credit-work-borrowing bundle to reduce the risk of earning a low grade even if her expected grade does not significantly change. As with the post-school wage distribution, the grade distribution can vary across individuals even if they spend the same amount of time studying per credit hour.

There are two important assumptions here. First, I assume that individuals have correct beliefs about their grade distributions. This precludes individuals from learning about their own ability or returns to studying. Second, I assume that the grade distribution does not vary over time. This implies that individuals do not become more efficient studiers, relative to course difficulty, as they spend more time in college.

1.4.1.7 Maximization problem

Individual i maximizes the expected discounted value of her lifetime utility subject to the aforementioned constraints. The solution to her lifetime maximization problem at period one is given by the laws of motion for state variables and

$$\begin{aligned}
V_{i1}(S_{i1},\varepsilon_{i1}) \equiv & \max_{\{a \in A_t\}_{t=1}^{T}} E\left[\sum_{t=1}^{T+1} \beta^{t-1} U_t(a, S_{it}, \varepsilon_{it}) \mid S_{i1}, \varepsilon_{i1}\right] \\
\text{s.t. } & c_{it}(a_{it}, S_{it}) = \max\{w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}), \underline{c}\} \qquad (1.6) \\
& l_{it}(a_{it}) = L_t - study_i(a_{it}) - h_{it} \\
& l_{it}(a_{it}) \geq 0
\end{aligned}$$

where β is the discount factor.[17] The expectation is taken with respect to future choice-specific preference shocks, grades, and the future full-time wage offer.

[17] The above equation is a slight abuse of notation, as the individual does not make any further choices once she leaves school, which can occur before T. The implicit assumption is that the individual's utility is fixed after leaving school and her choice set is the null set.

1.4.2 Solution method

The maximization problem for individual i can be re-written at any period $t \leq T$ as a recursive function of the future period value function:

$$V_{it}(S_{it}, \varepsilon_{it}) = \max_{\{a \in A_t\}} \{U_t(a, S_{it}, \varepsilon_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a, S_{it}]\}. \tag{1.7}$$

This recursive nature implies that the value function can be solved via backward induction. In period T, the final possible period in school, individual i solves:

$$V_{iT}(S_{iT}, \varepsilon_{iT}) = \max_{a \in A_T} \left\{ u_T^{sch}(c_{aiT}, l_{aiT}, g_{iT}) + \varepsilon_{aiT} + \beta E[U_{T+1}^{post}(S_{i,T+1})|a, S_{iT}] \right\} \tag{1.8}$$

where the expectation is with respect to grades and the post-school wage offer. With a solution for V_{iT}, individual i (or the econometrician) proceeds backwards to solve the remaining value functions.

In the $t < T$ value functions, the expectation generally does not have a closed-form solution. So to proceed, I consider the expectation in two parts: the expectation of the value function with respect to the choice-specific preference shocks but conditional on the future state variables (commonly referred to as the "Emax" function), and the expected Emax function with respect to the future state variables. The Emax function has a closed-form solution given the distribution of the choice-specific preferences shocks:

$$\begin{aligned} &E[V_{it}(S_{it}, \varepsilon_{it})|S_{it}] = \\ &\quad \text{E.C.} + \log \left(\sum_{a' \in A_t} \exp \left\{ u_t^{sch}(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a', S_{it}] \right\} \right) \end{aligned} \tag{1.9}$$

where E.C. is Euler's constant. The Emax function can theoretically be solved by backward induction; however, this is computationally infeasible in practice.[18]

[18] To see why, note that the value function must be solved at every possible combination of state variables that can be reached in a given time period. Given the continuous nature of the state space, a full-solution method would require discretizing the state space. With 985 individuals, 28 elements of the choice set, and ten choice periods, a coarse grid of 25 elements for each of the three time-varying state variables would required evaluating 4.309 billion functions for each iteration of parameter values.

A popular approach for estimating the Emax function in similarly complex models is an interpolation method proposed by Keane and Wolpin (1994). Starting at the terminal period, I take R values from the set of feasible state variables and solve for the exact Emax function for each individual at all R states. I then fit a flexible individual-specific interpolating function to approximate the value function for all other possible state variable combinations. Moving backward to period $T-1$, I again take R values from the set of feasible state variables and solve for the approximate Emax function using the interpolating function for the period T Emax function. This process continues until I have interpolating functions for every individual in all periods.

The interpolation method provides an approximation of the Emax function; the next step is solving for the expected Emax function with respect to the future state variables. Given a distribution on the grade and post-school wage error terms, this is a straightforward exercise.

1.4.3 Model parameterizations

I specify individual i's observable in-school utility function as:

$$\begin{aligned} u_t^{sch}(c_{ait}, l_{ait}, g_{it}) &= \alpha_c \ln(c_{ait}) + \alpha_{lt} \ln(l_{ait}) + \alpha_g \ln(g_{it}) \\ &+ \alpha_{h0t} 1[h_{it} > 0] + \alpha_{k0} 1[k_{it} = 0] + \alpha_{k30} 1[k_{it} = 30] \\ &+ \alpha_{b1} 1[b_{it} = \text{Stafford only}] + \alpha_{b2} 1[b_{it} = \text{Max eligiblity}] \end{aligned} \tag{1.10}$$

where α_{lt} and α_{h0t} are allowed to vary between fall / spring and summer periods.[19] I restrict α_c, α_l, and α_g to positive values, and the log specification imposes diminishing marginal utility from consumption, leisure, and grades.[20] In addition to the payoff variables, I include fixed costs for various alternatives.[21]

[19] In the fall and spring, I divide consumption and leisure by two and specify utility as $u_t^{sch}(c_{ait}/2, l_{ait}/2, g_{it}) + \beta u_t^{sch}(c_{ait}/2, l_{ait}/2, g_{it})$. This captures the difference in period length between the fall / spring period and summer period.

[20] Because semester GPA can take on the value of zero, I use the inverse hyperbolic sine function in place of the natural log. The inverse hyperbolic sine yields nearly identical marginal utilities as the natural log except when semester GPA is very close to zero.

[21] A fixed cost of labor is common in the labor supply literature and can capture the additional effort associated with attending a job regardless of hours worked (Löeffler et al. 2018). I include

The net tuition function $edu_t(a_{it}, S_{it})$ is equal to expected fees, tuition, and textbooks less grants and scholarships. Fees, tuition, and textbooks can vary based on attempted credit hours and the individual's characteristics in X_i, such as independence status and residency. Loan offers are also based on net tuition. Neither Stafford loan offers nor private loan offers can exceed individual i's net tuition function plus expected living expenses. Furthermore, Stafford loans have a maximum value specified by the federal government and require the individual is enrolled in at least six credit hours.

Individual i's family financial support is given by:

$$fam(a_{it}, S_{it}) = \mathrm{fl}_i + edu_t(a_{it}, S_{it}) \times \mathrm{fp}_i \tag{1.11}$$

where $\mathrm{fl}_i \in X_i$ is the individual's lump-sum family transfers and $\mathrm{fp}_i \in X_i$ is the individual's family transfers for education expenses as a percent of education expenses.[22]

I model individual i's study time function as:

$$study_i(a_{it}) = \left(\delta_{0i} + \delta_{1i}k_{it} + \delta_{2i}h_{it} + \delta_{3i}h_{it}^2\right) k_{it}. \tag{1.12}$$

This specification allows the individual to change her study time per credit hour as she changes her credit hour enrollment or work hours.

I model the grade process with a heteroskedastic ordered probit. Individual i's unobserved "knowledge" for a particular credit hour g^*_{ikt} is a function of her knowledge without any studying γ_{0i}, her individual-specific return to studying rate γ_{1i}, study hours per credit hour, and a normally

a fixed utility term for attempting zero credit hours to capture similar fixed costs associated with enrolling in any classes regardless of the number of classes. Marx and Turner (2018) find empirical evidence that students face a fixed non-monetary cost for borrowing, which I capture with α_{b1} and α_{b2}. I allow this cost to vary between Stafford loans and the maximum loan eligibility because students have to actively seek out and apply for loans beyond the Stafford loan offer, and the search costs may have a utility cost.

[22]This functional form reflects how the SEES measured family financial support. Respondents specified how much they received in support for living expenses as a fixed dollar amount and how much they received for education expenses as either a fixed dollar amount or as a percentage of education expenses. For students who receive both as a fixed dollar amount, fp_i is zero.

distributed error term ν_{ikt}.[23] When her knowledge passes particular thresholds, she earns higher discrete grades. I assume all individuals face the same thresholds to earn each grade and the same variance factor for the error term.

$$g^*_{ikt} = \gamma_{0i} + \gamma_{1i}\frac{study_i}{k_{it}} + \nu_{ikt} \tag{1.13}$$

$$\nu_{ikt} \sim N\left(0, \exp\left(\frac{study_i}{k_{it}}\sigma^g\right)\right)$$

$$g_{ikt} = \begin{cases} 0 & \text{if} \quad g^*_{ikt} \leq 0 \\ 1.25 & \text{if} \quad 0 < g^*_{ikt} \leq \gamma_C \\ 2.25 & \text{if} \quad \gamma_C < g^*_{ikt} \leq \gamma_B \\ 3.25 & \text{if} \quad \gamma_B < g^*_{ikt} \leq \gamma_A \\ 4 & \text{if} \quad \gamma_A < g^*_{ikt}. \end{cases}$$

F^g_i is defined by $\gamma_i \equiv \{\gamma_{0i}, \gamma_{1i}, \sigma^g, \gamma_C, \gamma_B, \gamma_A\}$.

I specify individual i's post-school value function as:

$$U^{post}(S_{it}) = \alpha_w \ln(w^{post}_i(S_{it})) + \alpha_B \ln(B_{it}) \tag{1.14}$$

where the log specification imposes diminishing marginal returns to post-school earnings and post-school cumulative debt.[24] I restrict α_w to positive values and α_B to negative values.

Individual i's post-school wage offer is modeled as:

$$w^{post}_i(S_{it}) = \exp\{\omega_{0i} + 1[K_{it} \geq \bar{K}](\omega_{1i} + \omega_{2i}(G_{it} - 2) + \omega_{3i}(G_{it} - 2)^2) + \xi_i\} \tag{1.15}$$

where $\xi_i \sim N(0, \sigma^w_i)$. This specification includes a college degree premium and a return to graduating with a GPA above the minimum for a degree.[25] F^w_i is defined by $\omega_i \equiv \{\omega_{0i}, \omega_{1i}, \omega_{2i}, \omega_{3i}, \sigma^w_i\}$.

[23] In practice, I model the error distribution such that there is perfect correlation between errors in groups of three credits. This reflects that students earn grades at the course level, and courses are typically three credit hours each.

[24] Because cumulative debt can take on the value of zero, I use the inverse hyperbolic sine function in place of the natural log.

[25] To reduce the computational burden of estimating the model, I assume there are no returns to in-school work experience. Researchers have found conflicting evidence on the returns to in-school work experience (e.g., see Baert et al. 2016; Häkkinen 2006; Hotz et al. 2002).

I set $T = 10$ so individuals have five full years to complete college before entering the post-school labor market. I set $L_t = 3360$ for the fall and spring period and $L_t = 1680$ for the summer period corresponding to a time endowment of 112 hours per week or 16 hours per day. I assume an annual interest rate of 4.44%, which is approximately the average interest rate on Federal Stafford loans for in-sample years. I also specify a discount rate instead of estimating it, as it is typically not well identified (Aguirregabiria and Mira 2010). Given existing research suggests that young adults have higher discount rates than older adults (e.g., see Green et al. 1994), I choose an annual discount rate of 0.8. Finally, I set the consumption floor at $50 per week.

1.4.4 Criterion function

Before estimating the structural model, I estimate the studying model parameters δ_i, grade model parameters γ_i, and wage model parameters ω_i using the subjective expectations elicited in the SEES. With these individual-specific parameters in hand, I estimate the utility parameters $\alpha \equiv \{\alpha_c, \alpha_{lt}, \alpha_g, \alpha_{h0t}, \alpha_{k0}, \alpha_{k30}, \alpha_{b1}, \alpha_{b2}, \alpha_w, \alpha_B\}$ via maximum likelihood. This two-step approach is common in the literature to reduce the computational burden of estimating the parameters jointly (Aguirregabiria and Mira 2010).[26]

The log-likelihood function for individual i is given by:

$$ll_i(\alpha) = \log Pr(a_{it}, \hat{S}_{it}, g_{ikt} : t = 1, \dots T_i \mid \alpha) \tag{1.16}$$

where a_{it} is the chosen bundle for individual i in period t, $\hat{S}_{it}$ is the set of observable state variables and predicted auxiliary model parameters, g_{ikt} is the vector of earned grades for individual i in credit hour k and period t, and T_i is the final period observed in the data for individual i.

Because the choice-specific preference shocks are independently distributed over time and the other state variables evolve independently from the preference shocks, I can re-write the likelihood

[26] I take the studying model, grade model, and wage model parameters as given for the second estimation step; I do not incorporate the standard errors on those parameters into the estimation of the utility parameters.

function as:

$$
\begin{aligned}
ll_i(\alpha) = & \sum_{t=1}^{T_i} \log Pr(a_{it}|\hat{S}_{it}, \alpha) + \sum_{t=1}^{T_i} \log Pr(g_{ikt}|a_{it}, \hat{S}_{it}) \\
& + \sum_{t=1}^{T_i - 1} \log Pr(\hat{S}_{i,t+1}|a_{it}, \hat{S}_{it}, g_{ikt}) + \log Pr(\hat{S}_{i1}|\alpha).
\end{aligned} \tag{1.17}
$$

The second and third terms are defined by the grade model described previously and do not depend on the parameters in α. The fourth term, the contribution of initial state variables to the likelihood function, can also be ignored under the assumption that the choice-specific preference shocks are independently distributed over time and uncorrelated with the initial states (Aguirregabiria and Mira 2010). Thus, the only term relevant for the maximization problem is the first term – the log of the conditional choice probability.

Given the type I extreme value distribution, the probability that alternative a is chosen by individual i in period t given states $\hat{S}_{it}$ is:

$$
Pr(a|\hat{S}_{it}, \alpha) = \frac{\exp\left\{u_t^{sch}(c_{ait}, l_{ait}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a_{it}, \hat{S}_{it}]\right\}}{\sum_{a' \in A_t} \exp\left\{u_t^{sch}(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a', \hat{S}_{it}]\right\}} \tag{1.18}
$$

where the expectations are taken with respect to the choice-specific preference shocks, grades, and the post-school wage offer. I follow the procedure outlined in Section 1.4.2 to approximate these expectations and then I estimate the utility parameters using maximum likelihood.

1.5 Results

1.5.1 Auxiliary model estimation

Table A.1.4 summarizes the variables in the structural model and specifies the time periods they are available in the data. The choice variables, time-varying state variables, and net education expense function are available for all time periods. In-school wages and family financial support are only known at the time of the survey, and I assume that they do not change over time (Appendix Sections A.2 and A.3 describe the calculation of these variables in more detail). In the rest of this section, I briefly describe how I use the survey responses to estimate students' study time function, grade production function, and post-school wage function.

As specified in equation 1.12, a student's time spent on schoolwork is an individual-specific function of their credit hours and labor supply. In the SEES, I asked students how much time they expect to spend on schoolwork given six hypothetical credit hour enrollment and work hour schedules. I use their responses to these six questions and estimate the study function parameters with a linear regression. Panel A of Table A.1.5 presents the distribution of study function parameters.

Equation 1.13 specifies that the relationship between schoolwork and grades follows a heteroskedastic order probit model with an individual-specific constant and return to schoolwork. I use students' reported probability of earning each discrete grade in the four schoolwork time scenarios to estimate this model. As described in Section 1.3.4, students placed ten balls in bins to convey the likelihood of earning a particular grade. Each ball placed is a separate observation, so there are 40 observations per student (ten balls placed in four schoolwork scenarios) to identify the individual-specific parameters. I assume that the variance term and thresholds are common across all students. I also normalize the lowest threshold to zero to report individual-specific constants for every student. Panel B of Table A.1.5 presents the distribution of the grade production function parameters.

Equation 1.15 specifies that a student's post-school wage is determined by an individual-specific constant, degree premium, and return to GPA. The variance of the error term is also individual-specific. To estimate these parameters, I use the conditional salary distributions elicited from each student for five GPA scenarios. Similar to the conditional grade distribution questions, students placed ten balls in bins to convey the likelihood of earning a particular post-school full-time salary. Each ball placed is a separate observation, so there are 50 observations per student (ten balls placed in five GPA scenarios) to identify individual-specific parameters. I estimate the wage offer model with a separate linear regression for each student. Panel C of Table A.1.5 presents the distribution of the post-school wage function parameters.

1.5.2 Structural model estimates

Table A.1.6 presents the estimated utility parameters and their standard errors.[27] There are a few takeaways worth noting. First, there is a significant increase in how much students value their leisure time in the summer relative to the fall and spring. This is not surprising, as students may have more leisure options available to them during the summer semester (e.g., traveling, spending time with family and friends from home) which makes their time more valuable. In addition to consumption and leisure, students also value their contemporaneous semester GPA independent of the future labor market returns.

The estimated parameters confirm the existence of non-zero fixed costs. Students have a non-trivial fixed cost of work that is similar in the fall / spring and summer periods. They also have a fixed cost of enrolling in classes during the summer period. Students have a fixed cost of borrowing the maximum amount of loans available to them which is expected given the additional steps students need to take to borrow beyond their Stafford loan offer. However, students have a near-zero fixed cost for accepting the Stafford loan offer suggesting that students do not face a “psychic cost of debt” when borrowing small amounts.

In isolation, utility parameters can only tell us so much, but before proceeding with further analysis, I verify that the model achieves a reasonable fit of the observed data. Table A.1.7 presents the observed probabilities of each choice, average predicted probabilities of each choice, and the difference between the two. Panel A confirms that the model does a good job fitting the observed credit hour choice probabilities in the fall and spring periods, but it struggles to capture the u-shaped pattern in the summer periods. Panel B tells a similar story; the model does well fitting the observed work hour probabilities in the fall and spring periods, but it does not capture the u-shaped pattern of work hours in the summer. Panel C shows the goodness of fit for borrowing choices. The

[27]Due to computation time, I estimate utility parameters with a random sample of 15% of observations. Goodness of fit statistics are very similar for the 15% random sample and the entire sample. I use the Berndt-Hall-Hall-Hausman (BHHH) algorithm for maximizing the log likelihood function to avoid calculating finite differences required to estimate the Hessian (Train 2009). I derive standard errors using the square root of the diagonal of the inverse outer product of the gradient.

model does a good job matching the distribution of borrowing choices in the fall and spring periods, and it correctly predicts that almost no students borrow in the summer. The model over predicts students' willingness to borrow up to their maximum loan eligibility in the summer, though this is likely related to the model under-predicting students' willingness to work 40 hours a week in the summer. Overall, the model and estimated utility parameters fit the observed distribution of choices well.

1.5.3 Elasticities

Tables A.1.8 and A.1.9 present statistics for a series of elasticities of credit hour, work, and borrowing behaviors. I derive these elasticities via simulation by comparing the weighted average of choices (weighted by the model-derived probability of the choice) with the baseline variables and with the simulated variables: a \$1,000 increase in grants (\$500 in the summer), a 10% increase in the per-credit hour tuition rate, a 10% increase in students' expected return to studying (γ_{1i}), a 10% increase in students' expected return to earning a higher GPA (ω_{2i} and ω_{3i}), and a 10% increase in students' in-school wage.[28] I estimate standard errors for the average elasticities across students with a parametric bootstrap using 30 draws from the joint distribution of utility parameters.

As shown in Panel A, I do not find evidence that students' credit hour decisions vary strongly with financial aid, tuition, beliefs, or wages. Almost all of the estimated elasticities are near-zero in both the fall and spring and summer periods. The largest elasticity, a 0.177 credit hour elasticity with respect to the return to GPA in the summer, is not practically significant. With a base of 2.43 average credit hours, a 10% increase in the returns to GPA increases the average student's credit hour enrollment by 0.04 credits. Furthermore, as the last three columns of the table show, credit hour elasticities are practically insignificant across the 25th and 75th percentiles of the elasticity distribution.

[28] Because these elasticities are numerically derived and not analytically derived "point elasticities", I use an arc elasticity formula where the percentage change in the numerator and denominator of the elasticity are relative to the midpoint between the two numbers. For the returns to GPA elasticity, I increase two parameters – ω_{2i} and ω_{3i} – so I use the percentage change in the marginal effect of an increase in GPA at a GPA of 3.0 as the denominator.

Students are more responsive on the labor supply margin than the credit hour margin. As shown in the last row of Panel B, the average wage elasticity is 0.29 in the fall and spring and 0.24 in the summer; for a 10% increase in wages, students work 2.9% and 2.4% more hours on average. These wage elasticities are comparable to consensus estimates for prime-aged working adults in the United States, particularly for married women (McClelland and Mok 2012). Students decrease their labor supply with an increase in their subjective beliefs for the returns to studying and returns to GPA, at least in the fall and spring when they are more likely to face grade penalties for devoting more time to work; a 10% increase in students' beliefs about the returns to studying decreases hours worked by 1.19%, and a 10% increase in students' beliefs about the labor market returns to graduating with a higher GPA decreases hours worked by 2.11%. Worth noting, the distribution of these elasticities across students is skewed right, so the average response is not indicative of the median student's response. I do not find evidence that students' labor supply decisions are responsive to changes in financial aid or tuition – across the interquartile range, elasticities are near zero.

Panel C presents estimated elasticities for students' borrowing decisions. On average, students significantly change their borrowing behavior in response to a change in financial aid and tuition in the fall and spring. A 10% increase in financial aid reduces borrowing by 7.81%, and a 10% increase in tuition increases borrowing by 2.33%. This response is only present in the fall and spring, as students are unlikely to enroll in enough credit hours to be eligible for student loans. But once again, the distribution of these elasticities is highly skewed, and the median student does not change their borrowing to a meaningful degree. In the summer, students do increase their borrowing with a change in their beliefs about the returns to GPA. This likely reflects the positive credit hour elasticity in the summer; beliefs about the returns to GPA increase, students take marginally more credits in the summer when it is easier to earn a high GPA (fewer classes to distribute study hours across), and the small increase may cross the minimum credit hour threshold to begin borrowing. The final elasticity, borrowing with respect to wages, is negative in both the fall and spring (-0.09) and summer (-0.16), suggesting that students will substitute to labor from debt when the value of labor is higher.

For the elasticities that are highly skewed, a question naturally arises – what students are in the tail of the distribution? To answer this question, I conduct a series of two-sample t-tests on potential explanatory factors by comparing students in the bottom and top terciles of their elasticity distributions. I choose factors that should affect the marginal utility or cost of changing labor supply and borrowing such as unmet financial need, wages, and expected studying time response to work hours.[29] Table A.1.10 presents the results for the fall and spring periods.

Panel A compares students in the bottom and top terciles of the returns to studying elasticity of labor supply. The average elasticity is -0.12 but the median elasticity is only -0.02. Students in the bottom tercile, who reduce their labor supply more with an increase in the returns to studying, have larger expected increases in study time with their decrease in work hours and larger expected returns to graduating with a high GPA. In addition, these students have lower expected returns to studying originally, suggesting that there are diminishing marginal returns to studying. The more elastic students also have less unmet financial need and lower wages on average, so the opportunity cost of giving up work hours is smaller.

Panel B compares students in the bottom and top terciles of the returns to GPA elasticity of labor supply. The distribution of this elasticity is more skewed than the prior one, with a mean elasticity of -0.21 and a median elasticity of -0.03. As with the prior elasticity, the more elastic students here have larger expected study hours gains from work reductions; however, these students have similar unmet need and wages as students with smaller (in absolute value) elasticities. In addition, the more elastic students have higher returns to GPA originally, though it is difficult to draw conclusions from this correlation as a 10% increase in the returns to GPA is larger in absolute terms when the base is higher.

[29] Unmet financial need, in-school wage, return to studying, return to GPA, and cumulative credit hours are self-explanatory or discussed previously. The "study cost of work" is how many study hours per credit hour the student expects to give up with an increase in work hours; in other words, the derivative of $study_i(a_{it})/k_{it}$ with respect to h_{it} in equation 1.12. Because the derivative changes with work hours, I use the derivative at 6 work hours, which is approximately the mean work hours in the fall and spring.

Panels C and D compare students in the bottom and top terciles of two borrowing elasticities: financial aid elasticity and tuition elasticity. The average financial aid elasticity is -0.78 (median of -0.01), and the average tuition elasticity is 0.23 (median of 0.03). There is significant overlap between the more elastic students in each distribution – 70% of students in the bottom tercile of the financial aid distribution are in the top tercile of the tuition distribution, and 88% of students in the top tercile of the financial aid distribution are in the bottom tercile of the tuition distribution. When the budget constraint becomes tighter (financial aid decreases or tuition increases), the students who increase their borrowing the most have larger studying costs of work. They also have fewer cumulative credit hours and are further from graduating, so they are discounting the future repayment of their loans more heavily. The two groups of elastic students are not identical, however, as the more elastic students of the tuition distribution have significantly less unmet financial need than the less elastic students while the elastic students of the financial aid distribution have similar unmet financial need to the less elastic students.

1.5.4 Counterfactual simulations

Elasticities are helpful for predicting how small, equally sized (in percentage terms) changes in particular variables affect students' choices. I now turn to two counterfactual simulations that involve much larger changes that are not felt equally by all students. The first simulation models an increase in the minimum wage to $15 per hour. The second simulation makes in-state tuition free for all students. Both policies relax a student's budget constraint, albeit in very different ways, with different effects across the distribution of students.

1.5.4.1 Minimum wage increase

Federal and state minimum wage laws are a potential mechanism for reducing income inequality in the United States (Card and Krueger 2016, Dube 2019). Because of this, there is growing pressure to raise the federal minimum wage from its current rate of $7.25 per hour, which has not changed since 2009, to $15 per hour (Pramuk 2019). In Michigan, the state minimum wage increased on September 1, 2014 from \$7.40 to \$8.15, and it is set to increase each year until reaching \$12.05 in 2030 (Michigan Michigan Senate 99th Legislature 2018). At the beginning of spring 2019, the state minimum wage was \$9.45. In this first simulation, I model what would have happened if Michigan raised their minimum wage to \$15 per hour on September 1, 2014.[30]

A \$15 minimum wage would raise hourly wages for 93% of students in my sample and increase the average wage from \$10.95 to \$15.32. Notably, the wage increase is not significantly correlated with students' unmet financial need.

Panel A of Table A.1.11 presents the expected behaviors and outcomes for students under the baseline and counterfactual simulations.[31] Increasing the minimum wage to \$15 per hour increases average weekly work hours by 0.75 in the fall and spring and 1.70 in the summer. With the wage and hour increase, the average student's labor income increases by \$1,115 in the fall and spring year and \$1,003 in the summer. There is a small decrease in average borrowing, \$303 in the fall and spring and \$65 in the summer, which is not enough to offset the gains in labor income. There is no observable change in attempted credit hours or expected cumulative GPA. Thus, the primary effect of increasing the minimum wage is increasing students' consumption (at the expense of leisure or studying) as opposed to allowing students to maintain existing consumption with less debt or fewer hours working.

1.5.4.2 Free in-state tuition

Another policy proposal gaining momentum in the United States is making college tuition free (Murakami 2020). Multiple US presidential candidates in the 2020 election adopted free college plans in their platforms, and many states already have grant programs that cover the cost of tuition at two- and four-year colleges for low- to middle-income families (Dickler 2019). These programs

[30] I assume there are no changes in labor demand and only focus on the labor supply response. Based on a recent review of the minimum wage literature, this is not an unreasonable assumption (Belman and Wolfson 2014).

[31] The baseline simulation takes students' state variables in their first period as given and projects out their optimal decisions and evolution of state variables according to the estimated utility function parameters.

can increase enrollment in eligible colleges, and additional requirements (e.g., minimum GPA or minimum completed credits per year) can incentivize students to change their behavior (Quinton 2019). In this second simulation, I model what would happen to existing students if Michigan State University unconditionally waived the cost of in-state tuition for all students enrolled after September 2014.[32]

Free in-state tuition reduces the expected cost of attendance by $15,723 in the fall and spring and $964 in the summer. Expected credit hours are much lower in the summer, so the expected savings are less. Even with free in-state tuition, in-state students still have expected living costs of $14,148 in the fall and spring and $7,074 in the summer, as well as smaller program fees and textbook costs, and out-of-state students still have the remainder of their tuition ($24,483 in the fall and spring, $1,632 in the summer, on average). Unlike increasing the minimum wage as in the previous counterfactual, the actual benefit of free college varies significantly by students' financial need. Students with sufficiently high financial need benefit from the entire tuition reduction while students with sufficiently large grants, scholarships, and family financial support do not benefit at all.

Panel B of Table A.1.11 presents the expected responses and outcomes for students with and without free in-state tuition. Average credit hours attempted increase by 0.09 credits in the fall and spring and 0.04 credits in the summer, but this is a small effect in practice. Over the course of four years, this corresponds to less than one additional credit hour. There are similarly small changes in work hours. Given these small effects, there is no observable difference in expected cumulative GPA. Borrowing does change substantially, however, with average loan amounts decreasing by $1,922 in the fall and spring and $185 in the summer. Taken together, this counterfactual simulation suggests that making college tuition cheaper is largely a wealth transfer for Michigan State's already enrolled students; it reduces students' reliance on loans but does not improve other

[32] I assume no changes in enrollment or shifts in the university budget. I also assume that families do not change their family financial support plans, and any money previously allocated toward education expenses is not given to students. Out-of-state students are charged the difference between in-state and out-of-state tuition.

outcomes like credit accumulation or GPA.

1.6 Conclusion

In this paper, I show how wages, financial resources and beliefs influence college students' credit hour enrollment, labor supply, and borrowing decisions. I begin by presenting novel survey data from a random sample of undergraduates at Michigan State University. The survey contains students' work history, expected study hours for varying enrollment and work schedules, family financial support, beliefs about the returns to studying, and beliefs about the returns to graduating with a high GPA. The survey also contains administrative data on students' credit hour history, financial aid eligibility, and borrowing history. After presenting the data, I develop a dynamic structural model of college students' credit hour enrollment, labor supply, and borrowing which captures the key contemporaneous and future tradeoffs involving these decisions. I then estimate students' preferences for consumption, leisure, grades, future earnings, and future debt and derive elasticities for the three behaviors of interest. Finally, I simulate the effects of two counterfactual policies: a minimum wage increase and free college tuition.

Students' credit hour decisions are highly inelastic; the estimated elasticities with respect to changes in financial aid, tuition, returns to studying, returns to GPA, and in-school wage are all near zero. Students' work decisions are more responsive to changes in their budget and beliefs than their credit hour decisions. I estimate an average wage elasticity of 0.29 in the fall and spring and 0.24 in the summer which are both comparable to elasticities for prime-age workers in the United States. I find slightly smaller, but still practically significant, labor supply elasticities with respect to beliefs about the returns to studying and returns to GPA. The larger elasticities are driven by students who expect to gain more study hours back from a decline in work hours. These students also have large borrowing elasticities with respect to financial aid and tuition. Coupled with a wage elasticity of borrowing of -0.16, this supports that students substitute between labor income and borrowing.

The counterfactual simulations reveal similar patterns as the elasticities. A $15 minimum wage would increase average work hours by 0.75 hours per week in the fall and spring and 1.14 hours per week in the summer. It would also lead to small decreases in borrowing. Making in-state tuition free for all students would negligibly change credit hours or work hours, but it would reduce average borrowing by $1,922 in the fall and spring and $185 in the summer. Neither counterfactual policy leads to a significant change in expected GPA.

These results suggest how colleges and universities may (or may not) be able to change student behavior. Financial levers on their own do not appear to be effective in increasing students' credit hour enrollment and subsequently decreasing time-to-degree. Financial aid that is tied to maintaining certain credit hour benchmarks may hold more potential. There are also non-monetary levers not explored in this chapter that could be more effective, like utilizing academic advisors to change students' mindset about the default course schedule or offering more classes in the summer term so students have more opportunities to reach 30 hours beyond the fall and spring.

It is not clear ex ante that institutions should prefer that college students increase or decrease their labor supply, but it does appear that changing students' wages would be effective in shifting their willingness to work. Colleges can adjust pay scales for on-campus jobs, and policy makers can focus on changing the minimum wage. Importantly, these wage increases apply equally to high-need and low-need students, and because there does not appear to be strong income effects present, both high-need and low-need students will change their behavior. An alternative policy, such as increasing Federal Work-Study generosity, would be more targeted at high-need students than raising wages for everyone.

CHAPTER 2

PEER GENDER COMPOSITION AND NON-COGNITIVE OUTCOMES

2.1 Disclaimer

This chapter uses data from Add Health, a program project designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris, and funded by a grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 17 other agencies. Special acknowledgment is due to Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Persons interested in obtaining Data Files from Add Health should contact Add Health, The University of North Carolina at Chapel Hill, Carolina Population Center, 206 W. Franklin Street, Chapel Hill, NC 27516-2524 (addhealth_contracts@unc.edu). No direct support was received from grant P01-HD31921 for this analysis.

2.2 Introduction

Non-cognitive factors are significant determinants of both educational and labor market outcomes, in some settings explaining more variation in these outcomes than cognitive skills (Almlund et al. 2011; Borghans et al. 2008; Bowles et al. 2001). Despite their importance, we are still learning about the development of non-cognitive factors, particularly among adolescents (Kautz et al. 2014). Drawing from existing research that demonstrates how an adolescent's peers affects their cognitive skill formation, we may expect that an adolescent's peers could affect their non-cognitive factor formation, too (Epple and Romano 2011; Sacerdote 2011). This chapter investigates the relationship between a particular type of peer effect, peer gender composition, and non-cognitive factors.

Previous studies find that students with a higher share of female peers do better in the classroom (Gong et al. 2019; Hoxby 2000; Lavy and Schlosser 2011), and there are compelling reasons to believe that this relationship exists for non-cognitive factor formation. Being surrounded by similar peers may help a student feel like they belong in their community, make it easier to develop friendships, and improve the student's happiness and mental health. Dweck et al. (2014) and Farrington et al. (2012) provide extended commentary on these non-cognitive factors and how they may relate to peer groups. In two studies that examine the relationship between peer gender and non-cognitive factors directly, Gong et al. (2019) find that male students exhibit a higher life fulfillment and confidence for the future when they have more female classmates and female students report lower levels of unhappiness, and Lavy and Schlosser (2011) find that the self-reported quality of inter-student relationships improves for both male and female students when they have more female peers.

This chapter estimates the causal effect of peer gender composition on two additional non-cognitive factors – sense of belonging and self-worth – using a data set that is ubiquitous in the peer effects literature, the National Longitudinal Study of Adolescent to Adult Health (Add Health). Based on the aggregation of eight different measures, I find that male students report a stronger sense of belonging and self-worth when they have more female peers, but the effects are small in magnitude. The results also suggest that there are no appreciable effects for female students.

2.3 Data

Add Health is a nationally representative longitudinal survey of seventh to twelfth graders in the United States (Harris 2009). The first survey instrument, an in-school questionnaire, provides data on student demographics, peer groups, and non-cognitive factors for 90,118 students. I create a subset of this sample for my analysis by excluding the following students. One student is missing a valid school identifier, 803 students are missing a valid grade, 6,849 students are missing a survey weight, and 17,325 students did not provide a valid answer to at least one of the outcomes or control variable questions. I also exclude 3,767 students who attended schools that required explicit parental consent to take the in-school questionnaire; these schools tend to have lower in-school questionnaire participation rates which makes the calculation of the share of female peers more prone to measurement error. Finally, I exclude 100 students who had fewer than ten total students in their grade and 1,144 students who attended schools that were exclusively male or female, as there is no variation in peer gender across grades. I am left with 60,129 observations.

My explanatory variable of interest is the share of female peers in a student's school and grade which I calculate by dividing the number of students who answered the question, "what sex are you?" with "female" by the total number of students who answered the question either "male" or "female" in that student's school and grade.[1] To avoid correlations between the student's own gender and the share of female peers in their school and grade, I use a leave-out mean, where I do not include the student in the calculation of their peer group's mean. In addition to the share of female peers, I include the following control variables in my baseline model: biological sex, Hispanic or Spanish ethnicity, race (e.g., Black or African American, Asian or Pacific Islander, American Indian or Native American, White, other), if the student's age (in years) is above the median age for their grade across all schools, if the student reported being born in the United States, and dummy variables for the number of people that live in the student's household. Table B.1.1 presents descriptive statistics for the sample.

The in-school questionnaire contains four questions that measure sense of belonging – "I feel socially accepted", "I feel loved and wanted", "I feel close to people at this school", "I feel like I am part of this school" – and four questions that measure self-worth – "I have a lot of good qualities", "I have a lot to be proud of", "I like myself just the way I am", "I feel like I am doing everything just alright". Each question was asked on a 5-point Likert scale with options ranging from "Strongly disagree" to "Strongly agree". Given the ordinal nature of the responses, there is no obvious way to aggregate the individual questions into their broader non-cognitive factor. As my primary specification, I use the count of questions that a student answered in the affirmative ("Agree" or "Strongly agree") as my outcome variable. Table B.1.2 presents the probability of an affirmative response for each of the eight questions and the mean number of affirmative responses for the two broader categories. I also consider a specification where I assign a numerical value

[1] I calculate the share of female peers from the full sample of in-school questionnaire respondents before I remove students for my analytic sample.

to each possible response (e.g., Strong disagree = 1, Disagree = 2, ... , Strongly agree = 5) and estimate the effect of an increase in female peers on the average numerical response for the broader non-cognitive factor. Figures B.1.1 through B.1.3 present histograms of responses for each survey question, the count of affirmative responses, and the average numerical response.

2.4 Empirical strategy

I employ a similar method as Hoxby (2000) and Lavy and Schlosser (2011) to isolate plausibly exogenous variation in the share of female peers; I assume that variation in the share of female students within a school and across grades is uncorrelated with unobserved determinants of non-cognitive factors. By focusing on within school variation, this assumption is not violated by endogenous sorting into schools if the sorting occurs equally in all grades. I conduct a balance test to check for observable violations of this assumption by regressing the share of female peers in a school and grade on the aforementioned control variables, school dummy variables, and grade dummy variables. As shown in Table B.1.3, only one relationship is statistically significant at the 10% level which is to be expected given the number of control variables even if no true correlations exist in the population.

I estimate a linear-in-means model with school and grade dummy variables to measure the relationship between peer gender composition and non-cognitive factors. Let y_i be a non-cognitive factor for student i, $\overline{\text{female}}_{-isg}$ the share of female peers in student i's school s and grade g, excluding student i, X_i a vector of student characteristics, ϕ_s a vector of school-specific effects, and ψ_g a vector of grade-specific effects. The estimating equation is:

$$y_i = \beta \overline{female}_{-isg} + X_i + \phi_s + \psi_g + \varepsilon_{isg}. \tag{2.1}$$

I use the Add Health adjusted sample weights in all regressions, and I estimate standard errors using a Taylor linearization adjusting for the survey's regional stratification and clustering by school as prescribed by Chen and Chantala (2014).

2.5 Results

Table B.1.4 contains the estimated effect of a unit increase in the share of female peers in a student's school and grade on the count of affirmative sense of belonging and self-worth survey responses. Each pair of columns presents results for a different sample: the total sample, female students only, and male students only.

I do not find significant evidence that female students are more or less likely to have a higher sense of belonging or self-worth with an increase in the share of female peers, but the coefficients and standard errors rule out practically significant positive effects. I do find evidence that male students report both stronger belonging and self-worth, but while the effect is statistically significant, it is not large. A five percentage point increase in the share of female peers, (roughly equivalent to a one-standard deviation increase) leads to male students reporting 0.036 and 0.032 more affirmative responses to the four belonging and four self-worth questions, respectively. This corresponds to 1.4% and 1.1% of the mean or 2.6% and 2.6% of the standard deviation. These effect sizes for male students are comparable to those found by Lavy and Schlosser (2011) and Gong et al. (2019). In addition, while Gong et al. find that a higher share of female peers results in lower rates of reported unhappiness among female students, they find that only male students report greater life fulfillment, confidence for the future, and private recreation with their classmates.

I also examine specifications without individual level controls, using the average numerical response as opposed to the count of affirmative responses, and using the probability of an affirmative response for each individual non-cognitive question. Tables B.1.5 through B.1.7 contain the results. Across each specification, the results are similar. Male students report slightly higher sense of belonging and self-worth when exposed to more female peers while female students do not report sense of belonging or self-worth changes that are statistically different from zero.

Finally, I use simulation methods to test the robustness of the results to measurement error in the share of female peers. Share of female peers is based on individual-level responses to the in-school questionnaire and is not a precise measure of the true share of female students in a school and grade, as not every student in every school was in attendance or agreed to take the survey.

School administrators did report how many students were on their roster for the in-sample grades, allowing me to calculate the percentage of students who responded to the survey. As shown in Figure B.1.4, most students in my sample attended schools that had an 80% response rate or higher, and every student in my sample attended a school with at least a 50% response rate. The effect of measurement error on the point estimates is unknown ex ante, as the measurement error does not satisfy the classical assumptions. To account for this bias, I follow a multiple imputation procedure and adjust the standard errors according to the formula proposed by Rubin and Schenker (1986).

I assume that the observed share of female students in a school and grade is an unbiased estimate for the true share of female students, which would be true if in-school questionnaire participation is uncorrelated with gender. Next, I estimate the number of missing students in a grade by multiplying the number of missing responses in a school by the share of the grade within each school. I then create 100 simulated data sets filling in the missing students with draws from a Binomial distribution using the probability of being female and number of missing students in each school and grade. I re-estimate my model for each data set, replacing the observed share of female peers with a simulated share of female peers. The average point estimate is a consistent estimate for the theoretical point estimate without measurement error in the share of female peers, and the average standard error, plus a term to correct for the variation across simulations, is a consistent estimate for the standard error without measurement error. As shown in Table B.1.8, the point estimates for the share of female peers are slightly smaller than in the baseline model. The primary finding is unchanged.

2.6 Conclusion

Although many researchers have established the importance of non-cognitive factors, the literature on how to develop these factors is still growing. This chapter finds evidence that a mechanism for cognitive skill development, peer gender composition, is a minor input into the formation of two non-cognitive factors, sense of belonging and self-worth, for adolescent males. While I do not find evidence that peer gender composition is also a determinant of sense of belonging and self-worth for female adolescences, it may play an important role for other non-cognitive factors and should be explored further in subsequent research.

CHAPTER 3

THE EVOLUTION OF THE WAGE ELASTICITY OF LABOR SUPPLY OVER TIME

3.1 Disclaimer

This chapter was co-authored with Todd Elder (telder@msu.edu) and Steven J. Haider (haider@msu.edu). Both authors have approved that this work be included as a chapter in my dissertation.

3.2 Introduction

The wage elasticity of labor supply is arguably one of the most fundamental parameters in economics. This parameter captures how a change in the net wage, perhaps induced by a change in taxes, retirement credits, or productivity, affects labor supply, measured by the number of workers or work hours. With such a parameter in hand, and especially with knowledge of how it varies with observable characteristics, one can readily forecast how labor supply will respond to policy changes that affect wages. Moreover, the magnitude of the wage elasticity has implications for numerous questions, such as optimal taxation, the causes of business cycles, and the role of human capital formation, to just name a few.

Despite the importance of the wage elasticity of labor supply, there exists limited evidence about how this parameter has changed over time. Several papers have studied changes in women's elasticities, documenting a strong decline for both married (Kumar and Liang 2016; Blau and Kahn 2007; Heim 2007;) and single (Bishop et al. 2009) women. Most of these papers do not include data for years beyond the early 2000s, and one paper in particular finds that the declining trend slowed at the turn of the century, suggesting that newer estimates might tell a different story (Kumar and Liang 2016). A recent meta-analysis also finds declining elasticities for women in both Europe and the US (Bargain and Peichl 2016), but the authors conjecture that changes in how researchers have estimated labor elasticities may account for some of the intertemporal variation in the estimates. There is little formal analysis of the trend in labor supply elasticities for men outside of meta-analysis and cross-paper comparisons.

In this chapter, we use a consistent econometric approach to examine how the wage elasticity of labor supply has changed over time. First, we provide a theoretical discussion on why elasticities might evolve over time and a review of the existing literature on labor supply elasticity trends. We then propose a static discrete choice model and estimation strategy that exploits variation in wages due to variation in marginal tax rates across households and income ranges. At the same time, we critically examine the importance of our modeling decisions and test the robustness of our estimated trends to these decisions. In doing so, we contribute to the methodological literature that assesses the sensitivity of labor supply research to its modeling assumptions. See Löeffler et al. (2018) for an excellent recent example.

We have two primary findings. One, there is robust evidence that the labor supply elasticities for married and single men and women have increased modestly over the last two decades. For women, this is a reversal of previous trends. Second, our results suggest that many computationally costly decisions, like using maximum simulated likelihood to include time-invariant idiosyncratic preference heterogeneity and to integrate out measurement error in wages, do not significantly alter the estimated trends in elasticities.

3.3 Background and literature review

Numerous integrative surveys have summarized the vast literature on labor supply elasticities; see Blundell and MaCurdy (1999) and Keane (2011) for just two examples. In this section, we briefly lay out the basic issues related to our research question, heavily relying on the exposition in Keane (2011).

3.3.1 The key elasticities

In a static model, two key wage elasticities arise. The first is the Marshallian (or uncompensated) elasticity e_M, which measures how hours worked h change with a change in wage w:

$$e_M = \frac{w}{h}\frac{\partial h}{\partial w}. \tag{3.1}$$

The second is the Hicksian (or compensated) elasticity e_H, which measures how hours change with a change in wage, holding utility u constant:

$$e_H = \frac{w}{h}\frac{\partial h}{\partial w}\bigg|_u. \tag{3.2}$$

Letting e_I denote the income elasticity of labor supply and s denote the share of income accounted for by labor income, the Marshallian and Hicksian elasticities are related to each other based on the Slutsky equation when labor supply is a continuous choice:

$$e_M = e_H + \frac{s}{1-s}e_I. \tag{3.3}$$

Under the assumption that leisure is a normal good, the income elasticity is negative, implying that the Hicksian elasticity is greater than the Marshallian elasticity.

In a life-cycle model, these two elasticities measure the effect of a permanent (or parametric) change in wages – the Marshallian elasticity when the permanent wage change is uncompensated and the Hicksian elasticity when the permanent wage change is compensated. In addition, the life-cycle model introduces the Frisch (or intertemporal) elasticity, which measures how labor supply responds to known wage changes between two periods. Based on the standard assumption of diminishing marginal utility, we know that the Frisch elasticity is greater than the other two.

Which elasticity is relevant depends on the particular policy being considered. The effect of a newly imposed tax to fund a public good might be best approximated with the Marshallian elasticity, whereas the imposition of a tax to fund a universal income transfer might be best approximated by the Hicksian elasticity. The evaluation of a change in tax rate with age, such as that with the Social Security retirement earnings test, might be best approximated with the Frisch elasticity.

Regardless of which elasticity is most targeted, the econometrician's assumptions and empirical specifications may significantly affect their estimates of labor supply elasticities. Key issues include the simultaneity of wages and hours, the treatment of taxes, measurement error in wages and non-labor income, the treatment of missing wages for non-workers, the possibility of non-separabilities between consumption and leisure and over time, the choice of control set, what is considered to be exogenous, and the sources of dynamics like human capital accumulation. Blundell and MaCurdy (1999) and Keane (2011) include detailed discussions of these and other econometric issues. The literature is large and complex, and given this complexity, empirical studies often must make compromises at various points in their analysis.

3.3.2 Why might elasticities vary over time?

Within the canonical model of labor supply where jobs are only indexed by the wage rage and workers can freely choose their hours, a few hypotheses exist that can explain why labor supply elasticities might change. Secular changes in wages or non-labor income, including changes in government programs that provide income to non-workers and compositional changes in the population (e.g., age distribution, marriage rates, and number of children) that alter eligibility for existing programs, could affect the Marshallian elasticity (Bishop et al. 2009; Heim 2007). Compositional changes in the population can also affect the distribution of preferences for consumption and leisure even if the underlying conditional preferences are unchanged. For example, preferences for leisure might increase with number of children. As family size increases or decreases, so might the wage elasticity even if the relationship between children and utility of leisure does not. A less satisfying explanation is that preferences themselves have changed over time.

Additional explanations for evolving labor supply elasticities arise outside of the canonical model. Certain hours-wage bundles may be restricted by the demand side of the labor market, and these restrictions can loosen or tighten over time. Similarly, their could exist time-varying fixed costs of work (e.g., commuting) that make certain hours-wage bundles particularly unappealing. The composition of non-pecuniary job attributes can also change over time, affecting individuals' willingness to work at all or work long hours (Blau and Kahn 2007; Atrostic 1982). While we do not include non-pecuniary job attributes in this research, we are able to incorporate fixed costs of part-time work.

3.3.3 Evidence on trends in labor supply elasticities

Several papers have examined changes in the labor supply elasticities of women, and the title of one notable example succinctly summarizes the literature: "The Incredible Shrinking Elasticities: Married Female Labor Supply, 1978-2002" (Heim 2007). Based on March Current Population Survey (CPS) data from 1979 through 2003, Heim finds that the wage elasticity declined by about 60 percent from an initial base of 0.36.[1] Blau and Kahn (2007) examine changes for married women using 1980 through 2000 March CPS data. They find that the wage elasticity dropped by just over 50% from an initial base of about 0.80. Both papers use a continuous labor supply model with a Heckman selection correction to account for unobserved wages among non-working women. Important for our findings, neither paper finds that the downward trend diminished in later years. Kumar and Liang (2016) also examine the labor supply elasticities of married women, but they use the 1980 through 2006 Panel Study of Income Dynamics (PSID).[2] Kumar and Liang find large declines in elasticities, but they provide some evidence that the declines level off during the very last years of their sample period.

Moving from married women to single women, Bishop et al. (2009) estimate changes in the wage elasticity for single women using the March CPS from 1979 through 2003. With a continuous choice model, they conclude that the wage elasticity of labor supply declined by about 80 percent from an initial base of about 0.20. There is little evidence that the downward trend diminished towards the end of their sample period.

[1] Unless otherwise specified, we report Marshallian elasticities when referencing results from previous studies.

[2] Although the authors provide some estimates that exploit the panel nature of their data, we focus on the estimates obtained from pooled models that are similar to those estimated by Heim (2007) and Blau and Kahn (2007).

Several systematic literature reviews also provide evidence about how the wage elasticity has changed over time. Keane (2011) provides a list of estimates from eight different studies that exhibit little change from 1980 to 2001 in the wage elasticity for men. Based on an exhaustive list of studies from both the United States and Europe, Bargain and Peichl (2016) do not find evidence of a systematic trend in wage elasticities for men, but they do observe a downward trend in elasticities for married and single women. Interestingly, Bargain and Peichl (2016) demonstrate that researchers are increasingly using discrete choice estimation methods to estimate wage elasticities, and the downward trends in female elasticities are somewhat flatter when using estimates from these discrete choice studies as opposed to estimates from continuous choice studies.

3.4 Empirical methods

We rely on a static model of labor supply throughout our analysis. The motivation for doing so is that static models continue to play a prominent role in assessing the responsiveness of hours to wages. Bargain and Peichl (2016) list numerous examples of recent papers that estimate a static model, and two prominent papers that provide a synthesis of our understanding of Hicksian elasticities rely on estimates from static models (Keane 2011; Chetty et al. 2011). In addition, we are able to use the methods from other papers that allow us to isolate plausibly exogenous variation in wages that stems from between-state and intertemporal variation in marginal tax rates.

Many of the recent papers that estimate the wage elasticity of labor supply do so using a discrete choice framework pioneered by van Soest (1995).[3] This approach is particularly well-suited to examining our question. First, it directly incorporates non-participation into the labor supply decision, allowing us to study the extensive and intensive margins in a common framework. Second, it allows us to utilize plausibility exogenous variation in wages caused by variation in the marginal tax rate across states and across time. Third, it allows us to incorporate fixed costs of working as well as other nonconvexities of the wage-hours locus.

[3]In a recent literature review, Bargain and Peichl (2016) compile papers that have estimated wage elasticities by time and the method used. Pooling across European and US studies, there is a clear trend towards using the discrete choice framework.

3.4.1 A static discrete choice model of labor supply

For notational ease, we first describe our discrete choice model for single (non-married) individuals. Suppose an individual i chooses hours of work per week h_{ij} from a set of J different alternatives. For singles, $J = 7$ and $h_{ij} \in \{0, 10, 20, 30, 40, 50, 60\}$. We assume that the individual earns a constant pre-tax hourly wage w_i regardless of their hours choice. Each choice of weekly work hours delivers a different level of weekly consumption c_{ij} and leisure l_{ij}. Consumption is equal to the sum of household labor income ($w_i \times h_{ij}$) and non-labor income (y_i), after taxes and government benefits. Leisure is equal to the total time endowment per week (112 hours) less weekly work hours.[4] Thus, each individual has the choice of seven different bundles $\{c_{ij}, l_{ij}\}_{j \in J}$.

The portion of utility that depends on the hours-consumption bundles and individual taste shifters x_i is denoted by $u_{ij}(c_{ij}, l_{ij}, x_i)$. Total utility is defined by:

$$v_{ij} = u_{ij}(c_{ij}, l_{ij}, x_i) + \varepsilon_{ij} \tag{3.4}$$

where ε_{ij} is an i.i.d. extreme value type I error term. Based on this error assumption, the probability of individual i choosing choice j, denoted p_{ij}, is given by the closed-form expression:

$$p_{ij}(w_i, y_i) \equiv \Pr(v_{ij} \geq v_{ik},\ \forall k \neq j) = \frac{\exp\left(u_{ij}(c_{ij}, l_{ij}, x_i)\right)}{\sum_{k=1}^{J} \exp\left(u_{ik}(c_{ik}, l_{ik}, x_i)\right)}. \tag{3.5}$$

This expression is the familiar conditional logit form for choice probabilities.

For our baseline model, we adopt the translog function for u_{ij}, as specified by van Soest (1995):[5]

$$u_{ij} = \beta^c \ln c_{ij} + \beta^{cc} (\ln c_{ij})^2 + \beta_i^l \ln l_{ij} + \beta^{ll} (\ln l_{ij})^2 + \beta^{cl} \ln c_{ij} \ln l_{ij} + f(x_i, h_{ij}). \tag{3.6}$$

We allow the parameter β_i^l to vary with several individual characteristics (a quadratic in the logarithm of age, the number of dependents aged 0 to 2 years, and the number of dependents aged 18 or younger) as we discuss in more detail below. The term $f(x_i, h_{ij})$ allows for fixed utility decrements

[4] We assume that individuals have 112 total hours per week to devote to work or leisure with the remaining 56 hours spent on sleep and personal care.

[5] Other authors who use a translog function include Flood et al. (2004) and Haan (2006).

of working ten, twenty, and thirty hours per week; these utility decrements might arise due to the true fixed costs of working part time, or they might capture employers' choices to not offer these hours packages (van Soest 1995).

For married households, we amend the basic specification to include a quadratic function of the logarithm of leisure for both spouses, as well as an interaction between the logarithms of leisure of each. Each spouse has their own fixed utility decrements of working ten, twenty, and thirty hours per week. The choice set for married couples is all combinations of the seven hours choices for each spouse, delivering 49 different hours choices for the couple.

At this point, one could estimate the model via maximum likelihood, but researchers routinely incorporate two extensions. The first is in recognition that a conditional logit functional form imposes the independence of irrelevant alternatives property (IIA), which implies that if one choice is taken away, an individual must substitute towards all other choices proportionally. Introspection suggests that an individual would be more likely to substitute towards a "nearby" hours choice. To allow for richer substitution patterns, a random term is included in the individual-specific slope on leisure:

$$\beta_i^l = \delta_0 + \delta_1 \ln \text{age}_i + \delta_2 (\ln \text{age}_i)^2 + \delta_3 \text{dep2}_i + \delta_4 \text{dep18}_i + \xi_i \tag{3.7}$$

where dep2_i and dep18_i are the number of dependents under the ages of two and 18, respectively, and $\xi_i \sim N(0, \sigma_\xi^2)$ is idiosyncratic preference heterogeneity for leisure (random slope). This specification avoids imposing IIA for the pooled sample of observations; however, IIA is still present at the individual level once we condition on ξ_i.

The second extension reflects that wages must be predicted for non-workers (and possibly for workers, too), which generates measurement error in the wages used for elasticity estimation. Specifically, suppose true wages w_i^* are given by:

$$w_i^* = \hat{w}(x_i) + \eta_i \tag{3.8}$$

where $\hat{w}(x_i)$ are expected wages based on covariates x_i and η_i is the idiosyncratic component to wages. We follow the common practice of "integrating out" measurement error. In practice, this amounts to pre-specifying the distribution of η_i, taking draws from this assumed distribution, and integrating over the draws when we maximize the simulated likelihood function (see van Soest (1995) for a more rigorous description). We specify that the measurement error in wages is normally distributed with zero mean and variance given by a Heckman selection model. We describe our Heckman selection procedure in Appendix Section C.2.

To accommodate the random slope on leisure and measurement error in wages, we estimate our utility parameters using maximum simulated likelihood (MSL). Define the likelihood contribution for a single individual as:

$$L_i = \int\int \left[p_{ij}(w_i, y_i \mid \xi_i)^{1[j=j^*]} f(\xi_i)\right] dF_\eta(\eta_i) dF_\xi(\xi_i) \tag{3.9}$$

where $p_{ij}(w_i, y_i|\xi_i)$ is the probability of individual i choosing work hours j conditional on the random slope term ξ_i, j^* is the observed work hours choice, $f(\xi)$ is the density of ξ, F_η is the cumulative density of η, and F_ξ is the cumulative density of ξ. This likelihood contribution can be approximated by taking R independent draws of (ξ_i, η_i) from their joint distribution and averaging over the draws. Specifically:

$$L_{iR} = \sum_{r=1}^{R} p_{ij}(w_{ir}, y_i \mid \xi_{ir})^{1[j=j^*]}; \quad w_{ir} \sim_{iid} F_\eta; \quad \xi_{ir} \sim_{iid} F_\xi. \tag{3.10}$$

Our baseline estimation uses 100 draws from a Halton sequence for the wage error and random slope.[6]

3.4.2 Estimating the elasticities

With parameter estimates in hand, we can directly simulate counterfactuals and compute elasticities. Specifically, we use the parameter estimates and Equation 3.5 to predict the probability that each individual i choices each choice j. We then calculate the expected hours worked for

[6] Halton sequences are deterministic sequences that cover domains of integration more evenly than do independent pseudo-random draws. As Train (2009) argues, simulations using Halton draws exhibit greater accuracy than those using pseudo-random draws, particularly in the context of logit choice models.

each individual as the probability-weighted average of hours. Next, we vary the wage or non-labor income for each individual, depending on the elasticity, and recalculate the predicted probabilities of each choice and expected hours worked. The percent change in expected hours worked is the numerator for our elasticity, and the percent change in wages or non-labor income is the denominator. We report the mean elasticity across individuals and derive standard errors using a parametric bootstrap with 50 draws from the joint distribution of utility parameters.

For the Marshallian own-wage elasticity, our estimated elasticity for each individual is given by:

$$e_M = \frac{\sum_j h_j * \left(p_j(w^1) - p_j(w^0)\right)}{\sum_j h_j * p_j(w^0)} * \frac{1}{\Delta w} = \frac{\sum_j h_j * \left(p_j(w^1) - p_j(w^0)\right)}{\Delta w * \bar{h}(w^0)} \tag{3.11}$$

where w^0 is the individual's original wage, w^1 is a counterfactual wage that is $\Delta w\%$ higher, and $\bar{h}(w^k)$ is the estimated hours worked when an individual is faced with wage w^k, i.e., $\bar{h}(w^k) = \sum_j h_j * p_j(w^k)$. The quantities are evaluated for individual i with a non-labor income of y, which we suppress to simplify notation. For all of our reported elasticities, Δw is one percent, though our observed trends are nearly identical for Δw equal to ten percent.

To provide further information about the underlying source of hours changes, we decompose the Marshallian elasticity into extensive (e_M^{EXT}) and intensive (e_M^{INT}) components:

$$e_M^{EXT} = \frac{\left[\left(1 - p_0(w^1)\right) - \left(1 - p_0(w^0)\right)\right] * \sum_{j \neq 0} h_j * q_j(w^0)}{\Delta w * \bar{h}(w^0)} \tag{3.12}$$

and

$$e_M^{INT} = \frac{\left[\left(1 - p_0(w^1)\right)\right] * \sum_{j \neq 0} h_j * \left(q_j(w^1) - q_j(w^0)\right)}{\Delta w * \bar{h}(w^0)} \tag{3.13}$$

where $q_j(w^k) = p_j(w^k)/(1 - p_0(w^k))$. This decomposition ensures that the underlying components sum to the Marshallian elasticity ($e_M = e_M^{EXT} + e_M^{INT}$), with the first component measuring the change in the probability of not working and the second measuring the change in expected hours conditional on working.

We estimate income elasticities by increasing each individual's after-tax non-labor income by \$1,000 in nominal value, but because some individuals have no non-labor income, we compute an arc elasticity by using the average non-labor income (pre- and post-$1,000 increase) in the denominator, as opposed to the percentage change.

Rather than use the Slutsky decomposition in Equation 3.3 to derive the Hicksian elasticity, we calculate the Hicksian elasticity using an income compensation so individuals' expected earnings at $\bar{h}(w^1)$ and w^1 are attainable at $\bar{h}(w^1)$ and the original wage w^0:

$$e_H = \frac{\sum_j h_j * \left\{ p_j \left(w^1, y \right) - p_j(w^0, y + \left[\tilde{w}(w^1, y) - \tilde{w}(w^0, y) \right] * \bar{h}(w^1, y)) \right\}}{\Delta w * \bar{h}(w^0, y + \left[\tilde{w}(w^1, y) - \tilde{w}(w^0, y) \right] * \bar{h}(w^1, y))} \tag{3.14}$$

where $\tilde{w}(w^k, y)$ denotes the expected after-tax earnings when an individual faces wage w^k and non-labor income y.[7] Equation 3.14 shows that, in order to calculate the Hicksian elasticity, we should compute the choice probabilities at the original wage w^0 while increasing non-labor income by the expected increase in after-tax income due to the wage change from w^0 to w^1. This adjustment to non-labor income allows us to remove the income effect caused by the higher wage.[8]

3.5 Data

Our primary data source is the 1979 through 2017 Annual Social and Economic March Supplement of the Current Population Survey (CPS). These surveys provide total earnings and hours worked for the previous year, as well as demographic information like number of dependents and state of residence. We list all results by survey year throughout the paper.

The sample is restricted to adults in single-family households as defined by Census Bureau. Single adults must be between 26 and 55 years old, and couples must have one spouse between 26 to 55 years old and the other spouse between 22 and 59 years old. We exclude individuals

[7]The fact that the Slutsky equation may not hold in a discrete choice model is well-developed elsewhere, including Dagsvik and Karlström (2005) and Dagsvik et al. (2014). The formulation we implement is simpler than the approaches laid out in these studies, in part because we use income compensation rather than utility compensation for the worker.

[8]An alternative approach to the one stated here involves increasing the wage rate but reducing after-tax income by the difference between expected earnings at the higher wage and original wage. For some individuals, the non-labor income decrease results in negative consumption and undefined utility. However, for individuals with well defined utility under both approaches, the estimated Hicksian elasticities are nearly identical.

who are enrolled in school, disabled, self-employed, members of the armed forces, earn farm or business income, work unpaid in a family business, report wages less than \$4 per hour or more than \$150 per hour, or report non-labor income less than \$0 or greater than \$1,000,000. We do not exclude individuals with imputed survey responses. If either spouse meets our exclusion criteria, we exclude the entire household. For married couples, if the age-year sample is greater than 10,000 households, we take a random sample of 10,000 households to reduce the computational burden of estimating our models.

We use usual hours worked per week from the prior year and discretize hours into seven choices: 0, 10, 20, 30, 40, 50, and 60 hours per week. We compute the hourly wage from wage and salary income in the prior year divided by the usual work hours multiplied by weeks worked in the prior year. Non-labor income is the sum of dividend income, interest income, rental income and other property income, alimony, child support, and other non-property income. Wages, of course, are unobserved for non-workers, so we impute wages for non-workers based on a standard Heckman selection procedure. Appendix Section C.2 contains complete details of the sample construction, basic descriptive statistics, and parameters from the Heckman corrected wage estimation.

We supplement the CPS with two additional data sources. The first is NBER's TAXSIM, which allows us to calculate after-tax income by state and year utilizing micro-level information on earnings, state of residence, and household structure. The second is the Urban Institute's TRIM3, which allows us to calculate the social program benefits a household qualifies for (e.g., AFDC, SNAP, SSI) based on their household earnings, state of residence, and household structure. Data from TRIM3 is available from survey years 1994 to 2000 and 2002 onward, so we restrict most of our analysis to this time frame.[9] See Appendix Section C.3 for further details on how we incorporate TAXSIM and TRIM3.

As an initial look at the data, Figure C.1.1 shows the labor force participation rate, average

[9] While TRIM3 benefit simulations are available for 2001, they do not include observations from the SCHIP expansion, and the individual identifiers which are normally used to merge the TRIM3 data to the ASEC data do not match.

annual hours worked conditional on working, average wage conditional on working, and average non-labor income for our primary sample period and for four demographic groups (single and married men and women). The well-documented changes are readily apparent. Labor force participation decreased modestly for men, increased for single women during the 1990s, and remained relatively constant for married women. Among the employed, annual hours worked and wages increased for all four demographic groups despite a brief decline in the late 2000s. Non-labor income is very sensitive to broader business cycles and does not have a clear upward or downward trend over time.

For a more detailed look at labor force behavior, Table C.1.1 shows the distribution of hours worked for select years across our primary sample period. The modal choice of each demographic group is 40 hours per week, and for every group except for married women, approximately 60% choose 40 hours. Men, both single and married, are more likely to work 50 or more hours per week than work 30 or fewer hours. Married women are consistently more likely to work 30 or fewer hours than 50 or more hours.

3.6 Results

We first present our baseline results for Marshallian own-wage elasticities in Section 3.6.1, followed by results based on different utility function assumptions in Section 3.6.2. Section 3.6.3 contains results based on different approaches for addressing measurement error in wages. Finally, Section 3.6.4 presents results for other elasticities, including extensive and intensive Marshallian elasticities and Hicksian elasticities. Parameter estimates for our baseline specification are provided in the Appendix Section C.4

3.6.1 Baseline results

For our baseline results, we estimate the model outlined previously, except we impose that the variance on the random slope for leisure is zero ($\sigma_{\xi}^2 = 0$). While this implies that we are estimating a typical "conditional logit" model as opposed to a "random slope logit" model, we still utilize MSL to integrate out the measurement error in predicted wages for non-workers. We relax this assumption in the next subsection.

Figure C.1.2 presents in dark blue the mean own-wage elasticities from 1994 through 2017 as estimated from our baseline model. The same estimates are reported for select years in Tables C.1.2 and C.1.3. For three groups – single men, married men, and married women – we observe small increases in the labor supply elasticity over time. For example, the own-wage elasticity increases from 0.050 (standard error: 0.012) to 0.113 (0.012) for single men from 1994 to 2017, from 0.090 (0.004) to 0.118 (0.005) for married men, and from 0.261 (0.009) to 0.340 (0.010) for married women. For the fourth group, single women, the estimates increase after 2000, from 0.141 (0.011) in 2000 to 0.231 (0.012) in 2017, but given the decline in the elasticity from 1994 to 2000, the elasticity is relatively flat over the full time period. The modest increase in the own-wage elasticity over the last two decades across various groups represents one of the key findings of our paper.

The conclusion that own-wage elasticities were declining for single women up to 2000 is not surprising given previous work (e.g,. Heim 2007). But because our baseline estimates use a benefit simulator that begins in 1994, they are only partially comparable to previous papers that examine trends in own-wage elasticities. We can produce a consistent set of elasticity estimates, going back as early as 1979, by ignoring government assistance.[10] These estimates are presented in Figure C.1.2 with dark red lines and triangular markers.

The removal of the benefit simulator has little affect on the estimated elasticities for most demographic groups and years, especially for men. Elasticities for single and married women are more sensitive to removing the benefit simulator, but the trends observed from 1994 onward are still apparent. Additionally, the inclusion of data from 1979 to 1993 reveals a steady upward trend in the mean own-wage elasticity for single and married men and a downward trend for single and married women lasting until 2000. These patterns are similar to those found in previous studies

[10]Many previous papers that calculate own-wage elasticities do not include government assistance, such as Heim (2007), Blau and Kahn (2007), and Bishop et al. (2009). By excluding government assistance, not only do we obtain a consistent time series over a longer period, we also produce estimates that are more comparable to the existing literature.

that examined this earlier time period.[11]

3.6.2 Robustness to alternative utility function assumptions

A simplifying assumption that we made for our baseline results is that the variance of the idiosyncratic preference heterogeneity for leisure is zero. Although this assumption is at odds with the existing literature, it is not at odds with previous empirical findings – numerous papers report results that are consistent with the random slope being unimportant.[12] Regardless, we compare our baseline conditional logit results to results from a random slope logit model where the variance on the leisure preference heterogeneity term is not restricted to be zero.

As shown in Figure C.1.3, the effect of adding random slopes to leisure varies by demographic group. For single women, neither the level nor the trend are sensitive to this modeling change, though the standard errors are significantly noisier. This occurs because the estimated variance on the random slope for leisure is near zero in almost every year, but the standard errors on the variance are quite large. Elasticity estimates are nearly identical for married men with a random slope, but the estimates shift upward (while preserving the same the trend over time) for married women, and the standard errors are often incalculable.[13] The group for whom the random slope

[11]For single women, our baseline results suggest that the own-wage elasticity declined by 47% from 1979 to 2000, from 0.261 (standard error: 0.019) to 0.138 (0.011). In Bishop et al. (2009), the authors find an 80% decline from a base of 0.20 over a similar period.

[12]van Soest (1995) estimates random slopes with variances that are not statistically different from zero and very small relative to the mean value. Callan and van Soest (1996) estimate random slopes with variances that are not statistically different from zero, but the variance for women could be practically significant. van Soest et al. (2002) estimate a precise zero for random slope variances for women. Brewer et al. (2006) include random slopes on income, female hours, fixed costs of work, and welfare participation. For single mothers and couples, the first three variances are precisely estimated zeroes, and the fourth is large but statistically insignificant from zero. Two papers, Haan (2006) and Löeffler et al. (2018), examine this issue directly and conclude that labor supply elasticities tend to change very little when allowing for random slopes on just consumption or leisure individually, although both papers find that allowing for more unrestricted unobserved heterogeneity can have some small effects on point estimates.

[13]In some years, after including a random slope, the estimated hessian from the final evaluation of the likelihood function is invertible, but its inversion is not positive semidefinite. We use the inverse hessian as the covariance matrix when drawing parameter values for our bootstrap procedure,

specification seemingly matters the most is single men, as the elasticities are consistently larger and the trend over time is steeper. For single men, the random slope is large enough to roughly double the mean own-wage elasticity in most years.

In addition to the introduction of random slopes for leisure, we also test the robustness of our findings to a quadratic utility function, as used in Bargain et al. (2014), as opposed to our baseline translog utility function. We present these results in Appendix Section C.5. Both utility functions yield very similar elasticity estimates.

3.6.3 Measurement error in wages

In Figure C.1.4, we compare elasticity estimates with different strategies to address measurement error in wages. First, we compare estimates using the expected wage for non-workers as opposed to drawing from the conditional distribution of wages. Across all demographic groups, both methods yield similar elasticity estimates. One important caveat is both methods only use predicted wages for non-workers. Because most individuals in our samples are working, this procedure treats few individuals as having error-laden wages.[14] Some previous studies use predicted wages for both workers and non-workers alike, and accounting for measurement error in those circumstances likely matters more.[15]

To analyze this possibility, Figure C.1.4 also presents results that use predicted wages for everyone. The series labeled "All, 100 Draws" integrates out measurement error using 100 Halton draws, while the series labeled "All, 0 Draws" ignores measurement error and uses the mean predicted earnings for everyone. Our results suggest that the decision to predict wages for everyone or for only non-workers matters, as elasticities tend to be larger when we predict wages for ev-

so when this matrix is not positive semidefinite, it cannot be used as a valid covariance matrix.

[14]In 2014, the percent working is 93% among single men, 88% among single women, 95% among married men, and 74% among married women. See Appendix Tables C.2.1 and C.2.2 for the percentage of non-workers in other years.

[15]Studies that predict wages only for non-workers include van Soest (1995), Blundell et al. (1998), and Haan (2006). Studies that predict wages for the full sample include Flood et al. (2004) and Bargain et al. (2014). See Löeffler et al. (2018) for a discussion and analysis of this issue.

eryone; however, the estimated trends are insensitive to this choice. Once again, integrating out measurement error as opposed to using the mean predicted earnings preserves the estimated trends, especially for married men and women.[16]

This finding has two important implications. First, to the extent that adjusting for measurement error in wages is not necessary, we can use standard maximum likelihood estimation packages rather than the more computationally costly maximum simulated likelihood methods outlined above. Second, our analysis of measurement error has ignored the fact that, when adjusting for measurement error, we were pre-specifying its distribution. By instead relying just on the conditional mean wage, we need to make no such decision about the size of the variance.[17]

3.6.4 Other elasticities

We now provide estimates of other elasticities beyond the Marshallian total own-wage elasticity: extensive and intensive margin own-wage elasticities, cross-wage elasticities, Hicksian own-wage elasticities, and income elasticities. All of the following results are based on our baseline model.

Figure C.1.5 contains estimates for the extensive and intensive margin own-wage elasticities. Across all four demographic groups, the intensive margin elasticities are small and vary little over

[16]Why does accounting for measurement error matter little? For the case at hand, a reasonable representation of the measurement error process is $w^* = w + \eta$, where w denotes expected wages and w^* denotes actual wages. This measurement error process differs from the standard classical measurement error form (which reverses the role of w and w^*) because we are correcting for measurement error in cases where we utilize predicted wages based on a Heckman selection equation. In other words, we are using predicted wages w in estimation, whereas the actual wages w^* include an individual component η that is unobserved. While analytic results are not available for the nonlinear labor supply function we use for estimation, this alternative form of measurement error leads to little or no effects in other settings. For example, it is straightforward to show that the OLS estimate of a regression of y on w is consistent for an OLS regression of y on w^*(assuming that η is i.i.d. in both cases), which is contrary to the usual attenuation result under classical measurement error from the use of an error-ridden variable.

[17]Changes in the assumption on the size of the variance of the measurement error can appreciably change the results depending on its relative size compared to other parameters in the model. For example, when predicting wages for everyone (which leads to a large estimated variance), elasticities tend to be more sensitive to the assumption of its size.

time. Thus, changes in the total elasticities are driven almost exclusively by changes at the extensive margin. This finding aligns with the existing literature; for example, Heim (2007) studying married women and Bishop et al. (2009) studying single women find that the total own-wage elasticity and the extensive margin elasticity decline by the same magnitude during the 1980s and 1990s.

Figure C.1.6 contains estimates for cross-wage elasticities, Hicksian own-wage elasticities, and income elasticities. Cross-wage elasticities (an individual's hours response to a change in their spouse's wage) are small and relatively stable from 1994 to 2017 for married men (-0.019 to -0.035) and women (-0.144 to -0.157).

As expected, we find that the Hicksian elasticity is consistently larger than the Marshallian elasticity, and the two follow similar trends over time. The difference between the two elasticities is significantly larger for single men and women relative to married men and women, as individual labor income makes up a smaller share of total income for married households and the income elasticities for married couples are smaller. For single men, the Hicksian elasticity increases more rapidly than the Marshallian elasticity over the entire time period – a 0.152 increase versus a 0.062 increase – but slower in percentage terms – a 54.8% increase versus a 123.0% increase. For single women, the two have similar percentage declines from 1994 to 2000, but from 2000 onward, the Hicksian elasticity increases faster in both levels and percentages – a 0.189 (68.0%) increase versus a 0.058 (33.4%) increase.

The trends in income elasticities vary by demographic group. For single men, income elasticities oscillated up and down until steadily growing more negative after 2000, decreasing from -0.029 (standard error: 0.008) to -0.092 (0.014) in 2017. Income elasticities for single women increased rapidly between 1994 to 1999, from -0.369 (0.036) to -0.109 (0.017), before reversing throughout the 2000s back down to -0.264 (0.026) in 2017. For married men and women, income elasticities were relatively stable over the entire period with small increases from 1994 to 2005 and equally small decreases from 2005 to 2017.

3.7 Conclusion and discussion

In this paper, we examine trends in labor supply elasticities for four demographic groups: single and married men and single and married women. Our results suggest that own-wage elasticities have steadily increased over the last two decades for all four groups. For single and married women, this finding is a remarkable reversal of the "incredible shrinking elasticities" reported for the 1980s and 1990s in previous studies. These reversals were sufficiently large to reverse all of the previous declines for single women and about half of the previous declines for married women. For all groups, changes in the extensive margin account for nearly all of these trends; the intensive margin contributes little to overall elasticities regardless of group or time period.

Our results also show that the estimated trends are robust to some of the common alternative modeling assumptions used in the literature, including computationally demanding assumptions like the use of random slope logit and integrating out measurement error. This finding is significant because researchers who make simplifications in these dimensions can choose to increase complexity in other dimensions, like the size of the choice set or non-convexities in the budget set.

Taken together, our results raise an important question: why did labor supply elasticities increase over the last two decades? Because the extensive margin accounted for nearly all of the increases for all four groups, likely candidates include those factors that affect the decision to work. Abraham and Kearney (2020) suggest that one potential driver of labor force participation trends involves increases in the generosity of safety net assistance, namely through federal disability insurance, SNAP benefits, or publicly provided health insurance.[18] They argue that the latter two factors likely play small roles in participation trends because of timing inconsistencies, and that seems likely to be the case for the trends in elasticities as well. For example, the Affordable Care Act, which went into effect in 2009, cannot explain the increase in estimated elasticities be-

[18] Abraham and Kearney (2020) examine changes in labor force participation rates among young and prime-age adults between 1999 and 2018, assessing the evidence for a host of factors that could explain declining participation rates among men and women younger than 55. While the factors underlying trends in extensive margin elasticities and in participation rates are not necessarily identical, it would be surprising if they were wholly unrelated.

tween 1999 and 2008 that we find for each of the four demographic groups. On the other hand, federal disability caseloads grew steadily from 1999 to 2015, and Abraham and Kearney (in addition to Binder and Bound 2019) suggest that this growth may account for as much as five percent of the decline in participation rates over the same period. Increased access to disability assistance may have also contributed to rising extensive margin elasticities over that period by reducing the relative appeal of working for low wages.

Of course, the increasing trends in (pre-tax) labor supply elasticities may also stem from policies that increase, rather than decrease, participation rates. The primary candidates involve the expansions of the Earned Income Tax Credit in 1993, 1996, 2001, and 2009. However, our estimated elasticities for both single and married women decline until roughly 2000 (in agreement with previous estimates) before reversing, which is inconsistent with the steady expansions of the EITC. Moreover, the expansions cannot explain the evolution of elasticities for single (and, to some extent, married) men, who are largely ineligible for EITC benefits.

In sum, we find clear evidence that labor supply elasticities have increased in the last twenty years, but convincing explanations for these trends have not emerged. Our estimates suggest that social program benefits influence elasticities for women, but accounting for intertemporal variation in those benefits does not markedly influence trends. For men, we find that the treatment of benefits has no effect on either the estimated levels or trends in elasticities.

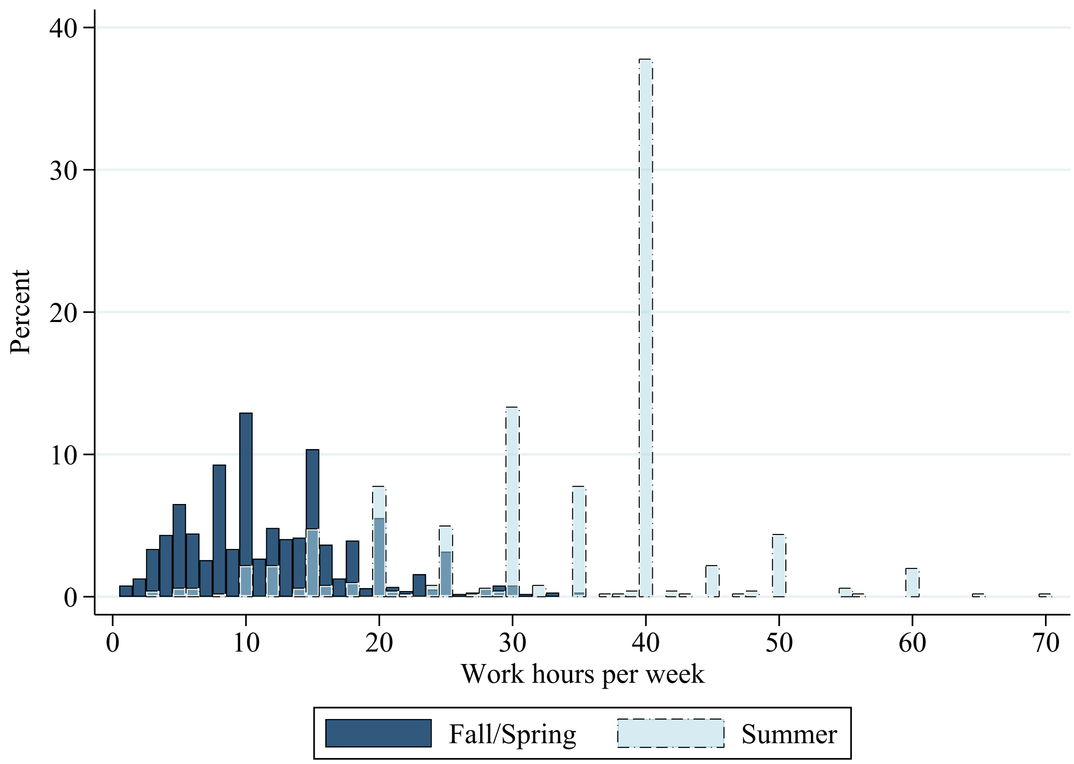
APPENDICES

APPENDIX A

CHAPTER 1 APPENDIX

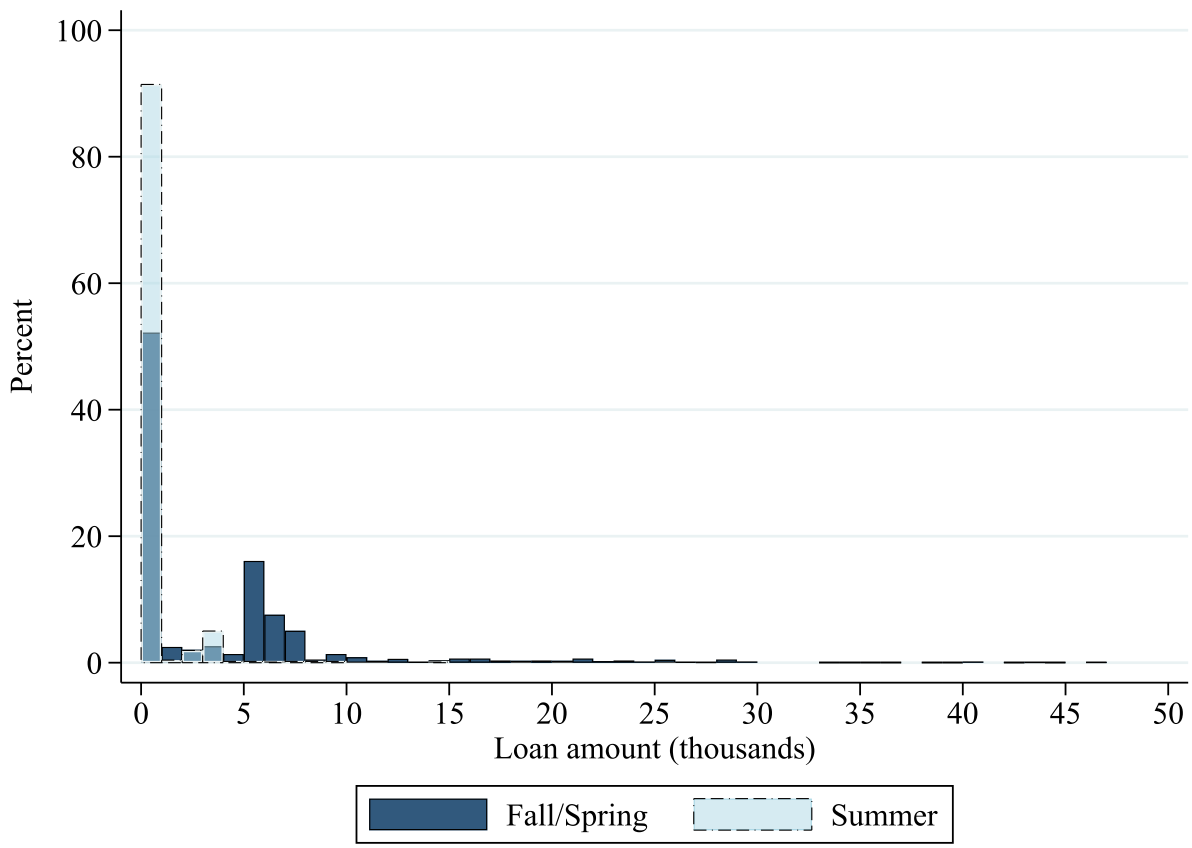
A.1 Main text figures & tables

Figure A.1.1 Distribution of Work Hours



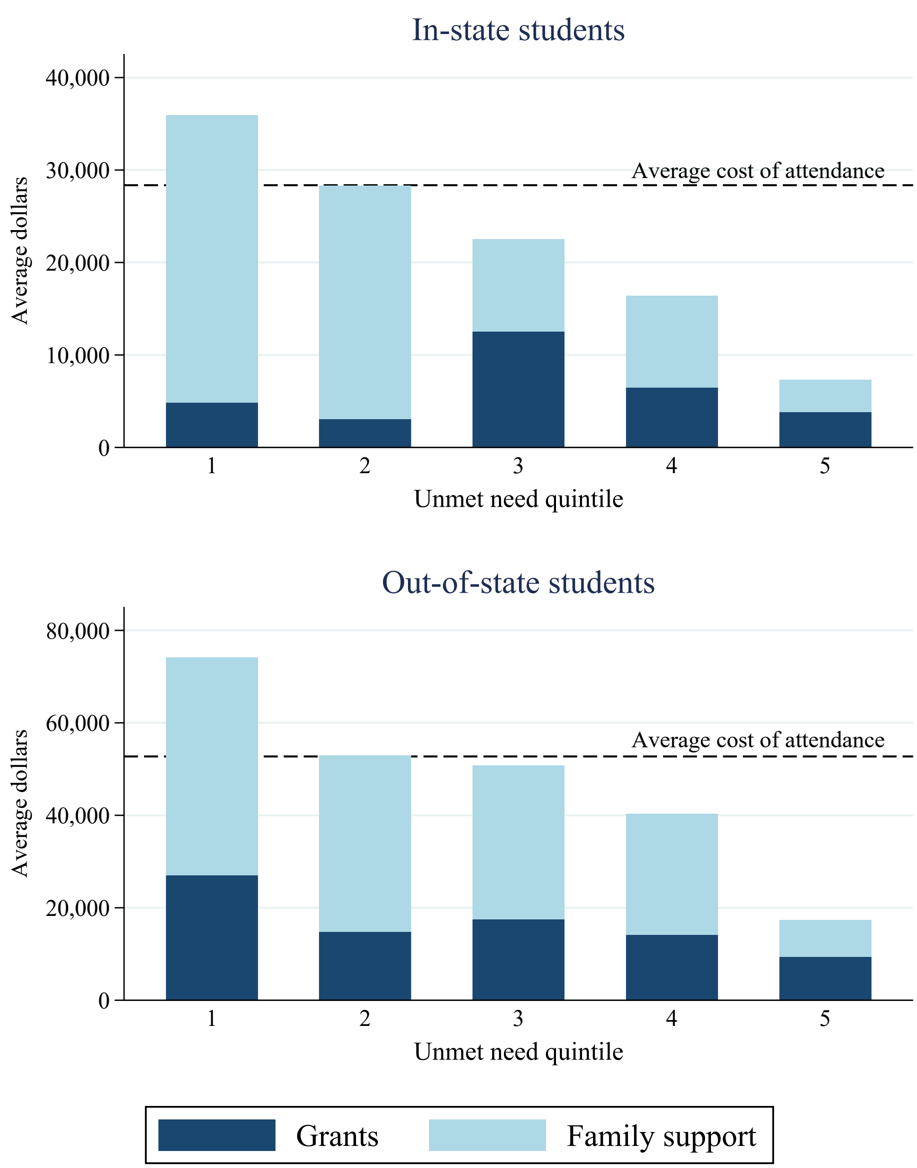
Notes: This figure presents the distribution of work hours among students with non-zero work hours. Hours worked in the fall and spring semesters are averaged together. Number of observations: 1,013 (fall and spring) and 503 (summer).

Figure A.1.2   Distribution of Borrowing Amounts



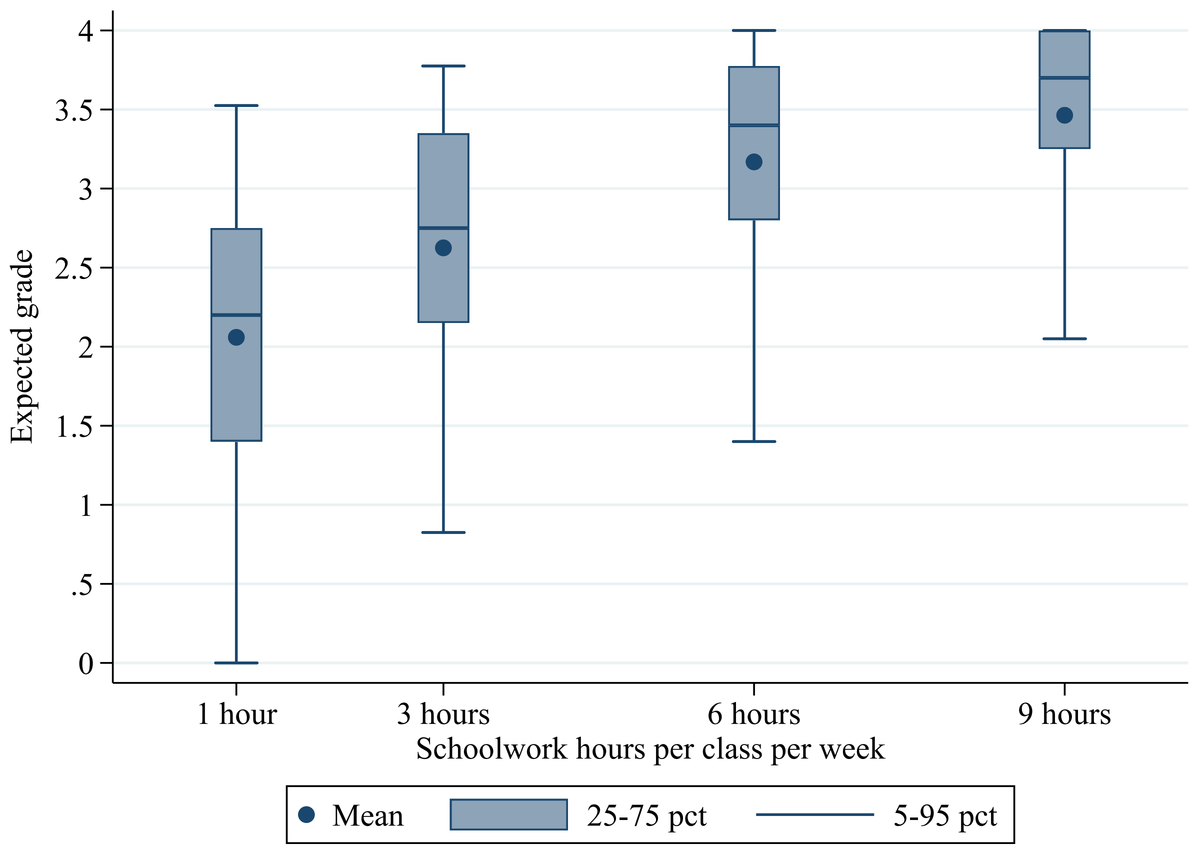
Notes: This figure presents the distribution of accepted student loans. Number of observations: 1,964 (fall and spring) and 979 (summer).

Figure A.1.3 Grants and Family Support by Unmet Need Quintile



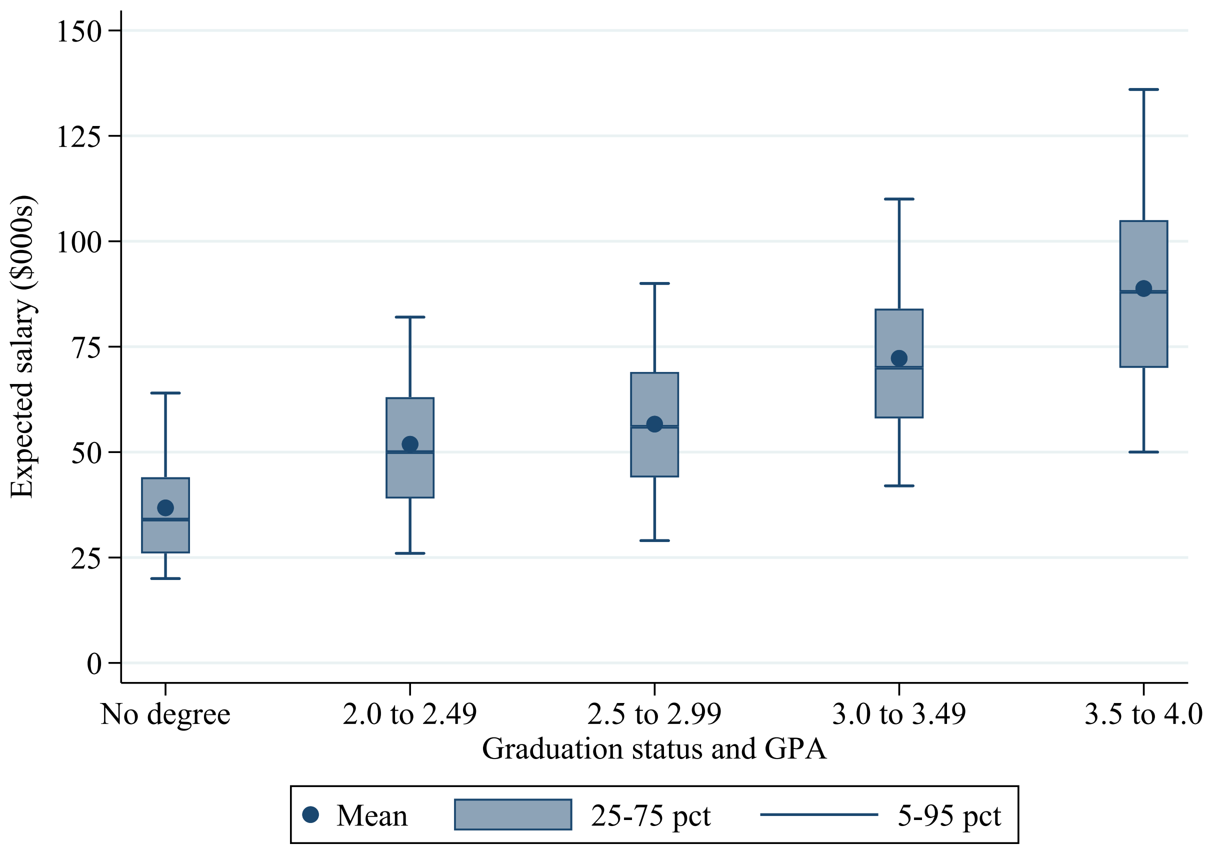
Notes: This figure presents the average amount of grants and family financial support received in the fall and spring term by quintile of unmet financial need. Unmet need is equal to cost of attendance less grants and family support. The dashed line denotes the average cost of attendance. Results are separated by residency status (in-state versus out-of-state). Number of observations: 1,767 (in-state) and 197 (out-of-state).

Figure A.1.4 Distribution of Expected Grades Conditional on Schoolwork



Notes: This figure presents the distribution of expected grades conditional on schoolwork time. Schoolwork time is measured as hours per class per week. Expected grades are calculated from students' probabilities of earning each discrete letter grade. Number of observations: 985.

Figure A.1.5 Distribution of Expected Salaries Conditional on GPA



Notes: This figure presents the distribution of post-school full-time salaries conditional on GPA upon graduation. Expected salaries are calculated from students' probabilities of receiving salary offers in particular ranges. Number of observations: 985.

Table A.1.1 Summary Statistics for SEES Respondents and Recipients

Variable	**Respondents**	**Recipients**
Female	0.683	0.534
White, non-Hispanic	0.813	0.778
Black or African American	0.069	0.104
Hispanic	0.050	0.054
Asian	0.093	0.088
American Indian or Alaskan Native	0.008	0.013
Native Hawaiian or Pacific Islander	0.007	0.005
Out-of-state	0.107	0.136
First generation	0.171	0.188
Freshman	0.263	0.267
Sophomore	0.285	0.286
Junior	0.308	0.301
Senior	0.144	0.146
Honors college	0.253	0.159
Business	0.136	0.181
Humanities	0.062	0.053
Health	0.031	0.025
STEM	0.491	0.453
Social Science	0.265	0.267
Undecided major	0.014	0.020
Cumulative GPA	3.485	3.270
Observations	985	4,356

Notes: This table presents summary statistics for the sample of survey respondents and the continuously enrolled domestic first-time-in-college survey recipients. Each respondent is only counted once regardless of how many terms they were enrolled at MSU. Class code, field of study, and cumulative GPA are current as of the end of spring 2019.

Table A.1.2 Credit Hour Enrollment by Semester

Credits	**Fall and Spring**	**Summer**	**Full Year**
0 to 2	0.00	61.70	0.00
3 to 5	0.00	15.22	0.00
6 to 8	0.00	16.14	0.00
9 to 11	0.00	4.90	0.00
12 to 14	0.10	1.12	0.10
15 to 17	0.20	0.61	0.10
18 to 20	0.51	0.31	0.10
21 to 23	0.87	0.00	0.41
24 to 26	19.30	0.00	10.83
27 to 29	46.59	0.00	34.83
30 to 32	28.67	0.00	25.64
33 to 35	3.11	0.00	12.46
36 to 38	0.61	0.00	9.91
39 to 41	0.05	0.00	3.47
42 to 52	0.00	0.00	2.15
Observations	1,964	979	979

Notes: This table presents the proportion of students enrolled in the specified number of credit hours for both fall and spring terms and summer terms. Credits hours are based on enrollment at the quarter point in the semester, which is the official census date for the University. The last column, credit hours for the full year, does not include the fall 2018-spring 2019 academic year because the data does not contain summer 2019 enrollment data.

Table A.1.3 Expected Schoolwork Hours

		Work Hours			
		0 hours	**10 hours**	**20 hours**	**30 hours**
Credit Hours	**12 hours**	21.98	–	18.48	–
		(10.87)	–	(9.41)	–
	15 hours	–	21.81	–	17.78
		–	(10.13)	–	(10.21)
	18 hours	27.71	–	20.81	–
		(11.23)	–	(11.60)	–

Notes: This table presents the mean (standard deviation in parentheses) expected schoolwork hours for each hypothetical schedule of credits and work hours. Number of observations: 985.

Table A.1.4 Data and Model Parameters

	Notation	**Periods Observed**
Choice variables		
Labor supply	h_{it}	$t = \{1, \ldots, T_i\}$
Credit hours	k_{it}	$t = \{1, \ldots, T_i\}$
Borrowing	b_{it}	$t = \{1, \ldots, T_i\}$
Time-varying state variables		
Cumulative credits earned	K_{it}	$t = \{1, \ldots, T_i\}$
Grade point average (GPA)	G_{it}	$t = \{1, \ldots, T_i\}$
Total debt	B_{it}	$t = \{1, \ldots, T_i\}$
Other variables		
In-school wages	w_i^{sch}	$\max\{t \mid h_{it} > 0\}$
Family financial support	$fam(\cdot)$	$t = T_i$
Net education expenses	$edu_t(\cdot)$	$t = \{1, \ldots, T_i\}$
Auxiliary model parameters		
Expected study hours	δ_i	
Returns to studying	γ_i	
Wage model	ω_i	

Notes: This table summarizes the key variables in the structural model and for what periods I observe them in the data. The student's first semester at MSU is denoted by period 1, and the semester of the survey is T_i. For example, if the student enrolled in the fall of 2017, I observe them for three periods, fall 2017-spring 2018, summer 2018, and fall 2018-spring 2019.

Table A.1.5 Auxiliary Model Parameters

Parameter	**Mean**	**Std. Dev.**	**25th Pct.**	**75th Pct.**
	Panel A: Studying function			
Constant: δ_{0i}	2.525	1.767	1.260	3.667
Credit hours: δ_{1i}	-0.056	0.086	-0.106	-0.002
Work hours: δ_{2i}	-0.020	0.046	-0.046	0.006
Work hours^2: δ_{3i}	0.00014	0.00128	-0.00057	0.00083
	Panel B: Grade production function			
Constant: γ_{0i}	1.279	1.551	0.451	2.263
Study hours: γ_{1i}	0.367	0.319	0.193	0.453
C threshold: γ_C	1.183			
B threshold: γ_B	2.423			
A threshold: γ_A	3.768			
Error variance: σ^g	-0.0017			
	Panel C: Post-school salary offer			
Constant: ω_{0i}	10.352	0.338	10.087	10.579
Degree premium: ω_{1i}	0.302	0.419	0.028	0.556
GPA x Degree: ω_{2i}	0.186	0.595	-0.101	0.473
GPA^2 x Degree: ω_{3i}	0.114	0.292	-0.016	0.260
Error variance: σ_i^w	0.359	0.144	0.267	0.461
Observations	985			

Notes: This table presents summary statistics for the distribution of parameters estimated before the structural model. The studying function can be found in Eq. 1.12, the grade production function in Eq. 1.13, and the post-school salary offer function in Eq. 1.15.

Table A.1.6 Structural Model Parameters

	Coefficient	Std. Err.
In-school utility		
Log(Consumption)	0.578	(0.033)
Log(Leisure)	0.465	(0.062)
Summer	2.637	(0.151)
Log(GPA)	0.899	(0.022)
1[Work $>$ 0]	-0.638	(0.064)
Summer	0.023	(0.185)
1[Credits = 0]	1.750	(0.394)
1[Credits = 15]	0.859	(0.070)
1[Stafford loan]	-0.040	(0.118)
1[Max loan]	-0.826	(0.206)
Post-school utility		
Log(Post-school wage)	26.646	(1.083)
Log(Post-school debt)	-1.213	(0.040)
Observations	142	

Notes: This table presents the estimated parameters to the utility functions specified in Eq. 1.10 and Eq. 1.14. To reduce computation time, I use a 15% sample of the data to estimate the parameters.

Table A.1.7 Observed and Predicted Choice Probabilities

	Observed	**Predicted**	**Difference**
	Panel A: Credit hours		
Fall and spring			
26 credits	0.332	0.382	-0.050
30 credits	0.630	0.570	0.060
34 credits	0.038	0.048	-0.010
Summer			
0 credits	0.613	0.647	-0.034
3 credits	0.147	0.256	-0.109
8 credits	0.240	0.097	0.143
	Panel B: Work hours		
Fall and spring			
0 hours	0.539	0.587	-0.048
10 hours	0.280	0.191	0.089
20 hours	0.181	0.222	-0.041
Summer			
0 hours	0.495	0.563	-0.068
20 hours	0.138	0.269	-0.132
40 hours	0.367	0.167	0.200
	Panel C: Borrowing		
Fall and spring			
No new loans	0.558	0.598	-0.040
Stafford loans	0.363	0.348	0.015
Maximum loans	0.079	0.054	0.025
Summer			
No new loans	0.924	0.893	0.031
Stafford loans	0.066	0.037	0.029
Maximum loans	0.009	0.070	-0.061

Notes: This table presents the observed and predicted probabilities of each discrete choice in the model. Number of observations: 1,964 (fall and spring) and 979 (summer).

Table A.1.8 Elasticities (Fall and Spring)

Elasticity	**Mean**		**25th Pct.**	**Median**	**75th Pct.**
Panel A: Credit hours elasticities (Mean: 28.36)					
Financial aid	0.0032	(0.0005)	-0.0024	-0.0002	0.0001
Tuition rate	-0.0028	(0.0003)	-0.0007	0.0000	0.0003
Return to studying	-0.0082	(0.0007)	-0.0100	-0.0008	0.0049
Return to GPA	0.0035	(0.0005)	-0.0003	0.0019	0.0082
Wage	-0.0010	(0.0001)	-0.0016	-0.0005	0.0001
Panel B: Work hours elasticities (Mean: 6.29)					
Financial aid	0.0012	(0.0029)	-0.0093	0.0000	0.0023
Tuition rate	0.004	(0.003)	-0.007	0.000	0.018
Return to studying	-0.119	(0.005)	-0.217	-0.022	0.094
Return to GPA	-0.211	(0.006)	-0.201	-0.034	0.000
Wage	0.291	(0.033)	0.188	0.262	0.357
Panel C: Borrowing elasticities (Mean: $3,947)					
Financial aid	-0.781	(0.043)	-0.166	-0.009	0.001
Tuition rate	0.233	(0.013)	-0.005	0.027	0.172
Return to studying	-0.059	(0.012)	-0.063	-0.006	0.009
Return to GPA	0.0057	(0.0080)	-0.0232	-0.0025	0.0059
Wage	-0.092	(0.013)	-0.140	-0.044	-0.022

Notes: This table presents estimated elasticities for the fall and spring periods. Elasticities estimated via simulation with (1) a $1,000 increase to financial aid (2) a 10% increase to tuition (3) a 10% increase to the return to studying parameter γ_{1i} (4) a 10% increase to the return to GPA parameters in the post-school wage function ω_{2i} and ω_{3i} (5) a 10% increase to the in-school wage rate. All elasticities are calculated as arc elasticities where percentage changes are based on the midpoint between the original and simulated variables. Standard errors estimated via a parametric bootstrap with 30 draws from the joint distribution of utility parameters. Number of observations: 1,964.

Table A.1.9 Elasticities (Summer)

Elasticity	**Mean**		**25th Pct.**	**Median**	**75th Pct.**
Panel A: Credit hours elasticities (Mean: 2.43)					
Financial aid	-0.028	(0.004)	-0.040	-0.022	-0.010
Tuition rate	-0.0058	(0.0020)	-0.0171	-0.0056	-0.0031
Return to studying	0.011	(0.033)	-0.004	0.075	0.181
Return to GPA	0.177	(0.011)	0.033	0.126	0.273
Wage	-0.051	(0.007)	-0.076	-0.043	-0.020
Panel B: Work hours elasticities (Mean: 17.01)					
Financial aid	-0.0029	(0.0010)	-0.0174	-0.0060	0.0192
Tuition rate	-0.0077	(0.0008)	-0.0065	0.0001	0.0006
Return to studying	-0.0084	(0.0019)	-0.0226	-0.0032	0.0096
Return to GPA	-0.019	(0.002)	-0.026	-0.010	-0.001
Wage	0.238	(0.031)	0.173	0.236	0.291
Panel C: Borrowing elasticities (Mean: $325.69)					
Financial aid	-0.049	(0.009)	-0.067	-0.038	-0.020
Tuition rate	0.038	(0.009)	-0.012	0.007	0.041
Return to studying	-0.019	(0.040)	-0.019	0.063	0.176
Return to GPA	0.142	(0.010)	0.015	0.092	0.208
Wage	-0.164	(0.020)	-0.242	-0.165	-0.062

Notes: This table presents estimated elasticities for the summer periods. Elasticities estimated via simulation with (1) a $500 increase to financial aid (2) a 10% increase to tuition (3) a 10% increase to the return to studying parameter γ_{1i} (4) a 10% increase to the return to GPA parameters in the post-school wage function ω_{2i} and ω_{3i} (5) a 10% increase to the in-school wage rate. All elasticities are calculated as arc elasticities where percentage changes are based on the midpoint between the original and simulated variables. Standard errors estimated via a parametric bootstrap with 30 draws from the joint distribution of utility parameters. Number of observations: 979.

Table A.1.10 Elasticity Heterogeneity (Fall and Spring)

Variable	**Bottom Tercile**	**Top Tercile**	**Difference**
Panel A: Work hours and returns to studying (N = 1,308)			
Unmet financial need	2,673	3,400	-727*
In-school wage	10.82	11.23	-0.40*
Study cost of work	-0.029	-0.015	-0.014***
Return to studying	0.357	0.403	-0.046***
Return to GPA at 3.0	0.466	0.411	0.055***
Cumulative credit hours	21.36	21.63	-0.27
Panel B: Work hours and returns to GPA (N = 1,315)			
Unmet financial need	2,844	3,038	-194
In-school wage	11.16	11.16	0.00
Study cost of work	-0.040	0.003	-0.043***
Return to studying	0.390	0.382	0.008
Return to GPA at 3.0	0.515	0.354	0.161***
Cumulative credit hours	23.32	20.51	2.81*
Panel C: Borrowing and financial aid (N = 1,311)			
Unmet financial need	2,931	3,344	-413
In-school wage	11.08	10.95	0.13
Study cost of work	-0.022	-0.016	-0.007***
Return to studying	0.373	0.376	-0.003
Return to GPA at 3.0	0.392	0.421	-0.028
Cumulative credit hours	17.30	27.55	-10.26***
Panel D: Borrowing and tuition (N = 1,309)			
Unmet financial need	3,828	1,734	2,095***
In-school wage	10.93	11.01	-0.08
Study cost of work	-0.015	-0.022	0.007***
Return to studying	0.380	0.357	0.023
Return to GPA at 3.0	0.417	0.391	0.026
Cumulative credit hours	27.87	17.86	10.01***

Notes: This table presents the means for particular variables separately for students in the bottom tercile and top tercile of the specified elasticity distribution. Statistical significance based on two-sample t-tests with unequal variances. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table A.1.11 Counterfactual Simulation Results

Outcome	**Baseline**	**Counterfactual**	**Difference**	**Std. Err.**
		Panel A: Increase minimum wage to \$15		
Credit hours				
Fall and spring	28.85	28.85	-0.004	(0.023)
Summer	1.76	1.70	-0.065	(0.027)*
Work hours				
Fall and spring	6.24	6.99	0.748	(0.056)***
Summer	11.80	12.94	1.142	(0.062)***
Borrowing				
Fall and spring	4,294.39	3,991.78	-302.61	(110.85)**
Summer	790.69	725.87	-64.82	(25.65)*
Cumulative GPA	2.96	2.95	-0.011	(0.037)
		Panel B: Set in-state tuition rate to \$0		
Credit hours				
Fall and spring	28.85	28.94	0.088	(0.023)***
Summer	1.76	1.81	0.044	(0.028)
Work hours				
Fall and spring	6.24	6.15	-0.094	(0.053)
Summer	11.80	11.90	0.101	(0.057)
Borrowing				
Fall and spring	4,294.39	2,372.50	-1,921.89	(86.69)***
Summer	790.69	605.85	-184.84	(20.17)***
Cumulative GPA	2.96	2.95	-0.012	(0.037)

Notes: This table presents the projected credit hour enrollment, work hours, borrowing, and terminal-period cumulative GPA under the baseline model and counterfactual model. The baseline model takes the state variables for individuals as given in the first period and simulates their choice history and outcomes for the remaining periods. The counterfactual models vary individuals' wage or tuition rate for all periods and simulate their choice history and outcomes given the changes. The final column presents the standard errors from a two-sided t-test with unequal variances. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A.2 In-school wage estimation

The SEES asked students to report their earnings from their most recent semester working. If students were paid hourly, they were asked to report their average hourly wage, including tips and after taxes. If students were paid a salary, they were asked to report their frequency of payment (e.g., weekly, bi-weekly, or monthly) and their typical payment, after taxes. I convert salary earnings to hourly wages using the student's reported frequency of payment and typical hours worked. I use a student's most recent hourly wage for their in-school wage across all in-school periods

To predict a wage for non-workers, the SEES asked students for their expected wages in fall 2019 if they were to work. Students were not asked this question if they were certain that they were not going to work in fall 2019 because I did not have confidence that these students had fully formed beliefs about the wage offers for college workers. For non-workers who did not provide an expected wage, I predict their potential wage using data from non-workers by regressing expected log wage on gender, race, residency, first-generation status, age, class level, honors status, and broad categories for major (e.g., Business, Humanities). The regression coefficients are presented below.

Table A.2.1 Predicting Wages for Non-Workers

Ln(Wage)	**Coef.**	**Std. Err.**
Female	-0.048	(0.019)
Black or African American	0.030	(0.035)
Hispanic	0.039	(0.039)
Asian	-0.050	(0.027)
American Indian or Alaskan Native	-0.029	(0.088)
Native Hawaiian or Pacific Islander	-0.101	(0.145)
Out-of-state	-0.021	(0.028)
First generation	-0.037	(0.024)
Age (months)	0.002	(0.001)
Sophomore	-0.005	(0.021)
Junior	-0.008	(0.036)
Senior	0.118	(0.077)
Honors college	-0.015	(0.021)
Business	0.024	(0.028)
Humanities	-0.018	(0.040)
Health	0.045	(0.051)
STEM	0.004	(0.020)
Undecided major	0.162	(0.086)
Constant	1.872	(0.321)
Observations	296	

Notes: This table presents the estimated coefficients from a regression of log wage (expected by non-workers) on a vector of student characteristics.

A.3 Measuring family financial support

The SEES elicits family financial support for education expenses and living expenses separately. For education expenses, student could report that their family provides no support for educational expenses, a fixed dollar amount of support for educational expenses, a percent of education expenses, enough support to pay for their tuition but not their textbooks, or enough support to pay for all of their education expenses. Responses were adjusted upward if the student's parents received a Direct PLUS loan from the Federal government in excess of the family financial support the student indicated.

For living expenses, students could report that their family provides no support, a fixed dollar amount of support for living expenses, or support for all of their living expenses. To convert "all of living expenses" to a dollar amount, I first estimate the student's expected living expenses. I use the student's self-reported monthly rent and calculate the ratio of her rent to the cost of a standard double-bed room on campus ($2,121 per semester). I then multiply this ratio by the total expected living expenses as specified by the University in their cost of attendance calculations. The assumption is that students who spend x% more on rent than they would if living on campus also spend x% more on other living expenses than they would if living on campus. This product is the student's expected living expenses and the dollar amount I assign to family financial support when the student reports their family pays for all of their living expenses. For students who live at home, I assume they receive 150% of the standard double-bed room on campus worth of support for rent.

Table A.3.1 Family Financial Support: Education Expenses

Education Support	**Percent**
No support	25.89
Dollar amount	8.32
Percentage	13.50
All tuition, no books, etc.	16.65
All education costs	35.63
Observations	985

Notes: This table presents the proportion of students who reported each level of family financial support for education expenses.

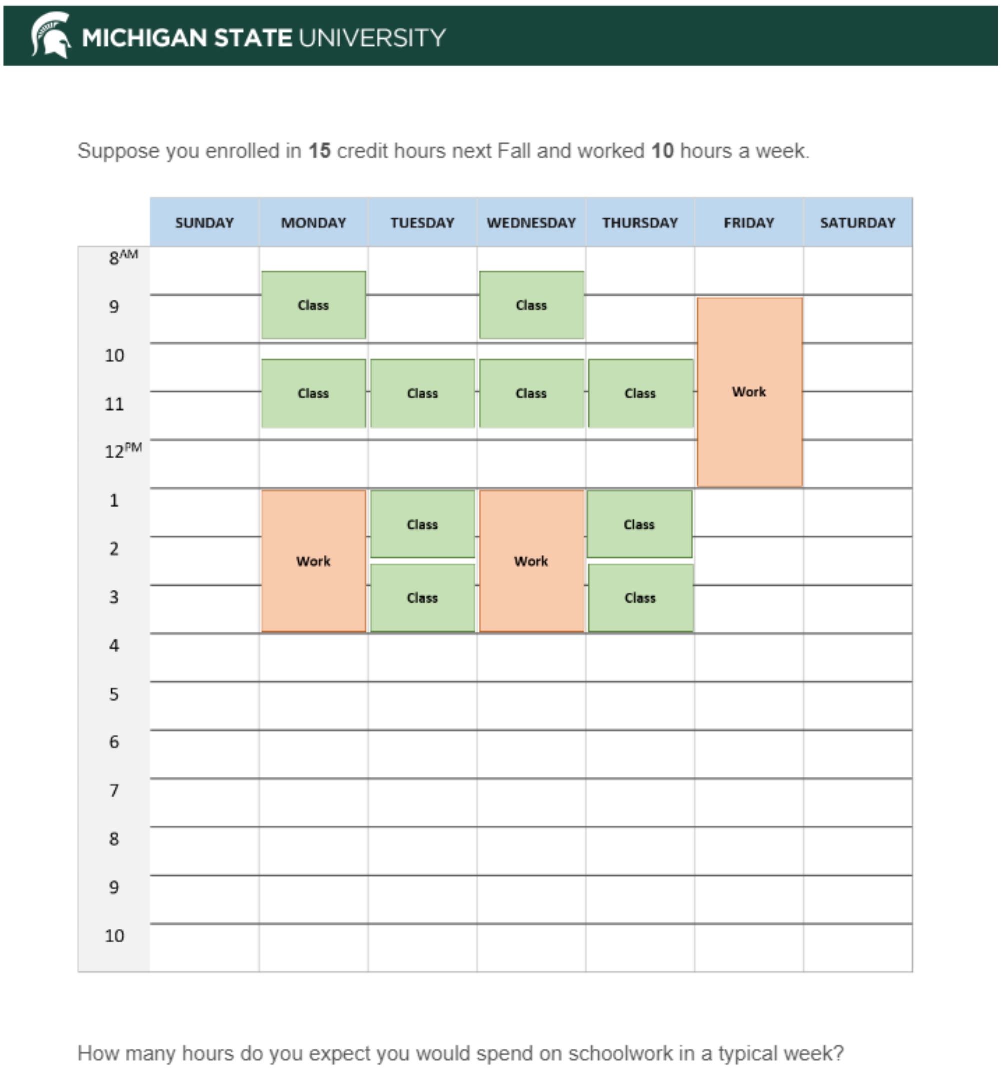
Table A.3.2 Family Financial Support: Living Expenses

Living Support	**Percent**
No support	33.91
Dollar amount	28.32
All living costs	37.77
Observations	985

Notes: This table presents the proportion of students who reported each level of family financial support for living expenses.

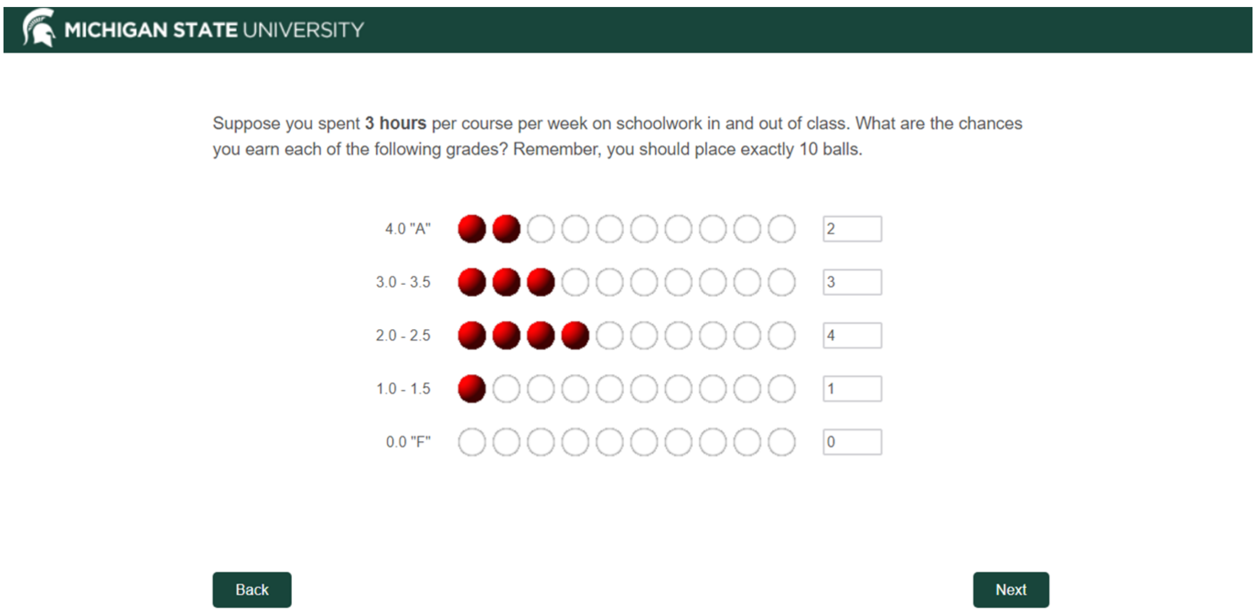
A.4 Supplemental figures & tables

Figure A.4.1 Expected Schoolwork Time Sample Question



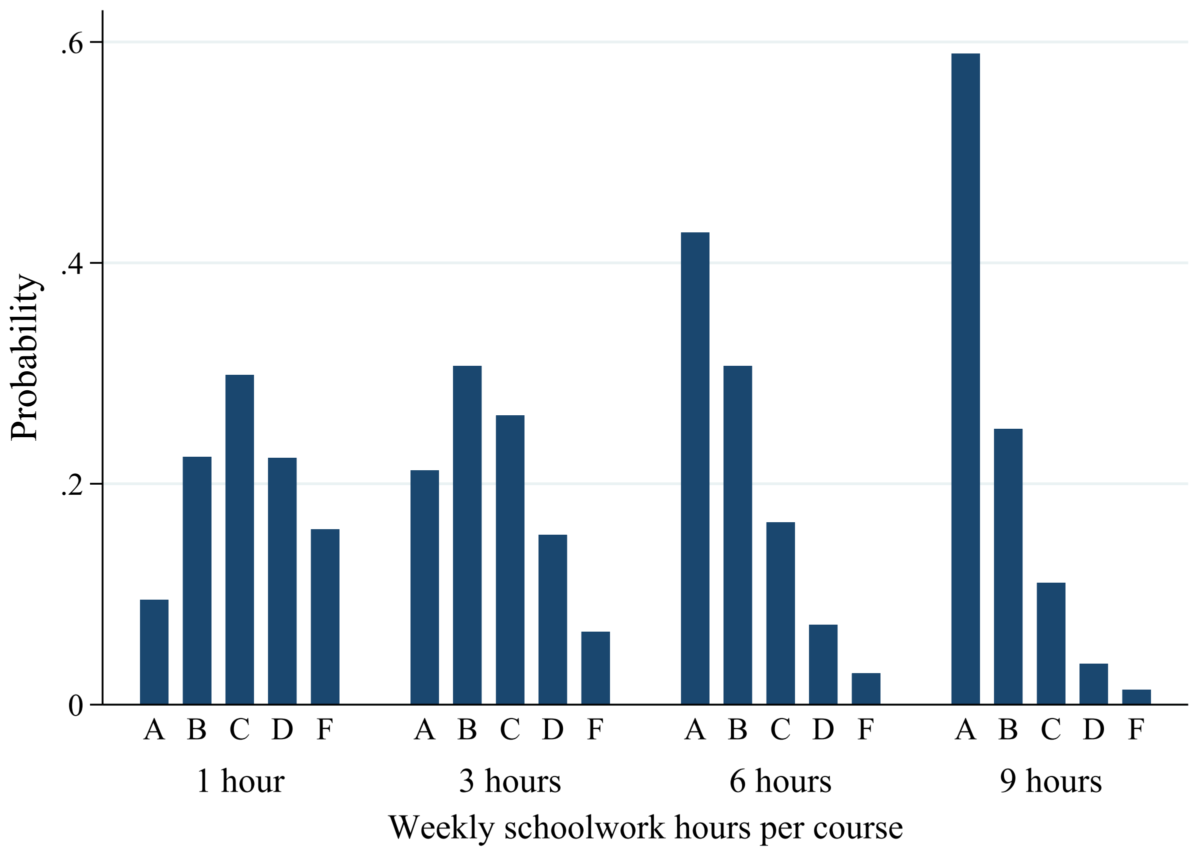
Notes: An example question in the SEES eliciting how much time the student expects to spend on schoolwork in a typical week. Respondents answered among a discrete set of possible answers: “0 to 5”, “6 to 10”, “11 to 15”, “16 to 20”,“21 to 25”, “26 to 30”, “31 to 35”,“36 to 40”, “41 to 45”, or “More than 45”.

Figure A.4.2 Grade Distribution Sample Question



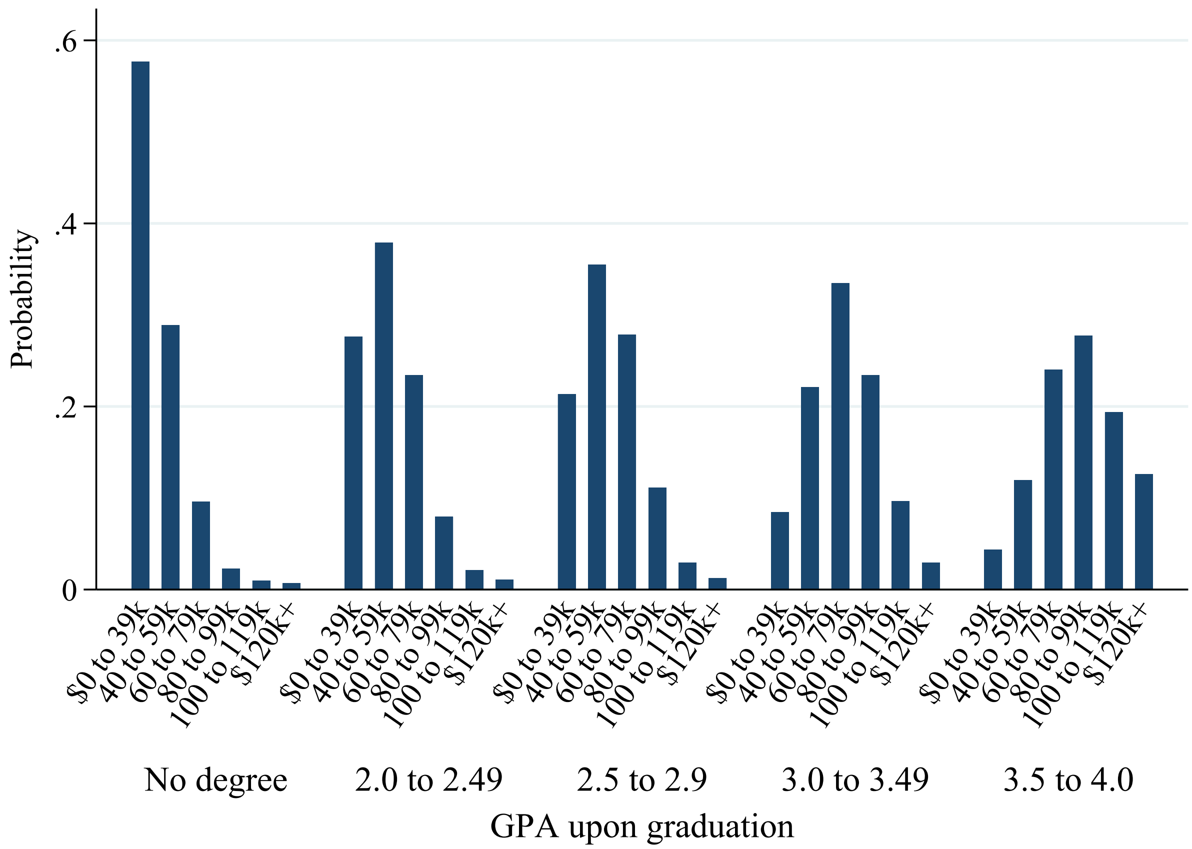
Notes: A sample response in the SEES module eliciting students' beliefs about how their time spent on schoolwork affects their distribution of grades. Respondents could fill each row with balls representing the likelihood that they would earn the specified grade.

Figure A.4.3 Distribution of Grades Conditional on Schoolwork



Notes: This figure presents the average probability that students believe they will receive each letter-grade conditional on time spent on schoolwork. Number of observations: 985.

Figure A.4.4   Distribution of Salaries Conditional on GPA



Notes: This figure presents the average probability that students believe they will earn a salary within each range conditional on GPA upon graduation (or leaving MSU without a degree). Number of observations: 985.

Table A.4.1 Michigan State and Peer Institutions

Variable	MSU Mean	Carnegie Peer Mean	Carnegie Peer S.D.	Public Four-Year Mean	Public Four-Year S.D.
Number of undergraduates	39,208	25,029	9,268	6,978	6,671
Female	0.507	0.515	0.060	0.575	0.117
White	0.681	0.541	0.200	0.551	0.259
Black or African American	0.075	0.073	0.067	0.150	0.206
Hispanic	0.048	0.148	0.134	0.151	0.193
Asian	0.057	0.110	0.095	0.040	0.057
American Indian or Alaskan Native	0.0018	0.0040	0.0081	0.0117	0.0566
Native Hawaiian or Pacific Islander	0.0008	0.0017	0.0030	0.0029	0.0208
First generation	0.210	0.291	0.082	0.356	0.092
Median family income	70,982	52,782	18,178	42,691	18,298
Admissions rate	0.777	0.636	0.203	0.717	0.180
Average SAT (ACT equivalent)	1,224	1,261	88	1,103	85
Average annual cost of attendance	28,194	26,306	4,377	21,091	4,397
Average net price	18,984	16,649	3,923	13,956	4,491
Average net price (income $<$ \$48k)	9,235	11,522	3,564	10,886	3,821
Pell Grant recipients	0.219	0.280	0.099	0.404	0.142
Median debt	21,250	15,713	2,506	14,641	3,650
Four-year completion rate	0.535	0.492	0.171	0.274	0.156
Six-year completion rate	0.800	0.713	0.128	0.476	0.153
Retention rate	0.919	0.872	0.066	0.734	0.095
Instructional spending per FTE	17,975	15,146	6,970	10,956	14,519
Observations	1	93		514	

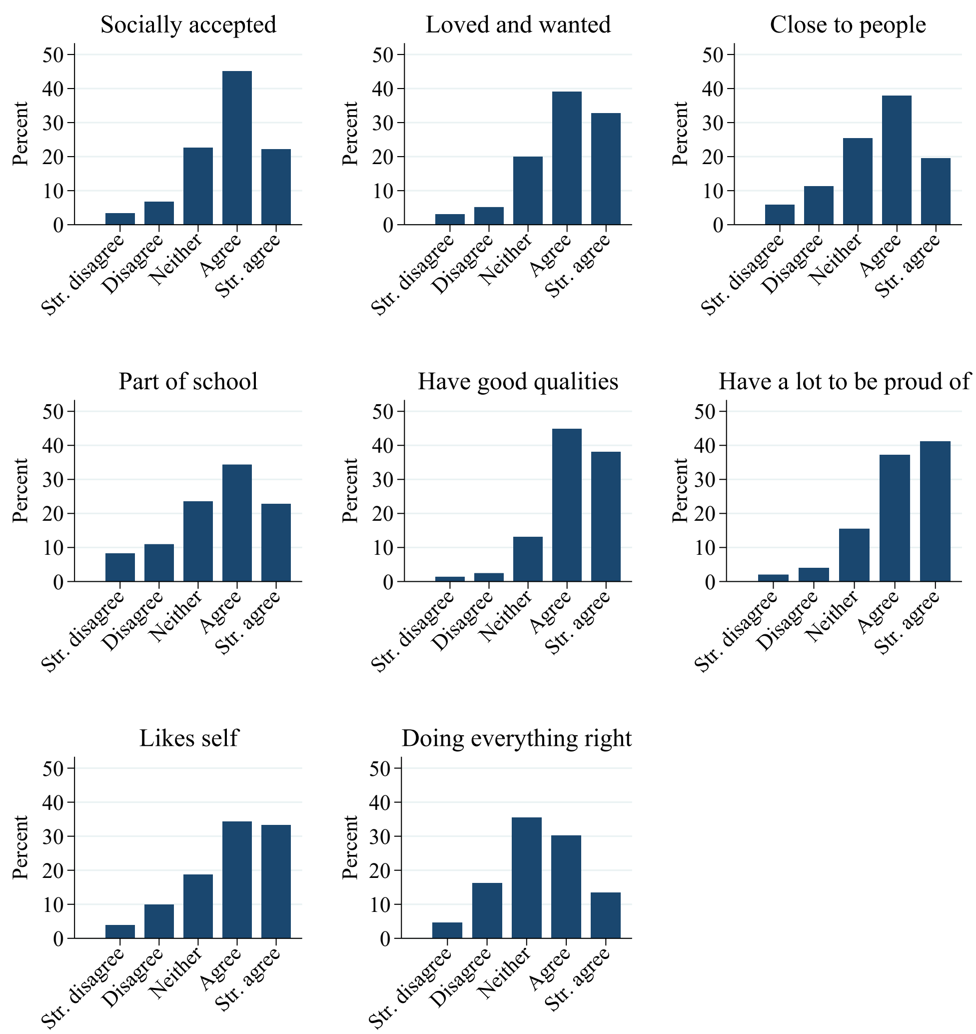
Notes: This table presents the mean and standard deviation of statistics for Michigan State University, four-year public universities with the same Carnegie Classification as MSU (doctoral universities with very high research activity), and four-year public universities regardless of Carnegie Classification. Data come from the U.S. Department of Education College Scorecard (2020), most recent institution-level year.

APPENDIX B

CHAPTER 2 APPENDIX

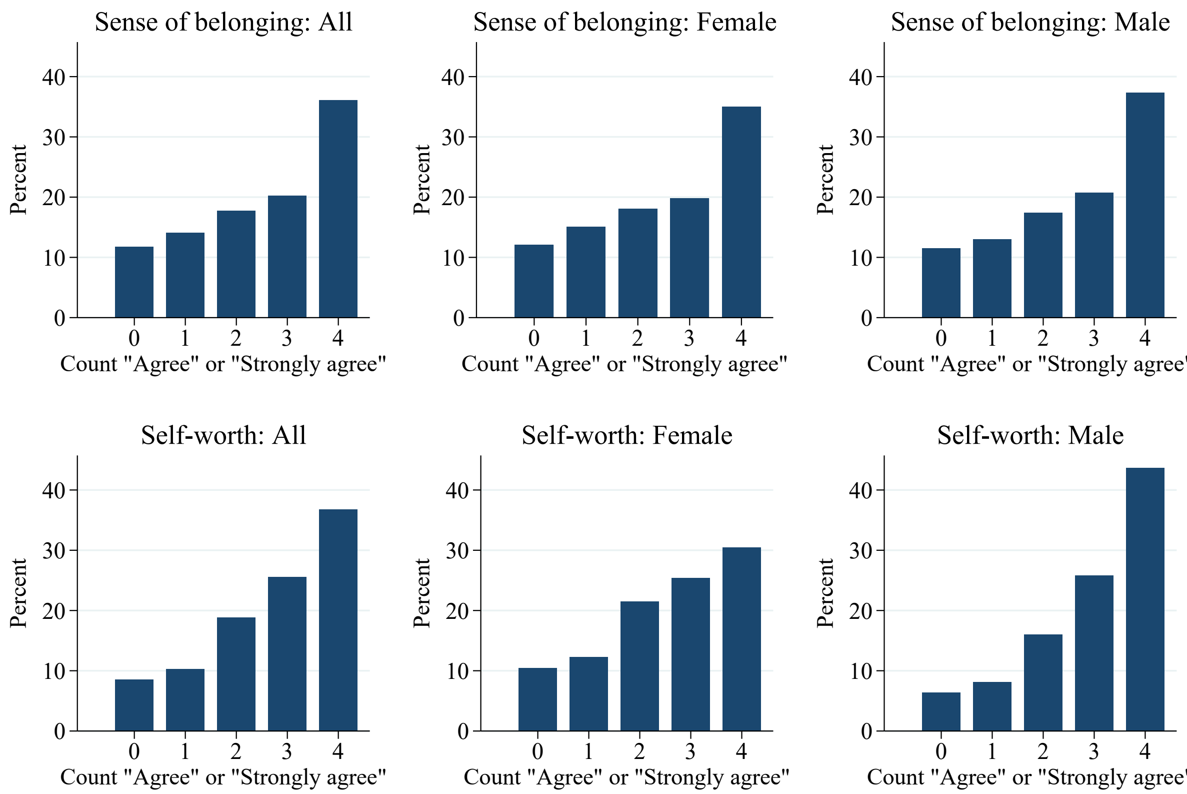
B.1 Figures & tables

Figure B.1.1 Distribution of Responses for Non-Cognitive Questions



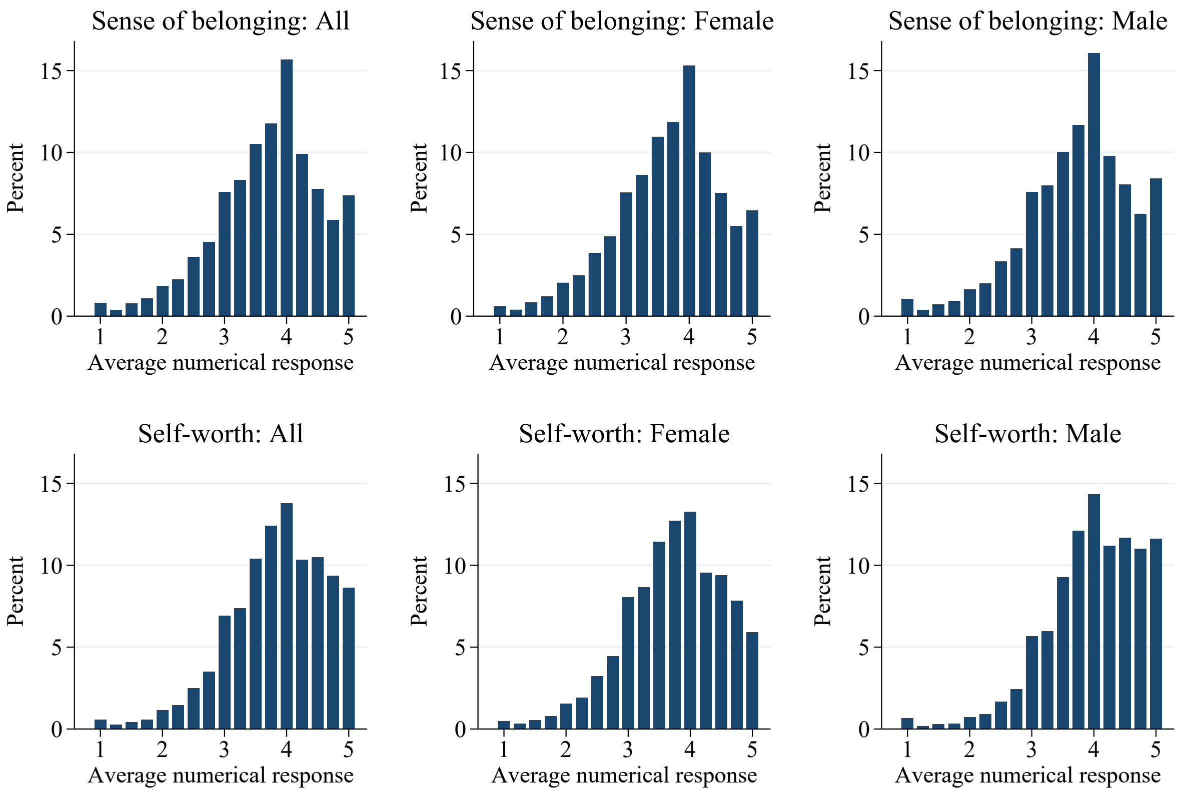
Notes: Each cell plots the percentage of students who answered the specified non-cognitive question with each of the five possible answers. Number of observations: 60,129. The distributions do not utilize survey weights.

Figure B.1.2 Distribution of Affirmative Responses



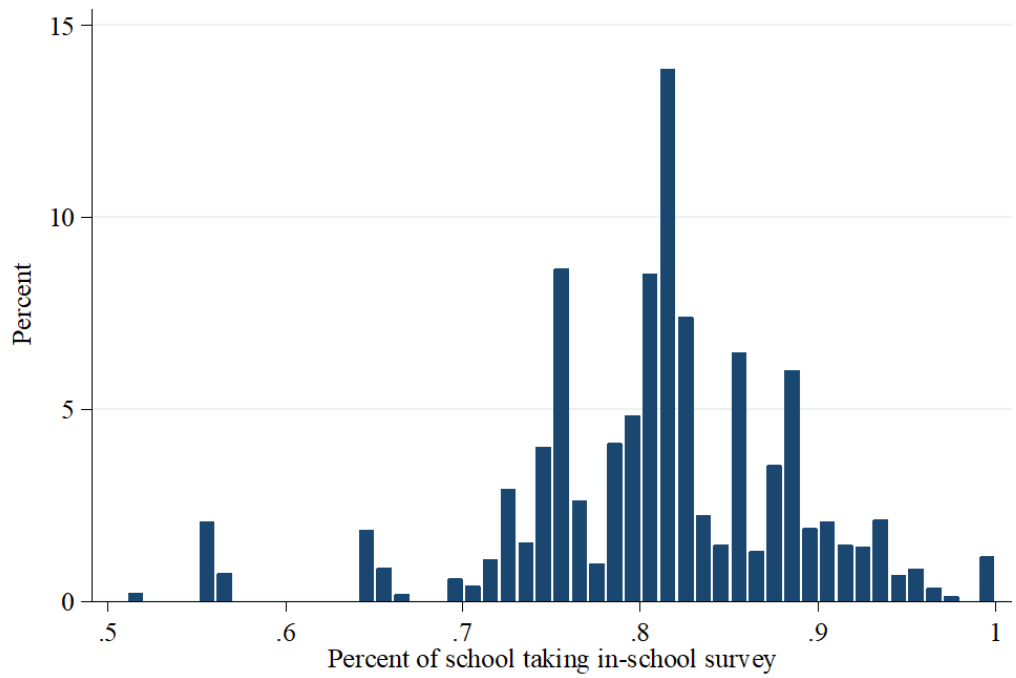
Notes: Each cell plots the percentage of students who answered in the affirmative ("Agree" or "Strongly Agree") for zero, one, two, three, or all four of their non-cognitive questions. The top row contains the count of affirmative responses for the four sense of belonging questions: I feel socially accepted, I feel loved and wanted, I feel close to people at this school, and I feel like I am a part of this school. The bottom row contains the count of affirmative responses for the four self-worth questions: I have a lot of good qualities, I have a lot to be proud of, I like myself just the way I am, and I feel like I am doing everything just about right. The left column contains the count of affirmative responses for the entire sample of 60,129 students, the middle column contains the count of affirmative responses for the 31,445 female students, and the right column contains the count of affirmative responses for the 28,684 male students. The distributions do not utilize survey weights.

Figure B.1.3 Distribution of Average Numerical Responses



Notes: Each cell plots the distribution of the average numerical response across the two broad non-cognitive questions. "Strongly disagree" was assigned a value of 1, "Disagree" a value of 2, "Neither agree nor disagree" a value of 3, "Agree" a value of 4, and "Strongly agree" a value of 5. The top row contains the average numerical response for the four sense of belonging questions: I feel socially accepted, I feel loved and wanted, I feel close to people at this school, and I feel like I am a part of this school. The bottom row contains the average numerical response for the four self-worth questions: I have a lot of good qualities, I have a lot to be proud of, I like myself just the way I am, and I feel like I am doing everything just about right. The left column contains the average numerical response for the entire sample of 60,129 students, the middle column contains the average numerical response for the 31,445 female students, and the right column contains the average numerical response for the 28,684 male students. The distributions do not utilize survey weights.

Figure B.1.4 In-School Questionnaire Response Rates



Notes: This figure plots the distribution of in-school questionnaire response rates for each participating school. Response rates are calculated by dividing the number of in-school questionnaire responses in the school by the number of students listed on a school's roster. The distribution does not utilize survey weights.

Table B.1.1 Add Health Descriptive Statistics

Variable	**Unweighted** Mean	S.D.	**Weighted** Mean	S.D.
Share female	0.503	0.045	0.503	0.054
Female	0.523	0.499	0.516	0.500
Hispanic or Latino	0.142	0.349	0.107	0.309
Black or African American	0.159	0.366	0.170	0.376
Asian or Pacific Islander	0.059	0.236	0.041	0.199
American Indian or Native American	0.033	0.178	0.037	0.189
Other race	0.024	0.154	0.023	0.150
Above median age	0.338	0.473	0.339	0.474
Born outside the United States	0.086	0.280	0.059	0.235
Household size				
One	0.005	0.071	0.005	0.073
Two	0.053	0.223	0.053	0.224
Three	0.183	0.387	0.185	0.388
Four to six	0.756	0.429	0.754	0.431
Shelter or group home	0.003	0.057	0.003	0.056
Observations	60,229		60,229	

Notes: Each column presents the mean or standard deviation for the explanatory variable of interest and control variables used in the regressions. The first two columns correspond to the unweighted sample of students, and the last two columns correspond to the sample weighted by the inverse probability of their selection using weights provided by Add Health.

Table B.1.2 Non-Cognitive Factors (Count "Agree" or "Strongly Agree")

	All		**Female**		**Male**	
Survey Question	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Sense of belonging	2.59	1.40	2.54	1.42	2.63	1.38
I feel socially accepted	0.68	0.47	0.65	0.48	0.71	0.45
I feel loved and wanted	0.73	0.45	0.73	0.45	0.73	0.44
I feel close to people at this school	0.58	0.49	0.58	0.50	0.59	0.49
I feel like I am part of this school	0.60	0.49	0.59	0.50	0.61	0.49
Self-worth	2.74	1.28	2.54	1.33	2.95	1.20
I have a lot of good qualities	0.83	0.38	0.80	0.40	0.86	0.35
I have a lot to be proud of	0.79	0.41	0.76	0.43	0.82	0.38
I like myself just the way I am	0.68	0.47	0.60	0.49	0.76	0.43
I feel like I am doing everything just about right	0.44	0.50	0.37	0.49	0.51	0.50
Observations	60,229		31,445		28,684	

Notes: Each column presents the mean or standard deviation for number of affirmative responses ("Agree" or "Strongly Agree") to the corresponding survey question. Sense of belonging and self-worth include the sum of the relevant individual questions. Observations are weighted by the inverse probability of their selection using weights provided by Add Health.

Table B.1.3 Balance of Share Female on Control Variables

	Female		Male	
Share Female	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Hispanic or Latino	0.0012	(0.0016)	-0.0010	(0.0013)
Black or African American	-0.0001	(0.0010)	0.0001	(0.0011)
Asian or Pacific Islander	0.0007	(0.0026)	-0.0002	(0.0019)
American Indian or Native American	0.0008	(0.0028)	0.0003	(0.0025)
Other race	0.0011	(0.0028)	0.0004	(0.0021)
Above median age	0.0016	(0.0013)	-0.0020*	(0.0011)
Born in the United States	0.0006	(0.0015)	-0.0005	(0.0015)
Household size				
One	-0.0295	(0.0363)	0.0062	(0.0084)
Two	0.0037	(0.0024)	0.0025	(0.0037)
Four to six	0.0012	(0.0012)	0.0013	(0.0011)
Shelter or group home	0.0051	(0.0064)	0.0016	(0.0040)
Constant	0.5492***	(0.0084)	0.5599***	(0.0092)
Observations	31,445		28,684	

Notes: This table contains estimates from regressions of the share of female peers on individual control variables, school dummy variables, and grade dummy variables. The first two columns correspond to the sample of female students, and the last two columns correspond to the sample of male students. Standard errors are adjusted for the stratification and clustering of the survey design. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.1.4 Baseline Regression Estimates

	All		**Female**		**Male**	
	Belonging	**Self-worth**	**Belonging**	**Self-worth**	**Belonging**	**Self-worth**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Share female	0.295	0.242	-0.00550	-0.197	0.714*	0.633*
	(0.318)	(0.176)	(0.408)	(0.258)	(0.352)	(0.270)
Female	-0.107***	-0.427***				
	(0.0149)	(0.0173)				
Controls	Y	Y	Y	Y	Y	Y
Observations	60,129	60,129	31,445	31,445	28,684	28,684

Notes: This table contains estimates from regressions of the number of affirmative responses ("Agree" or "Strongly Agree") to the sense of belonging and self-worth question categories on the share of female peers within a student's school and grade, individual covariates, and school and grade dummy variables. Standard errors are adjusted for the stratification and clustering of the survey design. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.1.5 Regression Estimates without Controls

	All		Female		Male	
	Belonging	**Self-worth**	**Belonging**	**Self-worth**	**Belonging**	**Self-worth**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Share female	0.335	0.455*	-0.0356	-0.191	0.736*	0.635*
	(0.317)	(0.177)	(0.423)	(0.267)	(0.348)	(0.273)
Constant	3.211***	2.799***	3.503***	3.223***	2.900***	2.626***
	(0.162)	(0.102)	(0.219)	(0.147)	(0.188)	(0.165)
Controls	N	N	N	N	N	N
Observations	60,129	60,129	31,445	31,445	28,684	28,684

Notes: This table contains estimates from regressions of the number of affirmative responses ("Agree" or "Strongly Agree") to the sense of belonging and self-worth question categories on the share of female peers within a student's school and grade and school and grade dummy variables. Standard errors are adjusted for the stratification and clustering of the survey design. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.1.6 Regression Estimates with Average Numerical Response

	All		Female		Male	
	Belonging	**Self-worth**	**Belonging**	**Self-worth**	**Belonging**	**Self-worth**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Share female	0.215	0.134	-0.0790	-0.204	0.561*	0.486*
	(0.196)	(0.128)	(0.246)	(0.169)	(0.248)	(0.186)
Female	-0.107***	-0.349***				
	(0.0116)	(0.0137)				
Controls	Y	Y	Y	Y	Y	Y
Observations	60,129	60,129	31,445	31,445	28,684	28,684

Notes: This table contains estimates from regressions of the average numerical responses (e.g., "Strongly Disagree" = 1, "Strongly Agree" = 5) to the sense of belonging and self-worth question categories on the share of female peers within a student's school and grade, individual covariates, and school and grade dummy variables. Standard errors are adjusted for the stratification and clustering of the survey design. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.1.7 Disaggregated Regression Estimates for Each Non-Cognitive Factor

	Socially accepted (1)	**Loved and wanted (2)**	**Close to people (3)**	**Part of school (4)**	**Good qualities (5)**	**Proud of a lot (6)**	**Likes self (7)**	**Doing things right (8)**
				Panel A: Female				
Share female	0.0380	-0.129	-0.0914	-0.0816	0.0924	0.0530	-0.461	-0.325
	(0.246)	(0.193)	(0.238)	(0.302)	(0.175)	(0.171)	(0.276)	(0.192)
Constant	3.911***	4.751***	4.305***	4.507***	4.283***	4.565***	4.488***	3.627***
(0.133)	(0.107)	(0.130)	(0.160)	(0.0964)	(0.101)	(0.145)	(0.105)	
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	31,445	31,445	31,445	31,445	31,445	31,445	31,445	31,445
				Panel B: Male				
Share female	0.341	0.458	0.631*	0.441*	0.121	0.304	0.634**	0.469*
	(0.208)	(0.299)	(0.274)	(0.219)	(0.169)	(0.167)	(0.240)	(0.227)
Constant	3.928***	4.051***	3.768***	4.115***	4.284***	4.513***	3.712***	2.913***
	(0.117)	(0.168)	(0.162)	(0.114)	(0.0966)	(0.103)	(0.133)	(0.126)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	28,684	28,684	28,684	28,684	28,684	28,684	28,684	28,684

Notes: This table contains estimates from regressions of the probability of affirmative response ("Agree" or "Strongly Agree") to each non-cognitive question on the share of female peers within a student's school and grade, individual covariates, and school and grade dummy variables. Panel A contains estimates for the subsample of female students, and Panel B contains estimates for the subsample of male students. Standard errors are adjusted for the stratification and clustering of the survey design. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B.1.8 Regression Estimates Accounting for Measurement Error

	All		**Female**		**Male**	
	Belonging	**Self-worth**	**Belonging**	**Self-worth**	**Belonging**	**Self-worth**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Share female	0.247	0.197	-0.00112	-0.182	0.613^{*}	0.537^{*}
	(0.315)	(0.192)	(0.398)	(0.268)	(0.367)	(0.276)
Female	-0.107^{***}	-0.427^{***}				
	(0.0149)	(0.0173)				
Controls	Y	Y	Y	Y	Y	Y
Observations	60,129	60,129	31,445	31,445	28,684	28,684

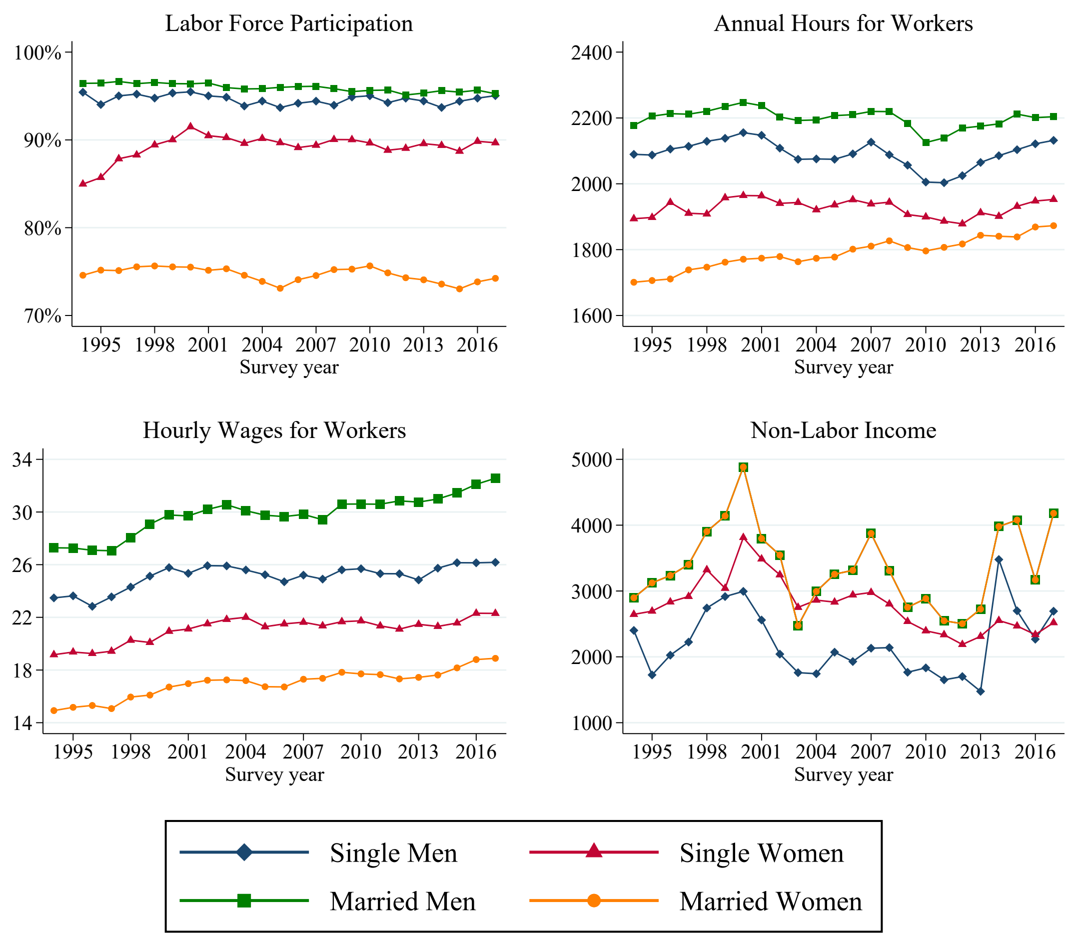
Notes: This table contains estimates from regressions of the number of affirmative responses ("Agree" or "Strongly Agree") to the sense of belonging and self-worth question categories on the share of female peers within a student's school and grade, individual covariates, and school and grade dummy variables using 100 simulated data sets to account for measurement error in the share of female students. Standard errors are adjusted for the stratification and clustering of the survey design and for the uncertainty introduced by measurement error in the share of female peers. Observations are weighted by the inverse probability of their selection using weights provided by Add Health. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

APPENDIX C

CHAPTER 3 APPENDIX

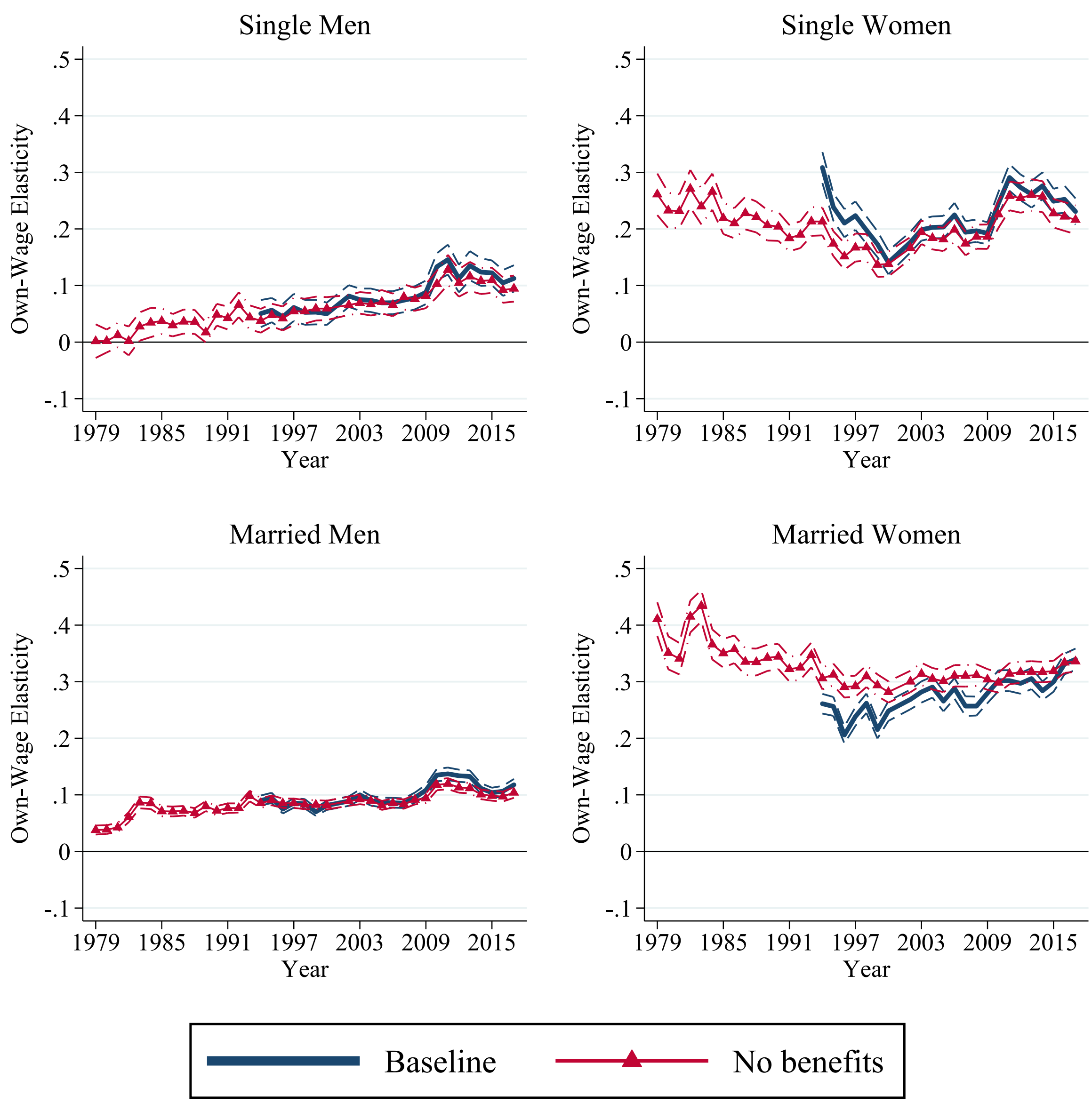
C.1 Main text figures & tables

Figure C.1.1 Labor Force Trends by Demographic Group



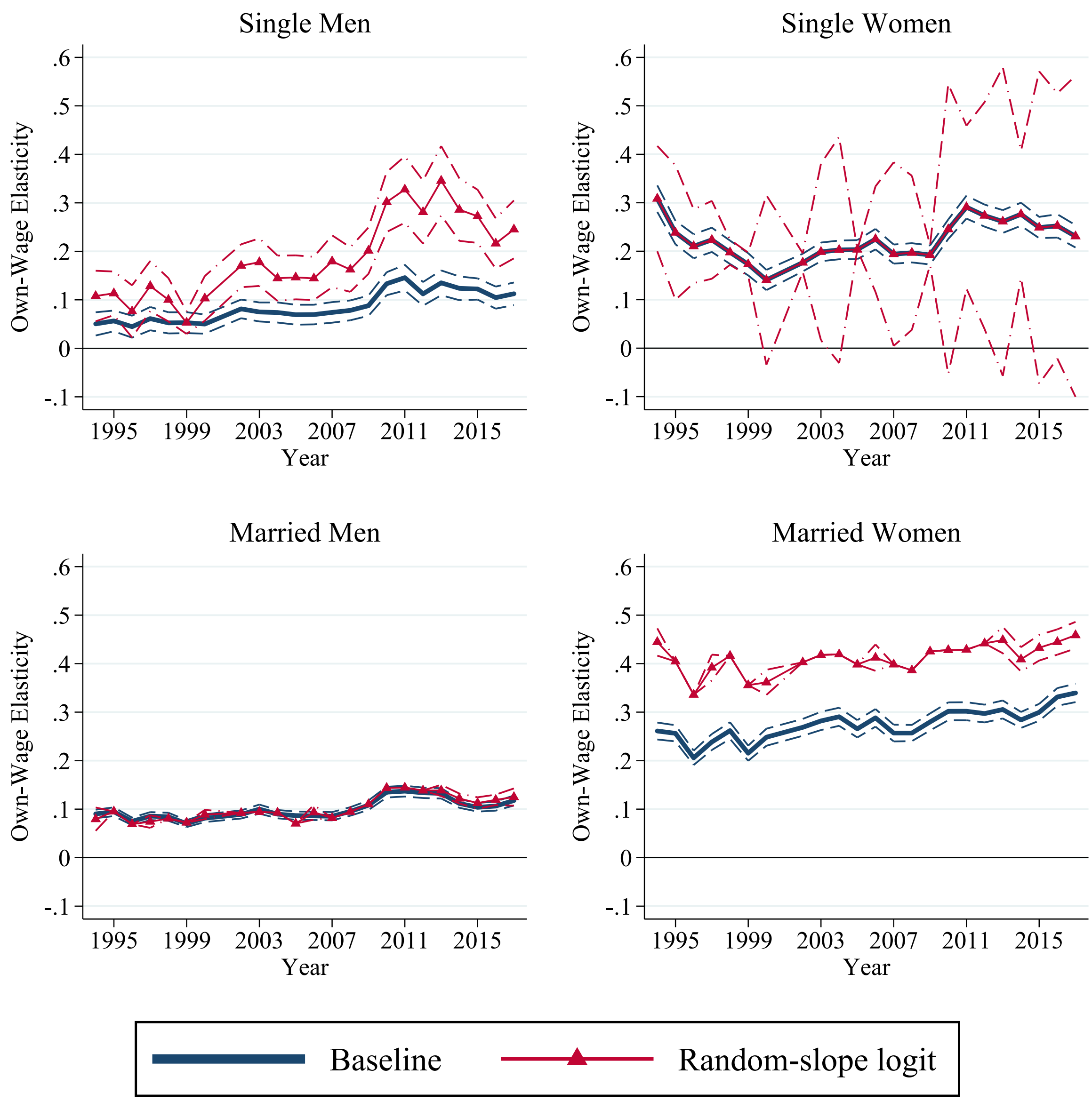
Notes: This figure presents trends in labor force participation, annual hours worked, hourly wages, and non-labor income separately by sex and marital status. Annual hours worked are the product of usual hours worked per week in the prior year and weeks worked in the prior year. Hourly wages are quotient of pre-tax wage and salary income in the prior year and annual hours worked. Hourly wages and non-labor income are in 2017 dollars. Observations are weighted by their ASEC person-level survey weight.

Figure C.1.2 Mean Own-Wage Elasticities, Baseline Estimates (1994-2017) versus Estimates with No Benefit Simulator (1979-2017)



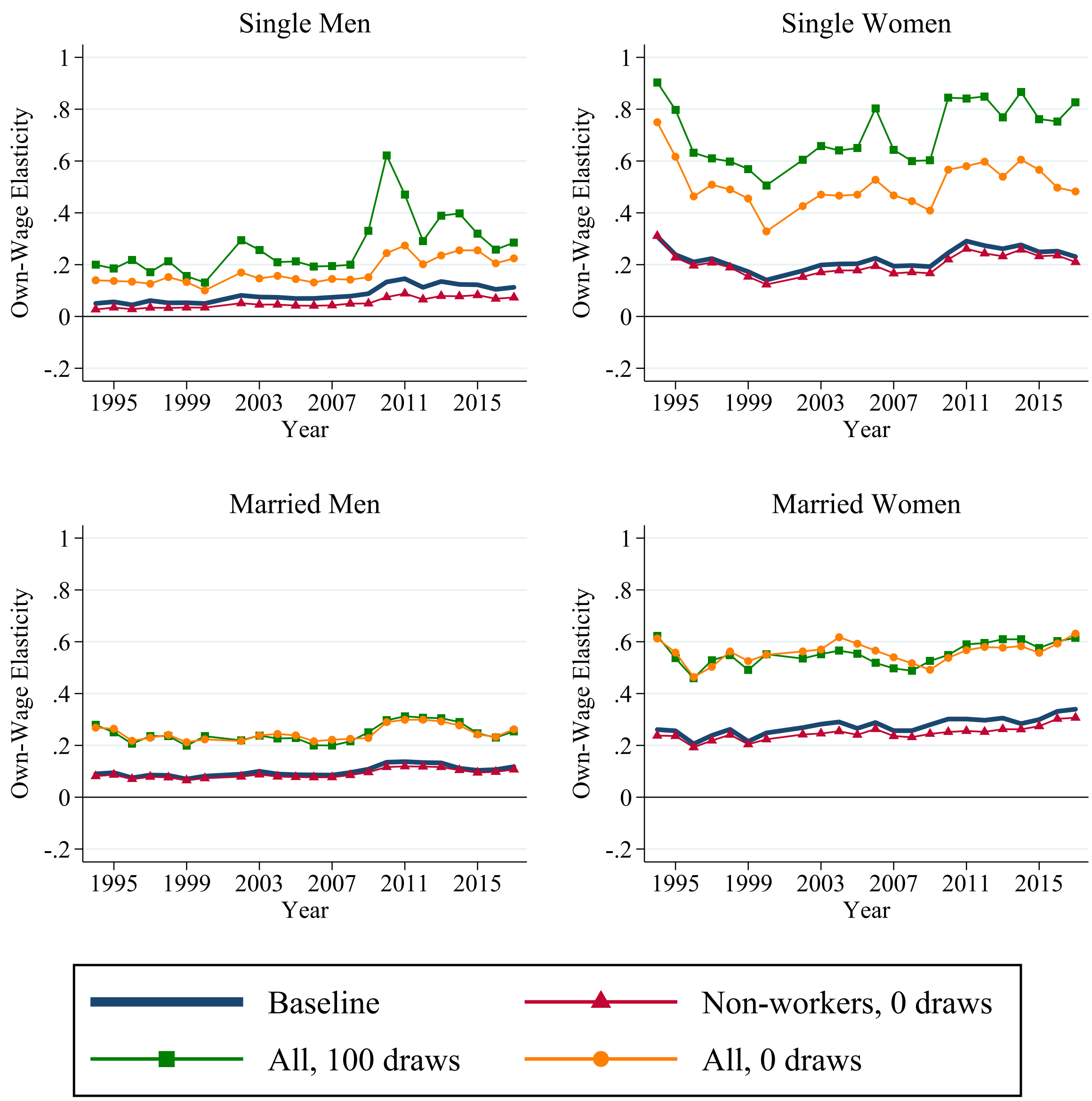
Notes: This figure presents the estimated trends in mean own-wage elasticities separately by sex and marital status. Our baseline model (blue) has a translog utility function, no random slopes, benefit simulator from TRIM3, and predicted wages for non-workers using 100 draws from their conditional wage distribution. Our model without the benefit simulator (red with triangle markers) is identical to the baseline model except for the absence of the benefit simulator. Standard errors, computed with a parametric bootstrap of 50 draws from the joint distribution of parameters, are denoted by dashed lines.

Figure C.1.3 Mean Own-Wage Elasticities, Baseline Estimates versus Estimates from Random-Slope Logit Model



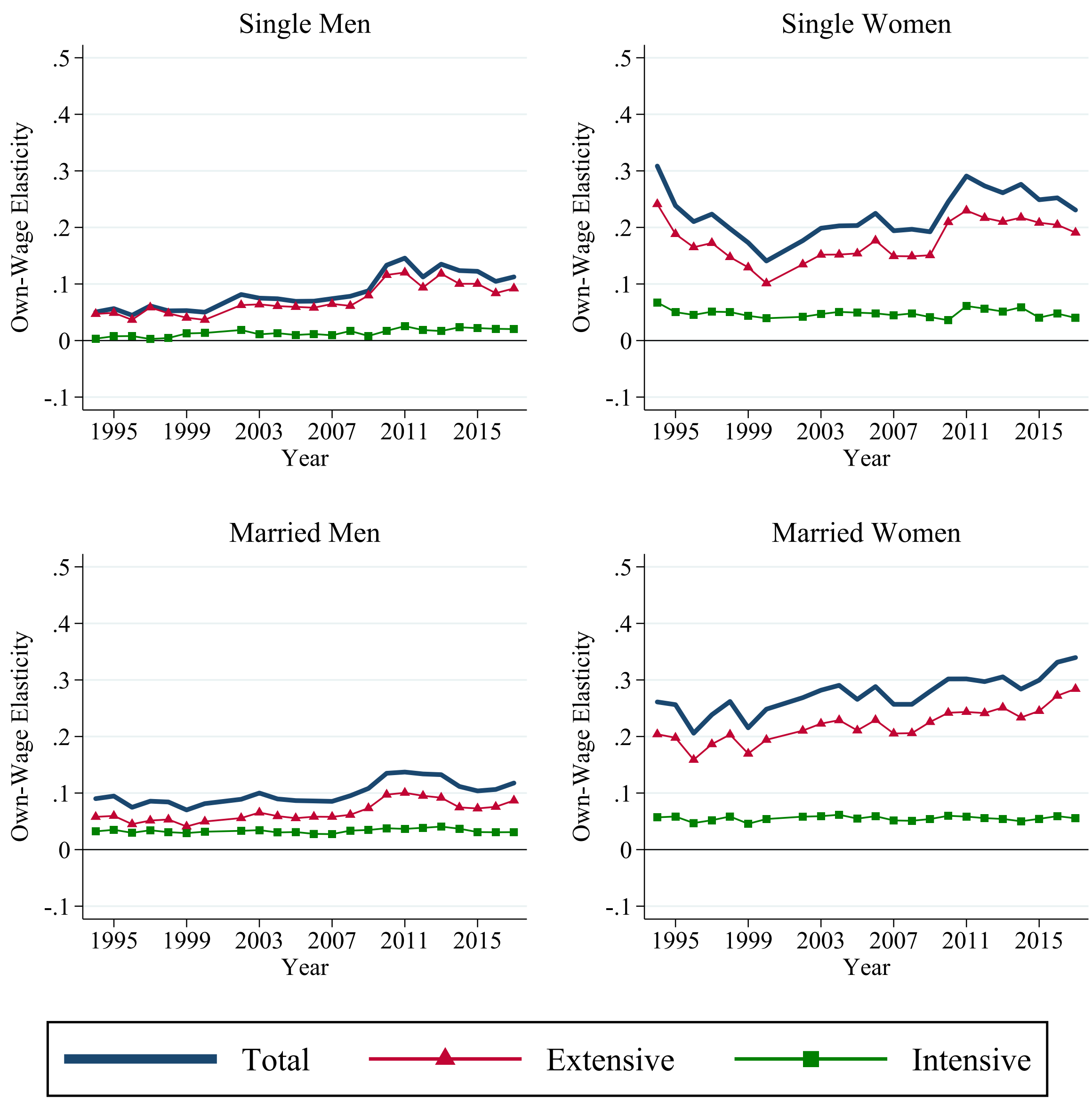
Notes: This figure presents the estimated trends in mean own-wage elasticities separately by sex and marital status. Our baseline model (blue) has a translog utility function, no random slopes, benefit simulator from TRIM3, and predicted wages for non-workers using 100 draws from their conditional wage distribution. Our random-slope logit model (red with triangle markers) is identical to the baseline model except for the addition of random slopes on the leisure term in the utility function. Standard errors, computed with a parametric bootstrap of 50 draws from the joint distribution of parameters, are denoted by dashed lines. Standard errors are missing for years where the estimated covariance matrix is not positive semi-definite.

Figure C.1.4 Mean Own-Wage Elasticities, Baseline Estimates versus Estimates with Different Treatments for Measurement Error



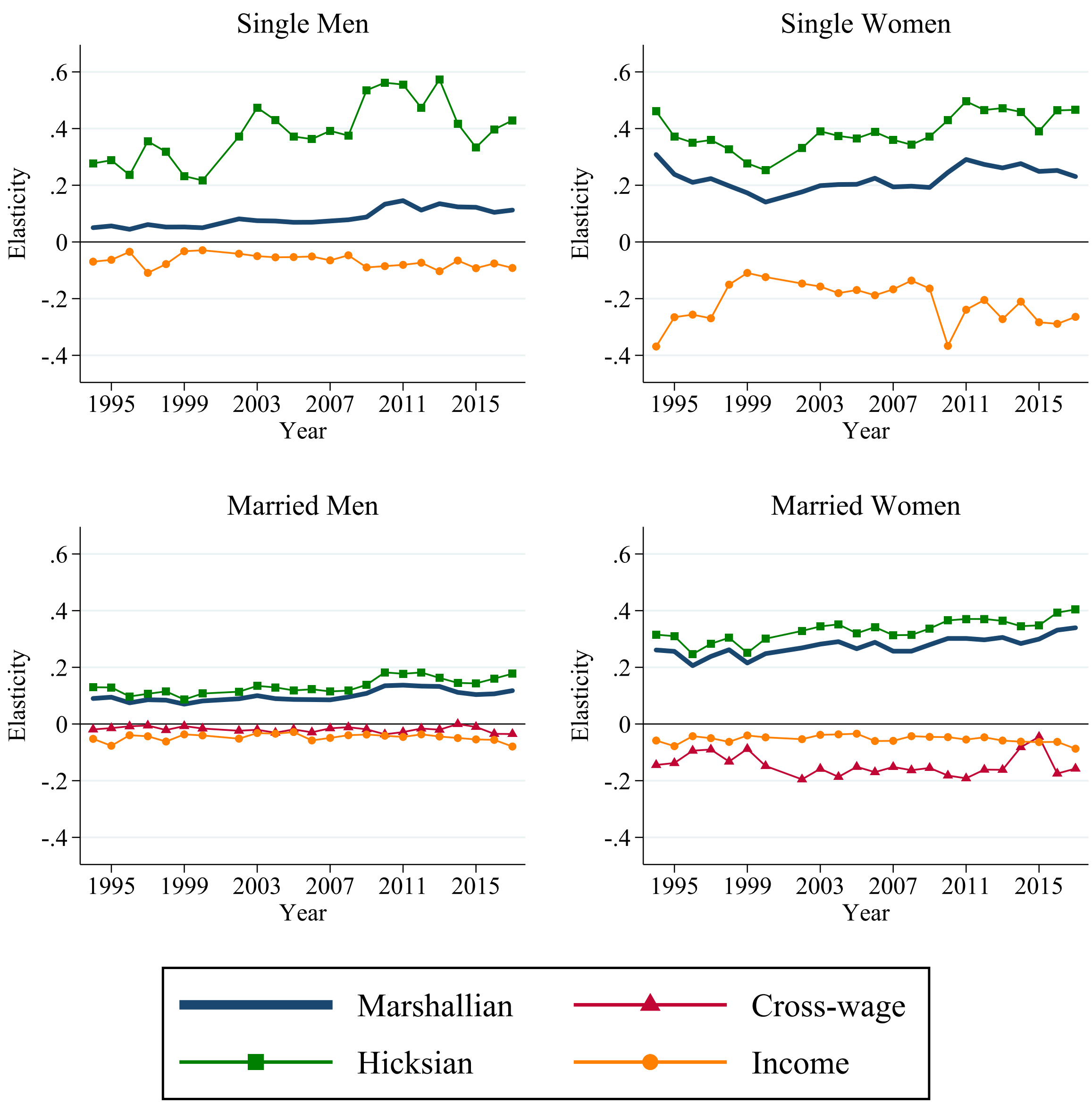
Notes: This figure presents the estimated trends in mean own-wage elasticities separately by sex and marital status. Our baseline model (in blue) has a translog utility function, no random slopes, benefit simulator from TRIM3, and predicted wages for non-workers using 100 draws from their conditional wage distribution. The three other models are identical to the baseline model except they use the mean wage for non-workers as opposed to drawing from the distribution (red with triangle markers), predicted wages for workers and non-workers using 100 draws from their conditional wage distribution (green with square markers), and predicted wages for workers and non-workers using the mean wage (orange with round markers).

Figure C.1.5 Mean Own-Wage Elasticities Decomposed by Extensive and Intensive Margins



Notes: This figure presents the estimated trends in mean total, extensive margin, and intensive margin own-wage elasticities separately by sex and marital status. We decompose the total own-wage elasticity (blue) into the extensive margin elasticity (red with triangle markers) and intensive margin elasticity (green with square markers) according to the formulas in Section 3.4.2. Estimates based on our baseline model.

Figure C.1.6 Mean Marshallian, Cross-Wage, Hicksian, and Income Elasticities



Notes: This figure presents the estimated trends in mean Marshallian own-wage (blue), cross-wage (red with triangle markers), Hicksian (green with square markers), and income (orange with round markers) elasticities separately by sex and marital status. Estimates based on our baseline model.

Table C.1.1 Distribution of Work Hours

	1996	2000	2004	2008	2012	2016
Panel A: Single Men						
0 hours	3.25	2.39	4.50	4.65	7.06	5.19
10 hours	0.38	0.45	0.57	1.04	0.72	0.61
20 hours	1.97	1.85	2.30	2.01	2.18	2.24
30 hours	3.62	2.13	3.11	2.36	4.18	3.33
40 hours	56.73	57.09	61.00	61.72	60.45	59.96
50 hours	21.59	24.84	18.77	18.41	16.46	18.70
60 hours	12.47	11.24	9.74	9.80	8.95	9.98
Observations	2,930	3,159	4,260	4,374	4,254	3,690
Panel B: Single Women						
0 hours	11.02	5.98	8.54	8.51	12.44	10.20
10 hours	1.03	0.78	1.14	0.97	1.19	1.01
20 hours	3.88	4.15	4.29	4.10	4.57	4.07
30 hours	6.62	6.11	6.17	5.98	7.66	7.79
40 hours	58.57	62.53	63.53	64.06	59.54	60.32
50 hours	12.02	13.78	11.50	11.44	10.27	11.40
60 hours	6.86	6.67	4.83	4.94	4.33	5.21
Observations	4,651	4,763	7,658	7,300	7,013	5,733
Panel C: Married Men						
0 hours	2.52	2.25	3.61	3.50	5.98	3.89
10 hours	0.31	0.19	0.20	0.11	0.32	0.22
20 hours	0.80	0.75	0.82	0.82	1.26	0.97
30 hours	1.40	1.11	1.46	1.61	2.12	1.62
40 hours	58.21	57.59	60.57	60.66	59.50	61.62
50 hours	23.70	24.66	22.17	21.76	19.66	21.16
60 hours	13.05	13.46	11.18	11.53	11.16	10.52
Panel D: Married Women						
0 hours	21.61	21.30	24.12	23.36	25.52	25.39
10 hours	2.73	2.59	2.34	2.17	2.22	1.68
20 hours	8.55	7.35	7.05	6.33	6.35	5.79
30 hours	8.22	7.64	7.61	6.88	7.27	6.26
40 hours	48.67	49.69	48.95	50.66	48.12	48.85
50 hours	7.74	9.10	7.58	8.03	7.88	9.01
60 hours	2.49	2.35	2.35	2.57	2.63	3.01
Observations	12,251	12,722	20,417	18,802	17,383	14,414

Notes: This table contains the percent of individuals within each demographic group that worked the specified number of hours per week in the prior year. Observations are weighted by their ASEC person-level survey weight.

Table C.1.2 Baseline Model Elasticities for Select Years, Single Men and Women

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
			Panel A: Single Men			
Own-wage	0.045	0.050	0.074	0.078	0.112	0.105
	(0.012)	(0.010)	(0.011)	(0.010)	(0.012)	(0.012)
Extensive margin	0.037	0.037	0.061	0.061	0.094	0.084
	(0.008)	(0.007)	(0.008)	(0.008)	(0.010)	(0.009)
Intensive margin	0.008	0.013	0.013	0.017	0.019	0.021
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Hicksian	0.236	0.217	0.430	0.375	0.473	0.397
	(0.030)	(0.027)	(0.031)	(0.030)	(0.034)	(0.027)
Income	-0.035	-0.029	-0.054	-0.047	-0.073	-0.076
	(0.010)	(0.008)	(0.009)	(0.008)	(0.012)	(0.013)
Observations	2,930	3,159	4,260	4,374	4,254	3,690
			Panel B: Single Women			
Own-wage	0.210	0.141	0.203	0.197	0.273	0.252
	(0.013)	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)
Extensive margin	0.165	0.101	0.152	0.149	0.217	0.205
	(0.010)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Intensive margin	0.045	0.039	0.051	0.048	0.056	0.048
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Hicksian	0.350	0.253	0.374	0.343	0.466	0.464
	(0.016)	(0.015)	(0.014)	(0.015)	(0.018)	(0.017)
Income	-0.256	-0.124	-0.180	-0.136	-0.205	-0.289
	(0.032)	(0.018)	(0.019)	(0.016)	(0.022)	(0.028)
Observations	4,651	4,763	7,658	7,300	7,013	5,733

Notes: This table contains the estimated elasticities for single men and women in a subset of years. Elasticity derivations are provided in Section 3.4. Standard errors are calculated using a parametric bootstrap with 50 draws from the joint distribution of utility parameters.

Table C.1.3 Baseline Model Elasticities for Select Years, Married Men and Women

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
			Panel A: Married Men			
Own-wage	0.075	0.081	0.090	0.095	0.134	0.106
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)
Extensive margin	0.045	0.050	0.059	0.062	0.095	0.076
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
Intensive margin	0.030	0.032	0.030	0.034	0.039	0.031
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cross-wage	-0.008	-0.016	-0.031	-0.011	-0.016	-0.035
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Hicksian	0.097	0.108	0.129	0.118	0.182	0.160
	(0.005)	(0.005)	(0.007)	(0.006)	(0.008)	(0.005)
Income	-0.040	-0.040	-0.034	-0.039	-0.036	-0.056
	(0.006)	(0.006)	(0.004)	(0.006)	(0.004)	(0.005)
Observations	10,000	10,000	10,000	10,000	10,000	10,000
			Panel B: Married Women			
Own-wage	0.206	0.248	0.291	0.257	0.297	0.331
	(0.008)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)
Extensive margin	0.159	0.194	0.229	0.206	0.241	0.272
	(0.006)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Intensive margin	0.047	0.054	0.062	0.051	0.056	0.059
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cross-wage	-0.094	-0.148	-0.187	-0.163	-0.161	-0.175
	(0.011)	(0.011)	(0.013)	(0.012)	(0.012)	(0.013)
Hicksian	0.247	0.301	0.352	0.314	0.371	0.393
	(0.009)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
Income	-0.043	-0.047	-0.036	-0.043	-0.047	-0.063
	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
Observations	10,000	10,000	10,000	10,000	10,000	10,000

Notes: This table contains the estimated elasticities for married men and women for a subset of years. Elasticity derivations are provided in Section 3.4. Standard errors are calculated using a parametric bootstrap with 50 draws from the joint distribution of utility parameters.

C.2 Construction of variables from March CPS

As described in the main text, we use data from the 1979 through 2017 Annual Social and Economic March Supplement of the Current Population Survey (CPS). In this section, we describe how we construct our variables from the CPS. Tables C.2.1 and C.2.2 present the basic descriptive statistics for all four demographic groups, and Tables C.2.3 and C.2.4 present the results from the Heckman corrected wage models for men and women.

Household construction We restrict our sample to single-family households, which are households that the Census Bureau defines as having only one sub-family. Within these households, we match spouses using the *sploc* variable from IPUMS. We identify dependents as any child, stepchild, grandchild, other relative under the age of 18, or sibling under the age of 18 that resides in the household. We topcode the number of dependents at nine.

Educational attainment We use the method proposed in Jaeger (1997) to map different education levels into five categories: did not complete high school, completed high school, attended some college, earned a college degree, earned an advanced degree.

Hours worked We use usual hours worked per week from the prior year as our continuous hours variable. We then discretize hours as follows: less than five hours, 0 hours; between five and 14 hours, 10 hours; between 15 and 24 hours, 20 hours; between 25 and 34 hours; 30 hours, between 35 and 44 hours, 40 hours; between 45 and 54 hours, 50 hours; greater than 54 hours, 60 hours.

Non-labor income We calculate non-labor income as the sum of dividend income, interest income, rental income and other property income, alimony, child support, and other non-property income. For years 1998 and later, dividend income and other property income are separately recorded in the CPS. Prior to 1998, they are recorded together in one category. If the combined category is positive, we assume that 16.5% of the combined category is dividend income and 83.5% is other property income. If the combined category is negative, we assume 100% of the combined category is other property income. This split approximates the relative ratio of dividend income to other property income from 1998 and later. We also assume that non-labor income is shared for the entire household.

Hourly wage We calculate hourly wages as pre-tax wage and salary income for the prior year divided by the product of usual hours worked per week in the prior year and weeks worked for pay in the prior year. We code hourly wage as "missing" if usual hours worked or weeks worked are zero or if wage and salary income is missing. Throughout our analysis, we use imputed wages for these non-workers (and occasionally for the workers, too). We use the standard Heckman selection model to estimate wages while accounting for selection into employment. First, we divide the sample into men and women and pool across five-year bins (e.g., 1979-1983, 1984-1988, etc.) for improved power. Then for each sex and pooled year sample, we jointly estimate a wage model (log wage as a function of a cubic in age, educational attainment, marital status, and number of dependents) and selection model (probability of working as a function of the wage variables with selection instruments of non-labor income and indicators for having children between the ages of zero to two, three to seven, eight to 13, 14 to 17, 18, and 19+). This procedure provides us with estimated wages for non-workers (and workers) and the variance of the conditional wage distribution.

Real wages and income We use the Consumer Price Index Research Series Using Current Methods (CPI-U-RS) to convert all after-tax wages and non-labor income to 2017 dollars.

Table C.2.1 Descriptive Statistics, Single Men and Women

	1980	**1988**	**1996**	**2000**	**2008**	**2016**
			Panel A: Men			
Working	0.97	0.96	0.97	0.98	0.95	0.95
Hours (> 0)	42.34	42.89	43.57	43.91	42.70	42.86
Hourly wage	22.06	24.22	22.84	25.78	24.90	26.14
Non-labor income	1,536	1,982	2,025	2,995	2,140	2,268
Age	37.60	37.49	39.00	39.69	40.63	40.75
Dependents (under 18)	0.18	0.18	0.20	0.17	0.19	0.18
Dependents (under 2)	0.01	0.01	0.01	0.01	0.01	0.01
High school completed	0.30	0.35	0.32	0.32	0.32	0.30
Some college	0.21	0.20	0.29	0.28	0.29	0.29
Bachelor's degree	0.19	0.21	0.20	0.22	0.22	0.23
Advanced degree	0.10	0.11	0.10	0.10	0.09	0.12
Observations	2,648	3,097	2,930	3,159	4,374	3,690
			Panel B: Women			
Working	0.84	0.84	0.89	0.94	0.92	0.90
Hours (> 0)	38.54	39.54	40.23	40.57	39.85	39.73
Hourly wage	15.65	18.45	19.25	20.94	21.36	22.31
Non-labor income	2,659	2,583	2,834	3,812	2,803	2,338
Age	38.91	38.27	39.68	40.38	40.94	40.64
Dependents (under 18)	1.21	0.96	0.94	0.85	0.88	0.87
Dependents (under 2)	0.09	0.08	0.07	0.06	0.07	0.07
High school completed	0.40	0.38	0.32	0.31	0.27	0.25
Some college	0.18	0.21	0.31	0.31	0.34	0.32
Bachelor's degree	0.12	0.15	0.17	0.19	0.20	0.22
Advanced degree	0.05	0.07	0.08	0.09	0.11	0.14
Observations	5,316	5,373	4,651	4,763	7,300	5,733

Notes: This table contains descriptive statistics for our analytic sample across time. Panel A presents statistics for single men and Panel B presents statistics for single women. Years correspond to the survey year in the CPS. Working is a binary variable equal to one if the observation had positive hours worked per week in a typical week last year. Hours (> 0) is the average hours worked for workers. Hourly wages and non-labor income are in 2017 dollars. Observations are weighted by their ASEC person-level survey weight.

Table C.2.2 Descriptive Statistics, Married Men and Women

	1980	1988	1996	2000	2008	2016
			Panel A: Men			
Working	0.99	0.98	0.98	0.98	0.97	0.96
Hours (> 0)	43.31	43.74	44.43	44.68	44.05	43.63
Hourly wage	25.37	27.23	27.10	29.78	29.41	32.10
Non-labor income	2,218	2,815	3,236	4,884	3,309	3,169
Age	40.09	39.66	40.71	41.44	42.16	42.91
Dependents (under 18)	1.50	1.33	1.31	1.30	1.30	1.31
Dependents (under 2)	0.20	0.21	0.20	0.19	0.20	0.19
High school completed	0.37	0.38	0.33	0.32	0.29	0.27
Some college	0.17	0.19	0.27	0.27	0.26	0.25
Bachelor's degree	0.12	0.15	0.19	0.21	0.25	0.28
Advanced degree	0.03	0.05	0.08	0.09	0.12	0.17
Bachelor's degree	0.16	0.18	0.19	0.21	0.23	0.24
Advanced degree	0.07	0.09	0.11	0.12	0.13	0.17
Observations	17,619	14,944	12,251	12,722	18,802	14,414
			Panel B: Women			
Working	0.66	0.74	0.79	0.79	0.77	0.75
Hours (> 0)	43.31	43.74	44.43	44.68	44.05	43.63
Hourly wage	9.66	12.79	15.31	16.71	17.37	18.80
Non-labor income	2,218	2,815	3,236	4,884	3,309	3,169
Age	37.42	37.24	38.58	39.36	40.18	40.99
Dependents (under 18)	1.50	1.33	1.31	1.30	1.30	1.31
Dependents (under 2)	0.20	0.21	0.20	0.19	0.20	0.19
High school completed	0.49	0.47	0.36	0.33	0.27	0.23
Some college	0.16	0.20	0.28	0.29	0.28	0.25
Bachelor's degree	0.12	0.15	0.19	0.21	0.25	0.28
Advanced degree	0.03	0.05	0.08	0.09	0.12	0.17
Observations	17,619	14,944	12,251	12,722	18,802	14,414

Notes: This table contains descriptive statistics for our analytic sample across time. Panel A presents statistics for married men and Panel B presents statistics for married women. Years correspond to the survey year in the CPS. Working is a binary variable equal to one if the observation had positive hours worked per week in a typical week last year. Hours (> 0) is the average hours worked for workers. Hourly wages and non-labor income are in 2017 dollars. Observations are weighted by their ASEC person-level survey weight.

Table C.2.3 Heckman Selection Wage Model, Men

	1979 to 1983	**1984 to 1988**	**1989 to 1993**	**1994 to 1998**	**1999 to 2003**	**2004 to 2008**	**2009 to 2013**	**2014 to 2018**
Selection equation								
Age	-0.135	-0.207	-0.176	-0.108	-0.145	-0.201	-0.206	-0.131
	(0.068)	(0.065)	(0.069)	(0.071)	(0.064)	(0.057)	(0.052)	(0.059)
$\text{Age}^2/100$	0.418	0.573	0.483	0.352	0.452	0.577	0.531	0.355
	(0.164)	(0.158)	(0.166)	(0.170)	(0.155)	(0.136)	(0.126)	(0.143)
$\text{Age}^3/1000$	-0.044	-0.055	-0.048	-0.040	-0.048	-0.056	-0.047	-0.033
	(0.013)	(0.012)	(0.013)	(0.013)	(0.012)	(0.011)	(0.010)	(0.011)
H.S. completed	0.189	0.298	0.325	0.269	0.178	0.183	0.229	0.127
	(0.024)	(0.023)	(0.024)	(0.028)	(0.028)	(0.025)	(0.022)	(0.027)
Some college	0.293	0.415	0.475	0.387	0.303	0.289	0.357	0.260
	(0.031)	(0.029)	(0.029)	(0.030)	(0.029)	(0.026)	(0.023)	(0.028)
Bachelor's degree	0.465	0.617	0.606	0.503	0.379	0.390	0.545	0.395
	(0.035)	(0.033)	(0.033)	(0.034)	(0.031)	(0.028)	(0.025)	(0.030)
Advanced degree	0.569	0.695	0.711	0.629	0.420	0.520	0.636	0.554
	(0.050)	(0.044)	(0.042)	(0.043)	(0.037)	(0.034)	(0.030)	(0.035)
Married	0.408	0.342	0.327	0.268	0.150	0.114	0.095	0.045
	(0.028)	(0.026)	(0.025)	(0.026)	(0.023)	(0.020)	(0.018)	(0.020)
Dependents	-0.088	-0.133	-0.114	-0.125	-0.043	-0.022	-0.021	0.040
	(0.018)	(0.017)	(0.019)	(0.020)	(0.019)	(0.017)	(0.014)	(0.017)
1[Dep. 0-2]	0.064	0.105	0.028	0.007	0.079	0.175	0.141	0.080
	(0.039)	(0.037)	(0.039)	(0.039)	(0.036)	(0.032)	(0.027)	(0.032)
1[Dep. 3-7]	0.047	0.115	0.093	0.089	0.109	0.026	0.067	0.035
	(0.036)	(0.035)	(0.037)	(0.037)	(0.034)	(0.029)	(0.025)	(0.029)
1[Dep. 8-13]	0.127	0.153	0.157	0.182	0.149	0.183	0.128	0.066
	(0.036)	(0.034)	(0.036)	(0.037)	(0.033)	(0.029)	(0.025)	(0.029)
1[Dep. 14-17]	0.145	0.225	0.193	0.263	0.220	0.170	0.179	0.087
	(0.035)	(0.033)	(0.035)	(0.037)	(0.032)	(0.028)	(0.024)	(0.028)
1[Dep. 18]	0.104	0.168	0.183	0.212	0.245	0.156	0.138	0.056
	(0.045)	(0.046)	(0.050)	(0.054)	(0.048)	(0.040)	(0.034)	(0.039)
1[Dep. 19+]	0.119	0.142	0.148	0.124	0.204	0.168	0.159	0.195
	(0.029)	(0.028)	(0.029)	(0.030)	(0.028)	(0.024)	(0.021)	(0.024)
Non-labor income	-0.010	-0.006	-0.007	-0.005	-0.004	-0.005	-0.003	-0.002
(in $1000s)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	2.794	3.764	3.537	2.573	3.207	3.852	3.876	3.036
	(0.898)	(0.869)	(0.924)	(0.947)	(0.870)	(0.760)	(0.701)	(0.801)

Table C.2.3 (cont'd)

	1979 to 1983	**1984 to 1988**	**1989 to 1993**	**1994 to 1998**	**1999 to 2003**	**2004 to 2008**	**2009 to 2013**	**2014 to 2018**
Wage equation								
Age	0.117	0.069	0.097	0.139	0.113	0.099	0.056	0.075
	(0.010)	(0.012)	(0.012)	(0.013)	(0.012)	(0.011)	(0.013)	(0.014)
$Age^2/100$	-0.201	-0.077	-0.154	-0.252	-0.196	-0.157	-0.059	-0.114
	(0.026)	(0.029)	(0.030)	(0.033)	(0.030)	(0.028)	(0.031)	(0.035)
$Age^3/1000$	0.011	0.001	0.008	0.015	0.011	0.008	0.000	0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
H.S. completed	0.270	0.281	0.289	0.305	0.328	0.306	0.301	0.313
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Some college	0.344	0.390	0.414	0.436	0.487	0.468	0.473	0.484
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Bachelor's deg.	0.483	0.579	0.633	0.668	0.751	0.741	0.775	0.807
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)
Advanced deg.	0.523	0.656	0.737	0.820	0.904	0.908	0.960	1.012
	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Married	0.134	0.129	0.138	0.137	0.143	0.141	0.146	0.137
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Dependents	0.001	-0.003	-0.003	-0.001	0.009	0.012	0.013	0.012
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.456	1.001	0.603	-0.018	0.375	0.540	1.098	0.894
	(0.136)	(0.153)	(0.159)	(0.177)	(0.161)	(0.152)	(0.169)	(0.191)
Observations	95,631	91,741	90,746	81,091	110,212	120,014	111,194	93,621

Notes: This table contains parameter estimates from the Heckman selection wage model described in Appendix Section C.2. The outcome variable is logged hourly wage in 2017 dollars. Standard errors in parentheses.

Table C.2.4   Heckman Selection Wage Model, Women

	1979 to 1983	**1984 to 1988**	**1989 to 1993**	**1994 to 1998**	**1999 to 2003**	**2004 to 2008**	**2009 to 2013**	**2014 to 2018**
Selection equation								
Age	-0.047	0.009	-0.048	0.032	-0.009	-0.004	0.086	0.165
	(0.029)	(0.032)	(0.035)	(0.038)	(0.032)	(0.031)	(0.032)	(0.035)
$\text{Age}^2/100$	0.113	-0.018	0.141	-0.038	0.063	0.041	-0.189	-0.369
	(0.075)	(0.083)	(0.091)	(0.099)	(0.084)	(0.078)	(0.081)	(0.088)
$\text{Age}^3/1000$	-0.015	-0.005	-0.018	-0.004	-0.011	-0.008	0.012	0.026
	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)
H.S. completed	0.369	0.490	0.538	0.544	0.507	0.537	0.481	0.477
	(0.011)	(0.012)	(0.013)	(0.016)	(0.015)	(0.014)	(0.016)	(0.018)
Some college	0.575	0.752	0.820	0.862	0.754	0.828	0.783	0.805
	(0.014)	(0.015)	(0.016)	(0.017)	(0.015)	(0.015)	(0.016)	(0.018)
Bachelor's degree	0.716	0.885	0.946	0.931	0.767	0.824	0.822	0.881
	(0.016)	(0.017)	(0.018)	(0.019)	(0.017)	(0.016)	(0.016)	(0.018)
Advanced degree	1.037	1.207	1.236	1.202	0.990	1.037	1.060	1.144
	(0.032)	(0.029)	(0.028)	(0.028)	(0.022)	(0.019)	(0.019)	(0.021)
Married	-0.500	-0.365	-0.307	-0.340	-0.578	-0.553	-0.471	-0.537
	(0.011)	(0.011)	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.012)
Dependents	-0.168	-0.249	-0.241	-0.239	-0.209	-0.213	-0.223	-0.186
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.008)
1[Dep. 0-2]	-0.492	-0.403	-0.396	-0.346	-0.324	-0.310	-0.215	-0.198
	(0.015)	(0.015)	(0.016)	(0.017)	(0.014)	(0.014)	(0.014)	(0.015)
1[Dep. 3-7]	-0.337	-0.247	-0.244	-0.234	-0.190	-0.165	-0.097	-0.125
	(0.014)	(0.015)	(0.015)	(0.016)	(0.014)	(0.013)	(0.013)	(0.014)
1[Dep. 8-13]	-0.020	0.071	0.087	0.086	0.122	0.122	0.133	0.069
	(0.013)	(0.014)	(0.015)	(0.016)	(0.014)	(0.013)	(0.013)	(0.014)
1[Dep. 14-17]	0.153	0.233	0.203	0.222	0.228	0.255	0.251	0.192
	(0.014)	(0.015)	(0.016)	(0.017)	(0.014)	(0.013)	(0.013)	(0.014)
1[Dep. 18]	0.148	0.207	0.232	0.225	0.233	0.241	0.208	0.205
	(0.018)	(0.021)	(0.023)	(0.025)	(0.021)	(0.020)	(0.019)	(0.021)
1[Dep. 19+]	0.003	0.013	0.001	-0.007	0.062	0.037	0.055	0.005
	(0.012)	(0.013)	(0.014)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)
Non-labor income	-0.008	-0.007	-0.007	-0.005	-0.004	-0.004	-0.005	-0.002
(in \$1000s)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	2.483	1.455	2.013	0.896	1.811	1.547	0.150	-0.969
	(0.358)	(0.398)	(0.437)	(0.482)	(0.410)	(0.389)	(0.413)	(0.450)

Table C.2.4 (cont'd)

	1979 to 1983	**1984 to 1988**	**1989 to 1993**	**1994 to 1998**	**1999 to 2003**	**2004 to 2008**	**2009 to 2013**	**2014 to 2018**
Wage equation								
Age	0.139	0.175	0.147	0.183	0.137	0.116	0.157	0.178
	(0.011)	(0.012)	(0.013)	(0.015)	(0.013)	(0.013)	(0.013)	(0.015)
$\text{Age}^2/100$	-0.302	-0.376	-0.292	-0.384	-0.272	-0.215	-0.318	-0.370
	(0.030)	(0.033)	(0.034)	(0.038)	(0.033)	(0.032)	(0.034)	(0.038)
$\text{Age}^3/1000$	0.021	0.025	0.018	0.026	0.017	0.012	0.021	0.026
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
H.S. completed	0.219	0.267	0.283	0.318	0.314	0.316	0.330	0.322
	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.010)
Some college	0.368	0.448	0.493	0.532	0.517	0.531	0.551	0.543
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.010)
Bachelor's deg.	0.537	0.634	0.735	0.807	0.808	0.823	0.861	0.887
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)
Advanced deg.	0.727	0.841	0.933	1.036	1.040	1.064	1.124	1.162
	(0.011)	(0.010)	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.011)
Married	-0.075	-0.046	-0.018	-0.007	-0.007	-0.012	0.006	0.016
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Dependents	-0.069	-0.079	-0.077	-0.064	-0.051	-0.046	-0.039	-0.040
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.441	-0.150	0.073	-0.497	0.168	0.373	-0.228	-0.569
	(0.140)	(0.155)	(0.165)	(0.186)	(0.162)	(0.161)	(0.173)	(0.200)
Observations	107,867	104,221	102,231	90,810	123,240	135,599	124,668	103,915

Notes: This table contains parameter estimates from the Heckman selection wage model described in Appendix Section C.2. The outcome variable is logged hourly wage in 2017 dollars. Standard errors in parentheses.

C.3 Using TAXSIM and TRIM3 to predict after-tax wages and social assistance benefits

To fully exploit variation in the tax system, we would like to calculate after-tax income for each hours choice a household could make (seven for single men and women, 49 for married couples). Given we are using simulation methods that rely on 100 wage draws for each household, this entails calculating post-tax income 700 times for each single man and woman and 4,900 times for each married couple in our sample. This amounts to calculating after-tax income upwards of 1.35 billion times (700*93,330 for single men, 700*153,494 for single women, and 4,900*240,000 for married couples).

To make this computationally feasible with TAXSIM, we rely on a strategy similar to that described by Löeffler et al. (2018), estimating a flexible parametric tax function and then using the tax function to predict after-tax wages. For each observation, we use NBER's TAXSIM version 27 to calculate after-tax income at seven weekly work hours choices conditional on working 50 weeks a year and their observed (or predicted) hourly wage and non-labor income. For single men and women, the seven hours choices comprise their entire choice set. For married couples, we specify that both spouses work the same number of hours and span the seven discrete hours choices (e.g., 0 and 0 hours, 10 and 10 hours, etc.). Using each observation's simulated after-tax income from TAXSIM, we fit an observation-specific function of after-tax income as a quadratic function of before-tax income. To ensure that taxes are zero when income is zero, we do not include a constant in the regression. Finally, when we use the observation-specific function to predict after-tax income, we do not allow after-tax income to be less than 60% of before-tax income, which should not happen in practice but would eventually happen for large enough before-tax income due to the negative quadratic term.

For social benefits, we use the Urban Institute's TRIM3 and a flexible regression to predict government assistance. TRIM3 provides information on eligibility and receipt of government assistance (i.e., SNAP/Food Stamps, TANF/ADFC, and SSI) for each household in our sample. TRIM3 requires users to input assumptions and/or interpretations about economic behavior and the rules governing federal programs. Therefore, the conclusions presented in this chapter are attributable only to the authors and not any researcher at the Urban Institute. We estimate a state-year-marital status-number of dependents-specific kinked regression model to predict benefits given counterfactual labor income bundles. The slope between household income and benefits received is allowed to change after the first \$10k and \$20k of (nominal) income. Between \$30k to \$50k, \$50k to \$70k, and \$70k+, we use the average benefits received in the range. When we use these flexible functions to predict benefits received, we truncate benefits at \$0 and \$50,000 in nominal dollars.

C.4 Utility function parameter estimates

Table C.4.1 Baseline Model Parameter Estimates, Single Men

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
Log(Consumption)	2.23	3.87	3.43	4.29	4.26	5.08
	(1.37)	(1.25)	(1.05)	(1.03)	(1.15)	(1.05)
Log(Leisure)	135.02	192.00	167.55	271.43	159.24	107.57
	(38.29)	(39.47)	(32.46)	(31.32)	(30.16)	(34.23)
$\times$ Log(Age)	-19.75	-42.29	-33.76	-85.50	-27.56	0.69
	(20.41)	(20.95)	(17.26)	(16.45)	(15.95)	(18.18)
$\times$ Log(Age)^2	3.12	6.24	4.82	11.90	4.06	0.23
	(2.80)	(2.87)	(2.36)	(2.25)	(2.18)	(2.48)
$\times$ Dep. (under 18)	-0.22	-0.15	-0.36	-0.35	-0.44	-0.39
	(0.20)	(0.22)	(0.15)	(0.16)	(0.16)	(0.16)
$\times$ Dep. (under 2)	2.32	-1.10	0.66	-0.66	1.33	1.02
	(1.11)	(1.38)	(1.05)	(0.74)	(0.81)	(0.81)
Log(Consumption)^2	0.06	0.08	0.10	0.09	0.11	0.13
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Log(Leisure)^2	-11.22	-12.59	-11.03	-11.97	-11.20	-10.96
	(0.86)	(0.80)	(0.72)	(0.68)	(0.73)	(0.73)
Log(C) $\times$ Log(L)	-0.55	-0.96	-0.88	-1.07	-1.08	-1.30
	(0.27)	(0.26)	(0.22)	(0.21)	(0.22)	(0.22)
Hours = 10	-3.31	-3.53	-3.45	-2.94	-3.50	-3.55
	(0.27)	(0.30)	(0.20)	(0.16)	(0.18)	(0.22)
Hours = 20	-2.72	-2.80	-2.97	-3.07	-3.00	-2.98
	(0.14)	(0.14)	(0.11)	(0.12)	(0.11)	(0.12)
Hours = 30	-2.58	-3.05	-2.91	-3.14	-2.74	-2.81
	(0.11)	(0.12)	(0.09)	(0.10)	(0.08)	(0.09)
Observations	2,930	3,159	4,260	4,374	4,254	3,690

Notes: This table contains parameter estimates for our baseline model for single men in a subset of years. The specific utility function is described in Section 3.4.1.

Table C.4.2 Baseline Model Parameter Estimates, Single Women

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
Log(Consumption)	10.63	11.21	13.56	14.09	15.76	14.16
	(1.14)	(1.09)	(0.85)	(0.89)	(0.99)	(1.02)
Log(Leisure)	320.14	255.76	308.36	255.64	269.93	246.72
	(29.51)	(31.38)	(24.20)	(24.86)	(24.25)	(27.65)
× Log(Age)	-88.52	-43.64	-61.02	-29.22	-38.78	-36.50
	(15.83)	(16.93)	(12.96)	(13.36)	(12.90)	(14.76)
× Log(Age)^2	12.42	6.34	8.49	4.22	5.47	5.19
	(2.18)	(2.32)	(1.78)	(1.83)	(1.77)	(2.02)
× Dep. (under 18)	0.46	0.57	0.25	0.28	0.28	0.08
	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)	(0.09)
× Dep. (under 2)	1.51	1.05	1.41	1.00	0.99	0.75
	(0.28)	(0.35)	(0.26)	(0.24)	(0.25)	(0.28)
Log(Consumption)^2	0.13	0.13	0.16	0.14	0.19	0.20
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Leisure)^2	-15.31	-17.31	-18.42	-19.11	-17.93	-16.14
	(0.58)	(0.60)	(0.52)	(0.53)	(0.58)	(0.60)
Log(C) × Log(L)	-2.45	-2.60	-3.15	-3.24	-3.70	-3.34
	(0.22)	(0.22)	(0.18)	(0.18)	(0.19)	(0.21)
Hours = 10	-3.18	-3.31	-3.11	-3.27	-3.38	-3.42
	(0.14)	(0.17)	(0.11)	(0.12)	(0.11)	(0.13)
Hours = 20	-2.49	-2.35	-2.56	-2.57	-2.62	-2.78
	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)
Hours = 30	-2.25	-2.28	-2.46	-2.45	-2.27	-2.35
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	4,651	4,763	7,658	7,300	7,013	5,733

Notes: This table contains parameter estimates for our baseline model for single women in a subset of years. The specific utility function is described in Section 3.4.1.

Table C.4.3 Baseline Model Parameter Estimates, Married Men and Women

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
Log(Consumption)	12.59	14.20	14.04	17.19	18.83	16.63
	(1.16)	(1.13)	(1.14)	(1.14)	(1.01)	(1.02)
Log(Leisure$_m$)	277.64	287.01	278.50	282.67	254.86	186.89
	(30.38)	(30.55)	(30.88)	(29.39)	(29.90)	(31.52)
$\times$ Log(Age$_m$)	-76.69	-86.62	-87.14	-74.71	-64.85	-40.29
	(16.47)	(16.47)	(16.59)	(15.79)	(16.06)	(16.94)
$\times$ Log(Age$_m$)^2	10.68	12.18	12.32	10.46	8.96	5.71
	(2.26)	(2.25)	(2.26)	(2.15)	(2.18)	(2.30)
$\times$ Dep. (under 18)	5.91	9.26	12.13	9.85	10.24	11.23
	(1.24)	(1.27)	(1.28)	(1.28)	(1.14)	(1.23)
$\times$ Dep. (under 2)	4.22	2.31	3.50	1.10	-3.94	-3.81
	(3.52)	(3.54)	(3.46)	(3.31)	(3.08)	(3.35)
Log(Leisure$_f$)	251.58	233.39	227.36	206.19	250.87	233.96
	(25.58)	(24.84)	(25.64)	(24.77)	(24.99)	(26.03)
$\times$ Log(Age$_f$)	-50.35	-46.41	-45.25	-27.77	-59.14	-54.46
	(14.10)	(13.68)	(14.01)	(13.53)	(13.59)	(14.13)
$\times$ Log(Age$_f$)^2	7.06	6.56	6.39	3.96	8.02	7.63
	(1.96)	(1.90)	(1.94)	(1.87)	(1.87)	(1.94)
$\times$ Dep. (under 18)	6.68	9.67	12.50	10.42	10.77	11.81
	(1.17)	(1.21)	(1.23)	(1.22)	(1.09)	(1.18)
$\times$ Dep. (under 2)	5.29	3.52	4.79	2.46	-2.79	-3.00
	(3.32)	(3.34)	(3.27)	(3.12)	(2.92)	(3.20)
Log(Consumption)^2	0.14	0.20	0.22	0.16	0.17	0.24
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log(Leisure$_m$)^2	-14.86	-14.46	-14.30	-15.49	-14.33	-13.80
	(0.32)	(0.34)	(0.34)	(0.33)	(0.33)	(0.33)
Log(Leisure$_f$)^2	-17.95	-17.46	-17.50	-17.82	-16.39	-16.13
	(0.34)	(0.33)	(0.35)	(0.34)	(0.34)	(0.32)

Table C.4.3 (cont'd)

	1996	**2000**	**2004**	**2008**	**2012**	**2016**
Log(C) × Log(L_m)	-1.88	-2.25	-2.11	-2.69	-2.91	-2.09
	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)	(0.16)
Log(C) × Log(L_f)	-1.08	-1.16	-1.29	-1.26	-1.41	-1.90
	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
Log(L_m) × Log(L_f)	2.42	-0.88	-6.39	-3.79	-15.90	-7.53
	(6.37)	(6.32)	(6.47)	(6.23)	(6.22)	(6.57)
× Log(Avg. Age)	-0.44	2.77	6.87	4.31	11.34	8.18
	(3.53)	(3.49)	(3.54)	(3.41)	(3.40)	(3.58)
× Log(Avg. Age)^2	0.12	-0.37	-0.96	-0.60	-1.52	-1.14
	(0.49)	(0.48)	(0.49)	(0.47)	(0.46)	(0.49)
× Dep. (under 18)	-1.36	-2.10	-2.80	-2.30	-2.41	-2.66
	(0.28)	(0.29)	(0.29)	(0.29)	(0.26)	(0.28)
× Dep. (under 2)	-0.98	-0.51	-0.76	-0.30	0.89	0.91
	(0.79)	(0.79)	(0.78)	(0.74)	(0.69)	(0.76)
Hours_m = 10	-3.59	-3.90	-3.88	-4.62	-3.87	-3.95
	(0.19)	(0.24)	(0.21)	(0.30)	(0.18)	(0.20)
Hours_m = 20	-3.22	-3.34	-3.51	-3.63	-3.23	-3.46
	(0.11)	(0.12)	(0.12)	(0.12)	(0.09)	(0.10)
Hours_m = 30	-3.33	-3.71	-3.32	-3.32	-3.21	-3.50
	(0.08)	(0.10)	(0.08)	(0.08)	(0.07)	(0.08)
Hours_f = 10	-2.86	-2.89	-2.88	-3.03	-3.00	-3.23
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
Hours_f = 20	-2.16	-2.28	-2.26	-2.43	-2.40	-2.52
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Hours_f = 30	-2.18	-2.30	-2.24	-2.37	-2.29	-2.50
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	10,000	10,000	10,000	10,000	10,000	10,000

Notes: This table contains parameter estimates for our baseline model for married men and women in a subset of years. The specific utility function is described in Section 3.4.1.

C.5 Quadratic versus translog utility results

While our baseline model uses a translog utility function, another common choice in the literature is a quadratic utility function (e.g., Bargain et al. 2014; Blundell et al. 2000). Löeffler et al. (2018) show that labor supply elasticity estimates tend to be robust to the choice of utility function, and when we estimate our baseline model with a quadratic utility function, we find similar results.

Following Bargain et al. (2014), our quadratic utility function for single men and women is:

$$u_{ij} = \beta_i^c c_{ij} + \beta^{cc}(c_{ij})^2 + \beta_i^l l_{ij} + \beta^{ll}(l_{ij})^2 + \beta^{cl} c_{ij} l_{ij} + f(x_i, h_{ij}) \tag{C.1}$$

where c_{ij} is weekly household consumption, $l_{ij} = 168 - h_{ij}$ is weekly leisure, and $f(x_i, h_{ij})$ are fixed costs of working more than zero hours. Three parameters vary with individual characteristics: β_i^c varies with a quadratic function of age and number of dependents under the age of 18, β_i^l varies with a quadratic function of age and an indicator for having dependents under the age of 2, and $f(x_i, h_{ij})$ varies with number of dependents under 18, an indicator for having dependents under two, and an indicator for having earned a college degree.

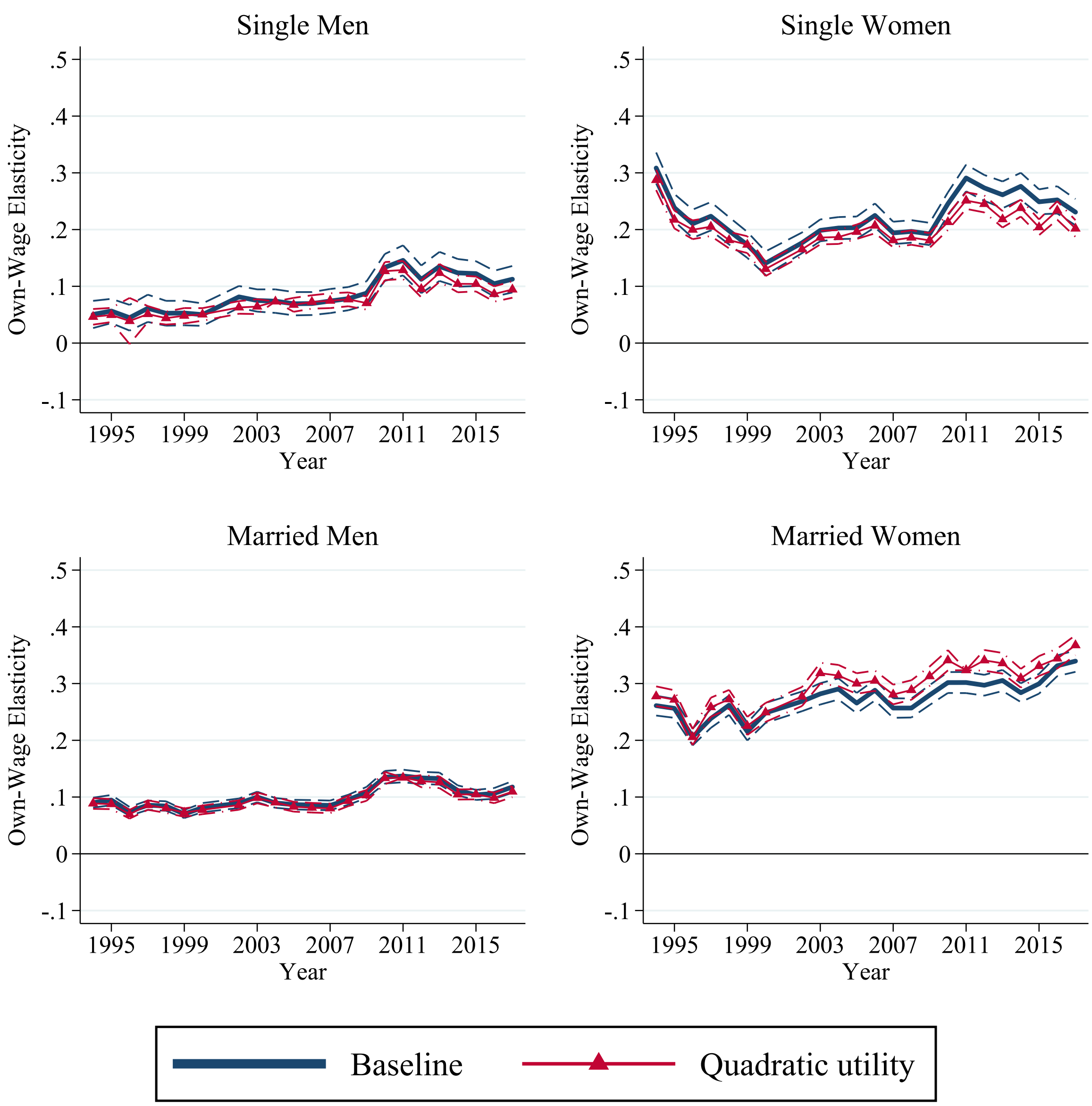
For married men and women, we add a quadratic function of leisure for the spouse, an interaction between household consumption and leisure for the spouse, the interaction of leisure for the head of household and leisure for the spouse, and a fixed cost of work for the spouse:

$$\begin{aligned} u_{ij} = {} & \beta_i^c c_{ij} + \beta^{cc}(c_{ij})^2 + \beta_i^{lm} l_{ij}^m + \beta^{lmm}(l_{ij}^m)^2 + \beta_i^{lf} l_{ij}^f + \beta^{lff}(l_{ij}^f)^2 + \\ & \beta^{clm} c_{ij} l_{ij}^m + \beta^{clf} c_{ij} l_{ij}^f + \beta^{lmf} l_{ij}^m l_{ij}^f + f^m(x_i^m, h_{ij}^m) + f^f(x_i^f, h_{ij}^f). \end{aligned} \tag{C.2}$$

Modeled preference heterogeneity is the same for the spouse as for the head of household, but now the quadratic function of age included in β_i^c is based on the average age of the head of household and spouse.

Figure C.5.1 presents our estimated elasticities from the baseline model and model with quadratic utility. Wages are predicted for non-workers using 100 Halton draws, and random slopes are set to zero. As expected, the estimated elasticities are very similar between the two models, and the trends we observe over time are unchanged.

Figure C.5.1 Mean Own-Wage Elasticities, Baseline Estimates versus Estimates from Quadratic Utility Model



Notes: This figure presents the estimated trends in mean own-wage elasticities separately by sex and marital status. Our baseline model (blue) has a translog utility function, no random slopes, benefit simulator from TRIM3, and predicted wages for non-workers using 100 draws from their conditional wage distribution. Our quadratic model (red with triangle markers) is identical to the baseline model except for quadratic utility function as described in Section C.5.

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