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 choose 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, I24, J22, J49

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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, Dundar, 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 6,000 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 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 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. Students' credit hour enrollment is largely unresponsive 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 fraction of students, labor supply is responsive to beliefs of the returns to studying and returns to graduating with a high GPA. At the 25th percentile, a 10% increase in either belief leads to a 19% reduction in work hours in the fall and spring. 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. However, students do substitute between labor earnings and debt. A 10% increase in wages reduces average borrowing by $350 in the fall and spring.

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 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 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 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 from 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. (2011) 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 (for examples, see recent literature reviews by Bargain and Peichl (2016) and McClelland and Mok (2012)). 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

[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.

men and women, with wage elasticities of 0.1 to 0.3 (McClelland and Mok, 2012).

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 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 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 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. A full text of the survey is available online.

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 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 987 students and 2,947 student-period pairs (1,967 fall and spring and 980 summer).

Table 1 presents summary statistics for the analytic sample, both unweighted and weighted by the inverse probability of survey response. Appendix Section A provides details on the weighting procedure.[4]

[Table 1 here]

[2] Appendix table A1 contains summary statistics for the MSU undergraduate population and population of undergraduate students at other public four-year-degree-granting institutions.

[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 that believe their grades will decrease as they increase their time on schoolwork (21) 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.

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

3.2 Observed credit hour enrollment and financing choices

The Office of the Registrar provided students' credit hour enrollment by term. I present the proportion of students who enrolled in varying credit hour amounts in table 2. In the fall and spring, 62% of students enrolled in 27 to 30 credit hours, and 95% of students enrolled in 24 to 32 credit hours. In the summer, 60% of students did not enroll in any credits. Among students who did enroll, 35% took 3 to 4 credits and 47% took 6 to 9 credits.

[Table 2 here]

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. Student workers worked an average of 12.2 hours per week in the fall and spring term, while those workers worked an average of 33.1 hours per week in the summer term. As shown in figure 1, the modal number of hours worked per week in the fall and spring was 10, though 8 and 15 hours were also common. In the summer, 40 hours per week was 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.[5] 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 possible borrowing choices for students: no loans, Stafford loans only, and total loan eligibility. In the fall and spring, 84% of students were eligible for some amount of loans. The average Stafford loan offer was $5,267, though students were typically eligible for significantly more in private loans. A majority of students chose not to borrow in the fall and spring, but among those who did borrow, the amount was closer to their Stafford loan offer than zero or their total loan eligibility. In the summer, 60% of students did not qualify for any loans, and 92% did not accept any loans.[6]

[Table 3 here]

The unconditional correlation between work hours and student loans in the fall and spring is positive but small (0.1224), and a simple linear regression shows that a $1,000 increase in borrowing in the fall and spring is associated with 0.3 more work hours per week (p-value < 0.000). However, this relationship may simply be a result of students with higher financial need being more likely to work and borrow. The next section introduces data on expected costs and financial need and illustrates how work hours and borrowing vary with need.

[5] A student's budget is equal to their expected cost of attendance (living expenses, tuition, fees, and books) minus their non-loan financial aid.

[6] 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.

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. 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.[7] 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.[8] In the fall and spring, the average in-state student received $6,066 in grants and $15,929 in family financial support, leaving $6,365 of unmet financial need. The average out-of-state received 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 received enough aid and support to cover their cost of attendance. At the other extreme, students in the highest quintile of unmet need required more than $21,400 (in-state) or $35,550 (out-of-state) of additional income or loans to cover their expected costs.

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[7] 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 a 30 credit hours; a similar out-of-state student paid $39,766. In addition to tuition, students purchased 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.

[8] See Appendix section C for details on how the SEES measured family financial support.

[Figure 2 here]

Figure 3 presents the average labor income and borrowing for each quintile of unmet need in the fall and spring.[9] Labor income is relatively constant across the unmet need distribution, but there is a small increase as students have more unmet need. Borrowing decreases from the first quintile to the second and third quintiles before rising substantially with the highest need quintile.

[Figure 3 here]

Controlling for unmet need decreases the correlation between work hours and borrowing, but the correlation is still positive and non-zero. After regressing work hours on student loans, unmet financial need, and residency, I find that a $1,000 increase in borrowing in the fall and spring is associated with 0.2 more work hours per week (p-value < 0.000). This suggests that students find it optimal to have a mix of labor income and debt to fund their college attendance, regardless of how much college attendance costs.

3.4 Subjective expectations

The SEES contains two sets of subjective expectations: students' beliefs of their distribution of grades conditional on schoolwork hours and beliefs of their distribution of post-school salaries conditional on GPA. I followed the method proposed by Delavande & Rohwedder (2008) to elicit 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

[9] Average labor income is equal to the number of weeks in the period (30) multiplied by weekly work hours and wage rate. See Appendix section D for details on how I estimate wages for non-workers using the SEES.

the likelihood of observing the outcome.[10] This exercise was 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. While a conditional expectation may be easier to elicit, observing the entire distribution allows me to incorporate risk into my model.

For the distribution of grades conditional on schoolwork, the SEES asked students to consider four scenarios: spending one hour on schoolwork, three hours on schoolwork, six hours on schoolwork, and nine hours on schoolwork per course per week. 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 A2 presents the average reported probability of earning each grade for each scenario. At only one hour of schoolwork, 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 4 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 4 here]

For the distribution of post-school salaries conditional on GPA, the SEES asked students to consider five scenarios: failing to graduate, graduating with a cumulative

[10] 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.

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 A3 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 5 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 5 here]

4 Structural Model

This section presents a dynamic structural model to formalize the relationship between a student's choices, financial resources, and beliefs. Individuals begin with their first year of college and choose their credit hour enrollment, labor supply, and borrowing to maximize the present discounted value of their lifetime utility. Individuals derive utility from consumption and leisure. They earn grades from their classes, which affect their future salary upon leaving college. Individuals leave college when they earn enough credits to graduate with a degree, reach the maximum allowable time in college, or choose to permanently exit. This section presents the model in detail and describes how I estimate its parameters.

4.1 Model structure

4.1.1 Decision periods

I take the college entrance decision as given and begin the individual's decision horizon at the state 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.[11] 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.[12] 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.[13] This simplification allows me to focus on the decisions made in college while still incorporating inter-temporal tradeoffs that involve post-college outcomes.

[11] 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.

[12] 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.

[13] 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, Ryu, et al., 2019). At a university like MSU, where the six-year completion rate is near 80% (College Scorecard 2020), it is unlikely that many students plan on temporarily leaving school and returning in the near future.

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.[14] 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.[15]

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, $\varepsilon_{it} \equiv \{\varepsilon_{ait} : a \in A_t\}$. 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

[14] 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).

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

random variables.[16] 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:

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

Cumulative credits earned is the number of credit hours where a passing (non-zero) grade was earned for that credit. Cumulative GPA is the weighted average of the individual's previous cumulative GPA and newly earned grades.[17] 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.

[16]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.

[17]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.

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,

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

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

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

[18] 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 and debt (e.g., Blundell and Walker, 1986)

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 $fam(\cdot)$ and net education expenses $edu_t(\cdot)$ can depend on individual i's choices and state variables.[19]

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

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 due to differences in beliefs. I assume beliefs of post-school wages do not change over time. Family support and net educational expenses are also 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 their total time endowment L_t less work hours and study hours $study_i(\cdot)$.

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

[19]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 net education expenses.

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.[20] To increase study time, she must change 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.

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 consequently, 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. 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 learn-

[20]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 specify study hours with data from the SEES. The alternative involves solving 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.

ing 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 as they spend more time in college.

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

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

where β is the individual's discount factor.[21] 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 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,

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

This recursive nature suggests that the value function can be solved via backward

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

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

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

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.

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

where E.C. is Euler's constant. The Emax function can theoretically be solved by backward induction; however, this is computationally infeasible in practice.[22]

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

[22]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.

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.

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.[23] 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.[24] In addition to the payoff variables, I include fixed costs for various alternatives.[25]

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

[24]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.

[25]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

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 major. 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,

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

where $\text{fl}_i \in X_i$ is the individual's lump-sum family transfers and $\text{fp}_i \in X_i$ is the individual's family transfers for education expenses as a percent of education expenses.[26]

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 works more hours.

I model the grade process with a heteroskedastic ordered probit. Individual i's

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.

[26] 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.

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}.[27] 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.

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

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

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

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.[28] I restrict α_w to positive values and α_B to negative values.

[27] 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.

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

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

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

where $\xi_i \sim N(0, \sigma_i^w)$. This specification includes a college degree premium and a return to graduating with a GPA above the minimum for a degree.[29] F_i^w is defined by $\omega_i \equiv \{\omega_{0i}, \omega_{1i}, \omega_{2i}, \omega_{3i}, \sigma_i^w\}$.

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

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 $\alpha \equiv \{\alpha_c, \alpha_{lt}, \alpha_g, \alpha_{h0t}, \alpha_{k0}, \alpha_{k15}, \alpha_{b1}, \alpha_{b2}, \alpha_w, \alpha_B\}$ via maximum likelihood. This two-step approach is common in the literature to reduce the computational burden of estimating the utility parameters (Aguirregabiria and

[29] 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).

Mira, 2010).[30]

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

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

where a_{it} is the chosen bundle for student i in period t, $\hat{S}_{it}$ is the set of observable state variables and predicted model parameters, 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 the other state variables evolve independently from the preference shocks, I can re-write the likelihood function as,

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

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

[30] 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.

is chosen by individual i in period t given states $\hat{S}_{it}$ is

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

where the expectations are taken with respect to the choice-specific heterogeneity, grades, and the post-school wage offer. I follow the procedure outlined in section 4.2 to approximate these expectations, and then I estimate the utility parameters using maximum likelihood.

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.

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.[31] 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 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

[31] 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 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.

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.[32]

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.[33] Increasing the minimum wage

[32] 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).

[33] The baseline simulation takes students' state variables in their first period as given and projects

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]

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.[34]

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

out their optimal decisions and evolution of state variables according to the estimated utility function parameters.

[34] 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.

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 in tuition is offset by reductions in grant aid and family financial support.

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

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. 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. It would also lead to 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.

References

Aguirregabiria, V., & Mira, P. (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics*, *156*(1), 38–67. https://doi.org/10.1016/j.jeconom.2009.09.007

Altonji, J. G. (1993). The demand for and return to education when education outcomes are uncertain. *Journal of Labor Economics*, *11*(1), 48–83. http://www.jstor.org/stable/2535184

Altonji, J. G., Blom, E., & Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college majors, and careers. *Annual Review of Economics*, *4*(1), 185–223. https://doi.org/10.1146/annurev-economics-080511-110908

Angrist, J., Autor, D., & Pallais, A. (2020). *Marginal effects of merit aid for low-income students* (Working Paper No. 27834). National Bureau of Economic Research. https://doi.org/10.3386/w27834

Arcidiacono, P. (2004). Ability sorting and the returns to college major. *Journal of Econometrics*, *121*, 343–375. https://doi.org/10.1016/j.jeconom.2003.10.010

Arteaga, C. (2018). The effect of human capital on earnings evidence from a reform at colombia's top university. *Journal of Public Economics*, *157*, 212–225. https://doi.org/10.1016/j.jpubeco.2017.10.007

Attewell, P., & Monaghan, D. (2016). How many credits should an undergraduate take? *Research in Higher Education*, *57*, 682–713. https://doi.org/10.1007/s11162-015-9401-z

Baert, S., Rotsaert, O., Verhaest, D., & Omey, E. (2016). Student employment and later labour market success: No evidence for higher employment chances. *KYKLOS*, *69*(3), 401–425. https://doi.org/10.1111/kykl.12115

Bargain, O., & Peichl, A. (2016). Own-wage labor supply elasticities: Variation across time and estimation methods. *IZA Journal of Labor Economics*, *5*(10). https://doi.org/10.1186/s40172-016-0050-z

Belfield, C., Jenkins, D., & Lahr, H. (2016). *Momentum: The academic and economic value of a 15-credit first-semester course load for college students in tennessee* (Working Paper No. 88). Community College Research Center. https://ccrc.tc.columbia.edu/publications/momentum-15-credit-course-load.html

Belman, D., & Wolfson, P. J. (2014). *What does the minimum wage do?* W.E. Upjohn Institute for Employment Research.

Black, D. A., & Smith, J. A. (2006). Estimating the returns to college quality with multiple proxies for quality. *Journal of Labor Economics*, *24*(3), 701–728. https://doi.org/10.1086/505067

Blundell, R., & Walker, I. (1986). A life-cycle consistent empirical model of family labour supply using cross-section data. *The Review of Economic Studies*, *53*(4), 539–558. https://doi.org/10.2307/2297605

Bound, J., Lovenheim, M. F., & Turner, S. (2012). Increasing time to baccalaureate degree in the united states. *Education Finance and Policy*, *7*(4), 375–424. http://www.jstor.org/stable/educfinapoli.7.4.375

Broton, K. M., Goldrick-Rab, S., & Benson, J. (2016). Working for college: The causal impacts of financial frants on undergraduate employment. *Educational Evaluation and Policy Analysis*, *38*(3), 477–494. https://doi.org/10.3102/0162373716638440

Card, D., & Krueger, A. B. (2016). *Myth and measurement: The new economics of the minimum wage - twentieth anniversary edition*. Princeton University Press.

Carneiro, P., Heckman, J. J., & Vytlacil, E. J. (2011). Estimating marginal returns to education. *American Economics Review*, *101*(6), 2754–2781. https://doi.org/10.1257/aer.101.6.2754

Dannenberg, M., & Mugglestone, K. (2017). *Making promises: Designing college promise plans worth keeping* (tech. rep.). Education Reform Now. https://edreformnow.org/wp-content/uploads/2017/11/ERN-Making-Promises-Final.pdf

Denning, J. T. (2019). Born under a lucky star: Financial aid, college completion, labor supply, and credit constraints. *Journal of Human Resources*, *54*(3), 760–784. https://doi.org/10.3368/jhr.54.3.1116.8359R1

Denning, J. T., & Jones, T. R. (2019). *Maxed out? the effect of larger student loan limits on borrowing and education outcomes* [Journal of Human Resources]. https://doi.org/10.3368/jhr.56.4.0419-10167R1

Denning, J. T., Marx, B. M., & Turner, L. J. (2019). Propelled: The effects of grants on graduation¡ earnings, and welfare. *American Economic Journal: Applied Economics*, *11*(3), 193–224. https://doi.org/10.1257/app.20180100

DesJardins, S. L., McCall, B. P., Ott, M., & Kim, J. (2010). A quasi-experimental investigation of how the gates millennium scholars program is related to college students' time use and activities. *Educational Evaluation and Policy Analysis*, *32*(4), 456–475. https://doi.org/10.3102/0162373710380739

Dickler, J. (2019). Tuition-free college is now a reality in nearly 20 states. *CNBC*. https://www.cnbc.com/2019/03/12/free-college-now-a-reality-in-these-states.html

Dube, A. (2019). Minimum wages and the distribution of family incomes. *American Economic Journal: Applied Economics*, *11*(4), 268–304. https://doi.org/10.1257/app.20170085

Ehrenberg, R. G., & Sherman, D. R. (1987). Employment while in college, academic achievement, and postcollege outcomes: A summary of results. *Journal of Human Resources*, *22*(1), 1–23. https://doi.org/10.2307/145864

Enrolled senate bill no. 1171. (2018). http://www.legislature.mi.gov/documents/2017-2018/publicact/pdf/2018-PA-0368.pdf

Gayle, W.-R. (2006). *A dynamic structural model of labor supply and educational attainment*.

Gong, Y., Lochner, L., Stinebrickner, R., & Stinebrickner, T. R. (2019). *The consumption value of college* (Working Paper No. 26335). National Bureau of Economic Research. https://doi.org/10.3386/w26335

Green, L., Fry, A. F., & Myerson, J. (1994). Discounting of delayed rewards: A lifespan comparison. *Psychological Science*, *5*(1), 33–36. http://www.jstor.org/stable/40062338

Häkkinen, I. (2006). Working while enrolled in a university: Does it pay? *Labour Economics*, *13*, 167–189. https://doi.org/10.1016/j.labeco.2004.10.003

Hemelt, S. W., & Stange, K. M. (2016). Marginal pricing and student investment in higher education. *Journal of Policy Analysis and Management*, *35*(2), 441–471. https://doi.org/10.1002/pam.21891

Hershbein, B. J. (2019). *Worker signals among new college graduates: The role of selectivity and gpa* (Upjohn Institute Working Paper No. 13-190). W.E. Upjohn Institute for Employment Research. https://doi.org/10.2139/ssrn.2201700

Hotz, V. J., Xu, L. C., Tienda, M., & Ahituv, A. (2002). Are there returns to the wages of young men from working while in school? *The Review of Economics and Statistics*, *84*(2), 221–236. https://doi.org/10.1162/003465302317411497

Hussey, A. J., & Swinton, O. H. (2011). Estimating the ex ante expected returns to college. *American Economics Review: Papers and Proceedings*, *101*(3), 598–602. https://doi.org/10.1257/aer.101.3.598

Jacob, B., McCall, B., & Stange, K. (2018). College as a country club: Do colleges cater to students' preferences for consumption. *Journal of Labor Economics*, *36*(2), 308–348. https://doi.org/10.1086/694654

Joensen, J. S. (2009). *Academic and labor market success: The impact of student employment, abilities, and preferences* [SSRN]. https://doi.org/10.2139/ssrn.1352077

Keane, M. P., & Wolpin, K. I. (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte carlo evidence. *The Review of Economics and Statistics*, *76*(4), 648–672. https://doi.org/10.2307/2109768

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. *Journal of Political Economy*, *105*(3), 473–522. https://doi.org/10.1086/262080

Keane, M. P., & Wolpin, K. I. (2001). The effect of parental transfers and borrowing constraints on educational attainment. *International Economic Review*, *42*(4), 1051–1103. http://www.jstor.org/stable/826985

Kristensen, D., & Salanié, B. (2017). Higher-order properties of approximate estimators. *Journal of Econometrics*, *198*(2), 189–208. https://doi.org/10.1016/j.jeconom.2016.10.008

Löffler, M., Peichl, A., & Siegloch, S. (2018). *The sensitivity of structural labor supply estimations to modeling assumptions* (Working Paper No. 11425). IZA Institute of Labor Economics. https://www.iza.org/publications/dp/11425/the-sensitivity-of-structural-labor-supply-estimations-to-modeling-assumptions

Manski, C. F. (1993). Adolescent econometricians: How do youth infer the returns to schooling? *Studies of supply and demand in higher education* (pp. 43–60). University of Chicago Press. http://www.nber.org/chapters/c6097

Marx, B. M., & Turner, L. J. (2018). Borrowing trouble? human capital investment with opt-in costs and implications for the effectiveness of grant aid. *American Economic Journal: Applied Economics*, *10*(2), 163–201. https://doi.org/10.1257/app.20160127

McClelland, R., & Mok, S. (2012). *A review of recent research on labor supply elasticities* (Working Paper No. 12). Congressional Budget Office. Washington D.C. https://www.cbo.gov/sites/default/files/112th-congress-2011-2012/workingpaper/10-25-2012-recentresearchonlaborsupplyelasticities.pdf

Miller, C., Binder, M., Harris, V., & Krause, K. (2011). *Staying on track: Early findings from a performance-based scholarship program at the university of new mexico* (tech. rep.). Herndon, VA. https://doi.org/10.2139/ssrn.1931097

Murakami, K. (2020). The nuances of the free college debate. *Inside Higher Ed*. https://www.insidehighered.com/news/2020/09/16/free-college-idea-divides-trump-and-biden-poll-finds-republican-support

Neyt, B., Omey, E., Verhaest, D., & Baert, S. (2019). Does student work really affect educational outcomes? a review of the literature. *Journal of Economic Surveys*, *33*(3), 896–921. https://doi.org/10.1111/joes.12301

of Education, U. D. (Ed.). (2020). College scorecard most recent institution-level data. https://collegescorecard.ed.gov/data/

Oreopoulos, P., & Petronijevic, U. (2013). Making college worth it: A review of the returns to higher education. *The Future of Children*, *23*(1), 41–65. https://doi.org/10.1353/foc.2013.0001

Pramuk, J. (2019). House passes bill to hike the federal minimum wage to 15 dollar per hour. *CNBC*. https://www.cnbc.com/2019/07/18/house-passes-raise-the-wage-act-15-per-hour-minimum-wage-bill.html

Quinton, S. (2019). 'free college' is increasingly popular – and complicated for states. *The Pew Charitable Trusts*. https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2019/03/05/free-college-is-increasingly-popular-and-complicated-for-states

Scott-Clayton, J. (2011). On money and motivation: A quasi-experimental analysis of financial incentives for college achievement. *Journal of Human Resources*, *46*(3), 614–646. https://doi.org/10.1353/jhr.2011.0013

Scott-Clayton, J. (2012). What explains trends in labor supply among u.s. undergraduates. *National Tax Journal*, *65*(1), 181–210. https://doi.org/10.17310/ntj.2012.1.07

Shapiro, D., Dundar, A., Huie, F., Wakhungu, P., Bhimdiwala, A., & Wilson, S. (2019). *Completing college: Eight year completion outcomes for the fall 2010 cohort* (Signature Report No. 12c). National Student Clearinghouse Research Center. Herndon, VA. https://nscresearchcenter.org/wp-content/uploads/NSC_Signature-Report_12_Update.pdf

Shapiro, D., Ryu, M., Huie, F., & Liu, Q. (2019). *Some college, no degree: A 2019 snapshot for the natioan and 50 states* (Signature Report No. 17). National Student Clearinghouse Research Center. Herndon, VA. https://https://nscresearchcenter.org/wp-content/uploads/SCND_Report_2019.pdf

Train, K. (2009). *Discrete choice models with simulation* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

7 Tables and Figures

Table 1: Summary statistics

Variable	**Unweighted Respondents**	**Weighted Respondents**	**Survey Recipients**
Female	0.682	0.529	0.531
White, non-Hispanic	0.814	0.765	0.782
Black or African American	0.068	0.095	0.101
Hispanic	0.050	0.055	0.053
Asian	0.094	0.096	0.089
American Indian or Alaskan Native	0.008	0.017	0.013
Native Hawaiian or Pacific Islander	0.007	0.004	0.005
Out-of-state	0.107	0.128	0.134
First generation	0.169	0.191	0.186
Freshman	0.264	0.282	0.266
Sophomore	0.283	0.270	0.283
Junior	0.308	0.295	0.301
Senior	0.144	0.153	0.150
ACT (SAT equivalent)	26.468	26.001	25.610
Honors college	0.253	0.156	0.158
Business	0.136	0.170	0.180
Humanities	0.061	0.050	0.053
Health	0.032	0.026	0.024
STEM	0.491	0.464	0.454
Social Science	0.264	0.266	0.268
Undecided major	0.015	0.025	0.021
Observations	987	987	4,432

This table presents summary statistics for the sample of survey respondents, unweighted and weighted by the inverse probability of responding to the survey, and the in-sample (domestic, first-at-any-college) survey recipients. Each respondent is only counted once, regardless of how many terms they were enrolled at MSU. Class code and field of study categories are based on a student's major at the end of Spring 2019.

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

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. Number of observations: 1,967 (fall and spring) and 980 (summer).

Table 3: Offered and accepted loans

Loan alternative	**Eligible**	**Mean**	**Max**	**Choice**
Panel A: Fall and spring				
No loan	100.00%	$0	$0	61.51%
Stafford loan offer	83.83%	$5,267	$6,750	31.72%
Total loan eligibility	83.83%	$10,669	$44,248	6.76%
Observations	1,967			
Panel B: Summer				
No loan	100.00%	$0	$0	91.73%
Stafford loan offer	23.16%	$743	$1,367	6.22%
Total loan eligibility	40.31%	$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.**
Panel A: In-state students		
Cost of attendance	28,359	1,877
Grants and scholarships	6,066	8,100
Family financial support	15,929	13,211
Unmet financial need	6,365	10,755
Observations	1,770	
Panel B: Out-of-state students		
Cost of attendance	52,728	3,972
Grants and scholarships	16,608	15,830
Family financial support	30,614	24,115
Unmet financial need	5,505	22,469
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 C: 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				

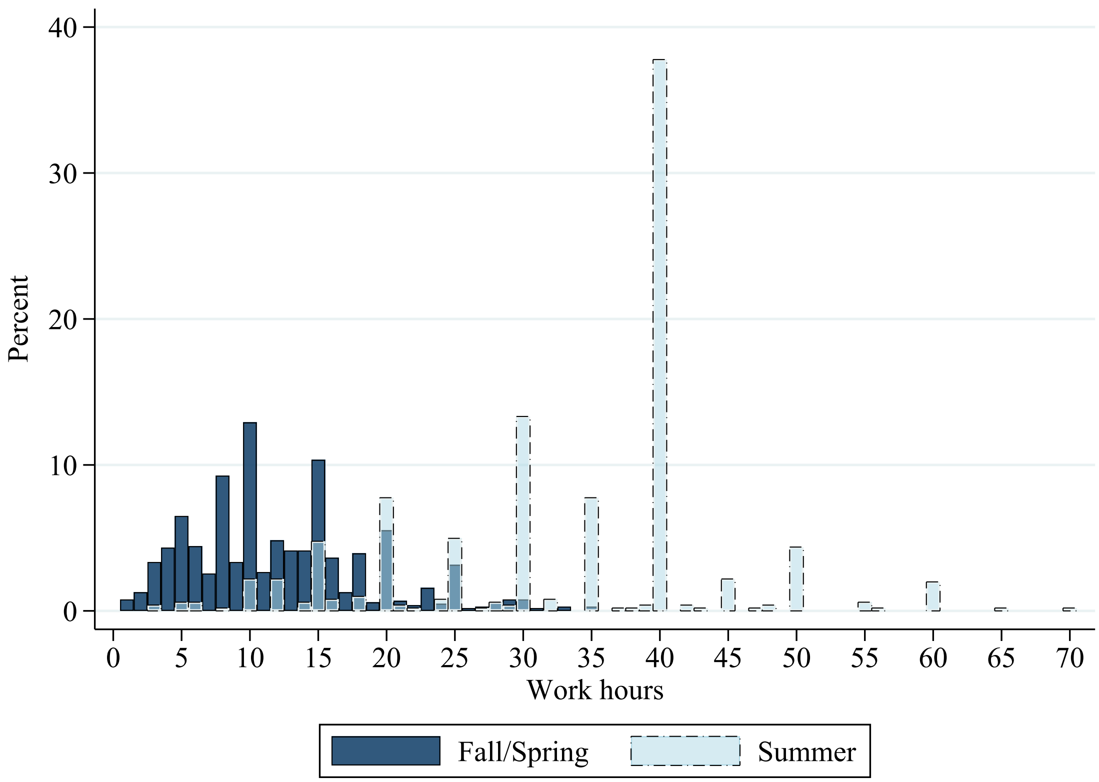
This table presents estimated elasticities during the summer periods. Panel A contains the percentage change in attempted credit hours, panel B contains the percentage change in work hours, and panel C contains the dollar change in borrowing. Each row corresponds to a different denominator: a $500 increase 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)

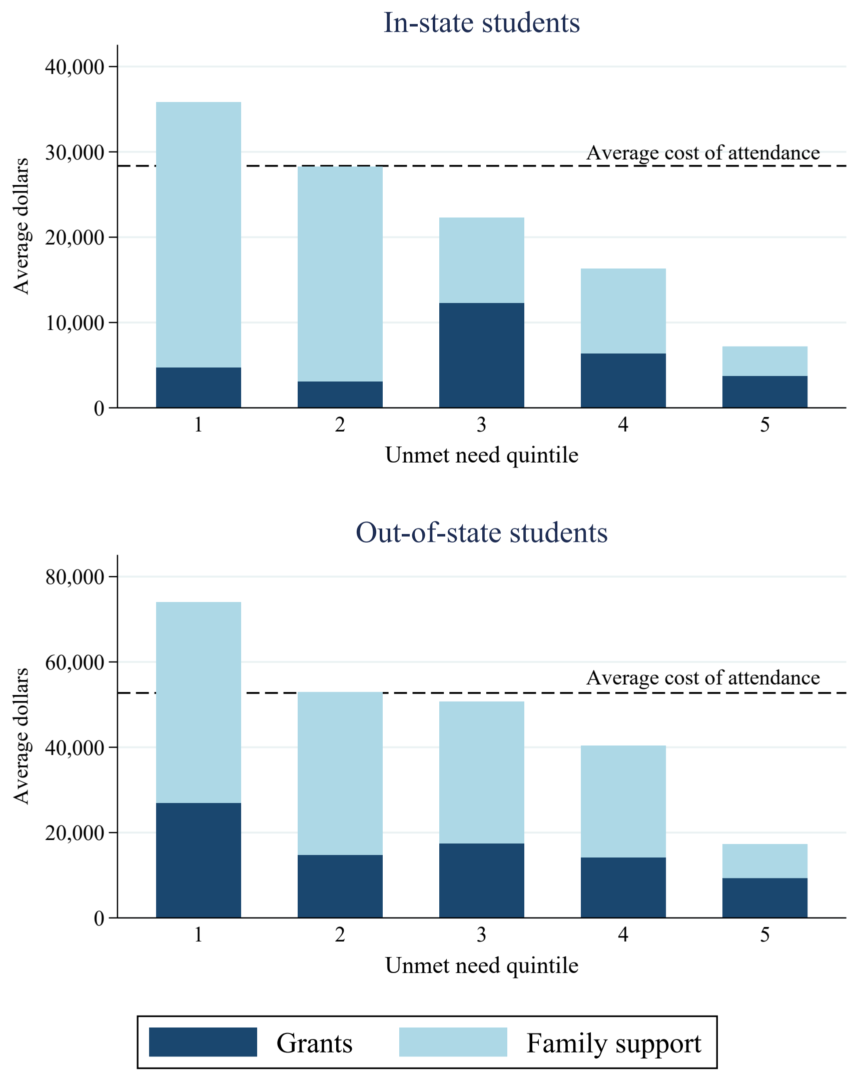
This table presents the projected credit hour enrollment, work hours, borrowing, and terminal-period cumulative GPA under the baseline model and counterfactual model. The baseline model takes the state variables for individuals as given in the first period and simulates their choice history and outcomes 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



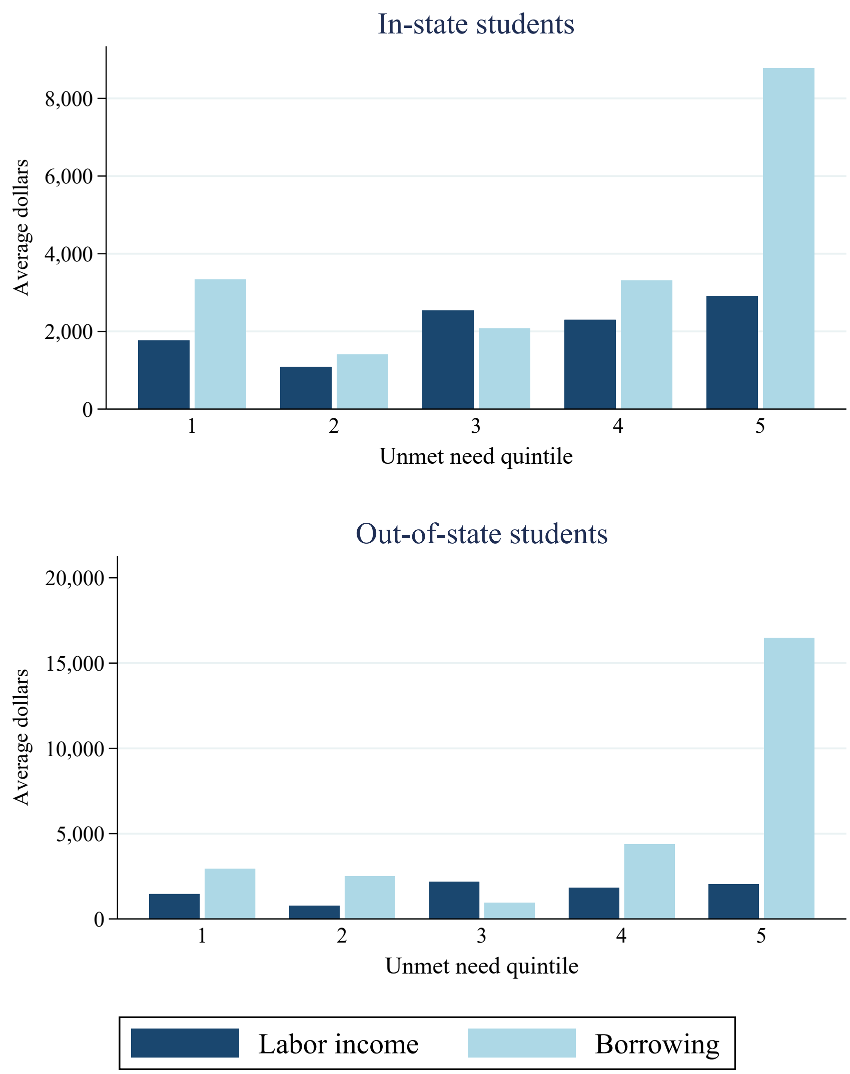
This figure presents the distribution of work hours among students with positive work hours. Hours worked in the fall and spring semesters are averaged together. Number of observations: 1,014 (fall and spring) and 503 (summer).

Figure 2: Grants and family support by financial need quintile



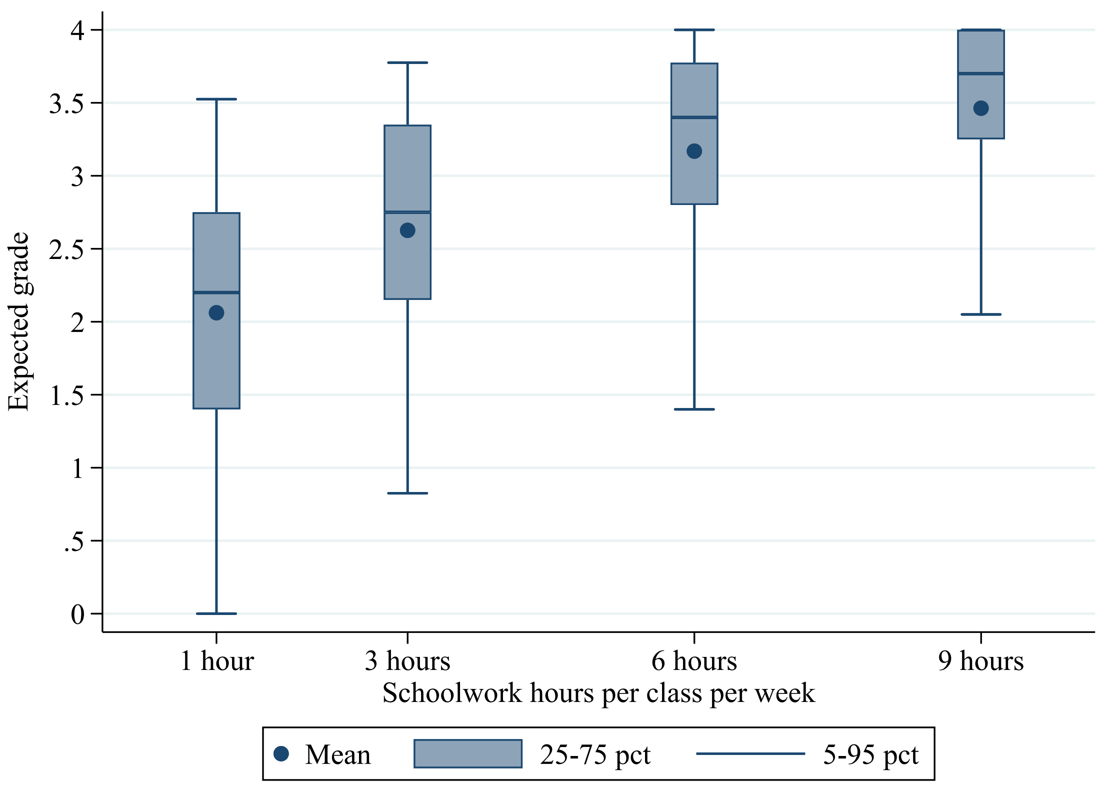
This figure presents the average amount of grants / scholarships and family financial support received by quintile of unmet financial need in the fall and spring term. Unmet need is equal to cost of attendance less grants and family support. The dashed line denotes the average cost of attendance. Results 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: Labor income and borrowing by financial need quintile



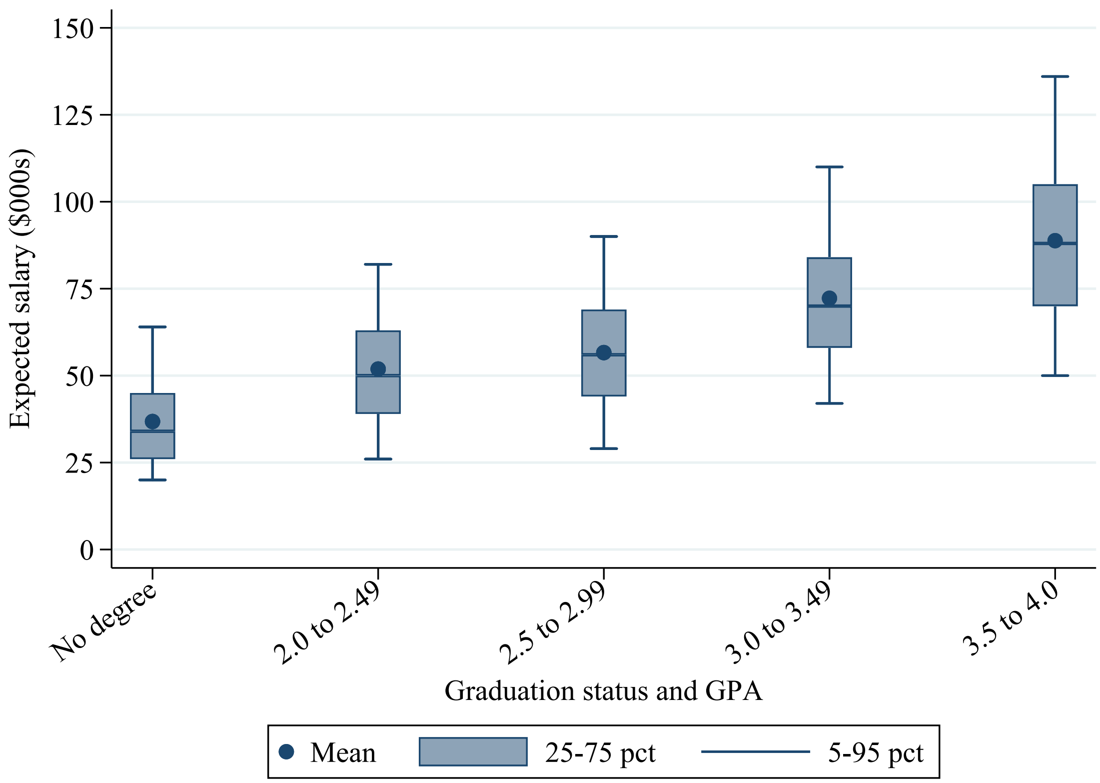
This figure presents the average amount of labor income (15 x work hours x wage) and borrowing for each quintile of unmet financial need in the fall and spring term. Unmet need is equal to cost of attendance less grants and family support. Results are separated by student's residency status (in-state versus out-of-state). Number of observations: 1,770 (in-state) and 197 (out-of-state)

Figure 4: 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 5: 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

Appendix

A Michigan State relative to other colleges

Table A1: Michigan State and Peer Institutions

Variable	**MSU**	**Carnegie Peer**		**Public 4 yr.**	
	Mean	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
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	

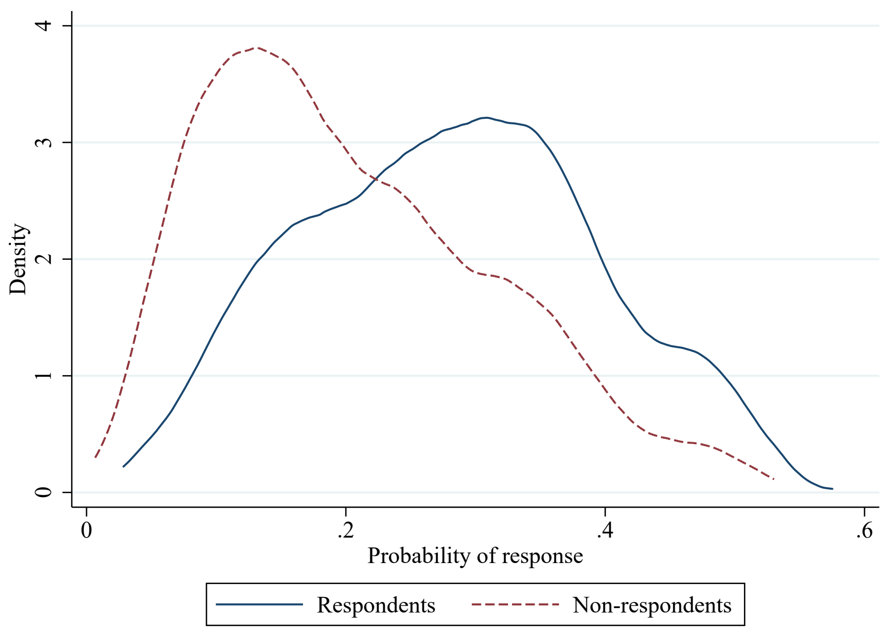
This table presents the mean and standard deviation of statistics for Michigan State University, 4-year public universities with the same Carnegie Classification as MSU (Doctoral universities with very high research activity), and 4-year public universities regardless of Carnegie Classification. Data come from the U.S. Department of Education College Scorecard (2020), most recent institution-level year.

B Calculation of survey weights

I create survey weights by estimating the probability of a student completing the srurvey and using the inverse probability of their response as their survey weight. I use data on respondents and non-respondents from the Office of the Registrar. I estimate a logit model with the following covariates: gender, race, residency, first-generation status, class level, honors status, broad field of study (e.g., Business, Humanities), a cubic of Spring 2019 credit hours, a cubic of Spring 2019 GPA, and a cubic of cumulative GPA as of Spring 2019.

Figure A1 plots the distribution of the estimated probability of response for respondents and non-respondents.

Figure A1: Estimated probability of response for respondents and non-respondents



C Family financial support measurement

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.

Table A2: Family financial support: Education

Education support	**Percent**
No support	26.04
Dollar amount	8.31
Percentage	13.48
Tuition only	16.62
All education costs	35.56
Observations	987

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 the estimated cost of living on campus (see "cost of tuition" above) and multiply it by this ratio. 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 A3: Family financial support: Living

Living support	**Percent**
No support	34.04
Dollar amount	28.27
All living costs	37.69
Observations	987

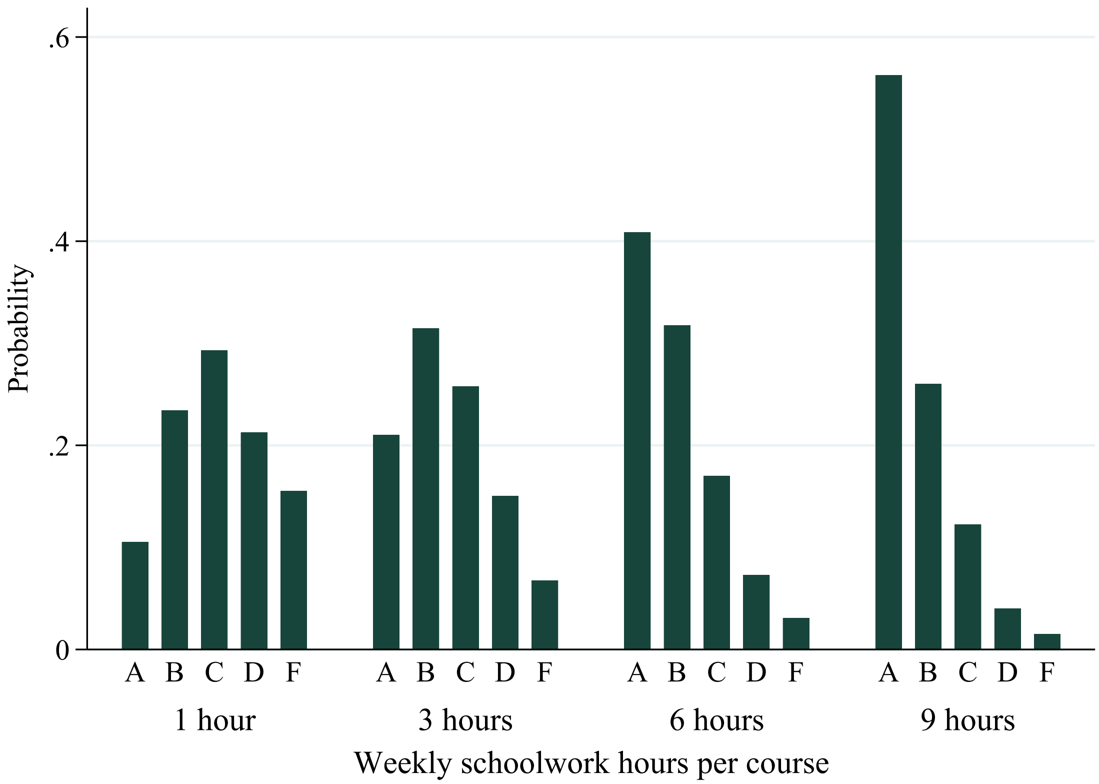
D In-school wage estimation

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.

The SEES also 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. Over 86% of past workers expected to earn a similar wage in Fall 2019 as they did earned previously. I use a worker's most recent hourly wage for their in-school wage across all in-school periods, and I use a non-worker's expected hourly wage for Fall 2019 as their in-school wage across all in-school periods. For non-workers who did not provide an expected wage, I predict their wages using data from non-workers by regressing expected log wages for non-workers on gender, race, residency, first-generation status, age, class level, honors status, and broad categories for major (e.g., Business, Humanities).

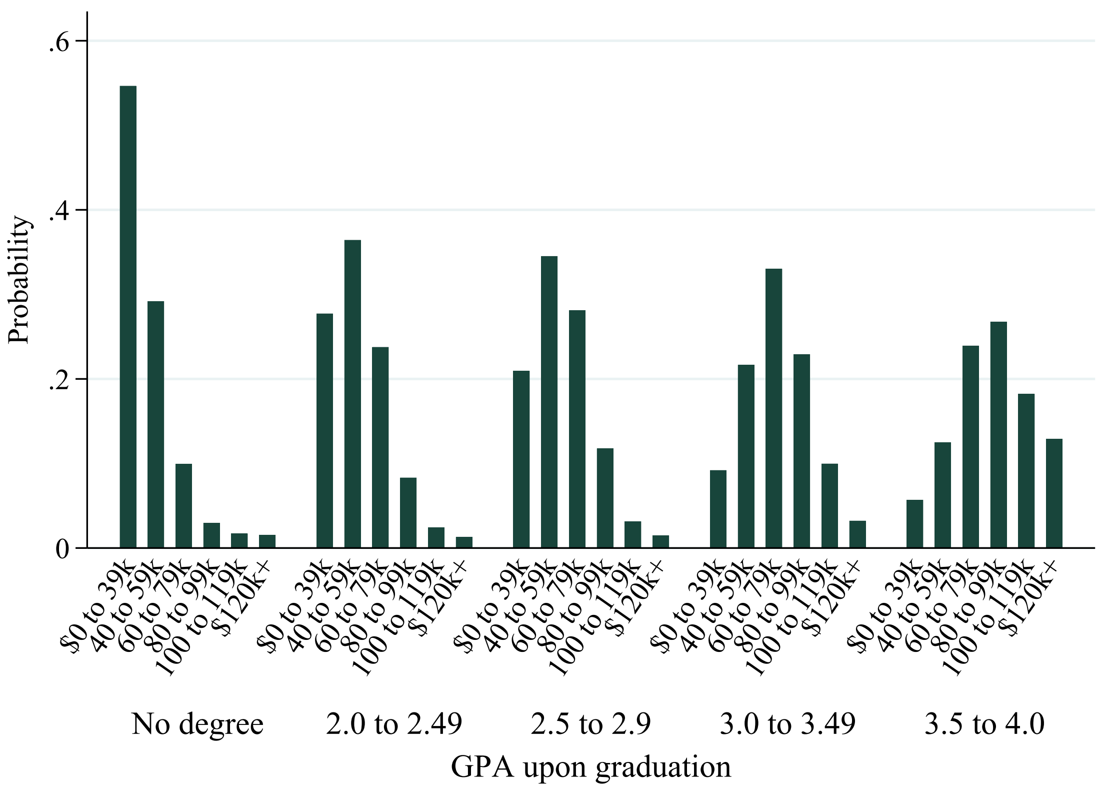
E Grade and post-school salary distributions

Figure A2: Probabilities of grades conditional on schoolwork hours



This figure presents the average probability that students believe they will receive each letter-grade conditional on time spent on schoolwork. Number of observations: 987

Figure A3: Probabilities of post-school salaries conditional on GPA



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: 987