Clocking into Work and Out of Class: College Student Enrollment, Labor Supply, and Borrowing

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April 26, 2021

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Abstract

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

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

JEL classification: I22, I24, J22, J49

*Department of Economics, Michigan State University. I am very grateful to my advisors, Steven Haider, Scott Imberman, Michael Conlin, and Kris Renn, for their generous support and feedback. I would also like to thank Justin Bruner, Karen Clark, Mark Largent, James Murphy, Dean Valenti, the Office of the Associate Provost for Undergraduate Education, Office of Financial Aid, Office of the Registrar, Residential and Hospitality Services, and Department of Student Life at Michigan State University for providing data and the resources, both intellectual and financial, to create and distribute the Student Employment and Enrollment Survey. Email: orrcody@msu.edu. Website: https://orrcody.github.io/

1 Introduction

Post-secondary education yields significant returns in the labor market (Oreopoulos and Petronijevic, 2013; Carneiro et al., 2011; Hussey and Swinton, 2011). Nevertheless, there are many factors that prevent a college enrollee from realizing the full return of a college degree. A third of students who begin college will leave without earning a bachelor's degree, thus incurring the direct financial and opportunity costs of college without the return to graduating (Shapiro, 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 alter the value of their investment. Recent research also highlights the non-monetary returns to attending college, which can be diminished if students lack the leisure time to take advantage of their college's amenities (Jacob et al., 2018; Gong et al., 2019).

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

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

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

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

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

This paper makes several contributions. It develops an estimable model that emphasizes the credit hour decision and relationship between credits, grades, and future earnings. This is one of the first papers to propose such a structural model of the credit hour decision beyond the part-time and full-time margins. This paper also contributes to the literature by estimating labor supply elasticities specifically for college students. I pay particular attention to the unique financial resources and constraints students face and explicitly model the additional cost of labor on expected grades and credit accumulation. Finally, this paper adds to the growing literature on dynamic discrete choice estimation that incorporates subjective expectations, and it is the first to do so with expectations of the GPA returns to studying and labor market returns to graduating with a high GPA. The standard approach to estimating dynamic models requires estimating laws of motion of state variables from panel data, assuming heterogeneity in the process is fully captured by observable characteristics of individuals, and imposing individuals' expectations of the future match the predicted laws of motion (Aguirregabiria and Mira, 2010). Eliciting subjective expectations allows one to directly incorporate heterogeneity in beliefs. Furthermore, subjective expectations are required to separately identify the role of preferences from beliefs, an important distinction for this research (Manski, 1993).

The 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 auxiliary model parameters, utility parameters, elasticities, and results from counterfactual simulations. Section 6 concludes.

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

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

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

2.2 Labor supply

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

Despite the frequency and ramifications of student employment, there is very little research on wage elasticities for college students; in fact, many researchers that estimate labor supply elasticities remove students from their sample to focus exclusively on prime-age workers. For examples, see literature reviews by Bargain and Peichl (2016) and McClelland and Mok (2012). Elasticities for students may differ from elasticities for non-students due to the added costs of working while in school (e.g., fewer credit hours, lower grades) and the added need for money to pay for tuition.

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

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;

[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.

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

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

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

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 985 students and 2,943 student-period pairs (1,964 fall and spring and

[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 who believe their grades will decrease as they increase their time on schoolwork (23) or believe their future wage will be lower after graduating with a 4.0 GPA as opposed to dropping out (26), as this strongly suggests that the student did not properly understand the questions.

979 summer).

Table 1 presents summary statistics for the analytic sample and survey recipients. The sample of respondents is more likely to be female, white (non-Hispanic) or Asian, in-state, and in the honors college than the broader sample of domestic first-time-in-college students who received the survey invitation.

[Table 1 here]

3.2 Observed credit hour enrollment and financing choices

The Office of the Registrar provided students' credit hour enrollment by term. Table 2 presents the proportion of students who enrolled in varying credit hour amounts. In the fall and spring, almost half of students enrolled in 27 to 29 credits, and 95% of students enrolled in 24 to 32 credit hours. In the summer, 62% of students did not enroll in any credits, and among students who did enroll, 40% took three to five credits and 42% took six to eight credits. Notably, many students may not be enrolled in enough credits to graduate within four years of starting at MSU. Without any transfer credits, the typical student needs to complete at least 120 credit hours to graduate, or 30 credits per year over four years. As shown in the last column of Table 2, 46% of students enroll in fewer than 30 credits across the entire year.

[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 across terms.

Student workers worked an average of 12 hours per week in the fall and spring term, while workers worked an average of 33 hours per week in the summer term. As shown in Figure 1, the modal number of hours worked per week in the fall and spring was ten, though eight and 15 hours were also common. In the summer, 40 hours per week was the modal choice by a large margin.

[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, ranging from $5,500 for dependent freshmen to $12,500 for independent juniors and seniors, and students cannot receive more in Stafford loans than their budget (expected cost of attendance minus non-loan financial aid) allows. In the fall and spring, 85% of students were eligible for Stafford loans, and 48% of students accepted at least some non-zero loan amount. In the summer, only 23% were eligible for Stafford loans, and only 9% borrowed some non-zero loan amount. This is not surprising – students must be enrolled in at least six credit hours to be eligible for Stafford loans.

Students do not need to accept the full Stafford loan offer, though in the fall and spring only 8% of borrowers accept less. If students want to borrow beyond their Stafford loan offer, they must apply for loans from private vendors. As with Stafford loans, students cannot take out more private student loans than their budget allows, though the credit hour requirement may be lower than the six credits required for Stafford loans. In the fall and spring, 17% of students accepted private loans, and in the summer, 3% of students accepted private loans. Figure 2 presents the distribution of accepted student loan amounts.

[Figure 2 here]

3.3 Cost of attendance and financial need

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

Averages hide significant heterogeneity across students as Figure 3 shows. Each panel presents the average amount of grant aid and family financial support received by students in different quintiles of the unmet need distribution. For both in-state and out-of-state students, students in the bottom two quintiles received enough aid and support to cover their cost of attendance. At the other extreme, students in the highest quintile of unmet need required $21,364 (in-state) or $35,557 (out-of-state) of additional income or loans to cover their expected costs.

[Figure 3 here]

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

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

3.4 Subjective expectations

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

To elicit beliefs about time spent on schoolwork, I showed students six work hour and credit hour schedules (e.g., working ten hours per week while enrolled in 15 credit hours) and asked them how many hours they expect to spend on schoolwork during a typical non-exam week. Students were instructed to include class attendance, completing assignments, and reviewing notes within "schoolwork", and they were given attention check questions to verify they understood what "time spent on schoolwork" should include. Appendix Figure A1 contains an example of what students were given for one schedule, and Table 3 presents the distribution of expected schoolwork hours for all six schedules.

[Table 3 here]

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

To elicit beliefs about the distribution of grades conditional on schoolwork, I followed the method proposed by Delavande and Rohwedder (2008). Students were shown a set of bins representing different outcomes – 0.0 (F), 1.0 to 1.5 (D), 2.0 to 2.5 (C), 3.0 to 3.5 (B), and 4.0 (A) – and asked to place ten balls across the bins where each ball represented the likelihood of observing the outcome.[6] This exercise was repeated for a series of scenarios: spending one hour on schoolwork per course per week, three hours on schoolwork, six hours on schoolwork, and nine hours on schoolwork.[7] Appendix Figure A3 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 1.40 to 2.75, which spans a third of all available grades. The range of expected grades decreases as students spend more time on schoolwork, but there are still meaningful differences at nine hours of schoolwork; a quarter of students believe they will earn less than a 3.25, while a quarter believe they will earn a 4.0.

[Figure 4 here]

To elicit beliefs about the distribution of post-school salaries conditional on GPA, I again used the balls-in-bins method. The SEES asked students to consider five scenarios: failing to graduate, graduating with a cumulative GPA between 2.0 and 2.49, graduating with a cumulative GPA between 2.5 and 2.9, graduating with a cumulative GPA between 3.0 and 3.49, and graduating with a cumulative GPA between 3.5 and 4.0. Students were given six bins of possible full-time salaries: less than $40 thousand, $40 to $59 thousand, $60 to $79 thousand, $80 to $99 thousand, $100 to $119 thousand, and greater than $120 thousand. Appendix Figure A4 presents the average reported probability of earning each salary for each GPA scenario. The majority of students believe they will earn less than $40

[6] Eliciting distributions with the balls-in-bins method has two advantages. First, the visual frequency representation can be understood by a respondent with limited formal education of probability (Delavande et al., 2011). Second, the balls-in-bins method always yields a valid probability distribution, as respondents cannot violate monotonicity of the cumulative distribution function or the bounding of probabilities between zero and one. A sample response is provided in Appendix Figure A2.

[7] A typical course is three credit hours.

thousand a year if they left MSU without a degree. Students believe they are more likely to earn higher salaries as they increase their GPA. As with the distribution of grades, there is significant heterogeneity in these beliefs. Figure 5 presents the distribution of expected salaries across students. The interquartile range of expected salaries without a degree is $26 to $44 thousand, and this spread only increases with graduating and receiving a higher GPA. With a 3.5 to 4.0 GPA upon graduation, a quarter of students expect to earn less than $70 thousand while a quarter believe they will earn more than $105 thousand.

[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. The student begins with her first year of college and chooses her credit hour enrollment, labor supply, and borrowing to maximize the present discounted value of her lifetime utility. She derives utility from consumption, leisure, and the grades she earns from her classes. Grades also affect her future salary upon leaving college. The student leaves college when she earns enough credits to graduate with a degree, reaches the maximum allowable time in college, or chooses to permanently exit.

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

4.1.2 Choices

Each period in school, individual i decides whether to continue in school or drop-out and enter the full-time labor market. If she chooses to continue in school, she makes three additional decisions: her labor supply h_{it}, credit hour enrollment k_{it}, and new student loans b_{it}. Individual i chooses her labor supply from the discrete set of 0 hours, 300 hours, and 600 hours which corresponds to 0, 10, and 20 hours per week in the fall and spring periods and 0, 20, and 40 hours per week in the summer periods.[11] Credit hour enrollment is

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

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

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

[11] Discretization of the choice set simplifies the estimation procedure. It avoids the solving of first-order conditions, and it easily incorporates corner solutions (e.g., no work, no classes, and no or maximum borrowing). One drawback is the modeler must specify the number of feasible choices; however, previous work in

also restricted to a discrete set. In the fall and spring, individual i can choose 26 credits, 30 credits, or 34 credits; in the summer, individual i can choose 0 credits, 3 credits, or 8 credits. In addition, she can choose not to borrow additional loans, borrow her Stafford loan offer, or borrow her maximum student loan eligibility. I denote the entire set of feasible choices in period t with A_t.[12]

4.1.3 State variables

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

$$
\begin{aligned}
K_{i,t+1} &= K_{it} + \sum_{k=1}^{k_{it}} 1[g_{ikt} > 0] \\
G_{i,t+1} &= G_{it}\left(\frac{K_{it}}{K_{it}+k_{it}}\right) + \left(\frac{\sum_{k=1}^{k_{it}} g_{ikt}}{K_{it}+k_{it}}\right) \qquad (1) \\
B_{i,t+1} &= (1+r_t)(B_{it}+b_{it})
\end{aligned}
$$

Cumulative credits earned is the number of credit hours where a passing grade (greater than 0.0) was earned for that credit. Cumulative GPA is the weighted average of the individual's previous cumulative GPA and newly earned grades.[13] I denote the grade earned

the labor supply literature has found estimated utility parameters are robust to this decision (Löeffler et al., 2018).

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

[13] The weighted average formula for cumulative GPA is not correct for students that earned a 0.0 (failing) grade in a course, as credits that received a 0.0 do not contribute to K_{it}, but fewer than 4% of student-term pairs include a 0.0 grade, so this formula is correct for the vast majority of observations. A precise calculation requires tracking separately the number of credits attempted and the number of credits passed and using credits attempted in the weights. If this were the only shortcoming, the current formula would over-estimate cumulative GPA; however, students are allowed to retake a failed class and replace their 0.0 grade with a

for credit k by individual i in period t with g_{ikt}. Cumulative debt is equal to prior debt plus new borrowing, after interest accumulation.

4.1.4 Preferences

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

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

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

Once the individual leaves school and enters the post-school labor market, she receives a single utility realization equal to the discounted present value of her lifetime utility in the labor market, $U_t^{post}(S_{it})$. This utility sum is a function of her wage and cumulative debt upon entry into the post-school labor market which jointly determine her "full income".[14]

higher grade from a second attempt. I do not record when students do this. If I did track cumulative credits attempted separately and used it in place of K_{it}, I would not correctly replace 0.0 grades with their revised grade. In this regard, the current formula underestimates cumulative GPA. Considering both factors together, it is ambiguous whether the formula over- or under-estimates cumulative GPA, as the errors partially cancel each other out.

[14] Instead of modeling the individual's entire lifetime labor supply problem, I assume she can maximize her utility according to a two-stage budgeting model, and her lifetime value function is simply a function of

Finally, I use $U_t(a,S,\varepsilon)$ to denote individual i's utility when her entrance into the post-school labor market is unknown ex ante:

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

4.1.5 Constraints

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

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

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

Individual i's leisure time is equal to her total time endowment L_t less study hours

her wage and debt (e.g., Blundell and Walker, 1986).

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

$study_i(a_{it})$ and work hours:

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

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

4.1.6 Grades

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

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

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

4.1.7 Maximization problem

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

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

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

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

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

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

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

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

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

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

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

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

4.3 Model parameterizations

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

$$\begin{aligned} u_t^{sch}(c_{ait}, l_{ait}, g_{it}) &= \alpha_c \ln(c_{ait}) + \alpha_{lt} \ln(l_{ait}) + \alpha_g \ln(g_{it}) \\ &+ \alpha_{h0t} 1[h_{it} > 0] + \alpha_{k0} 1[k_{it} = 0] + \alpha_{k30} 1[k_{it} = 30] \\ &+ \alpha_{b1} 1[b_{it} = \text{Stafford only}] + \alpha_{b2} 1[b_{it} = \text{Max eligiblity}] \end{aligned} \tag{10}$$

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

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

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

Individual i's family financial support is given by:

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

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.[22]

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

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

[21] A fixed cost of labor is common in the labor supply literature and can capture the additional effort associated with attending a job regardless of hours worked (Löeffler et al., 2018). I include a fixed utility term for attempting zero credit hours to capture similar fixed costs associated with enrolling in any classes regardless of the number of classes. Marx and Turner (2018) find empirical evidence that students face a fixed non-monetary cost for borrowing, which I capture with α_{b1} and α_{b2}. I allow this cost to vary between Stafford loans and the maximum loan eligibility because students have to actively seek out and apply for loans beyond the Stafford loan offer, and the search costs may have a utility cost.

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

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 change her study time per credit hour as she changes her credit hour enrollment or work hours.

I model the grade process with a heteroskedastic ordered probit. Individual i's unobserved "knowledge" for a particular credit hour g_{ikt}^* is a function of her knowledge without any studying γ_{0i}, her individual-specific return to studying rate γ_{1i}, study hours per credit hour, and a normally distributed error term ν_{ikt}.[23] When her knowledge passes particular thresholds, she earns higher discrete grades. I assume all individuals face the same thresholds to earn each grade and the same variance factor for the error term.

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

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

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

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

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

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

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

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

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

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

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.[25] 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 existing research suggests that young adults have higher discount rates than older adults (e.g., see Green et al., 1994), I choose an annual discount rate of 0.8. Finally, I set the consumption floor at $50 per week.

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

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

4.4 Criterion function

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

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

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

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

Because the choice-specific preference shocks are independently distributed over time and the other state variables evolve independently from the preference shocks, I can re-write the likelihood 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 and third terms are defined by the grade model described previously and do not depend on the parameters in α. The fourth term, the contribution of initial state

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

variables to the likelihood function, can also be ignored under the assumption that the choice-specific preference shocks are independently distributed over time and uncorrelated with the initial states (Aguirregabiria and Mira, 2010). Thus, the only term relevant for the maximization problem is the first term – the log of the conditional choice probability.

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

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

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

5 Results

5.1 Auxiliary model estimation

Table 4 summarizes the variables in the structural model and specifies the time periods they are available in the data. The choice variables, time-varying state variables, and net education expense function are available for all time periods. In-school wages and family financial support are only known at the time of the survey, and I assume that they do not change over time (Appendix Sections F and B describe the calculation of these variables in more detail). In the rest of this section, I briefly describe how I use the survey responses to estimate students' study time function, grade production function, and post-school wage function.

[Table 4 here]

As specified in equation 12, a student's time spent on schoolwork is an individual-specific function of their credit hours and labor supply. In the SEES, I asked students how much time they expect to spend on schoolwork given six hypothetical credit hour enrollment and work hour schedules. I use their responses to these six questions and estimate the study function parameters with a linear regression. Panel A of Table 5 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. Each ball placed is a separate observation, so there are 40 observations per student (ten balls placed in four schoolwork scenarios) to identify the individual-specific parameters. I assume that the variance term and thresholds are common across all students. I also normalize the lowest threshold to zero to report individual-specific constants for every student. Panel B of Table 5 presents the distribution of the grade production function parameters.

Equation 15 specifies that a student's post-school wage is determined by an individual-specific constant, degree premium, and return to GPA. The variance of the error term is also individual-specific. To estimate these parameters, I use the conditional salary distributions elicited from each student for five GPA scenarios. Similar to the conditional grade distribution questions, students placed ten balls in bins to convey the likelihood of earning a particular post-school full-time salary. Each ball placed is a separate observation, so there are 50 observations per student (ten balls placed in five GPA scenarios) to identify individual-specific parameters. I estimate the wage offer model with a separate linear regression for each student. Panel C of Table 5 presents the distribution of the post-school wage function parameters.

[Table 5 here]

5.2 Structural model estimates

Table 6 presents the estimated utility parameters and their standard errors.[27] There are a few takeaways worth noting. First, there is a significant increase in how much students value their leisure time in the summer relative to the fall and spring. This is not surprising, as students may have more leisure options available to them during the summer semester (e.g., traveling, spending time with family and friends from home) which makes their time more valuable. In addition to consumption and leisure, students also value their contemporaneous semester GPA independent of the future labor market returns.

[Table 6 here]

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

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

In isolation, utility parameters can only tell us so much, but before proceeding with further analysis, I verify that the model achieves a reasonable fit of the observed data. Table 7 presents the observed probabilities of each choice, average predicted probabilities of each choice, and the difference between the two. Panel A confirms that the model does a good job fitting the observed credit hour choice probabilities in the fall and spring periods, but it struggles to capture the u-shaped pattern in the summer periods. Panel B tells a similar story; the model does well fitting the observed work hour probabilities in the fall and spring periods, but it does not capture the u-shaped pattern of work hours in the summer. Panel C shows the goodness of fit for borrowing choices. The model does a good job matching the distribution of borrowing choices in the fall and spring periods, and it correctly predicts that almost no students borrow in the summer. The model over predicts students' willingness to borrow up to their maximum loan eligibility in the summer, though this is likely related to the model under-predicting students' willingness to work 40 hours a week in the summer. Overall, the model and estimated utility parameters fit the observed distribution of choices well.

[Table 7 here]

5.3 Elasticities

Tables 8 and 9 present statistics for a series of elasticities of credit hour, work, and borrowing behaviors. I derive these elasticities via simulation by comparing the weighted average of choices (weighted by the model-derived probability of the choice) with the baseline variables and with the simulated variables: a \$1,000 increase in grants (\$500 in the summer), a 10% increase in the per-credit hour tuition rate, a 10% increase in students' expected return to studying (γ_{1i}), a 10% increase in students' expected return to earning a higher GPA (ω_{2i}

and ω_{3i}), and a 10% increase in students' in-school wage.[28] I estimate standard errors for the average elasticities across students with a parametric bootstrap using 30 draws from the joint distribution of utility parameters.

[Tables 8 and 9 here]

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

Students are more responsive on the labor supply margin than the credit hour margin. As shown in the last row of Panel B, the average wage elasticity is 0.29 in the fall and spring and 0.24 in the summer; for a 10% increase in wages, students work 2.9% and 2.4% more hours on average. These wage elasticities are comparable to consensus estimates for prime-aged working adults in the United States, particularly for married women (McClelland and Mok, 2012). Students decrease their labor supply with an increase in their subjective beliefs for the returns to studying and returns to GPA, at least in the fall and spring when they are more likely to face grade penalties for devoting more time to work; a 10% increase in students' beliefs about the returns to studying decreases hours worked by 1.19%, and a 10% increase in students' beliefs about the labor market returns to graduating with a higher GPA

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

decreases hours worked by 2.11%. Worth noting, the distribution of these elasticities across students is skewed right, so the average response is not indicative of the median student's response. I do not find evidence that students' labor supply decisions are responsive to changes in financial aid or tuition – across the interquartile range, elasticities are near zero.

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

For the elasticities that are highly skewed, a question naturally arises – what students are in the tail of the distribution? To answer this question, I conduct a series of two-sample t-tests on potential explanatory factors by comparing students in the bottom and top terciles of their elasticity distributions. I choose factors that should affect the marginal utility or cost of changing labor supply and borrowing such as unmet financial need, wages, and expected studying time response to work hours.[29] Table 10 presents the results for the fall

[29] Unmet financial need, in-school wage, return to studying, return to GPA, and cumulative credit hours are

and spring periods.

[Table 10 here]

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

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

Panels C and D compare students in the bottom and top terciles of two borrowing elasticities: financial aid elasticity and tuition elasticity. The average financial aid elasticity is -0.78 (median of -0.01), and the average tuition elasticity is 0.23 (median of 0.03). There

self-explanatory or discussed previously. The "study cost of work" is how many study hours per credit hour the student expects to give up with an increase in work hours; in other words, the derivative of $study_i(a_{it})/k_{it}$ with respect to h_{it} in equation 12. Because the derivative changes with work hours, I use the derivative at 6 work hours, which is approximately the mean work hours in the fall and spring.

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

5.4 Counterfactual simulations

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

5.4.1 Minimum wage increase

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

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

Panel A of Table 11 presents the expected behaviors and outcomes for students under the baseline and counterfactual simulations.[31] Increasing the minimum wage to \$15 per hour increases average weekly work hours by 0.75 in the fall and spring and 1.70 in the summer. With the wage and hour increase, the average student's labor income increases by \$1,115 in the fall and spring year and \$1,003 in the summer. There is a small decrease in average borrowing, \$303 in the fall and spring and \$65 in the summer, which is not enough to offset the gains in labor income. There is no observable change in attempted credit hours or expected cumulative GPA. Thus, the primary effect of increasing the minimum wage is increasing students' consumption (at the expense of leisure or studying) as opposed to allowing students to maintain existing consumption with less debt or fewer hours working.

[Table 11 here]

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

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

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 to existing students if Michigan State University unconditionally waived the cost of in-state tuition for all students enrolled after September 2014.[32]

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

Panel B of Table 11 presents the expected responses and outcomes for students with and without free in-state tuition. Average credit hours attempted increase by 0.09 credits in the fall and spring and 0.04 credits in the summer, but this is a small effect in practice. Over

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

the course of four years, this corresponds to less than one additional credit hour. There are similarly small changes in work hours. Given these small effects, there is no observable difference in expected cumulative GPA. Borrowing does change substantially, however, with average loan amounts decreasing by $1,922 in the fall and spring and $185 in the summer. Taken together, this counterfactual simulation suggests that making college tuition cheaper is largely a wealth transfer for Michigan State's already enrolled students; it reduces students' reliance on loans but does not improve other outcomes like credit accumulation or GPA.

6 Conclusion

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

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

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

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

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

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7 Tables and Figures

Table 1: Summary Statistics for SEES Respondents and Recipients

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

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

Table 2: Credit Hour Enrollment by Semester

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

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

Table 3: Expected Schoolwork Hours

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

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

Table 4: Data and Model Parameters

	Notation	**Periods Observed**
Choice variables		
Labor supply	h_{it}	$t = \{1, \dots, T_i\}$
Credit hours	k_{it}	$t = \{1, \dots, T_i\}$
Borrowing	b_{it}	$t = \{1, \dots, T_i\}$
Time-varying state variables		
Cumulative credits earned	K_{it}	$t = \{1, \dots, T_i\}$
Grade point average (GPA)	G_{it}	$t = \{1, \dots, T_i\}$
Total debt	B_{it}	$t = \{1, \dots, T_i\}$
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	$edu_t(\cdot)$	$t = \{1, \dots, T_i\}$
Auxiliary model parameters		
Expected study hours	δ_i	
Returns to studying	γ_i	
Wage model	ω_i	

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

Table 5: Auxiliary Model Parameters

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

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

Table 6: Structural Model Parameters

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

Notes: This table presents the estimated parameters to the utility functions specified in Eq. 10 and Eq. 14. To reduce computation time, I use a 15% sample of the data to estimate the parameters.

Table 7: Observed and Predicted Choice Probabilities

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

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

Table 8: Elasticities (Fall and Spring)

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

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

Table 9: Elasticities (Summer)

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

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

Table 10: Elasticity Heterogeneity (Fall and Spring)

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

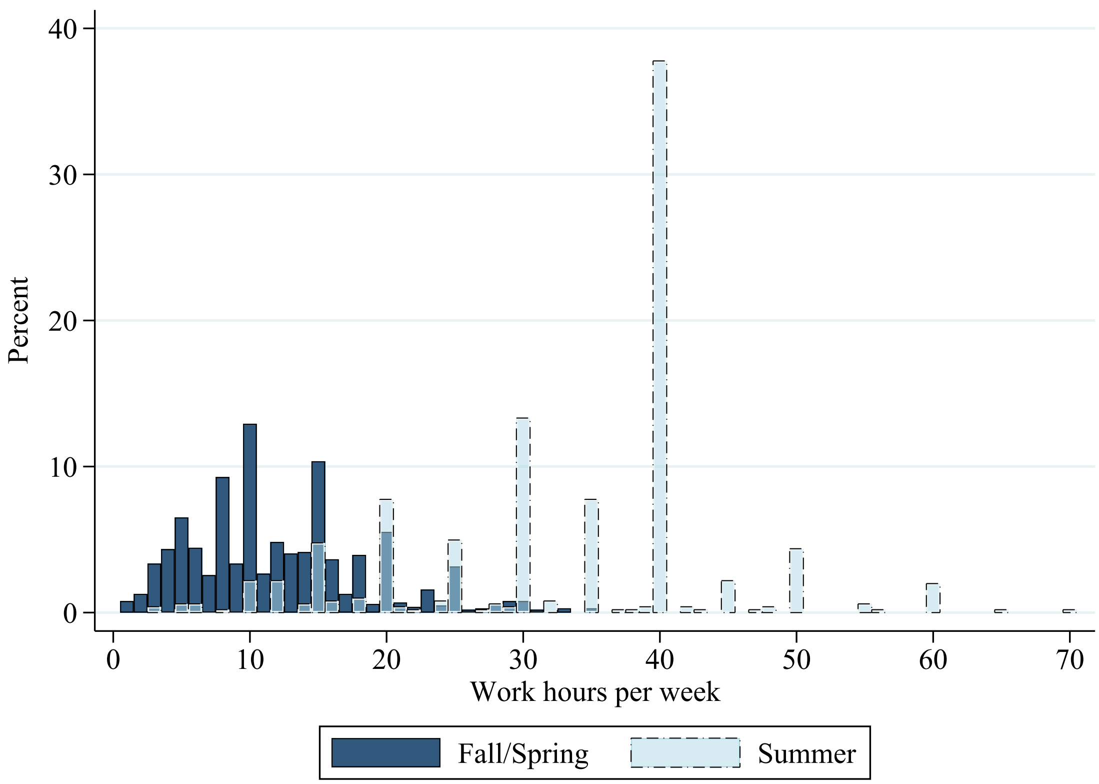
Notes: This table presents the means for particular variables separately for students in the bottom tercile and top tercile of the specified elasticity distribution. Statistical significance based on two-sample t-tests with unequal variances. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 11: Counterfactual Simulation Results

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

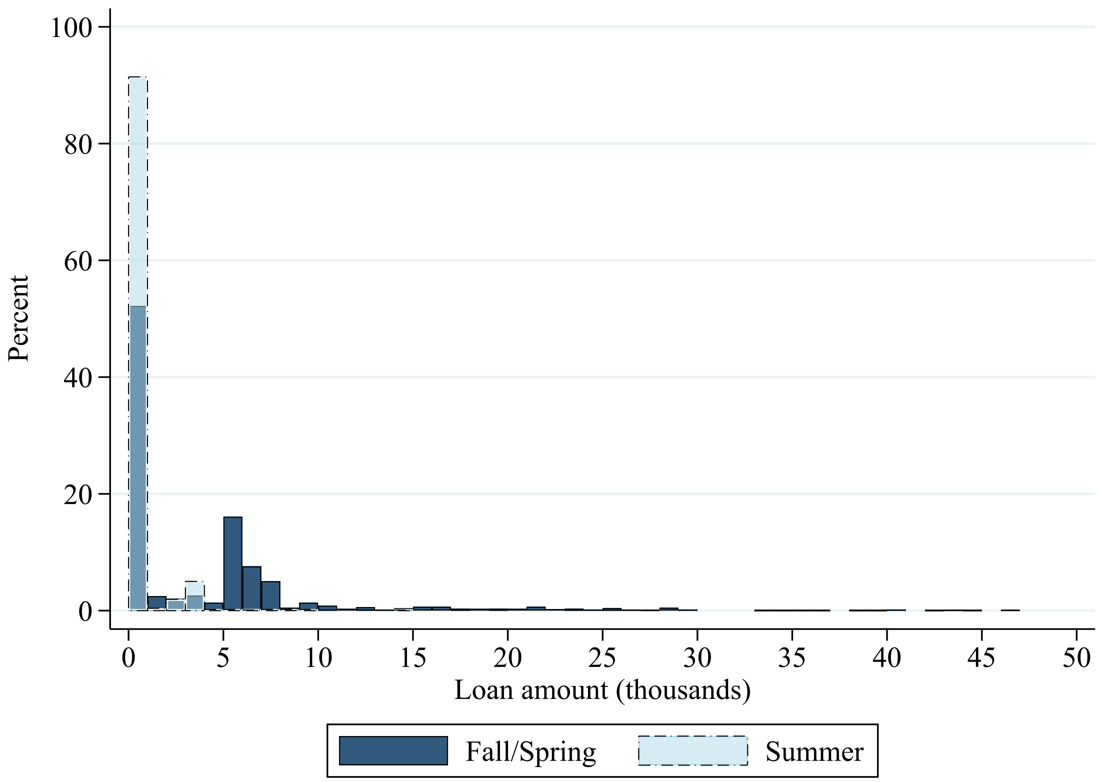
Notes: This table presents the projected credit hour enrollment, work hours, borrowing, and terminal-period cumulative GPA under the baseline model and counterfactual model. The baseline model takes the state variables for individuals as given in the first period and simulates their choice history and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

Figure 1: Distribution of Work Hours



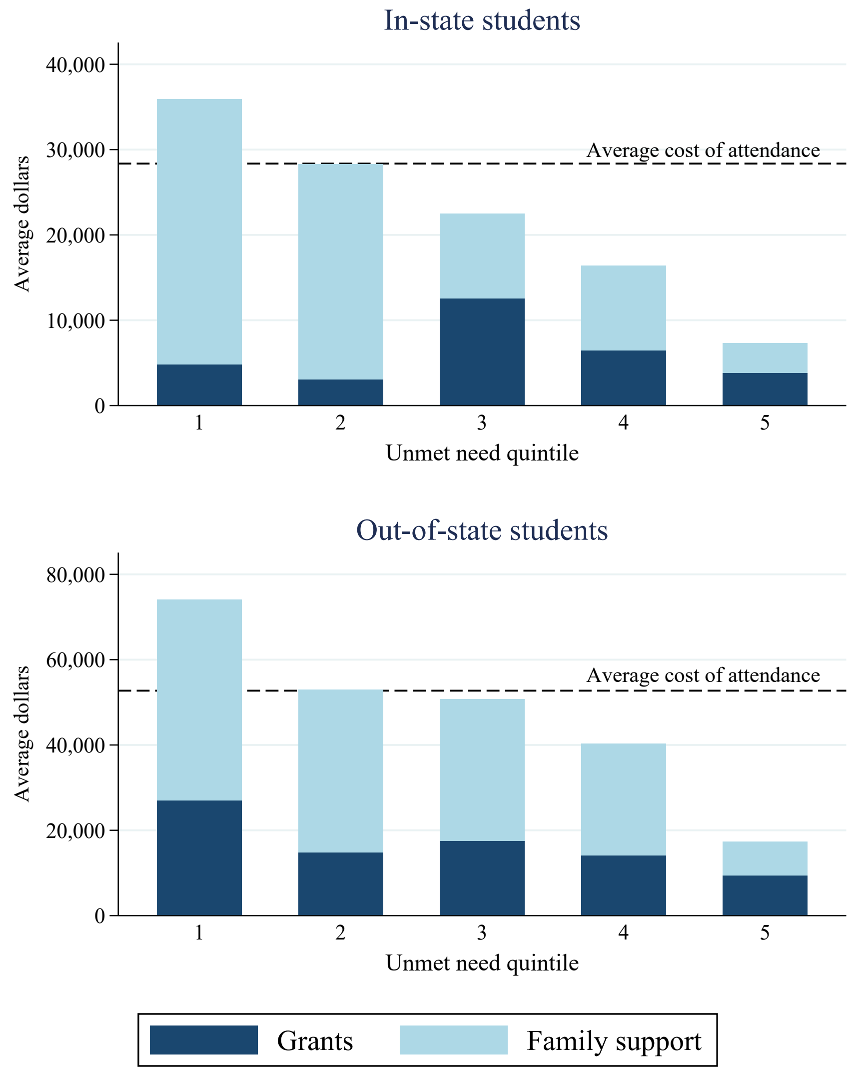
Notes: This figure presents the distribution of work hours among students with non-zero work hours. Hours worked in the fall and spring semesters are averaged together. Number of observations: 1,013 (fall and spring) and 503 (summer).

Figure 2: Distribution of Borrowing Amounts



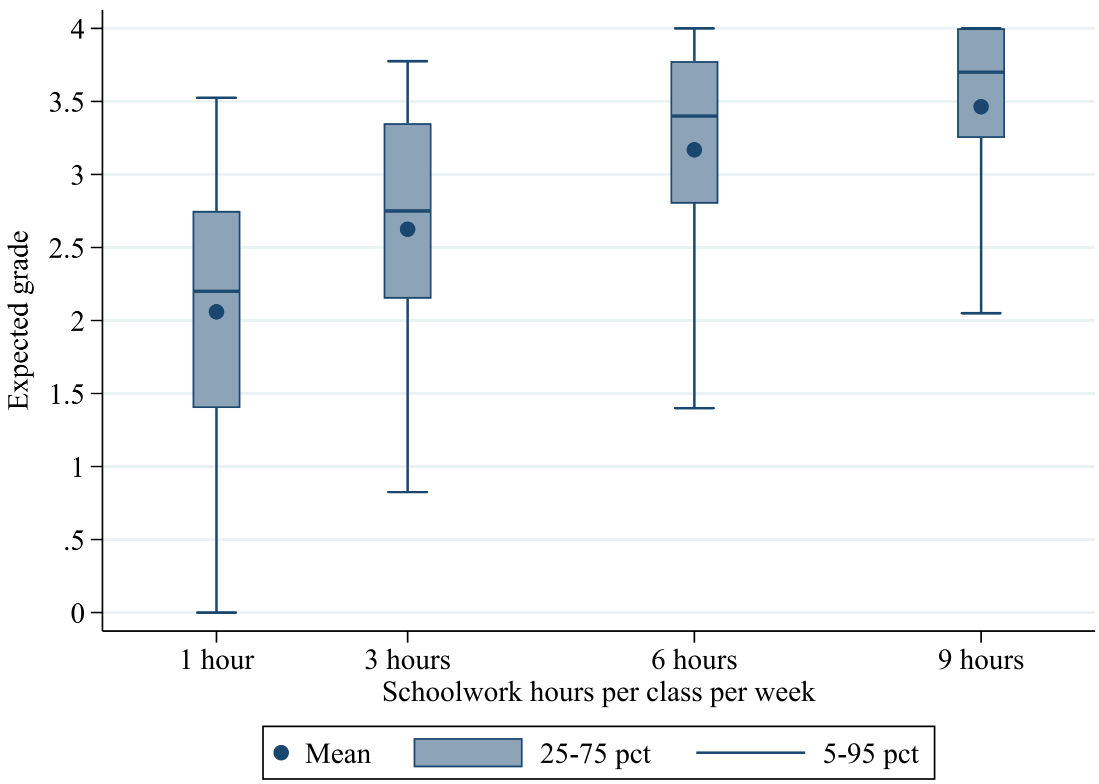
Notes: This figure presents the distribution of accepted student loans. Number of observations: 1,964 (fall and spring) and 979 (summer).

Figure 3: Grants and Family Support by Unmet Need Quintile



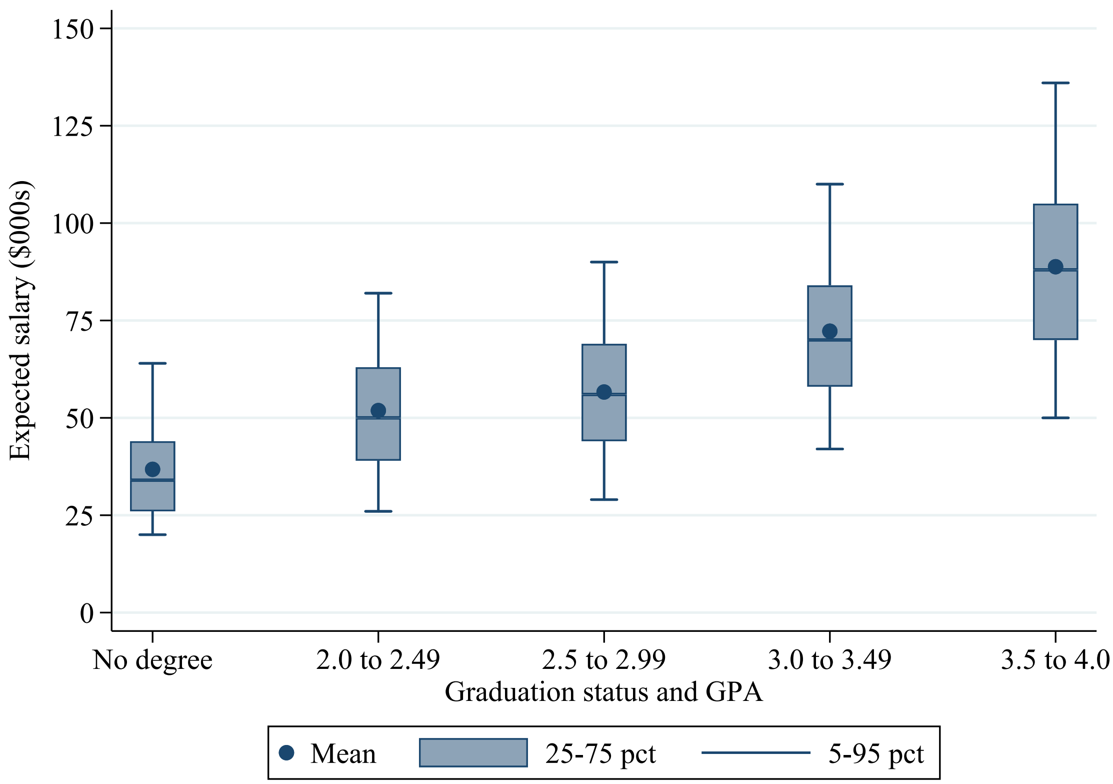
Notes: This figure presents the average amount of grants and family financial support received in the fall and spring term by quintile of unmet financial need. Unmet need is equal to cost of attendance less grants and family support. The dashed line denotes the average cost of attendance. Results are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

Figure 4: Distribution of Expected Grades Conditional on Schoolwork



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

Figure 5: Distribution of Expected Salaries Conditional on GPA



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

Appendix

A Michigan State relative to other colleges

Table A1: Michigan State and Peer Institutions

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

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

B Measuring family financial support

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

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

Table A2: Family Financial Support: Education Expenses

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

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

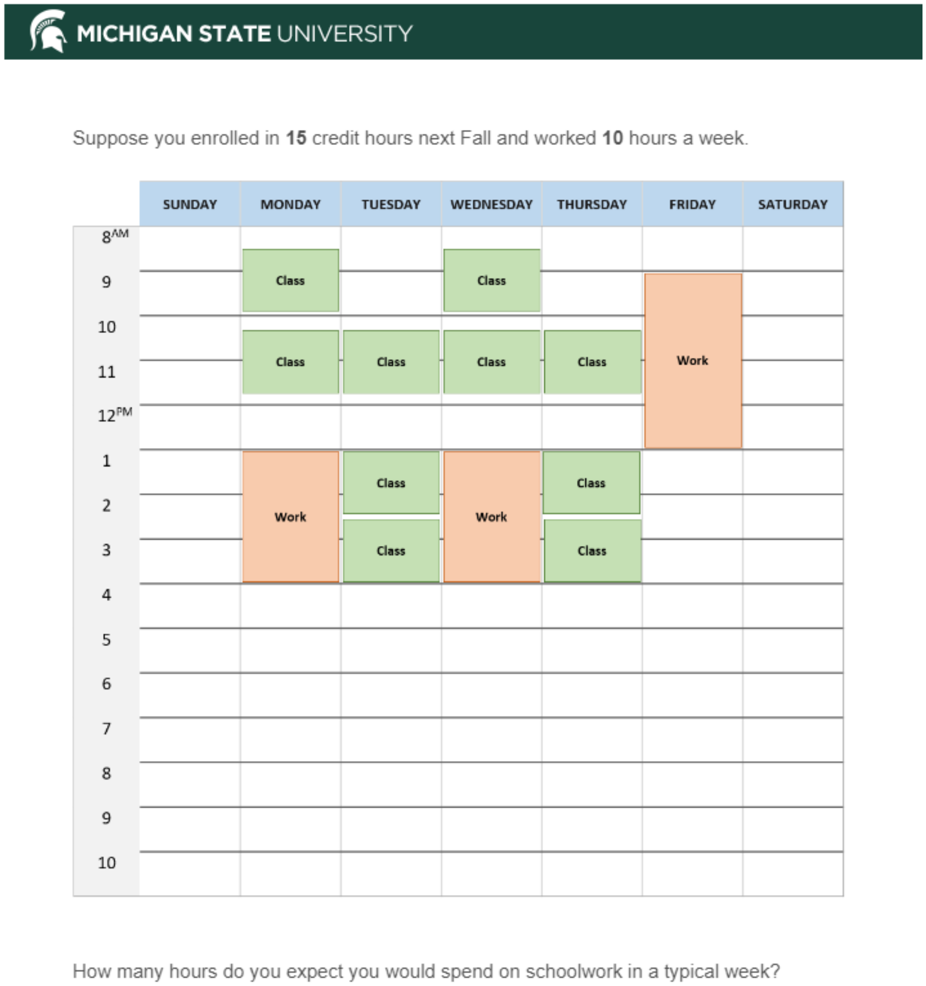
Table A3: Family Financial Support: Living Expenses

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

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

C Expected schoolwork time example question

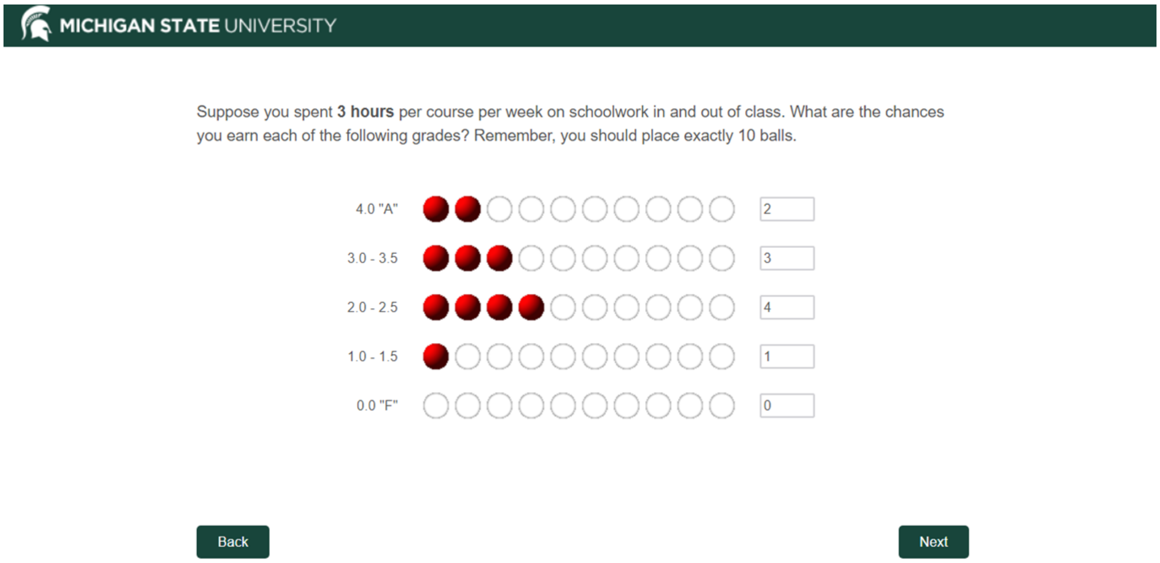
Figure A1: Expected Schoolwork Time Sample Question



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

D Expected grade sample response

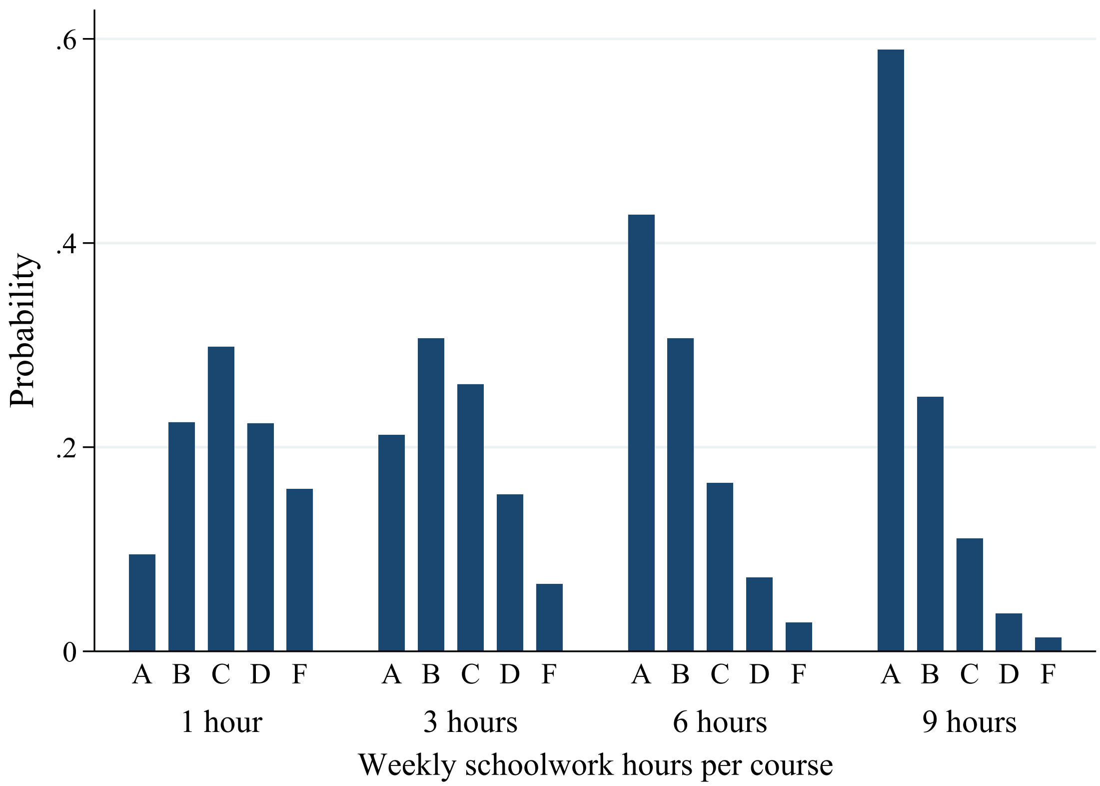
Figure A2: Grade Distribution Sample Question



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

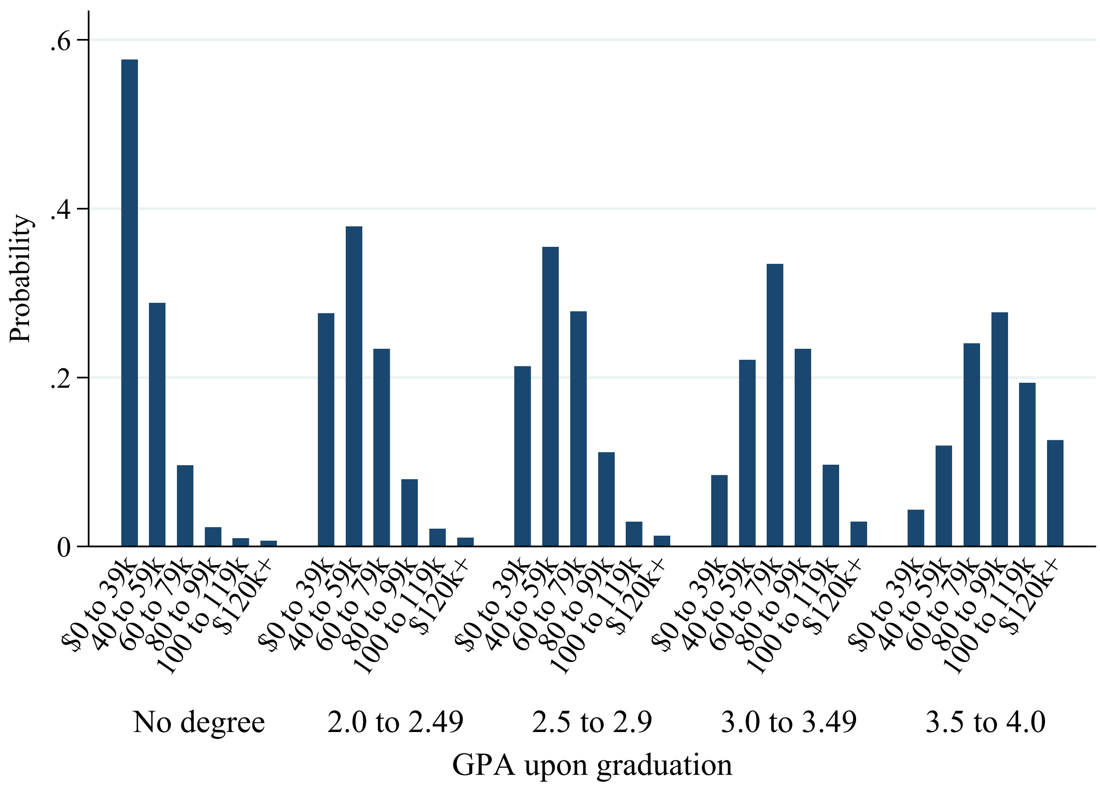
E Grade and post-school salary distributions

Figure A3: Distribution of Grades Conditional on Schoolwork



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

Figure A4: Distribution of Salaries Conditional on GPA



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

F In-school wage estimation

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

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

Table A4: Predicting Wages for Non-Workers

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

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