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

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Abstract

This paper studies how college students make and finance their human capital investment decisions under financial constraints and uncertainty. I estimate a dynamic structural model where agents choose their labor supply, enrollment intensity, and borrowing to maximize lifetime utility. Data come from two sources: unique survey data of students' employment history, family financial support, and beliefs about the returns to studying and returns to earning higher grades, and merged administrative data containing students' enrollment and borrowing histories. I find that...

Keywords: Labor supply, post-secondary education, time-to-degree, subjective expectations

JEL classification: I22, I23, J22, J24

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1 Introduction

Economists believe that post-secondary education yields significant returns in the labor market; recent research suggests that graduating from college can increase the earnings of a worker by 10% to 20% a year over the worker's lifetime (Oreopoulos and Petronijevic, 2013; Carneiro et al., 2011; Hussey and Swinton, 2011). Nevertheless, there are many factors that prevent a college enrollee from realizing the full return of a college degree. A third of students who begin college will leave without earning a bachelor's degree, thus incurring the direct financial and opportunity costs of college without the return to graduating (Shapiro et al., 2019). Even among students that eventually complete their degree, their college's quality (Black and Smith, 2006), major field of study (Altonji et al., 2012), cumulative grade point average upon graduation (Hershbein, 2019), net cost of attendance, level of student loans, and time-to-degree (Dannenberg and Mugglestone, 2017) can all reduce the value of their investment. More recent research also highlights the non-monetary utility returns to attending college, which can be diminished if students lack the leisure time to take advantage of their college's amenities (Jacob et al., 2018; Gong et al., 2019).

Many of the benefits and costs to college are intrinsically linked to the student's enrollment intensity and school financing decisions. The more classes a student takes, the quicker she can complete her degree, reducing direct costs of tuition, 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). But unless the student increases her total time spent on schoolwork to maintain a similar level of effort across those additional classes, her grades can suffer, increasing the likelihood of failing a course and adversely affecting the labor market's perception of her ability. Spending more time on schoolwork carries a cost – it reduces the student's time available for leisure or part-time employment, the latter being a method of financing her education. Students can substitute debt for employment, accepting the cost of interest payments and forgoing the work experience. It is not clear ex ante how students should behave or why they behave the way they do.

This paper aims to increase our understanding of how students navigate the aforementioned trade-offs to maximize their lifetime utility, paying particular attention to the role of financial resources, constraints, and beliefs. Variables such as family financial support, part-time wages for off-campus jobs, and expected labor market returns to graduating with a high GPA are not readily available in administrative data. To measure the effect of such variables, I developed a survey that elicits students' employment history, wages, family financial support, expected study hours, and subjective expectations on the returns to studying and returns to earning a high GPA. After distributing my survey to a random sample of undergraduates at Michigan State University, I obtained administrative records from the University's Office of the Registrar and Office of Financial Aid containing students' high school grades, course history at MSU, financial aid eligibility by term, and borrowing history.

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

The structural model allows me to estimate a utility function over in-school consumption, leisure and grades, future earnings, and cumulative debt. I then derive 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 strongly inelastic to all of these variables. The labor supply decision, on the other hand, is much more responsive. I find a wage elasticity of 0.28 in the Fall and Spring semesters, which is in line with elasticities for prime-age men and women (McClelland and Mok, 2012). The other labor supply elasticities are near-zero for most students, but I do find meaningful elasticities with respect to beliefs closer to the tails of the distribution. For example, a 10% increase in either the returns to studying or returns to earning a high GPA leads to at least a 20% reduction in work hours in the Fall and Spring for a quarter of students. Borrowing elasticities tend to follow a similar pattern. Most students do not substantively change their borrowing choices after changes in aid, tuition, or beliefs, but there are meaningful elasticities at the tails of the distribution. I do find that students substitute between labor earnings and debt; a 10% increase in wages reduces borrowing by $350 in the Fall and Spring, on average.

Another benefit of estimating a structural model is that I can simulate the effects of counterfactual policies on students' behaviors and outcomes. I evaluate two policies that increase the affordability of college but affect incentives in very different ways: an increase in minimum wage to $15 per hour and making tuition free for all students. An increase in minimum wage increases work hours by 0.66 hours a week in the Fall and Spring and by 1.1 hours a week in the Summer. It also reduces borrowing by $200 per year. I do not find any significant changes in credit hours, expected GPA, time-to-degree, or graduation rates. Making tuition free increases credit hours by 0.10 hours in the Fall and Spring and 0.13 hours in the Summer. While there are minimal changes in work hours, average borrowing decreases by $2,323 per year. As with the increase in minimum wage, making college tuition free does not significantly change expected GPA, time-to-degree, or graduation rates.

This paper contributes to three literatures. It introduces an estimable model to the human capital investment and economics of education literature that emphasizes the credit hour decision and relationship between credits, grades, and future earnings. To my knowledge, this is the first paper to propose such a structural model of the credit hour decision beyond the part-time and full-time margins (e.g., Keane and Wolpin, 2001). In doing so, this paper can simulate counterfactual policies and predict how they affect credit intensity, time-to-degree, and expected grades. This paper also contributes to the labor supply literature by estimating labor supply elasticities for college students. Most researchers estimate life-cycle models with an emphasis on the labor supply elasticity of workers in prime working ages. I pay particular attention to the unique financial resources and constraints students face and explicitly model the additional cost of labor on expected grades and credit accumulation. Ignoring these features of the in-school labor market may lead to inaccurate estimates for college student elasticities. Finally, this paper adds to the growing dynamic discrete choice literature which incorporates subjective expectations, and it is the first to do so with subjective expectations of the GPA returns to studying and labor market returns to a high GPA. The standard approach to estimating dynamic models requires estimating laws of motion for state variables from panel data, assuming heterogeneity in this process is fully captured by observable characteristics of individuals, and imposing individuals' expectations of the future match the predicted laws of motion. Using subjective expectations permits individual-specific heterogeneity in beliefs and avoids the computational burden of estimating the laws of motion. Furthermore, subjective expectations are required to separately identify the role of preferences from beliefs, an important distinction to for this research (Manski, 1993).

The paper proceeds as follows. In section 2, I summarize the existing literature on college student enrollment intensity, labor supply, and borrowing. In section 3, I introduce my data and describe the sample. Section 4 details the structural model and my estimation procedure. Section 5 presents the estimated utility parameters, elasticities, and counterfactual simulations. Section 6 concludes with a brief discussion on areas for future work.

2 Related literature

2.1 Credit hour enrollment

The vast majority of research on college student credit hour enrollment uses reduced form methods to estimate how variation in financial aid affects student outcomes. These papers typically exploit discontinuities in students' eligibility for need-based aid and find small or null effects on credit hours (Angrist et al. 2020, Denning et al. 2019, Denning and Jones 2019, Denning 2019). When effects are present, they seem to be mediated by decreases in labor supply. Worth noting, 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 effects could differ for students from households higher on the income distribution.

Related to financial aid is the cost of credit hours. In one of the few studies on the topic, Hemelt and Stange (2016) find that students who face no marginal cost to credit hours above the full-time minimum (savings of approximately $281 per credit) are seven percentage points more likely to enroll in one to three credit hours above the full-time minimum, but they are six percentage points more likely to withdraw from a class during the semester, leading to no significant increase in credit attainment.

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

2.2 Labor supply and financing

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, Lovenheim & Turner, 2012; Scott-Clayton, 2012; Garriga & Keightley, 2007; Stern & Nakata, 1991). Currently, 42% of full-time undergraduates work during the Fall semester, at an average of 25 hours per week, up from 33% in the 1970s (Scott-Clayton 2012).[1] These changes in labor are not inconsequential. The literature typically finds that student labor supply decreases study time, education enrollment, educational attainment, and to a lesser extent grades (Neyt, Omey, Verhaest & Baert (2017)).

Despite the frequency and importance of student employment, there is very little research on wage elasticities for college students specifically; in fact, many researchers

[1] Current results based on the author's own calculations using the October Education Supplement of the CPS for 2017 and 2018. I classify students as working if they report a positive number of usual hours worked per week. The sample is limited to full-time undergraduate students, and I use inverse probability weights. These rates are similar to those reported by Scott-Clayton (2012), which end in 2009.

that estimate labor supplies remove students from their sample to focus on prime-age workers. Elasticities for students may differ from elasticities for non-students due to the added costs of working while in school (e.g., fewer credit hours lower grades). As a baseline estimate, students with higher levels of family financial support may have similar elasticities to married women, with wage elasticities of 0.2 to 0.4, while students who are mostly financial independent may have similar elasticities to single men and women, with wage elasticities of 0.1 to 0.3 (McClelland and Mok, 2012).

An alternative to working is borrowing... add some statistics on how borrowing levels have increased significantly over time.

Add a paragraph on estimated substitutions between increases in debt and increases in labor supply. Any evidence on who is more likely to work versus borrow?

Family financial transfers are another source of financing one's schooling. Recent estimates suggest that, on average, approximately one third of educational expenses are paid for by parent or other family members, though there is significant heterogeneity across families (Park, 2016; Haider & McGarry, 2018). If leisure is a normal good, these transfers generate an income effect that increases the demand for leisure and reduces labor supply (Kalenkoski & Pabilonia, 2010). Family transfers loosen credit constraints and expand the feasible choice set of enrollment decisions (Park, 2016; Kalenkoski, 2005; Keane & Wolpin 2005). They also provide insurance against student loan defaults and mitigate the risk of borrowing (Lochner, Stinebrickner & Suleymanoglu, 2018).

2.3 Structural models of credit hour enrollment and financing

Much of the literature on human capital investment and labor supply models schooling and labor as mutually exclusive actions (e.g., Marx & Turner, 2018; Arcidiacono, 2004; Altonji, 1993), and when agents are allowed to work and enroll in school simultaneously, they do not choose the intensity of their schooling (Joensen, 2009; Ehrenberg & 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 agents choose schooling, leisure, and labor supply as continuous variables; however, studying and credit hour intensity are not separately considered, and time-to-degree considerations are abstracted away from. Keane and Wolpin (2011) also provide a finite-horizon model where agents choose school attendance, work participation, and borrowing. School attendance is either zero, part-time, or full-time. Family financial transfers and borrowing constraints are formally modeled.

3 Data

I use data from the Student Enrollment and Employment Survey (SEES), a survey I developed and distributed to a random sample of undergraduates at Michigan State University (MSU) in the spring of 2019. In addition, I obtain administrative records from the Office of the Registrar and Office of Financial Aid at the University, 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' expected cost of attendance, loan eligibility, grants and scholarships, living situation and rent, and actual family financial support for education and living expenses. The survey also elicited students' beliefs about the returns to studying on GPA and returns to graduating / graduating with a high GPA on future labor market earnings.

3.1 Sampling frame and survey distribution

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

All MSU undergraduate students who were 18 years old or older, not on an athletic scholarship, and with an expected graduation date of December 2019 or later were eligible to receive the survey. The Office of the Registrar provided me with 6,000 randomly selected email addresses from the sampling frame, and I distributed an invitation to take the survey to these students on March 12, 2019. Students were told the survey would take between 15 and 35 minutes to complete, and they would receive a $10 Amazon Gift Card upon completion. After two reminder emails, I closed the survey on April 23, 2019, with 1,665 partial and complete responses.

I exclude students who failed to reach the end of the survey (120), failed the attention check question on their first and second attempts (102), or skipped a question required for the model (81). I also exclude students that believe their grades will decrease as they increase their time on schoolwork (35) or believe their future wage will be lower graduate with a 4.0 GPA than dropping out (33), as this strongly suggests that the student did not properly understand the questions. I further limit the sample to domestic students, as international students (28) face additional restrictions on their employment and borrowing choices, and first-at-any-college students, as transfer students (233) have unobserved credit enrollment and borrowing histories from their prior institutions. Finally, I exclude students that were not continuously enrolled at least part-time at MSU for the Fall and Spring semesters (46). Students who temporarily "stop-out" of college may do so for reasons that are outside of the scope of the model, like serious illness, family emergencies, or having a child. After these restrictions, I am left with 987 students and 2,947 student-period pairs.

Orr (2020) contains a detailed description of the survey text and invitation email, quantification of non-response bias, and the procedure I used to calculate inverse probability weights to mitigate non-response bias. I present summary statistics for the unweighted and weighted sample in Table 2 below.

[Table 2 here]

3.2 Observed credit hour enrollment and financing choices

Table 4 presents the percentage of students who take each number of credit hours in the Fall/Spring and Summer terms. In the Fall and Spring, the vast majority of students take between 12 and 16 credit hours, with 15 being the modal choice by a narrow margin. In the Summer, almost 60% of students do not take any credit hours, and among those with positive credit hours, 3-4 and 6-7 are the most common choices.

[Table 4 here]

The SEES asked students to identify semesters they worked a part-time or full-time job for the majority of the semester, and if they worked, how many hours they usually worked per week. Students worked a job for at least 1 hour a week in 46.8% of available semesters, at an average of 8.5 hours per week. Figure 3 plots the distribution of hours worked among workers. The average hours worked is 18.23 hours per week with an interquartile range of 10 to 24 hours. There is significant bunching in 5 hour increments, with 10, 15, 20, and 40 hours being the most common responses.

[Figure 3 here]

Table 3 describes the likelihood of working and typical hours worked for students by class level and by semester. As students progress through the university, they are more likely to work, but conditional on working, all class levels work a similar number of hours. Freshmen are more likely to work in the Spring semester than Fall semester and more likely to work in the Summer semester than the other semesters while sophomores through seniors are equally likely to work in the Fall and Spring and are less likely to work in Summer semester than the other semesters. For all class levels, students work longer hours in the Summer semester than the Fall or Spring, conditional on working.

[Table 3 here]

There is a small negative relationship between credit hour enrollment and labor supply. Controlling for class code and including individual fixed effects, a 10 hour increase in working hours is associated with a 0.39 credit hour reduction in the fall/spring semesters (p-value < 0.000). I cannot reject the null hypothesis of a zero relationship for the summer semesters (p-value $= 0.407$).

4 Structural Model

In the following section, I present a model of human capital investment and labor supply for college students with heterogeneous beliefs and financial constraints across students. After describing the basic structure, I outline how the parameters of the model can be estimated and the data required for estimation.

4.1 Model structure

4.1.1 Decision periods

Individuals begin their decision horizon at the start of their first semester in college. Decision periods correspond with academic terms, with the Fall and Spring as period one, Summer as period two, Fall and Spring of the next year as period three, etc.[2] Individuals remain in college until they graduate, choose to leave without a degree, or reach period T. Individual i graduates when their cumulative credit hours earned exceeds their graduation threshold $\bar{K}_i$ and their cumulative GPA exceeds a 2.0.[3]

[2] 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.

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

After leaving college, either voluntarily, due to graduation, or because they reached the maximum time permitted, individuals enter the full-time labor market. I model the full-time labor market as an absorbing state where individuals' remaining lifetime utility is a function of their post-school wage and cumulative debt. This simplification allows me to focus on the decisions made at college while still incorporating intertemporal tradeoffs that involve post-college outcomes.

4.1.2 Choices

Each period in school, individual i decides whether to continue in school or dropout and immediately enter the full-time labor market. If they choose to continue in school, they make three additional decisions: their labor supply h_{it}, credit hour enrollment k_{it}, and new student loans b_{it}. Individual i chooses their 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.[4] Credit hour enrollment is also restricted to a discrete set. In the Fall and Spring, individual i can choose 26 credits, 30 credits, or 34 credits; in the Summer, individual i can choose 0 credits, 3 credits, or 8 credits. New loans are restricted to zero, the individual's Federal Stafford loan offer, or the individual's maximum student loan eligibility, as specified by their school. I denote the entire set of feasible choices in period t with A_t.[5]

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

[5]A_t depends on t to reflect that the credit hour choice set differs in the Fall and Spring from the Summer.

4.1.3 State variables

Individual i enters each period with a set of observable state variables: cumulative work experience H_{it}, cumulative credit hours earned K_{it}, cumulative grade point average G_{it}, cumulative debt B_{it}, and time-invariant characteristics X_i. I denote this collection of observable state variables with S_{it}. In addition, individuals enter each period with a vector of choice-specific preference shocks, $\varepsilon_{it} \equiv \{\varepsilon_{ait}\ \forall a \in A_t\}$. The choice-specific preference shocks are known by the individual at the beginning of the period but not observed by the econometrician. I specify that these preference shocks are iid Type 1 Extreme Value random variables. This provides convenient functional forms when solving the model, and unlike in the static case, the Type 1 Extreme Value distribution does not impose the independence of irrelevant alternatives condition. The entire set of state variables can be partitioned as $\{S_{it}, \varepsilon_{it}\}$.

Individual i begins college with no work experience, credit hours, GPA, or debt.[6] State variables evolve according to the following laws of motion:

$$H_{i,t+1} = H_{it} + h_{it} \tag{1}$$

$$K_{i,t+1} = K_{it} + \sum_{k=1}^{k_{it}} 1[g_{ikt} > 0] \tag{2}$$

$$G_{i,t+1} = G_{it}\left(\frac{K_{it}}{K_{it}+k_{it}}\right) + \left(\frac{\sum_{k=1}^{k_{it}} g_{ikt}}{K_{it}+k_{it}}\right) \tag{3}$$

$$B_{i,t+1} = (1 + r_t^B)(B_{it} + b_{it}) \tag{4}$$

$$\varepsilon_{ait} \sim_{iid} \exp(-\exp(-\varepsilon)) \tag{5}$$

[6]The implicit assumption is that work before college does not contribute to human capital. For the other state variables, first-time enrollees in college do have zero credits, GPA, or student loans. Transfer students have their previous credits captured in $\bar{K}_i$. For many colleges, grades earned at other institutions are not reported on the student's transcript, so a 0 GPA is reasonable. The zero debt assumption is the least realistic. Federal loans accepted at other universities are observed for some transfer students, but private loans are not.

Cumulative work experience is simply the total number of hours worked. Cumulative credits earned is the number of credit hours where a passing grade was earned for that credit. Denote the grade earned in credit k by individual i in period t with g_{ikt}. A passing grade is any grade greater than zero. Cumulative GPA is the weighted average of the individual's previous cumulative GPA and newly earned grades.[7] Cumulative debt is equal to prior debt plus new borrowing, after interest. The choice-specific preference shocks are independently distributed across choices, individuals, and time according to the distribution F^{ε}.

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 $g_{it} = \sum_k g_{ikt}$. All three payoffs variables are functions of individual i's choice a and current state variables. I denote the end-of-period utility function that represents in-school preferences with $U_t^{sch}(c, l, g, \varepsilon)$. I assume the choice-specific preferences shocks are additively separable from the payoff variables, so an individual's utility can be written as the sum of the observable utility component $u_t^{sch}(c, l, g)$ and unobservable preference shocks. For notational convenience, I will sometimes suppress the payoff function arguments and use subscripts to denote the individual, choice, and time period. Then the utility

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

from individual i choosing action a_{it} in period t is given by,

$$U_t^{sch}(c_{ait}, l_{ait}, g_{it}, \varepsilon_{ait}) = u_t^{sch}(c_{ait}, l_{ait}, g_{it}) + \varepsilon_{ait}. \tag{6}$$

Once the individual leaves school and enters the post-school labor market, they receive a single utility realization equal to the discounted present value of their lifetime utility in the labor market, $U^{post}(S_{it})$. This utility sum is a function of their wage and cumulative debt upon entry into the post-school labor market, which jointly determine the individual's "full income".[8] I use $U(a, S)$ to denote individual i's utility when their entrance into the post-school labor market is unknown ex ante:

$$U(a_{it}, S_{it}, \varepsilon_{it}) = 1[\text{in-school}]U_t^{sch}(c_{ait}, l_{ait}, g_{ait}, \varepsilon_{ait}) + 1[\text{post-school}]U_t^{post}(S_{it}). \tag{7}$$

4.1.5 Constraints

Individuals face constraints on consumption, leisure, and borrowing each period. Individual i's consumption is equal to their labor income, increases in debt, and family financial transfers less net (of grants) education expenses. Labor income is the product of an hourly wage w_i^{sch} and hours worked. Both family transfers and net education expenses can depend on individual i's choices and state variables.

$$c_{it}(a_{it}, S_{it}) = w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}). \tag{8}$$

When an individual is still in school, their wage is a constant individual-specific part-time wage. Once out of school, an individual's full-time wage w_i^{post} is drawn

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

from the distribution $F_i^w(S_{it})$. This distribution is a function of the individual's work experience, credit hours, and GPA, and the distribution can vary across individuals, even if they have identical work experience, credit hours, and grades. Both family transfers and net educational expenses are time-invariant functions of the individual's choices and state variables, and they 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 their consumption up to $\underline{c}$.

Individual i's leisure time is equal to their total time endowment L_t less work hours and study hours.

$$l_{it}(a_{it}, S_{it}) = L_t - study_i(a_{it}) - h_{it}. \tag{9}$$

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

4.1.6 Grades

At the end of each period, individual i receives a grade g_{ikt} for each credit hour they were enrolled in. Grades enter the utility function directly and affect the evolution of state variables, and as a result, future earnings. Grades are random variables drawn from the distribution $F_i^g(study_i/k_{it})$. This distribution is a function of individual i's study hours per credit hour, and she does not know what grades she will earn until the conclusion of the period. As with the post-school wage distribution, the grade distribution can vary across individuals, even if they spend the same amount of time studying per credit hour.

4.1.7 Maximization problem

Individual i maximizes the expected discounted value of her lifetime utility subject to the aforementioned constraints. The solution to her lifetime maximization problem at period 1 is given by the laws of motion for state variables and

$$\begin{aligned} V_{i1}(S_{i1},\varepsilon_{i1}) \equiv & \max_{\{a\in A_t\}_{t=1}^{T}} \; E\left[\sum_{t=1}^{T} \beta^{t-1} U_t(a, S_{i1}, \varepsilon_{i1}) \mid S_{i1}, \varepsilon_{i1}\right] \\ \text{s.t. } \; & c_{it}(a_{it}, S_{it}) = \max\{w_i^{sch} h_{it} + b_{it} + fam(a_{it}, S_{it}) - edu_t(a_{it}, S_{it}), \bar{c}\} \\ & l_{it}(a_{it}) = L_t - study_i(a_{it}) - h_{it} \\ & l_{it}(a_{it}) \geq 0 \end{aligned} \tag{10}$$

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

4.2 Solution method

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

$$V_{it}(S_{it}, \varepsilon_{it}) = \max_{\{a\in A_t\}} \{U_t(a, S_{it}, \varepsilon_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a, S_{it}]\}. \tag{11}$$

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

$$V_{iT}(S_{iT}, \varepsilon_{iT}) = \max_{a\in A_T} \left\{u_T^{sch}(c_{aiT}, l_{aiT}, g_{aiT}) + \varepsilon_{aiT} + \beta_{T+1} E[U_{T+1}^{post}(S_{i,T+1})|a, S_{iT}]\right\} \tag{12}$$

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

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

$$\begin{aligned} E[V_{it}(S_{it}, \varepsilon_{it})|S_{it}] = \\ \text{E.C.} + \log\left(\sum_{a' \in A_t} \exp\left\{u_t(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(S_{i,t+1}, \varepsilon_{i,t+1})|a', S_{it}]\right\}\right) \end{aligned} \tag{13}$$

where E.C. is Euler's constant. The Emax function can theoretically be solved by backward induction; however, this is computationally infeasible in practice.[9]

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

[9]To see why, note that the value function must be solved at every possible combination of state variables that can be reached in a given time period. Given the continuous nature of the state space, a full-solution method would require discretizing the state space. With 1,000 individuals, 28 elements of the choice set, and 10 choice periods, a coarse grid of 20 elements for each of the 4 time-varying state variables would required evaluating 4.03×10^{10} functions for each iteration of parameter values.

recursively 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 conditional on the individual's choice and current state variables. Given a distribution on the grade and post-school wage error terms, this is a straightforward exercise.

4.3 Model parameterizations

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

$$\begin{aligned} u_t(c_{ait}, l_{ait}, g_{it}) &= \alpha_c \ln(c_{ait}) + \alpha_{lt} \ln(l_{ait}) + \alpha_g \ln(g_{it}) \\ &+\alpha_{h0t} 1[h_{it} > 0] + \alpha_{k0} 1[k_{it} = 0] + \alpha_{k15} 1[k_{it} = 30] \\ &+\alpha_{b1} 1[b_{it} = \text{Stafford only}] + \alpha_{b2} 1[b_{it} = \text{Max offer}] \end{aligned} \tag{14}$$

where α_{lt} and α_{h0t} are allowed to vary between Fall / Spring and Summer periods.[10] The log specification imposes diminishing marginal utility from consumption, leisure, grades.[11] I restrict α_c, α_l, and α_g to positive values. In addition to the payoff variables, I include fixed costs for various alternatives.[12]

The net tuition function $edu_t(a_{it}, S_{it})$ is equal to expected fees, tuition, and text-

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

[11] 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.

[12] A fixed cost of labor is common in the labor supply literature (Löffler et al., 2018) and can capture the additional effort associated with attending a job regardless of hours worked. I include a fixed utility term for attempting zero credit hours to capture a 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 offer because students have to actively seek out and apply for loans beyond the Stafford loan offer while the University automatically includes Stafford loans in students' financial aid package.

books less grants and scholarships. Fees, tuition, and textbooks can vary based on attempted credit hours and individuals' characteristics in X_i, such as independence status, residency, and college. Loan offers are also based on net tuition. Neither Stafford loan offers nor private loan offers can exceed individual i's net tuition function plus expected living expenses. Stafford loans also have a maximum value specified by the federal government and require the individual is enrolled in at least six credit hours.

Individual i's family transfers are given by,

$$fam(a_{it}, S_{it}) = \mathrm{fl}_i + edu_t(a_{it}, S_{it}) \times \mathrm{fp}_i \tag{15}$$

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

I model individual i's study time function as,

$$study_i(a_{it}) = \left(\delta_{0i} + \delta_{1i}k_{it} + \delta_{2i}h_{it} + \delta_{3i}h_{it}^2\right) k_{it}. \tag{16}$$

This specification allows individuals to reduce their study time per credit hour as they take more credits or work more hours.

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

$$g^*_{ikt} = \gamma_{0i} + \gamma_{1i}\frac{study_i}{k_{it}} + \nu_{ikt} \tag{17}$$

$$\varepsilon^g_{ikt} \sim N\left(0, \exp\left(\frac{study_i}{k_{it}}\sigma^g\right)\right) \tag{18}$$

$$g_{ikt} = \begin{cases} 0 & \text{if} \quad g^*_{ikt} \leq 0 \\ 1.25 & \text{if} \quad 0 < g^*_{ikt} \leq \gamma_C \\ 2.25 & \text{if} \quad \gamma_C < g^*_{ikt} \leq \gamma_B \\ 3.25 & \text{if} \quad \gamma_B < g^*_{ikt} \leq \gamma_A \\ 4 & \text{if} \quad \gamma_A < g^*_{ikt} \end{cases} \tag{19}$$

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

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

$$U^{post}(S_{it}) = \alpha_w \ln(w^{post}_i(S_{it})) + \alpha_B \ln(B_{it}) \tag{20}$$

where the log specification imposes diminishing marginal returns to post-school earnings and post-school cumulative debt.[13] I restrict α_w to positive values and α_b to negative values.

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

$$w^{post}_i(S_{it}) = \exp\{\omega_{0i} + \omega_{1i}H_{it} + 1[K_{it} \geq \bar{K}](\omega_{2i} + \omega_{3i}G_{it}) + \xi_i\} \tag{21}$$

where $\xi_i \sim N(0, \sigma^w_i)$. This specification allows for returns to part-time work experience, a college degree premium, and a return to graduating with better grades.[14] F^w_i

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

[14] Researchers have found conflicting evidence on the returns to part-time work experience. (Baert, Rotsaert, Verhaest & Omey, 2016; Häkkinen, 2006; Little, 2005; Hotz, Xu, Tienda & Ahituv, 2002).

is defined by $\omega_i \equiv \{\omega_{0i}, \omega_{1i}, \omega_{2i}, \omega_{3i}, \sigma_i^w\}$.

I set $T = 10$ so individuals have five full years to complete college before entering the post-school labor market. I set $L_t = 3360$ for the Fall and Spring period and $L_t = 1680$ for the Summer period, corresponding to a time endowment of 112 hours per week or 16 hours per day. I assume an annual interest rate of 4.44%, which is approximately the average interest rate on Federal Stafford loans for in-sample years. I also specify a discount rate instead of estimating it, as it is typically not well identified (Aguirregabiria and Mira, 2010). Given estimates of discount rates for young adults (Green et al., 1994), I choose an annual discount rate of 0.8.

4.4 Criterion function

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

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

$$ll_i(\theta) = \log Pr(a_{it}, \hat{S}_{it}, g_{ikt} : t = 1, \ldots T_i \mid \alpha), \tag{22}$$

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

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

$$\begin{aligned} ll_i(\theta) = &\sum_{t=1}^{T_i} \log Pr(a_{it}|\hat{S}_{it}, \alpha) + \sum_{t=1}^{T_i} \log Pr(g_{ikt}|a_{it}, \hat{S}_{it}) \\ &+ \sum_{t=1}^{T_i-1} \log Pr(\hat{S}_{i,t+1}|a_{it}, \hat{S}_{it}, g_{ikt}) + \log Pr(\hat{S}_{i1}|\alpha) \end{aligned} \tag{23}$$

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

Given the Type 1 Extreme Value distribution, the probability that alternative a is chosen by individual i in period t given states $\hat{S}_{it}$ is

$$Pr(a|\hat{S}_{it}, \theta) = \frac{\exp\left\{u_t(c_{ait}, l_{ait}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a_{it}, \hat{S}_{it}]\right\}}{\sum_{a' \in A_t} \exp\left\{u_t(c_{a'it}, l_{a'it}, g_{it}) + \beta E[V_{i,t+1}(\hat{S}_{i,t+1}, \varepsilon_{i,t+1})|a', \hat{S}_{it}]\right\}} \tag{24}$$

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

5 Results

5.1 Pre-estimated functions

In table 7, I present estimates of the study time function, grade distribution [show these], and post-school wage distribution. Key takeaways: [skip wage equations]

- Study time per class decreases with work hours and credit hours
- Students believe that studying increases grades
- Students believe that GPA increases future wages
- Beliefs vary a lot between individuals, highlighting benefit of using subjective expectations

[Table 7 here]

5.2 Structural model estimates

Table 8 presents the estimated utility parameters and their standard errors for a 15% sample of available observations. There are a few takeaways worth noting. First, there is a significant increase in how much students value their leisure time in the summer. 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 8 here]

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

In isolation, utility parameters can only tell us so much, but before proceeding to presenting elasticities, I verify that the model achieves a reasonable fit of the observed data. Table 9 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 / Spring periods, but it struggles to capture the the u-shaped pattern in the Summer periods. Panel B tells a similar story – the model does well fitting the observed work hour probabilities in the Fall / 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 / Spring periods, and it correctly predicts that almost no students borrow in the Summer. The model over predicts students' willingness to borrow the maximum loan offer in the Summer, though this is likely related to the model underpredicting students' willingness to work 40 hours a week in the summer.

[Table 9 here]

5.3 Elasticities

I estimate elasticities using the estimated utility parameters and simulating counterfactual probabilities of each choice. Tables 10 and 11 present statistics for a series of elasticities and semi-elasticities for credit hour, work, and borrowing behavior. Each panel contains elasticities for a particular outcome. Each row denotes the denominator of the elasticity: 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' marginal return to studying, a 10% increase in students' marginal return to earning a higher GPA on post-school wages, and a 10% increase in students' in-school (actual or predicted) wage.

[Table 10 here]

[Table 11 here]

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

Students are more responsive on the labor supply margin than credit hour margin. I estimate an average wage elasticity of 0.281 in the Fall and Spring periods and 0.230 in the Summer periods, so for every 10% increase in wages, students work 2.8% and 2.3% more hours on average. I estimate near-zero income elasticities and tuition price elasticities for most students, though the distribution of income elasticities (Fall

/ Spring only) and tuition price elasticities (both Fall / Spring and Summer) is significantly skewed to the right. I find practically significant labor supply elasticities with respect to beliefs in the Fall and Spring but not the Summer. The median student is not very responsive to an increase in the returns to studying or returns to GPA, but a student near the 25th percentile decreases their work hours by approximately 2% for a 10% increase in either belief.

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

5.4 Counterfactual simulations

I conduct two counterfactual simulations to evaluate how different policies may affect student behaviors and outcomes. The first simulation models an increase in the minimum wage from $8.15 an hour in the Fall of 2014 to $15 per hour. The second simulation models making tuition free for all students. Both policies relax a student's budget constraint, albeit in very different ways.

5.4.1 Minimum wage increase

Federal and state minimum wage laws are a potential mechanism for reducing income inequality in the United States (Card and Krueger, 2016, Dube, 2019). Because of this, there is growing pressure in the United States to raise the federal minimum wage from its current rate of $7.25 per hour, which has not changed since 2009, to $15 per hour (Pramuk, 2019). In Michigan, the state minimum wage increased on September 1, 2014 from $7.40 to $8.15, and it is set to increase each year until reaching $12.05 in 2030 (Michigan "Enrolled Senate Bill No. 1171", 2018). At the beginning of Spring 2019, the state minimum wage was $9.45. In this first simulation, I model what would have happened if Michigan raised their minimum wage to $15 per hour on September 1, 2014.[15]

A $15 increase of the minimum wage would raise hourly wages for 93% of students in my sample and increase the average wage from $10.94 to $15.32. This increase is not significantly correlated with students' financial need, and it benefits those with high financial need (more than $15,000 of expected expenses after grants and family support) just as much as it benefits students with no unmet need.

[Figure 4 here]

5.4.2 Free college

Another policy proposal gaining momentum in the United States is making college tuition free (Murakami, 2020). Multiple US presidential candidates in the 2020 election adopted free college plans in their platforms, and many states already have grant

[15] 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)

programs that cover the cost of tuition at two- and four-year colleges for low- to middle-income families (Dickler, 2019). These programs can increase enrollment in eligible colleges, and additional requirements (e.g., minimum GPA or minimum completed credits per year) can incentivize students to change their behavior (Quinton, 2019). In this second simulation, I model what would happen if Michigan waived the cost of tuition at Michigan State University for all students enrolled after September 2014.[16]

Free tuition reduces the budgeted cost of attendance for in-state students by XXX and for out-of-state students by XXX, on average. However, students still have expected living costs of XXX. The distributional effects are interesting...some students had their families paying for their education expenses anyway, and some students have their grant dollars reduced.

[Figure 5 here]

6 Conclusion

In this paper, I show how financial constraints 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 linked administrative data on students' credit hour history, financial aid eligibility, and borrowing history. After presenting the data, I propose a dynamic

[16] I assume no changes in enrollment or shifts in the university budget. I also assume that families do not change their family financial support plans, and any support allocated toward education expenses are no longer used.

structural model of college students' credit hour enrollment, labor supply, and borrowing which takes advantage of the unique survey data. I then estimate students' preferences for consumption, leisure, grades, future earnings, and future debt and derive elasticities for the three behaviors of interest. Finally, I simulate the effects of three counterfactual policies – a minimum wage increase, free college tuition, and an information campaign that changes beliefs about the returns to studying.

I find that students' credit hour decisions are highly inelastic. The estimated elasticities with respect to changes in financial aid, tuition, returns to studying, returns to GPA, and in-school wage are all near zero. Students' work decisions are more responsive to changes in their budget and beliefs than their credit hour decision. I estimate an average wage elasticity of 0.28 in the Fall and Spring and 0.23 in the Summer, which are both comparable to elasticities for prime-age workers in the United States. I also find similar magnitude elasticities for changes in the returns to studying and returns to GPA, but only for students at or above the 75th percentile of the distribution. Student borrowing elasticities are near zero for most students, but there are large elasticities at the tails of the distribution. For example, a $1,000 increase in financial aid reduces borrowing by $263 on average in the Fall and Spring, but it reduces borrowing by only $19 at the median.

The counterfactual simulations reveal similar patterns as the elasticities. I estimate that a $15 minimum wage would induce 4% more workers to enter the part-time labor market each period, and work hours would increase by 0.65 hours per week in the Fall and Spring and 1.10 hours per week in the Summer, on average. Cumulative debt upon leaving school is $462 lower on average, graduation rates increase by 0.61 percentage points, but the average GPA upon leaving school is 0.01 points lower.

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

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

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

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7 Tables and Figures

Table 1: Data and model parameters

	Notation	**Periods observed**
Choice variables		
Labor supply	h_{it}	$t = \{1, \ldots, T_i\}$
Credit hours	k_{it}	$t = \{1, \ldots, T_i\}$
Borrowing	b_{it}	$t = \{1, \ldots, T_i\}$
State variables		
Work experience	H_{it}	$t = \{1, \ldots, T_i\}$
Cumulative credits earned	K_{it}	$t = \{1, \ldots, T_i\}$
Grade point average (GPA)	G_{it}	$t = \{1, \ldots, T_i\}$
Total debt	B_{it}	$t = \{1, \ldots, T_i\}$
Other data		
In-school wages	w_i^{sch}	$\max\{t \mid h_{it} > 0\}$
Family financial support	$fam(\cdot)$	$t = T_i$
Net tuition rate	$edu_t(\cdot)$	$t = \{1, \ldots, T_i\}$
Expected study hours	$study_i(\cdot)$	$t = T_i$
Class grades	g_{ikt}	$t = \{1, \ldots, T_i\}$
Pre-estimated parameters		
Wage model	ω_i	
Returns to studying	γ_i	
Expected study hours	δ_i	

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 Fall 2017, I observe them for three periods, Fall 17/Spring 18, Summer 18, and Fall18/Spring 19.

Table 2: Summary statistics

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

Summary statistics for the sample of survey respondents, unweighted and weighted by the inverse probability of responding to the survey.

Table 3: Work frequency by class level and semester

			Work		Work hours	
Class level	**Semester**	**Observations**	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**
Freshmen	Fall	934	0.248	0.015	12.65	0.43
	Spring	702	0.323	0.019	13.31	0.41
	Summer	51	0.466	0.079	34.89	1.38
Sophomore	Fall	596	0.551	0.022	13.57	0.40
	Spring	650	0.503	0.021	13.08	0.39
	Summer	527	0.461	0.023	32.62	0.78
Junior	Fall	364	0.660	0.027	14.11	0.51
	Spring	451	0.678	0.024	14.06	0.44
	Summer	348	0.606	0.029	33.38	0.91
Senior	Fall	73	0.833	0.045	14.71	1.11
	Spring	164	0.783	0.035	12.89	0.68
	Summer	54	0.703	0.068	36.19	2.09
Pooled		4,914	0.486	0.008	17.64	0.25

Each row presents the percentage of students working and average hours worked per week (conditional on working) for each class level and semester pair.

Table 4: Credit hour enrollment by semester

Credits	Fall/Spring	Summer
0	1.64	59.45
1	0.16	1.38
2	0.00	0.62
3	0.32	7.54
4	0.07	6.30
5	0.07	0.90
6	0.55	6.16
7	0.23	6.16
8	0.23	4.22
9	0.44	2.08
10	0.77	1.73
11	0.57	0.83
12	13.95	0.76
13	19.15	0.55
14	22.30	0.28
15	23.40	0.35
16	11.33	0.28
17	3.20	0.14
18	1.23	0.14
19	0.32	0.00
20	0.07	0.14
Observations	5,620	1,445

Credits hours reported as of the quarter point in the semester, which is the official census date for the University.

Table 5: Loan offer and acceptance statistics [NEEDS UPDATING]

	Offer			Accepted		
Loan	%0	Mean	Max	%0	Mean	Max
Stafford loan	0.545	802	5,500	0.667	609	5,037
Private loan	0.191	6,939	33,088	0.913	555	23,727
Total	0.126	9,307	35,986	0.567	1,715	27,459
Observations			6,968			

The first three columns present statistics regarding loan amounts offered to students by the University. Offer amounts for private and total loans based estimated maximum amounts the student is eligible to receive. The last three columns present statistics on accepted loan amounts by students. The first column in each set presents the percent of students who were not offered or accepted any loans. The second column presents the average loan amount, inclusive of zeros. The third column presents the maximum loan amount.

Table 6: Borrowing strategies [NEEDS UPDATING, COMBINE WITH ABOVE]

Strategy	Percent	Mean error
No loans	0.566	9.79
Max Stafford loan offer	0.268	308.30
Max loan offer	0.013	858.73
Observations	7,065	

The chosen borrowing strategy is the one with the minimum distance between the specified and actual borrowing amount. In case of a tie, the "less debt" strategy is chosen.

Table 7: Pre-estimated parameters [NEEDS UPDATING]

Parameter	Mean	Std. Dev.	25th Pct	75th Pct
Panel A: Study time				
Constant: δ_{0i}	2.536	0.046	1.271	3.677
Credit hours: δ_{1i}	-0.058	0.002	-0.106	-0.002
Work hours: δ_{2i}	-0.217	0.012	-0.486	0.042
Panel B: Returns to studying				
Constant: γ_{0i}	1.290	0.040	0.501	2.237
Study hours per credit: γ_{1i}	1.017	0.024	0.538	1.296
2.0 Threshold: γ_C	1.131			
3.0 Threshold: γ_B	2.360			
4.0 Threshold: γ_A	3.699			
Error variance: σ^g	-0.009			
Panel C: Post-school wage				
Constant: ω^f_{0i}	38,441	538	26,000	46,000
Experience: ω^f_{1i}	16,230	450	4,450	24,400
Degree: ω^f_{2i}	53,085	3,925	-21,550	123,750
Degree x GPA: ω^f_{3i}	-42,857	2,829	-94,800	12,400
Degree x GPA^2: ω^f_{4i}	11,156	503	0	20,000
Observations				

Blah

Table 8: Utility parameters

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

Standard errors in parentheses

Blah.

Table 9: Observed and predicted choice probabilities

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

Fall and Spring Observations: 1,967. Summer Observations: 980.

Notes go here

Table 10: College behavior elasticities (Fall and Spring)

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

Notes go here

Table 11: College behavior elasticities (Summer)

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

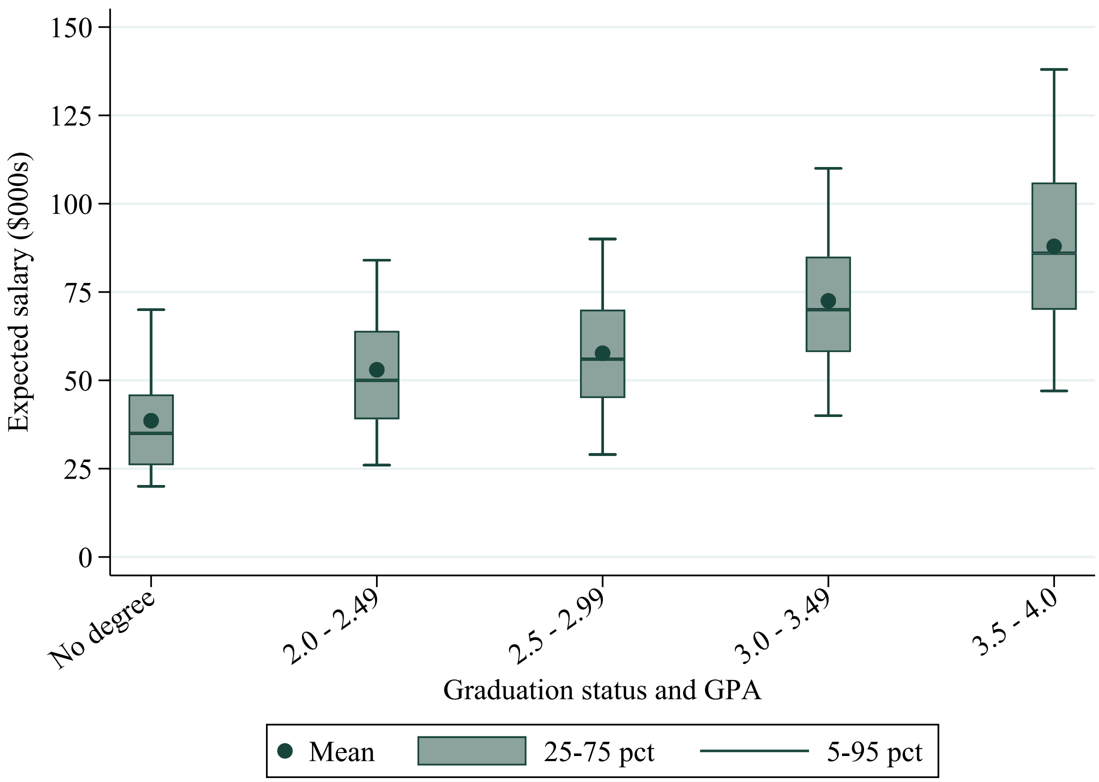
Notes go here

Table 12: Counterfactual simulations

Outcome	Mean	Std. Dev.	25th Pct	Median	75th Pct
		Panel A: $15 Minimum wage			
Credit hours (Fall/Spring)	-0.009	1.109	-0.088	-0.001	0.090
Credit hours (Summer)	-0.018	1.117	-0.276	-0.011	0.259
Work hours (Fall / Spring)	0.655	1.570	0.224	0.527	1.011
Work hours (Summer)	1.102	1.526	0.458	0.845	1.640
Graduation rate	0.410				
Time-to-degree	0.010	1.068	0.000	0.000	0.000
Cumulative GPA	-0.011	0.243	-0.119	0.000	0.098
Cumulative debt	-462	21,374	-6,999	0	6,898
		Panel B: Free tuition			
Credit hours (Fall/Spring)	0.121	1.233	-0.185	0.010	0.399
Credit hours (Summer)	0.174	1.328	-0.388	0.040	0.723
Work hours (Fall / Spring)	-0.390	2.641	-1.166	-0.222	0.247
Work hours (Summer)	-0.131	1.563	-0.510	-0.060	0.175
Graduation rate	-8.310				
Time-to-degree	-0.003	1.160	0.000	0.000	0.000
Cumulative GPA	-0.094	0.474	-0.354	0.000	0.186
Cumulative debt	946	23,211	-6,898	0	6,999
		Panel C: Information campaign			
Credit hours (Fall/Spring)	0.021	1.091	-0.063	0.000	0.091
Credit hours (Summer)	0.021	1.119	-0.266	0.000	0.274
Work hours (Fall / Spring)	-0.003	1.461	-0.059	0.000	0.056
Work hours (Summer)	-0.027	1.389	-0.120	0.000	0.115
Graduation rate	-0.710				
Time-to-degree	-0.033	1.055	0.000	0.000	0.000
Cumulative GPA	-0.005	0.245	-0.119	0.000	0.105
Cumulative debt	120	21,418	-6,999	0	6,999
Observations	987				

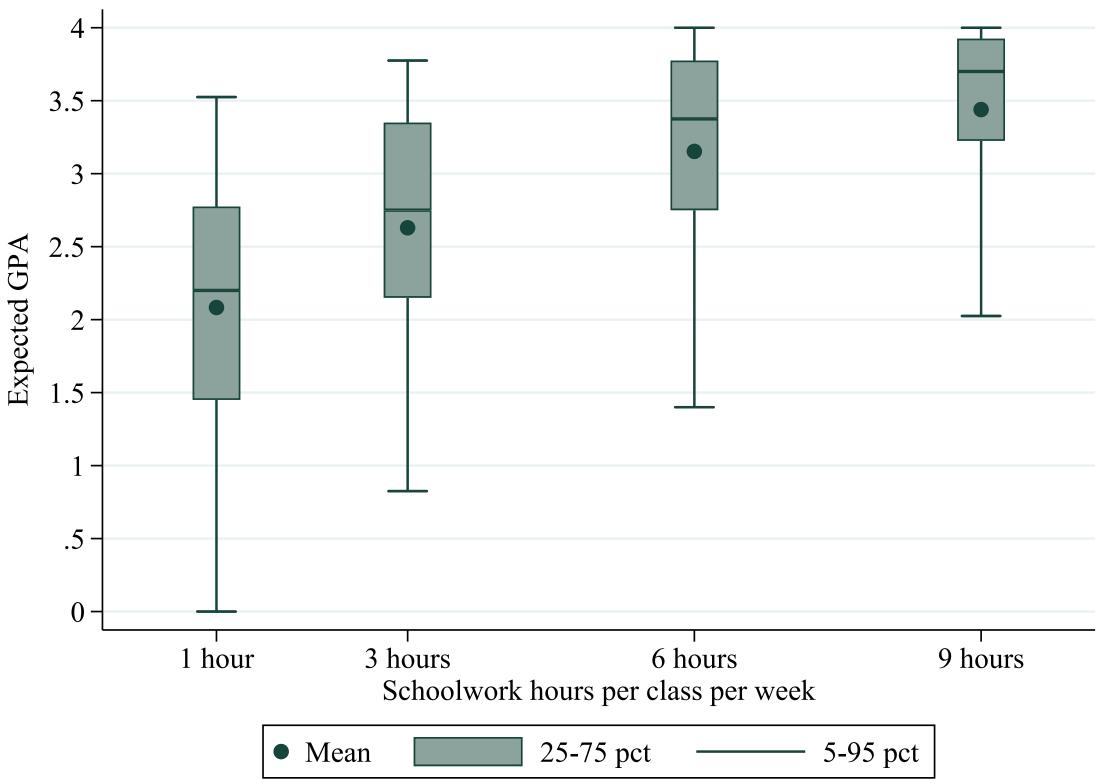
Notes go here

Figure 1: Distribution of expected future salaries



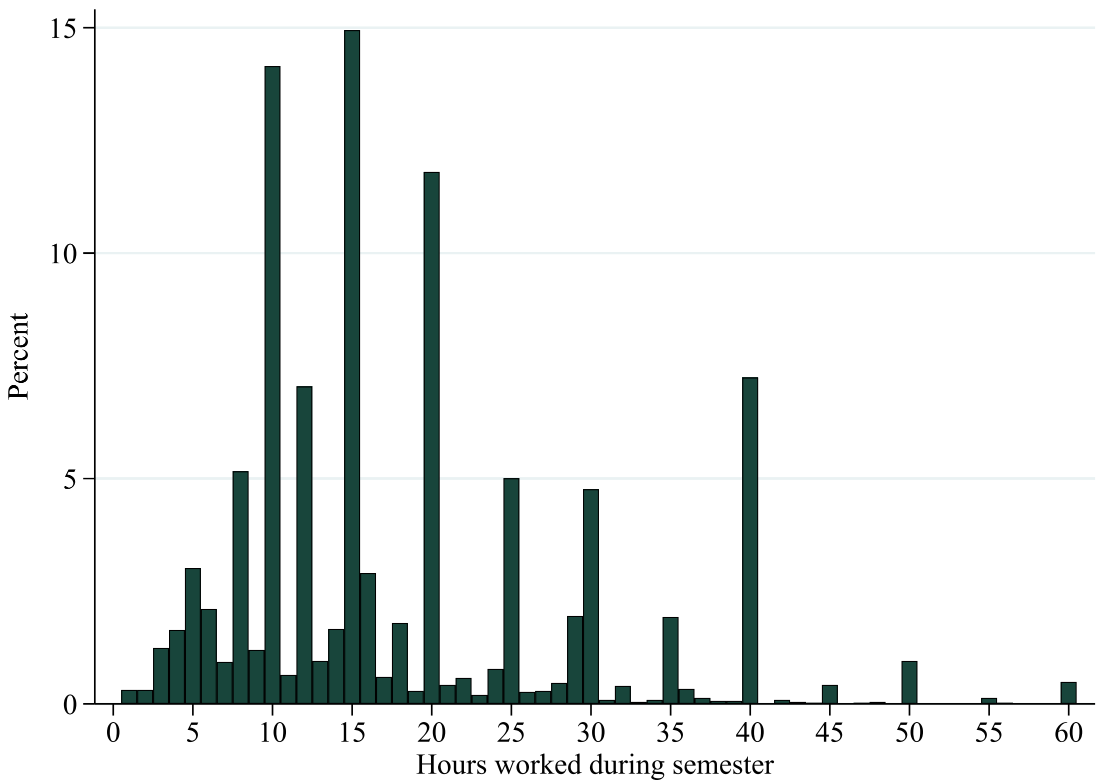
Notes go here

Figure 2: Distribution of expected grades



Notes go here

Figure 3: Work hours distribution



Notes go here

Figure 4: Counterfactual simulation: Increasing minimum wage to $15 per hour

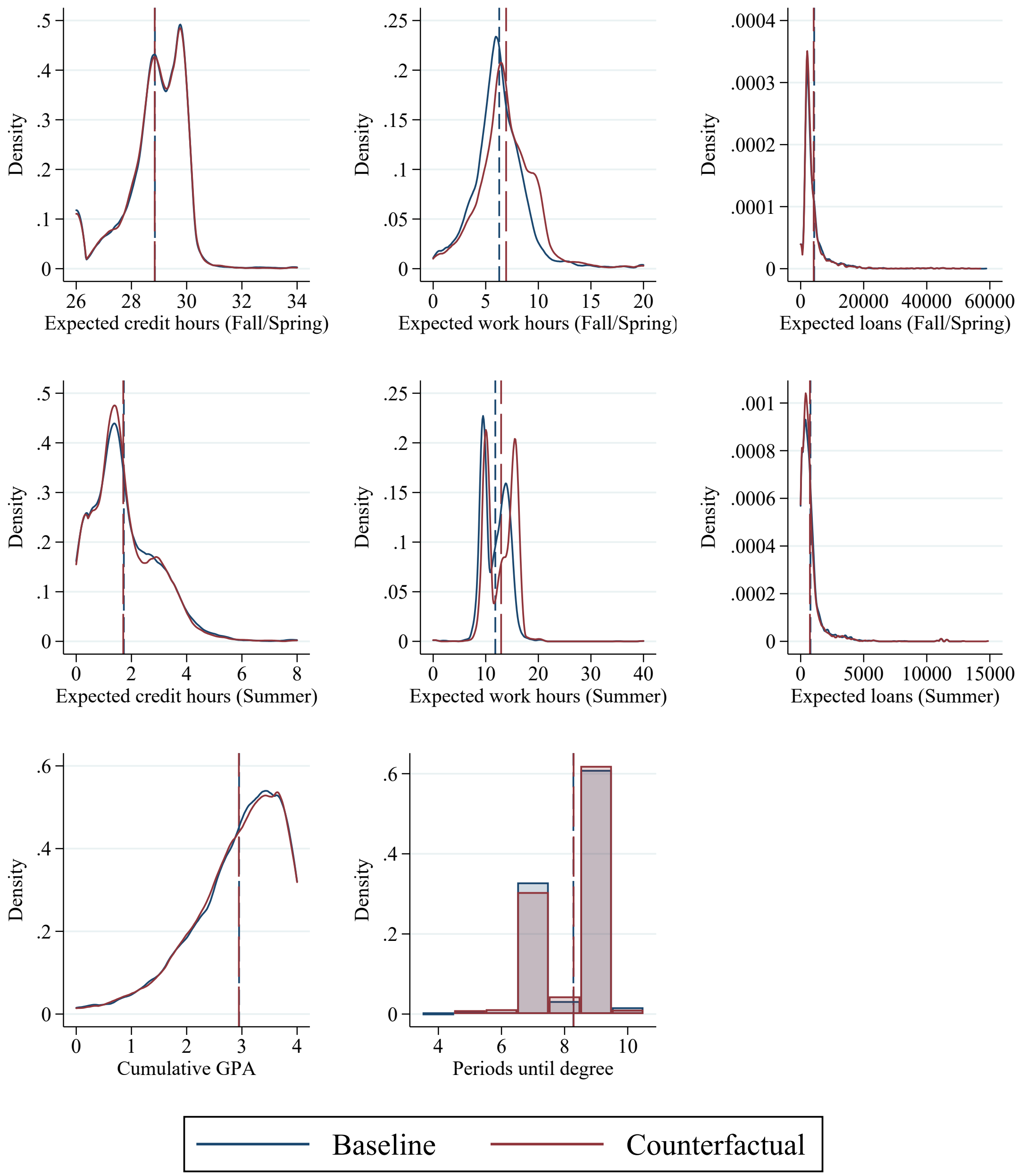


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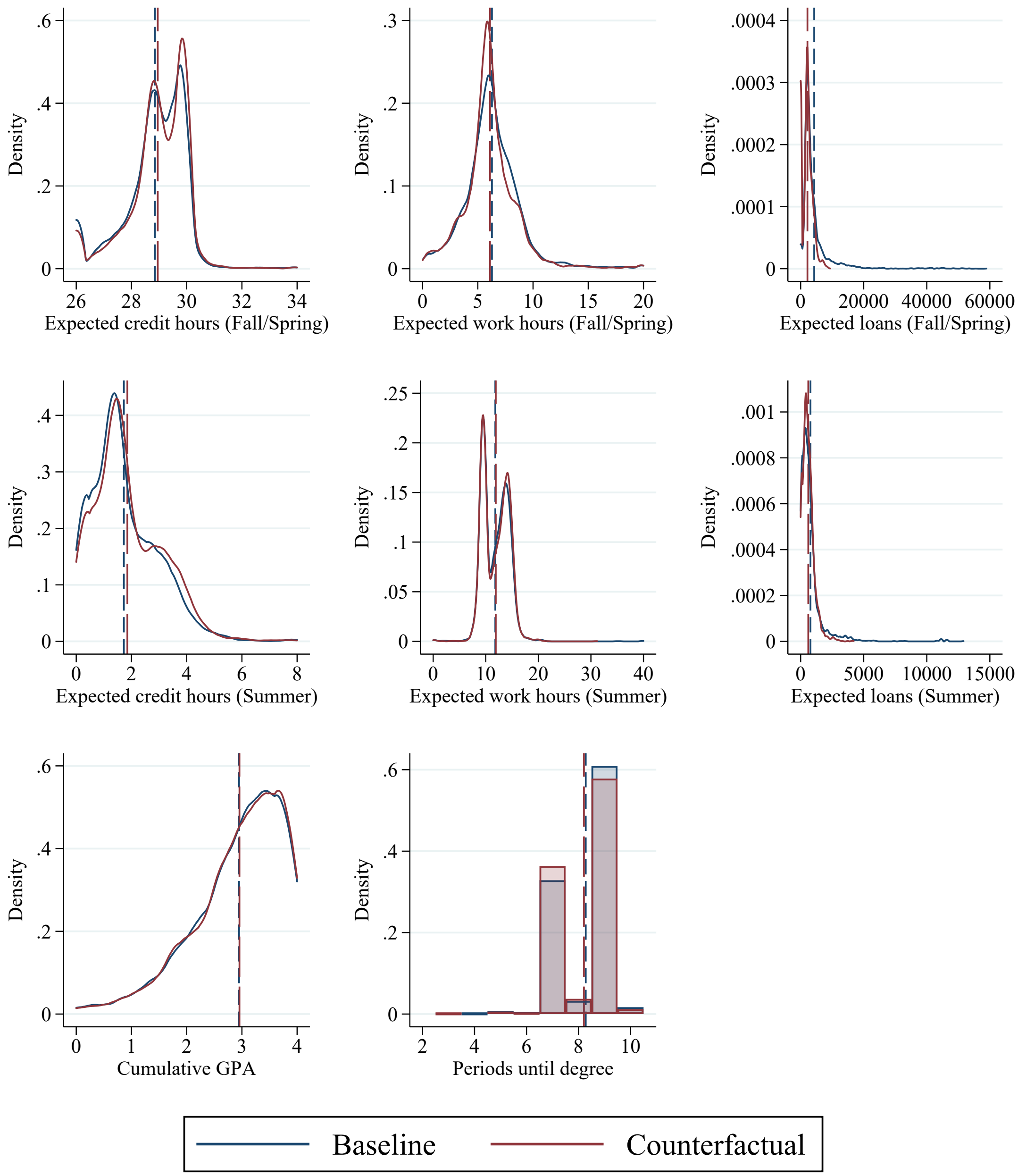
Figure 5: Counterfactual simulation: Setting tuition to $0



Notes go here

8 Appendix

Table A1: In-school wage regressions

	(1) Workers		(2) Non-workers	
Female	-0.0481*	(0.0268)	-0.0387*	(0.0219)
Black or African American	0.0734	(0.0473)	0.0306	(0.0351)
Hispanic	0.0636	(0.0453)	0.0728**	(0.0336)
American Indian or Alaskan Native	0.0895	(0.206)	-0.126	(0.117)
Native Hawaiian or Pacific Islander	0.0183	(0.0651)	-0.0903***	(0.0246)
Asian	0.0291	(0.0504)	-0.0298	(0.0248)
Out-of-state	0.0349	(0.0440)	-0.0153	(0.0292)
First generation	-0.0139	(0.0326)	-0.0370*	(0.0223)
Age (in months)	0.00150	(0.00208)	0.00213	(0.00171)
Sophomore	0.0391	(0.0361)	-0.0190	(0.0197)
Junior	0.0670	(0.0486)	-0.0195	(0.0366)
Senior	0.0515	(0.0620)	0.170	(0.172)
Cumulative GPA	0.0460*	(0.0262)	0.000995	(0.0170)
Honors college	-0.0140	(0.0336)	-0.00413	(0.0226)
College: Business	0.0950***	(0.0337)	0.0540	(0.0421)
College: Humanities	-0.0133	(0.0452)	0.00587	(0.0440)
College: Health	0.246**	(0.0971)	0.0634	(0.0520)
College: STEM	0.0789***	(0.0292)	0.00306	(0.0202)
College: Undecided	0.108**	(0.0450)	0.127**	(0.0549)
Worked part-time before MSU	0.0138	(0.0299)	0.00589	(0.0230)
Worked full-time before MSU	0.102***	(0.0391)	0.0448	(0.0307)
Cumulative work hours	0.000266	(0.000296)	0.000726	(0.000722)
Constant	1.711***	(0.464)	1.903***	(0.410)
Observations	617		314	
R^2	0.098		0.165	

Standard errors in parentheses

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

Column 1: observed in-school wage. Column 2: expected part-time wage for non-workers

Table A2: Family financial support

	(1)	
	Family transfers	
Female	64.08	(542.61)
Black or African American	-3336.43***	(989.55)
Hispanic	-3361.61***	(1041.45)
American Indian or Alaskan Native	5309.39	(5975.09)
Native Hawaiian or Pacific Islander	-2324.41	(2671.76)
Asian	1099.12	(835.60)
Out-of-state	6759.98***	(1106.71)
First generation	-4002.04***	(765.85)
Age (in months)	61.34	(37.85)
Sophomore	-581.64	(705.46)
Junior	-1169.67	(901.49)
Senior	-2870.61**	(1137.94)
ACT (SAT equivalent) score	153.44	(103.99)
Honors college	-806.93	(637.76)
College: Business	-553.79	(759.66)
College: Humanities	-1856.78*	(1049.68)
College: Health	-1996.40	(1511.10)
College: STEM	-1409.48**	(625.20)
College: Undecided	-4256.21*	(2565.69)
Constant	-7669.85	(8538.56)
Observations	1024	
R^2	0.188	

Standard errors in parentheses

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

Notes

Table A3: Expected time spent on schoolwork by student characteristics

	(1)		(2)	
	12 credits 0 work hours		12 credits 20 work hours	
Female	0.141**	(0.0634)	-0.0683	(0.0516)
Black or African American	0.0195	(0.132)	0.0424	(0.0992)
Hispanic	0.170	(0.149)	-0.286**	(0.114)
American Indian or Alaskan Native	0.388	(0.406)	-0.221	(0.415)
Native Hawaiian or Pacific Islander	0.234	(0.263)	-0.308	(0.261)
Asian	-0.0138	(0.0968)	-0.121	(0.0734)
Out-of-state	-0.0617	(0.102)	0.0487	(0.0700)
First generation	0.0966	(0.0838)	-0.0989	(0.0668)
Age (in months)	0.00310	(0.00411)	-0.00473	(0.00350)
Sophomore	-0.101	(0.0904)	0.0373	(0.0724)
Junior	0.0501	(0.123)	0.0475	(0.0949)
Senior	-0.165	(0.155)	0.163	(0.125)
ACT (SAT equivalent) score	-0.0158	(0.0109)	0.0165	(0.0102)
Honors college	0.208***	(0.0746)	-0.0724	(0.0597)
College: Business	0.00632	(0.0867)	-0.0302	(0.0803)
College: Humanities	0.118	(0.158)	0.0792	(0.0854)
College: Health	0.198	(0.171)	-0.120	(0.116)
College: STEM	0.376***	(0.0719)	-0.0897	(0.0601)
College: Undecided	-0.311	(0.210)	-0.0840	(0.148)
Constant	1.182	(1.053)	0.487	(0.869)
Observations	1024		1024	
R^2	0.069		0.036	

Standard errors in parentheses

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

Notes

Table A4: Expected post-school salary by student characteristics

	(1) No degree		(2) Degree premium		(3) GPA premium	
Female	-4082.40***	(1311.63)	-1698.17	(1436.55)	5278.23***	(1894.43)
Black or African American	1773.80	(2374.82)	4876.36*	(2678.13)	-8638.78*	(4549.08)
Hispanic	-1363.60	(2169.22)	5193.51*	(2798.76)	3330.79	(3549.87)
American Indian or Alaskan Native	20921.52**	(8632.80)	3236.55	(9881.94)	-11897.93	(10775.51)
Native Hawaiian or Pacific Islander	-2076.88	(5578.12)	3402.49	(8422.84)	3084.04	(7507.44)
Asian	-996.80	(2262.17)	-4157.04	(2821.32)	6328.38**	(3007.24)
Out-of-state	-636.34	(1876.81)	-1356.95	(1843.56)	-587.62	(3178.90)
First generation	-1784.87	(1495.77)	-1859.70	(1696.61)	-232.58	(2601.65)
Age (in months)	-119.00	(94.35)	61.58	(95.38)	-1.13	(126.94)
Sophomore	1765.37	(1747.30)	-1809.13	(2005.82)	-5264.65*	(2794.24)
Junior	3305.88	(2582.52)	-5265.39*	(2836.18)	-8326.60**	(3479.74)
Senior	336.24	(3106.78)	-3376.22	(3400.07)	-13129.32***	(4476.61)
ACT (SAT equivalent) score	-236.79	(204.34)	-72.65	(220.42)	-258.30	(309.52)
Honors college	-253.00	(1341.54)	-374.18	(1557.58)	3212.06	(2063.84)
College: Business	1549.59	(2046.36)	24.42	(2322.93)	1902.46	(2900.31)
College: Humanities	-438.88	(2333.21)	1584.67	(2955.33)	-4201.70	(4127.00)
College: Health	2109.60	(4434.50)	4716.58	(4866.66)	3177.72	(5486.51)
College: STEM	1004.11	(1407.45)	1697.34	(1602.56)	1364.80	(2232.39)
College: Undecided	1544.06	(5050.60)	-9539.99	(5818.63)	-5851.84	(6507.60)
Constant	73189.48***	(23468.93)	4561.02	(24124.16)	44293.28	(32595.47)
Observations	1024		1024		1024	
R^2	0.049		0.033		0.059	

Standard errors in parentheses

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

Notes

Table A5: Expected grades by student characteristics

	(1) 1 hour		(2) Return to 3 hours	
Female	-0.2582***	(0.0688)	0.0845**	(0.0371)
Black or African American	-0.0366	(0.1166)	0.0360	(0.0738)
Hispanic	-0.2038	(0.1577)	0.1191	(0.0888)
American Indian or Alaskan Native	-0.1206	(0.2074)	-0.0101	(0.1158)
Native Hawaiian or Pacific Islander	-0.4562*	(0.2767)	0.1680	(0.1575)
Asian	-0.1546	(0.1269)	0.0337	(0.0703)
Out-of-state	0.0348	(0.1010)	-0.0809	(0.0529)
First generation	-0.1053	(0.0886)	-0.0304	(0.0461)
Age (in months)	-0.0061	(0.0048)	-0.0004	(0.0024)
Sophomore	0.0202	(0.0975)	-0.0277	(0.0570)
Junior	0.1210	(0.1355)	-0.0652	(0.0737)
Senior	0.1595	(0.1803)	-0.0329	(0.0983)
ACT (SAT equivalent) score	-0.0090	(0.0114)	0.0148**	(0.0064)
Honors college	0.1443*	(0.0853)	-0.0302	(0.0479)
College: Business	0.2381**	(0.0967)	-0.0177	(0.0518)
College: Humanities	0.0235	(0.1399)	-0.0054	(0.0987)
College: Health	-0.2983	(0.2554)	0.0439	(0.1131)
College: STEM	-0.1154	(0.0766)	-0.0209	(0.0413)
College: Undecided	0.0547	(0.4237)	-0.0496	(0.2060)
Constant	3.9006***	(1.2011)	0.2533	(0.6093)
Observations	1024		1024	
R^2	0.049		0.020	

Standard errors in parentheses

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

Notes

Table A6: Relationship between work and student observables

	(1)		(2)		(3)		(4)		(5)	
	Pr(Work)		Work hours		Pr(Loans)		Loan amount		Credits	
Female	0.103***	(0.0175)	-0.420	(0.424)	0.0530***	(0.0178)	703.1**	(356.8)	-0.0206	(0.0606)
Black or African American	0.166***	(0.0317)	0.871	(0.674)	0.227***	(0.0292)	-4710.1***	(439.2)	-0.113	(0.104)
Hispanic	-0.0482	(0.0414)	-1.617**	(0.768)	0.151***	(0.0344)	-1118.4	(919.2)	-0.252*	(0.131)
American Indian or Alaskan Native	0.00360	(0.0558)	-3.071**	(1.351)	0.255***	(0.0785)	2150.1*	(1172.5)	-0.426*	(0.245)
Native Hawaiian or Pacific Islander	-0.0662	(0.0959)	-2.476**	(1.164)	0.0258	(0.0879)	-4020.4***	(678.8)	-0.214	(0.293)
Asian	-0.0142	(0.0281)	-0.0311	(0.635)	-0.140***	(0.0294)	-2622.0***	(482.0)	-0.132	(0.120)
Out-of-state	-0.0903***	(0.0250)	-2.229***	(0.562)	-0.0783***	(0.0265)	4975.6***	(888.0)	0.0765	(0.0835)
First generation	0.116***	(0.0222)	1.799***	(0.479)	0.165***	(0.0213)	-64.59	(404.2)	-0.0810	(0.0722)
Age (in months)	0.00103	(0.00117)	0.0737**	(0.0293)	0.00562***	(0.00116)	39.48*	(20.69)	-0.0207***	(0.00405)
Sophomore	0.120***	(0.0290)	0.000570	(0.725)	-0.00397	(0.0312)	1986.8***	(590.7)	-0.00883	(0.0919)
Junior	0.222***	(0.0368)	1.094	(0.857)	-0.0771**	(0.0362)	1846.8***	(667.9)	0.127	(0.121)
Senior	0.332***	(0.0453)	0.410	(1.076)	-0.154***	(0.0452)	1555.6*	(861.1)	0.0328	(0.157)
ACT (SAT equivalent) score	0.00373	(0.00294)	-0.270***	(0.0574)	-0.00135	(0.00295)	-392.5***	(58.52)	0.0180*	(0.0106)
Honors college	0.0694***	(0.0214)	-0.434	(0.493)	-0.114***	(0.0213)	-1070.2***	(410.9)	0.151**	(0.0696)
College: Business	-0.117***	(0.0260)	-0.946	(0.647)	-0.153***	(0.0266)	-179.9	(515.2)	-0.153*	(0.0860)
College: Humanities	-0.0462	(0.0349)	-2.398***	(0.738)	0.0146	(0.0359)	3475.3***	(701.6)	0.399***	(0.128)
College: Health	-0.0537	(0.0440)	-2.465**	(1.186)	-0.0257	(0.0524)	737.9	(1089.9)	-0.340***	(0.121)
College: STEM	-0.0690***	(0.0204)	-1.578***	(0.531)	0.000494	(0.0209)	1968.1***	(362.1)	-0.237***	(0.0751)
College: Undecided	-0.0494	(0.0551)	-3.327**	(1.667)	-0.0761	(0.0663)	-228.0	(1147.1)	-0.116	(0.211)
Predicted part-time wage	-0.00846***	(0.00224)	0.00116	(0.0415)	-0.00161	(0.00231)	-46.60	(36.65)	-0.0243***	(0.00796)
Unmet financial need ('000s)	0.0119***	(0.00129)	0.125***	(0.0327)	0.00432***	(0.00131)	444.1***	(27.46)	0.0126***	(0.00438)
Schoolwork time (12 credits, 0 work hours)	0.0228**	(0.0111)	0.207	(0.226)	-0.0378***	(0.0110)	-622.5**	(245.4)	-0.0163	(0.0370)
Increase in schoolwork from 20 work hours	-0.00228	(0.0142)	-0.248	(0.330)	-0.0670***	(0.0143)	-596.2**	(302.5)	-0.0147	(0.0443)
Post-school salary (no degree) ('000s)	0.000198	(0.000526)	0.0134	(0.0119)	-0.00135**	(0.000556)	18.87	(13.13)	0.000736	(0.00191)
Degree premium ('000s)	0.00178***	(0.000527)	0.00339	(0.0102)	0.00199***	(0.000531)	12.17	(10.20)	0.000952	(0.00181)
GPA premium ('000s)	-0.00168***	(0.000392)	-0.00228	(0.00869)	-0.000318	(0.000413)	-4.511	(8.177)	0.000465	(0.00126)
Return to work experience ('000s)	0.00141**	(0.000569)	-0.0258**	(0.0127)	-0.000311	(0.000588)	-7.259	(11.43)	0.00271	(0.00185)
Grade at 1 hour of schoolwork	-0.000941	(0.00911)	0.157	(0.210)	-0.0169*	(0.00953)	549.6***	(181.3)	-0.00219	(0.0317)
Return to 3 hours of schoolwork	-0.00731	(0.0170)	0.0940	(0.336)	-0.00588	(0.0165)	1387.9***	(296.5)	-0.0103	(0.0568)
Constant	-0.112	(0.300)	2.680	(7.276)	-0.662**	(0.301)	3897.2	(5281.9)	18.95***	(1.051)
Observations	4062		1845		4062		1989		4062	
R^2	0.137		0.119		0.139		0.335		0.054	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes.

Table A7: Relationship between work and student observables

	(1) Pr(Work)		(2) Work hours	
Female	0.111***	(0.0158)	-0.139	(0.560)
Black or African American	0.138***	(0.0286)	-0.134	(0.870)
Hispanic	-0.0620	(0.0379)	-1.098	(1.080)
American Indian or Alaskan Native	-0.00618	(0.0537)	-1.940	(2.149)
Native Hawaiian or Pacific Islander	-0.106	(0.0822)	-1.459	(2.510)
Asian	-0.0430*	(0.0256)	-2.035**	(0.881)
Out-of-state	-0.0988***	(0.0230)	-1.445	(0.941)
First generation	0.111***	(0.0197)	2.036***	(0.675)
Age (in months)	0.000638	(0.00106)	0.0492	(0.0347)
Sophomore	0.126***	(0.0279)	2.431***	(0.849)
Junior	0.244***	(0.0340)	4.936***	(1.017)
Senior	0.356***	(0.0415)	5.254***	(1.239)
ACT (SAT equivalent) score	0.00156	(0.00264)	-0.320***	(0.0784)
Honors college	0.0625***	(0.0194)	-0.593	(0.684)
College: Business	-0.0917***	(0.0237)	1.618*	(0.861)
College: Humanities	-0.0474	(0.0318)	-0.482	(1.029)
College: Health	-0.0502	(0.0399)	-0.886	(1.601)
College: STEM	-0.0539***	(0.0185)	-0.272	(0.661)
College: Undecided	0.0207	(0.0521)	0.668	(2.457)
Predicted part-time wage	-0.00519***	(0.00196)	0.144**	(0.0575)
Unmet financial need ('000s)	0.00831***	(0.00110)	-0.356***	(0.0420)
Schoolwork time (12 credits, 0 work hours)	0.0226**	(0.0101)	0.305	(0.338)
Change in schoolwork from 20 work hours	0.00395	(0.0129)	0.0156	(0.426)
Post-school salary (no degree) ('000s)	-0.000247	(0.000479)	0.0154	(0.0173)
Degree premium ('000s)	0.00125***	(0.000477)	-0.0139	(0.0144)
GPA premium ('000s)	-0.00203***	(0.000356)	-0.00360	(0.0122)
Return to work experience ('000s)	0.00179***	(0.000522)	-0.0386**	(0.0176)
Grade at 1 hour of schoolwork	0.00266	(0.00830)	0.129	(0.287)
Return to 3 hours of schoolwork	0.00119	(0.0155)	0.0233	(0.488)
Constant	0.0241	(0.272)	9.598	(8.852)
Observations	5078		2377	
R^2	0.120		0.100	

Standard errors in parentheses

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

Notes.

Table A8: Relationship between borrowing and student observables

	(1)		(2)	
	Pr(Loans)		Loan total	
Female	0.0453**	(0.0178)	703.1**	(356.8)
Black or African American	0.215***	(0.0291)	-4710.1***	(439.2)
Hispanic	0.155***	(0.0349)	-1118.4	(919.2)
American Indian or Alaskan Native	0.254***	(0.0777)	2150.1*	(1172.5)
Native Hawaiian or Pacific Islander	0.0307	(0.0891)	-4020.4***	(678.8)
Asian	-0.139***	(0.0295)	-2622.0***	(482.0)
Out-of-state	-0.0715***	(0.0267)	4975.6***	(888.0)
First generation	0.156***	(0.0214)	-64.59	(404.2)
Age (in months)	0.00555***	(0.00116)	39.48*	(20.69)
Sophomore	-0.0129	(0.0311)	1986.8***	(590.7)
Junior	-0.0937***	(0.0362)	1846.8***	(667.9)
Senior	-0.178***	(0.0454)	1555.6*	(861.1)
ACT (SAT equivalent) score	-0.00163	(0.00296)	-392.5***	(58.52)
Honors college	-0.119***	(0.0213)	-1070.2***	(410.9)
College: Business	-0.144***	(0.0265)	-179.9	(515.2)
College: Humanities	0.0181	(0.0360)	3475.3***	(701.6)
College: Health	-0.0217	(0.0523)	737.9	(1089.9)
College: STEM	0.00566	(0.0208)	1968.1***	(362.1)
College: Undecided	-0.0724	(0.0646)	-228.0	(1147.1)
Predicted part-time wage	-0.000976	(0.00231)	-46.60	(36.65)
Unmet financial need ('000s)	0.00343***	(0.00132)	444.1***	(27.46)
Schoolwork time (12 credits, 0 work hours)	-0.0395***	(0.0109)	-622.5**	(245.4)
Increase in schoolwork from 20 work hours	-0.0668***	(0.0142)	-596.2**	(302.5)
Post-school salary (no degree) ('000s)	-0.00137**	(0.000556)	18.87	(13.13)
Degree premium ('000s)	0.00186***	(0.000529)	12.17	(10.20)
GPA premium ('000s)	-0.000192	(0.000411)	-4.511	(8.177)
Return to work experience ('000s)	-0.000416	(0.000587)	-7.259	(11.43)
Grade at 1 hour of schoolwork	-0.0169*	(0.00951)	549.6***	(181.3)
Return to 3 hours of schoolwork	-0.00533	(0.0164)	1387.9***	(296.5)
Student worked during semester	0.0749***	(0.0171)		
Constant	-0.654**	(0.302)	3897.2	(5281.9)
Observations	4062		1989	
R^2	0.143		0.335	

Standard errors in parentheses

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

Notes.