Clocking Into Work and Out of Class: How College Students Make Their Credit Hour Enrollment and Financing Decisions

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Abstract

This paper studies how college students make and finance their credit hour enrollment, paying particular attention to the role of 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 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 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 minimum wage and making college tuition free, and evaluate how the policies affect student decisions and outcomes.

Keywords: Labor supply, student loans, postsecondary education, time-to-degree, subjective expectations

JEL classification: I22, I23, J22, J24

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1 Introduction

Economists believe that 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 reduce the value of their investment. More recent research also highlights the non-monetary utility 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 and school 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 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. It is not clear ex ante how students should behave or why they behave the way they do.

This paper studies how students navigate these trade-offs to maximize their lifetime utility, paying particular attention to the role of financial resources and beliefs. Information such as family financial support and 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, expected study hours, and subjective expectations on 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' high school grades, course history at MSU, financial aid eligibility by term, and borrowing history.

To analyze the data, I construct a dynamic model of student behavior in college. Students choose their credit hour enrollment, labor supply, 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 that students face borrowing constraints, receive financial support from their family, earn grades for their classes, and have 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 trade-offs. The choices of students in one period affect their 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 preferences over in-school consumption, leisure and 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. Students' credit hour enrollment is strongly inelastic to changes in these variables. The labor supply decision, on the other hand, is much more responsive. I find an average wage elasticity of 0.28 in the fall and spring semesters, which is similar to the wage elasticity for working-age married women in the United States (McClelland and Mok, 2012). For a subset of students, labor supply is responsive to beliefs of the returns to studying and returns to graduating with a high GPA. A 10% increase in either belief leads to at least a 19% reduction in work hours in the fall and spring for a quarter of students. Borrowing elasticities tend to follow a similar pattern. Most students do not substantively change their borrowing choices in response to changes in aid, tuition, or beliefs, but there are meaningful responses in the tails of the distribution. In addition, students substitute between labor earnings and debt. A 10% increase in wages reduces borrowing by $350 in the fall and spring, on average.

With the model estimates in hand, I can simulate the effects of counterfactual policies on students' behaviors and outcomes. I evaluate two policies that increase the affordability of college but affect incentives in very different ways: an increase in minimum wage to $15 per hour and making tuition free for all students. An increase in minimum wage increases work hours by 0.66 hours a week in the fall and spring and by 1.1 hours a week in the summer. I do not find any significant changes in credit hours, borrowing, or expected GPA. Making tuition free increases credit hours by 0.10 hours in the fall and spring and 0.13 hours in the summer. While there are only minimal changes in work hours, average borrowing decreases by $2,323 per year. As with the increase in minimum wage, making college tuition free does not significantly change expected GPA.

This paper contributes to three literatures. It introduces an estimable model to the human capital investment and economics of education literature 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 labor supply literature by estimating labor supply elasticities for college students. Most researchers estimate life-cycle models with an emphasis on the labor supply elasticity of workers in prime working ages. 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 dynamic discrete choice literature which incorporates subjective expectations, and it is the first to do so with expectations of the GPA returns to studying and labor market returns to a graduating with a high GPA. The standard approach to estimating dynamic models requires estimating laws of motion for state variables from panel data, assuming heterogeneity in this 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 to for this research (Manski, 1993).

The paper 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 utility parameters, elasticities, and results from counterfactual simulations. Section 6 concludes with a brief discussion on areas for future work.

2 Related literature

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. These papers typically 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 mediated by decreases 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. 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 (savings of approximately $281 per credit) 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 dissuade them for persisting in 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 credits 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. study a grant of only $1,000 per year.

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 recent literature review by Neyt et al., 2019).

Despite the frequency and importance of student employment, there is very little research on wage elasticities for college students; in fact, many researchers that estimate labor supplies remove students from their sample to focus exclusively on prime-age workers. Elasticities 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. As a first approximation, students with higher levels of family financial support may have similar elasticities to married women, with wage elasticities of 0.2 to 0.4, while students who are mostly financial independent may have similar elasticities to single men and women, with wage elasticities of 0.1 to 0.3 (McClelland and Mok, 2012).

[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.

Studies of increased financial aid provide a source of income elasticities of labor supply. Not surprisingly, larger grants appear to reduce labor supply by more than smaller grants. 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.

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), and when models allow individuals to work and enroll in school simultaneously, they do 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.

3 Data

For this paper 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 (MSU) in the spring of 2019. I also obtained administrative records from the Office of the Registrar and Office of Financial Aid at the University on 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 cost of attendance, loan eligibility, grants and scholarships, living situation and rent, and family financial support for education and living expenses. The survey also elicited students' expected study hours conditional on credit hour and work schedules, beliefs about the returns to studying on GPA and 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. For more information on how these variables were measured or constructed, see the appendix. A full text of the survey is available online.

3.1 Sampling frame and survey distribution

Michigan State University is a large, moderately selective public university in the midwest. The University offers one-year certificates through doctoral degrees, but I focus on the undergraduate-degree-seeking students in this research. Relative to the broader population of public four-year-degree-granting institutions, MSU students are more likely to be male, white, from higher income families, and earn high SAT/ACT scores. They are less likely to be first-generation college students. The mean cost of attendance and net price is higher at MSU than the average public four-year university, but the net price for low income families is lower. MSU's completion rate, retention rate, and expenditures per full-time student are all significantly above average. Appendix Table 1 contains summary statistics for the MSU undergraduate population and population of undergraduate students at other public four-year-degree-granting institutions.

All MSU undergraduate students who were 18 years old or older, not on an athletic scholarship, and had an expected graduation date of December 2019 or later were eligible to receive the survey. The Office of the Registrar provided me with 6,000 randomly selected email addresses from the 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 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 exclude students who failed to reach the end of the survey (120), failed the attention check question (102), or skipped a question required to estimate the model (81). I also exclude students that believe their grades will decrease as they increase their time on schoolwork (35) or believe their future wage will be lower after graduating with a 4.0 GPA as opposed to dropping out (33), as this strongly suggests that the student did not properly understand the questions. I further limit the sample to domestic students, as international students (28) face additional restrictions on their employment and borrowing choices, and first-at-any-college students, as transfer students (233) have unobserved credit enrollment and borrowing histories from their prior institutions. Finally, I exclude students that were not continuously enrolled at least part-time at MSU for the Fall and Spring semesters (46). Students who temporarily "stop-out" of college may do so for reasons that are outside of the scope of the model, like serious illness, family emergencies, or having a child. After these restrictions, I am left with 987 students and 2,947 student-period pairs (1,967 fall and spring periods and 980 summer terms).

Table 1 presents summary statistics for the sample, both unweighted and weighted by the inverse probability of survey response.[2]

[Table 1 here]

3.2 Observed credit hour enrollment and financing choices

The Office of the Registrar provided students' credit enrollment history by term. Table 2 presents the proportion of students who chose each credit hour option. In the fall and spring, over 60% of students enroll in 27 to 30 credit hours, and 95% of students enroll in 24 to 32 credit hours. In the summer, almost 60% of students do not enroll in any credits. Among students who do enroll, 14% take 3 to 4 credits and 19% take 6 to 9 credits.

[Table 2 here]

[2]The parameter estimates and results in this paper are currently based on the unweighted sample.

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 are equally likely to work during the fall and spring or summer terms – 51.55% of students work at least one hour per week in the fall and spring and 51.33% of students work at least one hour per week in the summer – but they do not work the same number of hours. Students who work in the fall and spring term work an average of 12.20 hours per week, while those who work in the summer term work an average of 33.11 hours per week. As shown in figure 1, the modal number of hours worked per week in the fall and spring is 10, though 8 and 15 hours are also common. In the summer, 40 hours per week is the modal choice by a large margin.

[Figure 1 here]

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, and students cannot receive more in Stafford loans than their budget allows.[3] Students do not need to accept the full Stafford loan offer, though the vast majority of borrowers do. If students want to borrow beyond their Stafford loan offer, they must apply for loans from private vendors. As with Stafford loans, students cannot borrow more than their budget allows.

Table 3 presents statistics for three loan options: no loans, Stafford loans only, and maximum Stafford and private loans. In the fall and spring, most students have room in their budget for some amount of loans. The average Stafford loan offer is $5,267, though students are typically eligible for significantly more in private loans. A majority of students choose not to borrow in the fall and spring, but among those

[3] A student's budget is equal to their expected cost of attendance (living expenses, tuition, fees, and books) minus their grant aid and Federal Work Study offer.

who do borrow, their amount borrowed is closest to their Stafford loan offer. In the summer, 60% students do not qualify for any loans, and 92% do not accept any loans.[4]

[Table 3 here]

3.3 Cost of attendance and financial need

A student's cost of attendance is the estimated amount of the money she will need to spend to attend the university for a year. There are four broad components of cost of attendance: tuition, books, fees, and living expenses. For all years in my sample, MSU charged students tuition per credit hour attempted. Rates vary by the student's residence (i.e., in-state, out-of-state, and international), independent status, college, and class level, but an in-state first-year student, without any additional tuition modifiers, pays $14,640 for a 30 credit hours. A similar out-of-state student pays $39,766. In addition to tuition, students have to purchase textbooks and other supplies, which the University budgets at 7% of the base per-credit rate. Some students also pay program fees, ranging from $100 to $670 a semester depending on their college. Expected living expenses range from $11,122 to $14,320 and include room and board and smaller miscellaneous expenses. All together, the average fall-spring cost of attendance is $28,359 for an in-state student and $52,728 for an out-of-state student.

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. Table 4 presents statistics for both. In the fall and spring, the average in-state student receives $6,066 in grants and $15,929 in family financial support, leaving $6,365 of

[4] Stafford loans are only available to students enrolled in more than six credits, and I assume that students cannot receive private loans if they are enrolled in zero credits. Actual credit hour requirements vary by individual loan providers.

unmet financial need. The average out-of-state receives over $10,000 more in grants and $14,000 in family financial support, leaving only $5,505 of unmet financial need.

[Table 4 here]

Averages hide significant heterogeneity across students, as figure 2 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 receive enough aid and support to cover their cost of attendance. At the other extreme, students in the highest quintile of unmet need require more than $21,400 (in-state) or $35,550 (out-of-state) of additional income or loans to cover their expected costs.

[Table 2 here]

3.4 Subjective expectations

The SEES elicited two sets of subjective expectations: students' beliefs of their distribution of grades conditional on schoolwork hours and beliefs of their distribution of post-school (40 hour per week) salaries conditional on GPA. I followed the method proposed by Delavande & Rohwedder (2008) to record both distributions. Students were shown a set of bins representing different outcomes (e.g., earning a B grade, earning a salary within $60 to $79k) and asked to place ten balls across the bins, where each ball represented the likelihood of observing the outcome.[5] This exercise was

[5]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, Giné & McKenzie, 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 the Appendix.

repeated for a series of scenarios (e.g., spending 3 hours on schoolwork, graduating with a GPA between 2.5 and 2.9) to trace out conditional distributions.

For the distribution of grades conditional on schoolwork, the SEES asked students to consider four scenarios: spending one hour of schoolwork per course per week, three hours of schoolwork, six hours of schoolwork, and nine hours of schoolwork. Students were given five bins of possible grades to place balls in: 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). Appendix figure A1 presents the average reported probability of earning each grade for each scenario. At only one hour of schoolwork per course per week, the average student believes they are 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 3 shows. The interquartile range of expected grades in a course with only one hour of schoolwork is 1.4 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.

[Figure 3 here]

For the distribution of post-school (40 hour per week) salaries conditional on GPA, 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, graduating with a cumulative GPA between 3.5 and 4.0. Students were given six bins of possible 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 A2 presents the average reported probability of earning each salary for each GPA scenario. The majority of students believe they will earn less than $34 thousand a year if they left MSU without a degree. As students increase their GPA, they believe they are more likely to earn higher salaries. As with the distribution of grades, there is significant heterogeneity in these beliefs. Figure 4 presents the distribution of expected salaries across students. The interquartile range of expected salaries without a degree is $26 to $45 thousand, and this spread only increases with 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.

[Figure 4 here]

4 Structural Model

I construct a dynamic structural model to capture how students' financial resources and beliefs influence their decisions in college. This section presents the model and describes how I estimate its parameters.

4.1 Model structure

4.1.1 Decision periods

Individuals begin their decision horizon at the start of their first semester 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.[6]

[6] 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.

Individuals remain in college until they graduate, choose to leave without a degree, or reach period T. Individual i graduates when her cumulative credit hours earned exceeds their graduation threshold $\bar{K}_i$ and her cumulative GPA exceeds a 2.0.[7] After leaving college, either voluntarily, due to graduation, or because they reached the maximum time permitted, individuals enter 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. This simplification allows me to focus on the decisions made in college while still incorporating intertemporal tradeoffs that involve post-college outcomes.

4.1.2 Choices

Each period in school, individual i decides whether to continue in school or dropout and immediately enter the full-time labor market. If she chooses to continue in school, she makes three additional decisions: 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.[8] 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. The individual can choose

[7] I allow the graduation threshold to vary with 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.

[8] 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 (Löffler et al., 2018).

not to borrow additional loans, borrow her Federal Stafford loan offer, or borrow up to her maximum student loan eligibility. I denote the entire set of feasible choices in period t with A_t.[9]

4.1.3 State variables

Individual i enters each period with a set of observable 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 observable state variables with S_{it}. In addition, individual i enters each period with a vector of choice-specific preference shocks, $\varepsilon_{it} \equiv \{\varepsilon_{ait} \; \forall a \in A_t\}$. The choice-specific preference shocks are known by the individual at the beginning of the period but not observed by the econometrician. I specify that these preference shocks are iid Type 1 Extreme Value random variables.[10] The entire set of state variables can be partitioned as $\{S_{it}, \varepsilon_{it}\}$.

Individual i begins college with no credit hours, GPA, or debt. State variables evolve according to the following laws of motion:

$$
\begin{aligned}
K_{i,t+1} &= K_{it} + \sum_{k=1}^{k_{it}} 1[g_{ikt} > 0] \\
G_{i,t+1} &= G_{it} \left(\frac{K_{it}}{K_{it} + k_{it}} \right) + \left(\frac{\sum_{k=1}^{k_{it}} g_{ikt}}{K_{it} + k_{it}} \right) \\
B_{i,t+1} &= (1 + r_t^B)(B_{it} + b_{it}) \\
\varepsilon_{ait} &\sim_{iid} \exp(-\exp(-\varepsilon))
\end{aligned}
\tag{1}
$$

Cumulative credits earned is the number of credit hours where a passing (non-

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

[10] This provides convenient functional forms when solving the model, and unlike in the case in static models, the Type 1 Extreme Value distribution does not impose the independence of irrelevant alternatives condition.

zero) grade was earned for that credit. Cumulative GPA is the weighted average of the individual's previous cumulative GPA and newly earned grades.[11] 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. The choice-specific preference shocks are independently distributed across choices, individuals, and time.

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 $g_{it} \equiv \frac{1}{k}\sum_k g_{ikt}$. All three payoffs variables are functions of individual i's choice and current state variables. I denote the end-of-period utility function that represents in-school preferences with $U_t^{sch}(c, l, g, \varepsilon)$. I assume the choice-specific preferences shocks are additively separable from the payoff variables, so an individual's utility can be written as the sum of the observable utility component $u_t^{sch}(c, l, g)$ and unobservable preference shocks. For notational convenience, I will sometimes suppress the payoff function arguments and use subscripts to denote the individual, choice, and time period. Then the utility from individual i choosing action a in period t is given by,

$$U_t^{sch}(c_{ait}, l_{ait}, g_{it}, \varepsilon_{ait}) = u_t^{sch}(c_{ait}, l_{ait}, g_{it}) + \varepsilon_{ait}. \tag{2}$$

[11] 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 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 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.

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, $U^{post}(S_{it})$. 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".[12] I use $U(a, S)$ to denote individual i's utility when her entrance into the post-school labor market is unknown ex ante:

$$U(a_{it}, S_{it}, \varepsilon_{it}) = 1[\text{in-school}]U_t^{sch}(c_{ait}, l_{ait}, g_{ait}, \varepsilon_{ait}) + 1[\text{post-school}]U_t^{post}(S_{it}). \quad (3)$$

4.1.5 Constraints

Individuals face constraints on consumption, leisure, and borrowing. Individual i's consumption is equal to her labor income, increases 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 and net education expenses can depend on individual i's choices and state variables.

$$c_{it}(a_{it}, S_{it}) = w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}). \quad (4)$$

When an individual is still in school, her wage is a constant individual-specific part-time wage. 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. Both family support and net educational expenses are time-invariant functions of the individual's choices and state variables, and they are known with

[12] 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 life-time value function is simply a function of her wage, debt, and current prices (e.g., Blundell and Walker, 1986)

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 their total time endowment L_t less work hours and study hours.

$$l_{it}(a_{it}, S_{it}) = L_t - study_i(a_{it}) - h_{it}. \tag{5}$$

I model study hours as a deterministic function of individual i's other choices, specifically, her labor supply and credit hour enrollment. There is also non-negativity constraint on leisure – individuals cannot choose to study and work so much that their leisure is negative.

4.1.6 Grades

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

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 1 is given by the laws of motion for state variables and

$$\begin{aligned} V_{i1}(S_{i1},\varepsilon_{i1}) \equiv & \max_{\{a\in A_t\}_{t=1}^{T}} \; E\left[\sum_{t=1}^{T} \beta^{t-1} U_t(a, S_{i1}, \varepsilon_{i1}) \mid S_{i1}, \varepsilon_{i1}\right] \\ \text{s.t.} \quad & c_{it}(a_{it}, S_{it}) = \max\{w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}), \bar{c}\} \\ & l_{it}(a_{it}) = L_t - study_i(a_{it}) - h_{it} \\ & l_{it}(a_{it}) \geq 0 \end{aligned} \tag{6}$$

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

4.2 Solution method

The lifetime problem for individual i can be re-written at any period $t \leq T$ as

$$V_{it}(S_{it}, \varepsilon_{it}) = \max_{\{a\in A_t\}} \{U_t(a, S_{it}, \varepsilon_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a, S_{it}]\}. \tag{7}$$

In period T, the final possible period in school, individual i solves,

$$V_{iT}(S_{iT}, \varepsilon_{iT}) = \max_{a\in A_T} \left\{u_T^{sch}(c_{aiT}, l_{aiT}, g_{aiT}) + \varepsilon_{aiT} + \beta E[U_{T+1}^{post}(S_{i,T+1})|a, S_{iT}]\right\} \tag{8}$$

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 $t \leq T$ value functions, the expectation generally does not have a closed-form solution. 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 stated previously.

$$E[V_{it}(S_{it}, \varepsilon_{it})|S_{it}] = \\ \text{E.C.} + \log\left(\sum_{a' \in A_t} \exp\left\{u_t(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a', S_{it}]\right\}\right) \tag{9}$$

where E.C. is Euler's constant. The Emax function can theoretically be solved by backward induction; however, this is computationally infeasible in practice.[13]

A popular approach in the literature for 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 recursively until I have interpolating functions for every individual in all periods.

The interpolation method provides an approximation of the Emax function; the

[13] 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 1,000 individuals, 28 elements of the choice set, and 10 choice periods, a coarse grid of 25 elements for each of the 3 time-varying state variables would required evaluating 4.375 billion functions for each iteration of parameter values.

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.

4.3 Model parameterizations

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

$$\begin{aligned} u_t(c_{ait}, l_{ait}, g_{it}) &= \alpha_c \ln(c_{ait}) + \alpha_{lt} \ln(l_{ait}) + \alpha_g \ln(g_{it}) \\ &+\alpha_{h0t} 1[h_{it} > 0] + \alpha_{k0} 1[k_{it} = 0] + \alpha_{k15} 1[k_{it} = 30] \\ &+\alpha_{b1} 1[b_{it} = \text{Stafford only}] + \alpha_{b2} 1[b_{it} = \text{Max eligiblity}] \end{aligned} \tag{10}$$

where α_{lt} and α_{h0t} are allowed to vary between fall / spring and summer periods.[14] The log specification imposes diminishing marginal utility from consumption, leisure, and grades.[15] I restrict α_c, α_l, and α_g to positive values. In addition to the payoff variables, I include fixed costs for various alternatives.[16]

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 individuals' characteristics in X_i, such as independence status, residency, and college. Loan offers are also based on net tuition. Neither

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

[15] 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.

[16] 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 (Löffler et al., 2018). I include 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 while the University automatically includes Stafford loans in students' financial aid package.

Stafford loan offers nor private loan offers can exceed individual i's net tuition function plus expected living expenses. Stafford loans also 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 transfers are given by,

$$fam(a_{it}, S_{it}) = \mathrm{fl}_i + edu_t(a_{it}, S_{it}) \times \mathrm{fp}_i \tag{11}$$

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.

I model individual i's study time function as,

$$study_i(a_{it}) = \left(\delta_{0i} + \delta_{1i} k_{it} + \delta_{2i} h_{it} + \delta_{3i} h_{it}^2\right) k_{it}. \tag{12}$$

This specification allows the individual to reduce her study time per credit hour as she takes more credits or work more 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 distributed error term ν_{ikt}. 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.

$$g^*_{ikt} = \gamma_{0i} + \gamma_{1i} \frac{study_i}{k_{it}} + \nu_{ikt} \tag{13}$$

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

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

F^g_i is defined by $\gamma_i \equiv \{\gamma_{0i}, \gamma_{1i}, \gamma_{2i}, \sigma^g, \gamma_C, \gamma_B, \gamma_A\}$.

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

$$U^{post}(S_{it}) = \alpha_w \ln(w^{post}_i(S_{it})) + \alpha_B \ln(B_{it}) \tag{14}$$

where the log specification imposes diminishing marginal returns to post-school earnings and post-school cumulative debt.[17] I restrict α_w to positive values and α_B to negative values.

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

$$w^{post}_i(S_{it}) = \exp\{\omega_{0i} + 1[K_{it} \geq \bar{K}](\omega_{1i} + \omega_{2i}(G_{it} - 2) + \omega_{3i}(G_{it} - 2)^2) + \xi_i\} \tag{15}$$

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.[18] F^w_i is defined by $\omega_i \equiv \{\omega_{0i}, \omega_{1i}, \omega_{2i}, \omega_{3i}, \sigma^w_i\}$.

I set $T = 10$ so individuals have five full years to complete college before entering

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

[18] 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 (Baert, Rotsaert, Verhaest & Omey, 2016; Häkkinen, 2006; Little, 2005; Hotz, Xu, Tienda & Ahituv, 2002).

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 estimates of discount rates for young adults (Green et al., 1994), I choose an annual discount rate of 0.8.

4.4 Criterion function

I estimate the studying model parameters δ_i, grade model parameters γ_i, and wage model parameters ω_i in separate regressions before I estimate the structural model. With these parameters in hand, I estimate the utility parameters $\alpha \equiv \{\alpha_c,\ \alpha_{lt},\ \alpha_g,\ \alpha_{h0t},\ \alpha_{k0},\ \alpha_{k15},\ \alpha_{b1},\ \alpha_{b2},\ \alpha_w,\ \alpha_B\}$ via maximum likelihood.

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

$$ll_i(\theta) = \log Pr(a_{it}, \hat{S}_{it}, g_{ikt} : t = 1, \ldots T_i \mid \alpha), \tag{16}$$

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

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

$$\begin{aligned} ll_i(\theta) = &\sum_{t=1}^{T_i} \log Pr(a_{it}|\hat{S}_{it}, \alpha) + \sum_{t=1}^{T_i} \log Pr(g_{ikt}|a_{it}, \hat{S}_{it}) \\ &+ \sum_{t=1}^{T_i-1} \log Pr(\hat{S}_{i,t+1}|a_{it}, \hat{S}_{it}, g_{ikt}) + \log Pr(\hat{S}_{i1}|\alpha) \end{aligned} \tag{17}$$

The second term and third terms are defined by the grade model described previously and do not depend on the parameters in α. The fourth term, which is 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 1 Extreme Value distribution, the probability that alternative a is chosen by individual i in period t given states $\hat{S}_{it}$ is

$$Pr(a|\hat{S}_{it}, \theta) = \frac{\exp\left\{u_t(c_{ait}, l_{ait}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a_{it}, \hat{S}_{it}]\right\}}{\sum_{a' \in A_t} \exp\left\{u_t(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a', \hat{S}_{it}]\right\}} \tag{18}$$

where the expectation is taken with respect to the choice-specific heterogeneity, grades, and the post-school wage offer. I follow the procedure outlined above to approximate these expectations.

5 Results

5.1 Pre-estimated functions

Table 6 summarizes the variables in the structural model and specifies the time periods I observe those variables 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. 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. I also present estimates of the function parameters. The appendix contains more details of how I convert survey responses to construct other inputs in the model.

As specified in equation 12, I impose that a students' 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 6 presents the distribution of study function parameters.

Equation 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 3.4, students placed ten balls in bins to convey the likelihood of earning a particular grade. I treat each ball placed as a separate observation, so I have forty observations per student (10 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 6 presents the distribution of the grade production function parameters.

Equation 15 specifies that students' 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 (40 hour per week) salary. I treat each ball placed as a separate observation, so I have fifty observations per student (10 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 6 presents the distribution of the post-school wage function parameters.

[Table 6 here]

5.2 Structural model estimates

Table 7 presents the estimated utility parameters and their standard errors for a 15% sample of available observations. 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.

[Table 7 here]

The estimated parameters also confirm multiple 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 also 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 presenting elasticities, I verify that the model achieves a reasonable fit of the observed data. Table 8 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 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 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.

[Table 8 here]

5.3 Elasticities

Tables 9 and 10 present statistics for a series of elasticities and semi-elasticities for credit hour, work, and borrowing behavior. I derive these elasticities using the estimated utility parameters from above and simulating the probabilities of each choice. I consider five different elasticities for each outcome: 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' return to studying (γ_{1i}), a 10% increase in students' return to earning a higher GPA (ω_{2i} and ω_{3i}), and a 10% increase in students' in-school wage.

[Tables 9 and 10 here]

I do not find evidence that students' credit hour decision varies strongly with financial resources or beliefs. Almost all of the estimated elasticities are near-zero for a majority of students in the fall and spring periods. Students are more responsive in the summer periods, but even the larger elasticities lead to practically insignificant increases in attempted credit hours. For example, a 10% increase in the returns to studying leads to a 1.7% increase in attempted credit hours in the summer, but on a base of 2.44 credits, this corresponds to only 0.04 more credits.

Students are more responsive on the labor supply margin than the credit hour margin. I estimate an average wage elasticity of 0.281 in the fall and spring periods and 0.230 in the summer periods, so for every 10% increase in wages, students work 2.8% and 2.3% more hours on average. I estimate near-zero income elasticities and tuition price elasticities for most students, though the distribution of income elasticities (fall and spring) and tuition price elasticities (all periods) is significantly skewed to the right. I find practically significant labor supply elasticities with respect to beliefs in the fall and spring but not the summer. The median student is not very responsive to an increase in the returns to studying or returns to GPA, but a student near the 25th percentile decreases their work hours by approximately 2% for a 10% increase in either belief.

Students' borrowing behavior also changes with financial resources. A $1,000 increase in financial aid reduces borrowing by $263 on average in the fall and spring, but this is driven by very large changes at the far left tail of the distribution. The reduction in borrowing in the summer is much smaller, though this may be a result of most students not enrolling in the summer and not being eligible to borrow Stafford loans at all. A 10% increase in tuition increases borrowing by $8,680 in the fall and spring and $1,160 in the Summer, but this is driven by very large changes at the far right tail of the distribution. Students' borrowing behavior is not consistently responsive to changes in beliefs. Finally, I find evidence that students partially substitute between labor income and borrowing, as a 10% increase in wages reduces borrowing by $350 in the fall and spring and $119 in the summer.

5.4 Counterfactual simulations

I conduct two counterfactual simulations to evaluate how different policies may affect student behaviors and outcomes. The first simulation models an increase in the minimum wage to $15 per hour for all periods. The second simulation makes tuition free for all students. Both policies relax a student's budget constraint, albeit in very different ways.

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 "Enrolled Senate Bill No. 1171", 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.[19]

A \$15 increase of the minimum wage would raise hourly wages for 93% of students in my sample and increase the average wage from \$10.94 to \$15.32. This increase is not significantly correlated with students' financial need, and it benefits those with high unmet need just as much as it benefits students with low unmet need.

Panel A of table 11 presents the expected behaviors and outcomes for students under the baseline and counterfactual simulations.[20] Increasing the minimum wage to \$15 per hour increases average weekly work hours by 0.66 in the fall and spring and by 1.11 in the summer. This translates to an increase in total labor income for the average student by \$1,128 in the fall and spring and \$1,032 in the summer. There is a small decrease in average borrowing, \$158 in the fall and spring and \$42 in the summer, which are not enough to offset the gains in labor income. There is no observable change in attempted credit hours or cumulative GPA.

[Table 11 here]

[19] 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).

[20] 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.

5.4.2 Free college

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 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 if Michigan State University unconditionally waived the cost of tuition for all students enrolled after September 2014.[21]

Free tuition reduces the expected cost of attendance in the fall and spring by $15,728 for in-state students and $40,195 for out-of-state students. Expected credit hours are much lower in the summer, so the expected savings are less: $945 for in-state students and $2,491 for out-of-state students. Even with free tuition, students still have expected living costs of $14,149 in the fall and spring and $7,074 in the summer, as well as smaller program fees and textbook costs. Unlike minimum wage in the previous counterfactual, the actual benefit of free college varies significantly by students' financial need. Students with high financial need experience reductions in their unmet need of $13,117 in the fall and spring while students with low financial hardly benefit. For these students, the reduction is tuition is mostly or completely offset by reductions in grant aid and family financial support.

Panel B of table 11 presents the expected behaviors and outcomes for students

[21] 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 support allocated toward education expenses are no longer used.

with and without free tuition. Average credit hours attempted increase by 0.10 credits in the fall and spring and 0.13 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 decreases in work hours. Unsurprisingly given these small effects, there is no observable difference in cumulative GPA. Borrowing does change substantially, however, with average loan amounts decreasing by $2,148 in the fall and spring and $175 in the summer. Taken together, this counterfacutal simulation suggests that making college free reduces students' reliance on loans, but it does not improve other outcomes like credit accumulation or GPA.

6 Conclusion

In this paper, I show how 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 present a dynamic structural model of college students' credit hour enrollment, labor supply, and borrowing which takes advantage of the unique survey data. 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.

I find that 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 decision; I estimate an average wage elasticity of 0.28 in the fall and spring and 0.23 in the summer, which are both comparable to elasticities for prime-age workers in the United States. I also find similar magnitude elasticities for changes in the returns to studying and returns to GPA, but only for students at or above the 75th percentile of the distribution. Student borrowing elasticities are near zero for most students, but there are large elasticities at the tail of the distribution. For example, a $1,000 increase in financial aid reduces borrowing by $263 on average in the fall and spring, but it reduces borrowing by only $19 at the median.

The counterfactual simulations reveal similar patterns as the elasticities. I estimate that a $15 minimum wage would increase average work hours by 0.66 hours per week in the fall and spring and by 1.11 hours per week in the summer. I also find small decreases in borrowing. Making college free for all students would increase average credit hours by 0.10 in the fall and spring and by 0.13 in the summer. It would also reduce average borrowing by $2,148 in the fall and spring and $175 in the summer. Neither counterfactual policy leads to a significant change in expected GPA.

There are three main areas where this work can be improved. First, the current model does not allow for unobserved heterogeneity in preferences. Under the assumption that there is no permanent unobserved preference heterogeneity and the choice-specific preference shocks are independent of the state variables, this is not a problem. However, if there is permanent unobserved preference heterogeneity and the heterogeneity is correlated with the initial state variables (e.g., major choice, family financial support, beliefs), the estimated utility parameters are biased. A common approach in the literature involves adopting a latent class mixture model and using the Expectation-Maximization algorithm to estimate the new utility parameters and probabilities that each individual belongs to each class (Aguirregabiria and Mira, 2010).

Another area for future work involves improving the accuracy of the interpolating function used to approximate the Emax functions. Because I am maximizing an approximate log-likelihood function, the estimated utility parameters will be biased and the standard errors inefficient. Kristensen and Salanié (2017) quantify the bias and inefficiency and propose a two-step method for correcting the approximation error.

A third opportunity for future work is allowing individuals to save their labor market earnings between periods while in school. Higher work hours in the summer suggest that students might work in the summer when they take fewer classes and save some of their earnings for the following fall and spring when the cost of working is greater. Modeling an intertemporal saving decision requires solving a first-order condition for every individual, in every time period, at every state variable draw in the interpolation function, for every possible choice, and for every parameter value trial.

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7 Tables and Figures

Table 1: Summary statistics

Variable	Unweighted	Weighted
Female	0.682	0.783
White, non-Hispanic	0.814	0.832
Black or African American	0.069	0.053
Hispanic	0.050	0.048
Asian	0.093	0.088
American Indian or Alaskan Native	0.008	0.008
Native Hawaiian or Pacific Islander	0.007	0.011
Out-of-state	0.106	0.101
First generation	0.170	0.155
Age (in months)	238.188	243.205
Freshman	0.263	0.109
Sophomore	0.286	0.223
Junior	0.307	0.413
Senior	0.144	0.254
ACT (SAT equivalent) score	26.468	27.111
Honors college	0.252	0.323
College: Business	0.132	0.107
College: Humanities	0.064	0.075
College: Health	0.027	0.034
College: STEM	0.482	0.523
College: Social Science	0.287	0.248
College: Undecided	0.008	0.013
Observations	987	

This table presents summary statistics for the sample of survey respondents, unweighted and weighted by the inverse probability of responding to the survey. Each respondent is only counted once, regardless of how many terms they were enrolled at MSU. Students are classified into broad college categories based on their major at the time of the survey.

Table 2: Credit hour enrollment by semester

Credits	**Fall & Spring**	**Credits**	**Summer**
13 to 23	1.67	0	59.69
24	3.61	1	1.53
25	6.56	2	0.41
26	9.10	3	8.27
27	12.30	4	6.02
28	18.30	5	0.92
29	15.96	6	6.12
30	15.20	7	5.71
31	8.69	8	4.39
32	4.83	9	2.86
33	2.14	10	1.63
34	0.61	11	0.41
35	0.36	12	0.71
36	0.36	13	0.31
37	0.15	14	0.10
38	0.10	15	0.41
39	0.00	16	0.10
40	0.05	17 to 20	0.40
Observations	1,967	980	

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.

Table 3: Offered and accepted loans

Loan alternative	%0	Mean	Max	Choice
Panel A: Fall and spring				
No loan	100.00%	$0	$0	61.51%
Stafford loan offer	16.17	5,267	6,750	31.72
Stafford and private loan eligibility	16.17	10,669	44,248	6.76
Observations	1,967			
Panel B: Summer				
No loan	100.00%	$0	$0	91.73%
Stafford loan offer	76.84	743	1,367	6.22
Stafford and private loan eligibility	59.69	1,442	2,254	2.04
Observations	980			

This table presents statistics on the offered and accepted loan amounts by term. The first column describes the type of loan: none, the Stafford loan offer, and the combined Stafford and private loan eligibility. The second column presents the percent of loan offers that were $0 for each type of loan. Columns three and four present the mean and maximum offer for each type of loan. The final column shows the percent of students whose actual borrowing amount was closest to specified type of loan.

Table 4: Cost of attendance and financial need

Variable	**Mean**	**Std. Dev.**	**25th Pct**	**Median**	**75th Pct**
	Panel A: In-state students (fall and spring)				
Cost of attendance	28,359	1,877	27,088	28,458	29,370
Grants and scholarships	6,066	8,100	0	1,175	10,806
Family financial support	15,929	13,211	1,385	15,628	27,357
Unmet financial need	6,365	10,755	0	5,371	13,356
Observations	1,770				
	Panel B: Out-of-state students (fall and spring)				
Cost of attendance	52,728	3,972	50,548	52,228	54,914
Grants and scholarships	16,608	15,830	8,000	9,000	24,000
Family financial support	30,614	24,115	15,853	29,172	42,554
Unmet financial need	5,505	22,469	0	1,977	13,890
Observations	197				

This table presents summary statistics for students' cost of attendance, grants and scholarships received, family financial support, and remaining unmet financial need in the fall and spring term. Unmet need is equal to cost of attendance less grants and family support. Results are separated by student's residency status (in-state versus out-of-state).

Table 5: 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	$edu_t(\cdot)$	$t = \{1, \ldots, T_i\}$
Pre-estimated parameters		
Expected study hours	δ_i	
Returns to studying	γ_i	
Wage model	ω_i	

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 6: Pre-estimated parameters

Parameter	**Mean**	**Std. Dev.**	**25th Pct**	**75th Pct**
		Panel A: Studying function		
Constant: δ_{0i}	2.522	1.767	1.254	3.667
Credit hours: δ_{1i}	-0.056	0.086	-0.011	-0.002
Work hours: δ_{2i}	-0.020	0.046	-0.046	0.006
Work hours^2: δ_{3i}	0.0001	0.0013	-0.0006	0.0008
		Panel B: Grade production function		
Constant: γ_{0i}	1.239	1.524	0.426	2.202
Study hours: γ_{1i}	0.361	0.314	0.191	0.448
C threshold: γ_C	1.131			
B threshold: γ_B	2.355			
A threshold: γ_A	3.687			
Error variance: σ^g	-0.003			
		Panel C: Post-school salary offer		
Constant: ω_{0i}	10.353	0.338	10.087	10.579
Degree premium: ω_{1i}	0.302	0.418	0.280	0.556
GPA x Degree: ω_{2i}	0.184	0.595	-0.102	0.473
GPA^2 x Degree: ω_{3i}	0.114	0.292	-0.016	0.261
Error variance: σ_i^w	0.358	0.144	0.267	0.461
Observations	987			

This table presents summary statistics for the distribution of parameters estimated before the structural model. The studying function can be found in 12, the grade production function in 13, and the post-school salary offer function in 15.

Table 7: Utility parameters

	Coefficient	**Std. Err.**
Log Consumption	0.578	(0.031)
Log Leisure (Fall / Spring)	0.465	(0.087)
Summer Leisure Modifier	2.637	(0.246)
Log GPA	0.899	(0.020)
F.C. of Work	-0.638	(0.064)
Summer F.C. of Work Modifier	0.023	(0.235)
F.C. of 0 Credits	1.750	(0.324)
F.C. of 15 Credits	0.859	(0.077)
F.C. of Stafford Loans	-0.040	(0.119)
F.C. of Max Loans	-0.826	(0.209)
Log Post-school Wage	26.646	(0.865)
Log Post-school Debt	-1.213	(0.038)
Observations	142	

This table presents the estimated parameters to the utility functions specified in 10 and 14. Due to computation time, I use a 15% sample of the data to estimate the parameters. F.C. stands for fixed costs.

Table 8: Observed and predicted choice probabilities

	Observed	**Predicted**	**Difference**
	Panel A: Credit hours		
Fall and Spring			
26 credits	0.332	0.381	-0.049
30 credits	0.630	0.571	0.059
34 credits	0.038	0.048	-0.010
Summer			
0 credits	0.612	0.646	-0.034
3 credits	0.147	0.256	-0.109
8 credits	0.241	0.098	0.143
	Panel B: Work hours		
Fall and Spring			
0 hours	0.539	0.587	-0.047
10 hours	0.280	0.192	0.088
20 hours	0.180	0.221	-0.041
Summer			
0 hours	0.496	0.564	-0.068
20 hours	0.138	0.269	-0.131
40 hours	0.366	0.167	0.199
	Panel B: Borrowing		
Fall and Spring			
No new loans	0.558	0.597	-0.039
Stafford loans	0.362	0.348	0.014
Maximum loans	0.079	0.054	0.025
Summer			
No new loans	0.924	0.893	0.032
Stafford loans	0.066	0.037	0.029
Maximum loans	0.009	0.070	-0.061

This table presents the observed and predicted probabilities of each discrete choice in the model. Number of observations: 1,967 (fall and spring) and 980 (summer).

Table 9: College behavior elasticities (Fall and Spring)

Elasticity	**Mean**	**Std. Dev.**	**25th Pct**	**Median**	**75th Pct**
Panel A: Credit hours elasticities (Mean: 28.36)					
Financial aid	0.0001	0.0070	-0.0006	-0.0002	0.0001
Tuition rate	-0.0092	0.1643	-0.0025	0.0000	0.0012
Return to studying	-0.0079	0.0443	-0.0102	-0.0009	0.0045
Return to GPA	0.0032	0.0407	-0.0003	0.0018	0.0078
Wage	-0.0009	0.0030	-0.0016	-0.0005	0.0001
Panel B: Work hours elasticities (Mean: 6.29)					
Financial aid	2.0156	89.0028	-0.0035	0.0000	0.0016
Tuition rate	0.3476	8.0503	-0.0250	0.0004	0.0703
Return to studying	-0.0573	1.3489	-0.2050	-0.0199	0.0835
Return to GPA	-0.1772	0.4713	-0.1901	-0.0311	0.0004
Wage	0.2808	0.1586	0.1799	0.2517	0.3444
Panel C: Borrowing semi-elasticities (Mean: $3,941)					
Financial aid	-263	2,745	-157	-19	2
Tuition rate	8,680	53,021	-42	292	2,654
Return to studying	-28	9,214	-163	-15	22
Return to GPA	343	11,880	-64	-6	16
Wage	-350	941	-478	-101	-38
Observations	1,967				

This table presents estimated elasticities during the fall and spring periods. Panel A contains the percentage change in attempted credit hours, panel B contains the percentage change in work hours, and panel C contains the dollar change in borrowing. Each row corresponds to a different denominator: a $1,000 increase in grant aid, a 10% increase in the per-credit tuition rate, a 10% increase in the return to studying, a 10% increase in the return to graduating with a high GPA, and a 10% increase in the individual's in-school wage.

Table 10: College behavior elasticities (Summer)

Elasticity	**Mean**	**Std. Dev.**	**25th Pct**	**Median**	**75th Pct**
Panel A: Credit hours elasticities (Mean: 2.44)					
Financial aid	-0.027	0.036	-0.039	-0.022	-0.010
Tuition rate	0.133	3.196	-0.064	-0.021	-0.012
Return to studying	0.018	0.458	-0.017	0.067	0.180
Return to GPA	0.171	0.209	0.030	0.120	0.258
Wage	-0.048	0.047	-0.072	-0.041	-0.019
Panel B: Work hours elasticities (Mean: 17.00)					
Financial aid	-0.0023	0.0268	-0.0173	-0.0060	0.0195
Tuition rate	0.0223	1.3788	-0.0251	0.0005	0.0023
Return to studying	-0.0073	0.0878	-0.0225	-0.0029	0.0095
Return to GPA	-0.0181	0.0345	-0.0245	-0.0091	-0.0013
Wage	0.2301	0.0659	0.1664	0.2276	0.2823
Panel C: Borrowing semi-elasticities (Mean: $325.36)					
Financial aid	-58	467	-51	-23	-8
Tuition rate	1,160	11,802	-17	16	131
Return to studying	-19	448	-11	30	89
Return to GPA	88	294	7	50	117
Wage	-119	108	-188	-91	-22
Observations	980				

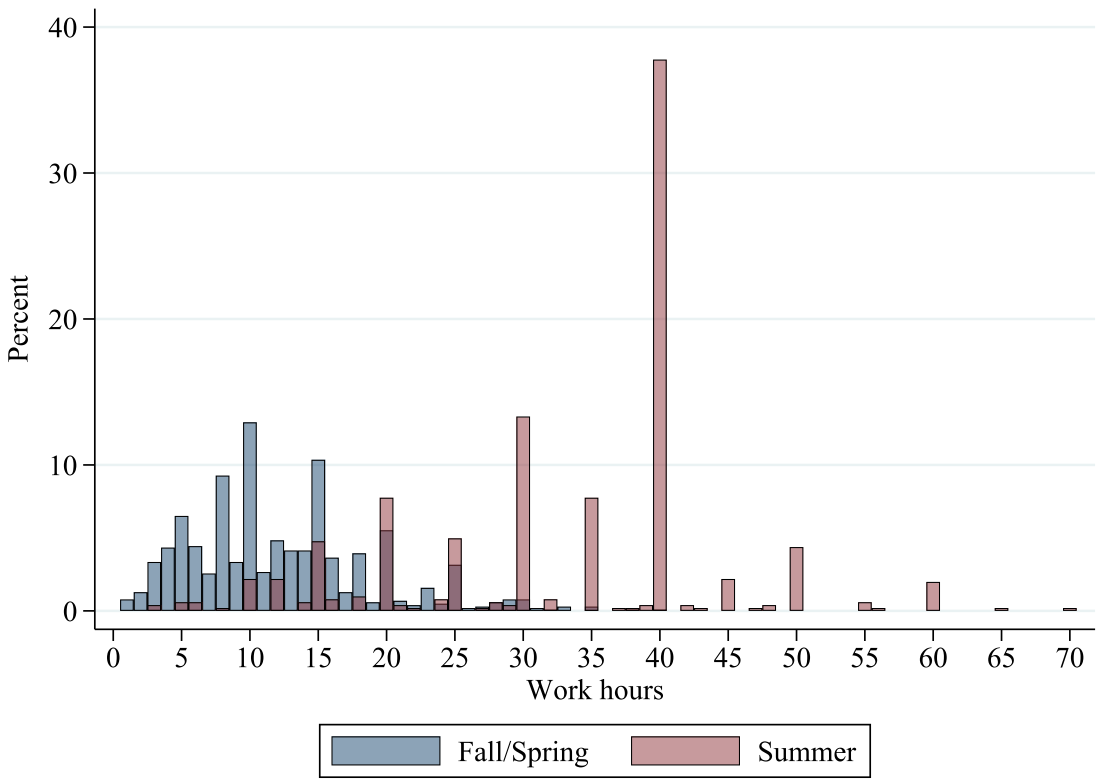
This table presents estimated elasticities during the summer periods. Panel A contains the percentage change in attempted credit hours, panel B contains the percentage change in work hours, and panel C contains the dollar change in borrowing. Each row corresponds to a different denominator: a $500 increase in grant aid, a 10% increase in the per-credit tuition rate, a 10% increase in the return to studying, a 10% increase in the return to graduating with a high GPA, and a 10% increase in the individual's in-school wage.

Table 11: Counterfactual simulation results

Outcome	**Baseline**	**Counterfactual**	**Difference**	**Std. Err.**
		Panel A: Increase minimum wage to $15		
Credit hours				
Fall and spring	28.85	28.84	-0.006	(0.023)
Summer	1.73	1.70	-0.023	(0.027)
Work hours				
Fall and spring	6.28	6.94	0.658	(0.056)***
Summer	11.82	12.93	1.112	(0.061)***
Borrowing				
Fall and spring	4,300.73	4,142.98	-157.75	(114.06)
Summer	778.61	736.44	-42.17	(24.93)*
Cumulative GPA	2.95	2.95	-0.003	(0.037)
		Panel B: Set tuition rate to $0		
Credit hours				
Fall and spring	28.85	28.95	0.103	(0.023)***
Summer	1.73	1.85	0.126	(0.028)***
Work hours				
Fall and spring	6.28	6.11	-0.175	(0.053)***
Summer	11.82	11.91	0.090	(0.057)
Borrowing				
Fall and spring	4,300.73	2,153.16	-2,147.57	(84.28)***
Summer	778.61	603.55	-175.06	(19.35)***
Cumulative GPA	2.95	2.96	0.007	(0.037)

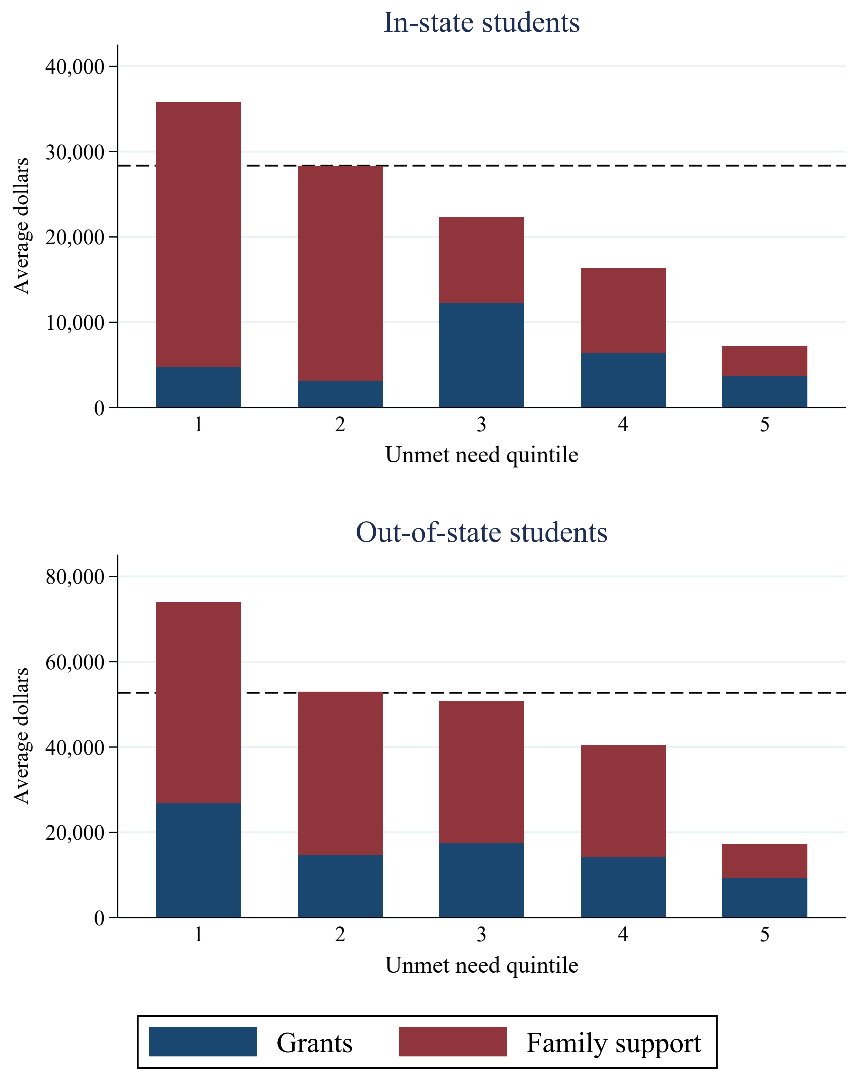
This table presents the projected credit hour enrollment, work hours, borrowing, and terminal-period cumulative GPA under the baseline model and counterfactual model. The baseline model takes the state variables for individuals as given in the first period and simulates their choice history and outcomes for the remaining periods. The counterfactual models vary the 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-value $\leq$ 0.10; (**) p-value $\leq$ 0.05; (***) p-value $\leq$ 0.01.

Figure 1: Work hours distribution



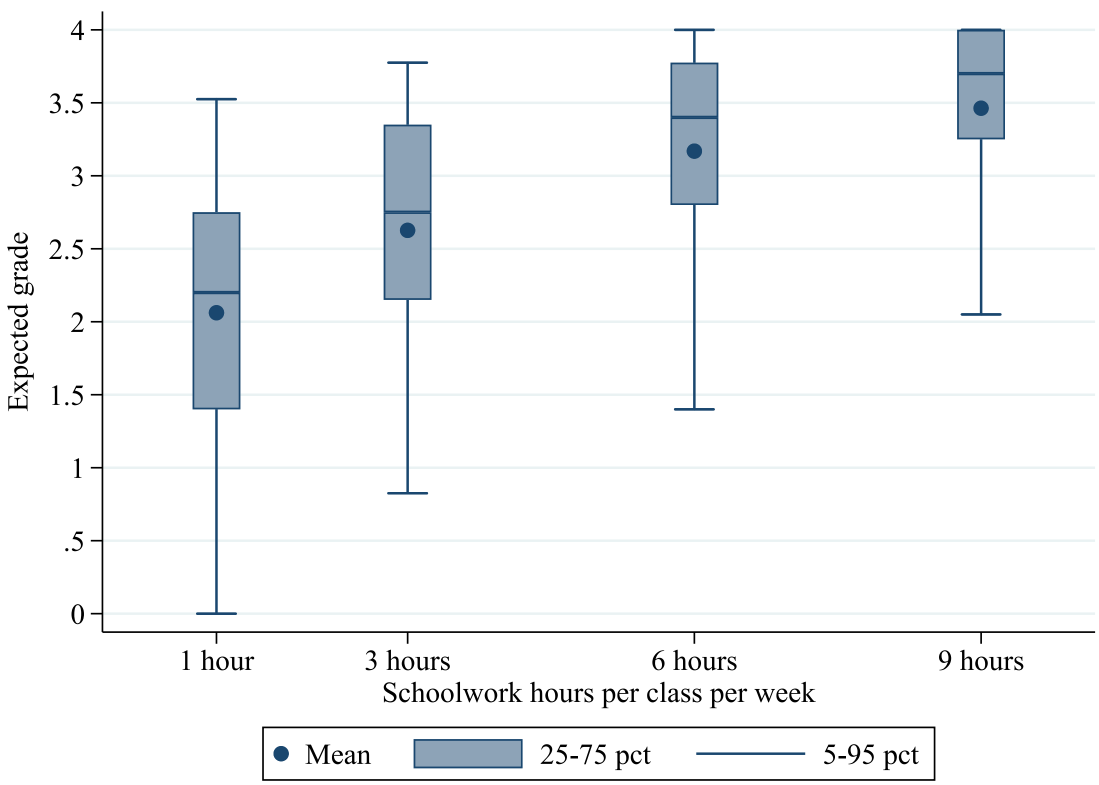
This figure presents the distribution of work hours among students with positive work hours. Hours worked in the fall and spring semesters are averaged together. Number of observations: 1,014 (fall and spring) and 503 (summer).

Figure 2: Grants and family support by financial need quintile



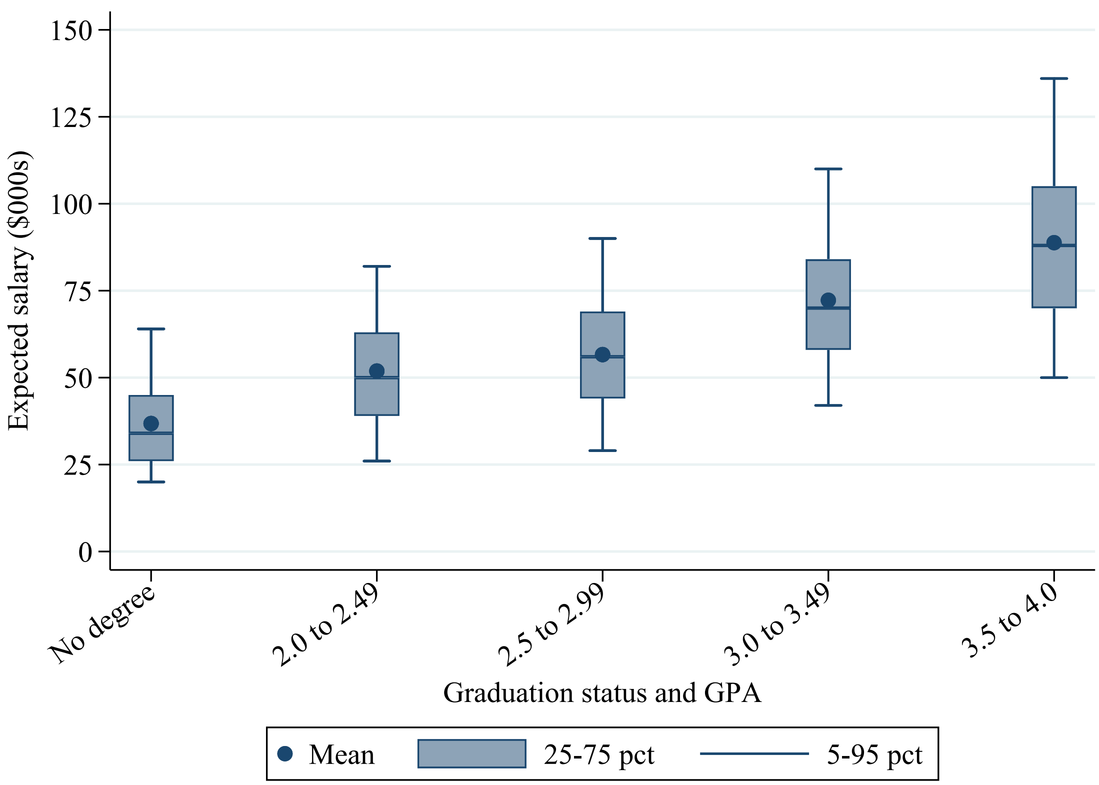
This figure presents the average amount of grants / scholarships and family financial support received by quintile of unmet financial need in the fall and spring term. Unmet need is equal to cost of attendance less grants and family support. The dashed line denotes the average cost of attendance. Results are separated by student's residency status (in-state versus out-of-state). Number of observations: 1,770 (in-state) and 197 (out-of-state)

Figure 3: Distribution of expected grades conditional on schoolwork



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: 987

Figure 4: Distribution of expected post-school salaries conditional on GPA



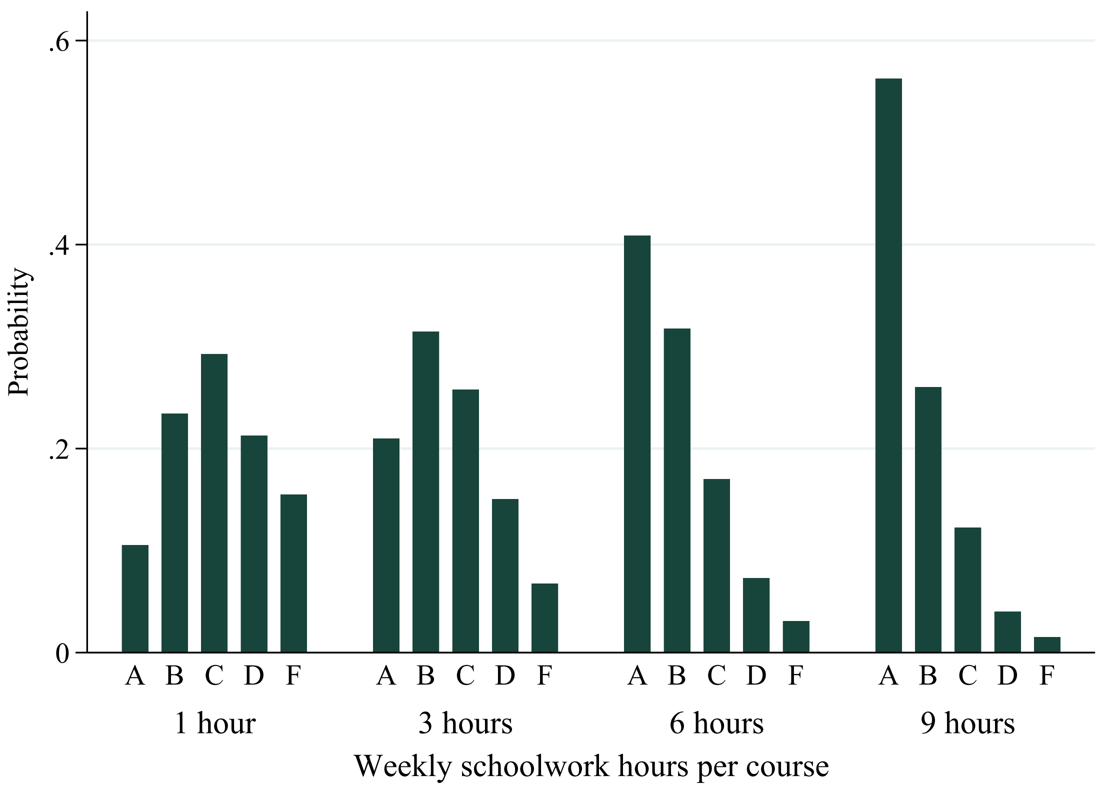
This figure presents the distribution of post-school (40 hour per week) salaries conditional on GPA upon graduation. Expected salaries are calculated from students' probabilities of receiving salary offers in particular ranges. Number of observations: 987

8 Appendix

8.1 Michigan State relative to other four-year colleges

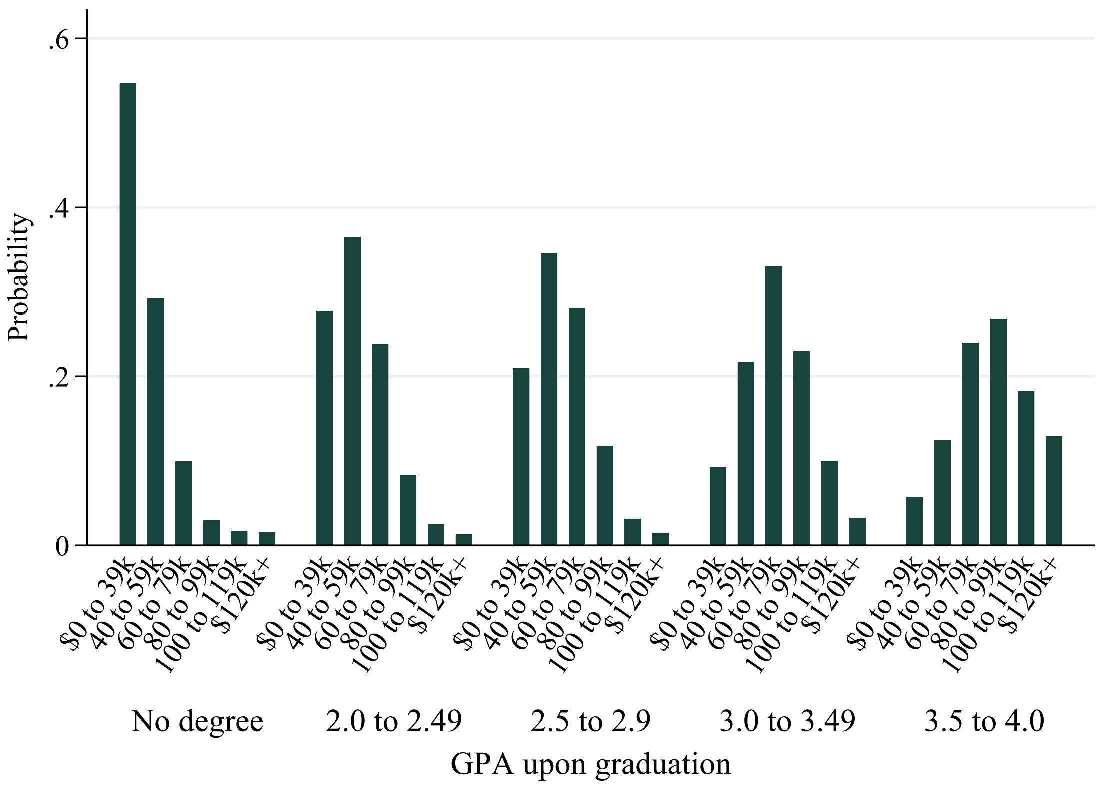
8.2 Variable construction

Figure A1: Probabilities of grades conditional on schoolwork hours



Notes go here

Figure A2: Probabilities of post-school salaries conditional on GPA



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