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Assessing the costs of balancing college and work activities: The gig economy meets online education

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Abstract
Balancing the demands of work and schooling is a challenging task for an increasing number of students who have to pay their way through college and for workers who intend to upgrade their skills. However, flexible learning and working environments could play an important role in easing many frictions associated with performing both activities simultaneously. Using detailed (work and study effort) data – from a partnership between Arizona State University and Uber that allows eligible drivers to enroll in online college courses for free – we analyze how labor supply and study efforts respond to changes in labor market conditions and college activities/tasks. Our findings indicate that a 10% increase in average weekly online college activities reduces weekly time spent on the Uber platform by about 1%, indicating a low "short run" opportunity cost of studying when working. We also show that study time is not particularly sensitive to changes in labor market conditions, where a 10% increase in average weekly pay reduces study hours by only 2%. Consistent with these results, we find that workers take advantage of their flexible schedules by changing their usual working hours when their college courses are more demanding. We do not find adverse effects of work hours on academic performance in this context, or of study hours on workplace performance (as measured by driver ratings or tips). Finally, the (elicited) value assigned to flexible working and educational formats is high among the students in our sample, who view online education as an important vehicle for increasing expected future income. Overall, this study underscores that combining flexible working and learning formats could constitute a suitable path for many (low-SES) students who work to afford an increasingly expensive college education and for workers aiming to improve their skill set.

Keywords: gig economy, education, flexible working

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1 Introduction

In 2019, 45% of full-time and 84% of part-time undergraduate students in the United States worked for pay (US Department of Education, 2020). The vast majority of these students—64% (86%) of undergraduate students enrolled full-time (part-time)—worked at least 20 hours per week. In addition, the share of students working while attending higher education has been rising over time: the average labor supply among 18 to 22-year-old full-time undergraduates nearly doubled between 1970 and 2000 (Scott-Clayton, 2012).[1] This trajectory is likely to continue for two key reasons. First, the cost of a college education has drastically risen over recent decades, forcing many students to work to pay their way through college.[2] Second, the acceleration of technological change has substantially decreased the demand for low-skill/routine labor, driving many workers to upgrade their skills by re-enrolling in post-secondary education programs while working either full- or part-time (Saliola et al., 2020). Similarly, artificial intelligence is expected to affect almost 40 percent of jobs around the world (Cazzaniga et al., 2024), also requiring many high-skill individuals to adapt their skills to the new demands of the labor market.

At the same time, existing evidence suggests that working while attending college meaningfully crowds out schooling time, generally (though not always) negatively affecting college outcomes (Stinebrickner and Stinebrickner, 2003; Beffy et al., 2010; Kalenkoski and Pabilonia, 2010; Scott-Clayton, 2012; Darolia, 2014; Neyt et al., 2019; Le Barbanchon et al., 2020). Taken together, these facts highlight the potential value of exploring new alternatives/policies that could help students balance both activities.

The aim of this study is twofold. First, we analyze whether adopting and integrating flexible learning and working modalities can mitigate the obstacles students typically face when combining work with a college education (e.g., commuting time, scheduling conflicts,

[1] The share of students working in college has increased by approximately 10% since 2010 (US Department of Education, 2020).

[2] Between 2006 and 2020, after adjusting for inflation, the average attendance cost at public and non-profit private four-year universities increased by almost 20%. However, average net prices increased more steadily during this period (Ma and Pender, 2022).

working crowding out study hours, and impacting academic performance). To this end, we estimate key cross-elasticities that quantify the tradeoffs associated with performing both activities in a highly flexible context (i.e., online learning while working flexible hours).[3] To our knowledge, this is the first paper quantifying the interdependence of college and work demands. While many studies have focused on the effect of work on schooling performance, to date, there is no evidence of the causal impact of college activities on labor supply or the effects of earnings on the effort exerted in college classes.

Secondly, we analyze the potential for dual flexibility to broaden the demand for higher education. The presence of an increasing trend towards greater flexibility is evidenced by the growth in online learning, with the proportion of post-secondary students taking distance courses rising from 28% in 2014 to 37% in 2019 (U.S. Department of Education, National Center for Education Statistics, 2020) and by the gig economy's workforce expansion of 133% between 2016 and 2021 (Denes et al., 2023). Such flexible environments can be instrumental not only to upgrading the skills of many individuals but also to level the playing field in higher education. For example, flexibility could be especially beneficial for "older" students and those from lower socioeconomic status (SES) backgrounds. Considering that students from less affluent backgrounds are more likely to work while studying (Chen and Nunnery, 2019), evaluating the potential impacts of flexible formats could be of first-order importance for addressing educational disparities among different socioeconomic groups. To this end, we study students' valuation of flexible environments and their expected gains in labor market returns from completing an online degree. This analysis will help us determine the scope of expanding dual flexibility in higher education.

Uncovering elasticities associated with simultaneously performing learning and working activities is often complex and, in many cases, intractable due to data limitations, as well as problems of selection and endogeneity. To overcome these challenges, we focus on a

[3] Estimating these elasticities can also be relevant to inform other settings. For example, if working college students have to substantially decrease their labor supply to complete their studies (high opportunity cost in the short-run), even in a very flexible context, then the scope for many individuals to successfully perform both activities simultaneously is likely limited.

partnership between Arizona State University (ASU) and Uber, which allows eligible drivers to enroll in online classes at ASU tuition-free; henceforth, we refer to the drivers enrolled in the ASU program as Uber-students. This setting is unique for three reasons. First, Uber-students face a uniquely flexible environment where work and study hours can be easily accommodated. This allows us to determine whether the usual frictions that arise from balancing work and learning still play an important role in this context. Second, Uber and ASU online platforms provide granular and high-frequency information about drivers and students over time, offering a unique opportunity to explore how effort responds to changes in work and college conditions. Third, the degree of complementarity between working activities in this setting and the skills acquired in college is expected to be much lower than in other contexts (i.e., college courses are unlikely to improve a student's capabilities as an Uber driver), making the interpretation of our findings more transparent.

This partnership provides us with two unique datasets that we combine for our main empirical analysis. The first, provided by Uber, includes information on drivers enrolled in online BA degree-seeking programs at ASU and a subset of their co-workers who qualified for but did not enroll in the ASU program. The second source of data, provided by ASU, includes academic information on the universe of Uber-students and their online classmates who are not program participants. In particular, we have access to most of the weekly student and driver activity recorded on the Uber and ASU online platforms. The ASU-related information includes student background characteristics, transcript data, and weekly level information collected from their online activity (i.e., points earned, assignments submitted, and Canvas logins, clicks, and minutes online). Finally, the Uber-related data include weekly information on completed trips, total pay, minutes on the application, driving habits, city-level labor market conditions, and background characteristics, among other covariates.

Our econometric specifications are derived from a simple analytical framework that not only provides justification for our empirical models but also helps to further characterize the cost of performing learning and working activities simultaneously. To overcome common problems of selection and endogeneity, our empirical strategy exploits within-individual and classroom-level variation jointly with instrumental variables to identify the costs associated with balancing work and learning activities. More specifically, we exploit weekly-level variation in the Uber and ASU platforms and (arguably) exogenous changes in labor market demand and course-week learning tasks (i.e., course demand) to identify key cross-elasticities.[4] Finally, the fact that our empirical approach relies on individual-level variation within a short period (academic terms) allows us to overcome concerns related to whether (if any) previous disengagement from school or work can be driving our main results.

Our main findings indicate that average weekly course demand decreases weekly driving time by approximately 1.7 hours: more specifically, a 10% increase in average online learning activities decreases average driving time by approximately 1%; henceforth, driving time refers to the number of hours that drivers spend connected to the Uber platform. This implies a decrease in Uber-students' incomes of $41 per week or $180 per month, suggesting that the "short-run" opportunity cost (in terms of current income) of online classes is quite low.[5] We also find that a 10% increase in market-level hourly pay only decreases study time for the average Uber-student by approximately 2%, indicating that study time is relatively insensitive to labor market conditions. Overall, these cross-elasticities signal little crowd-out between school and labor market activities in this setting.

Consistent with these findings, we show that drivers take advantage of the flexibility specific to this context by adjusting their driving patterns when college activities become more demanding. This behavior likely limits the scope of crowd-out. It is worth noting that we see no meaningful effect of college activities on the quality of work (as measured by the impact on driver ratings or tips). In a similar vein, we do not find that driving hours have a negative impact on academic performance. This last result contrasts with the findings of

[4]Given that our data come from drivers in a large number of cities, changes in labor demand could be driven, for example, by different social events that may happen in these cities. We show that variations in hotel occupancy rates are consistent predictors of labor market pay at the city-week level, even after including a large set of controls.

[5]As a point of comparison, the online tuition for a part-time student is approximately $3,000 per term, while Uber drivers earn $2,200 per month when not taking ASU classes.

Stinebrickner and Stinebrickner (2003), where an additional hour of work in a very different context of in-person classes has a large and statistically significant negative impact on grades.

Finally, we surveyed the participants of the ASU-Uber program and their classmates to elicit expected returns from completing an online degree and individual valuations for flexible learning and working formats. The survey also allows us to investigate whether the program contributed to creating additional demand for higher education or if it simply reshuffled students across institutions. We have three main sets of findings: (1) students expect substantial increases in income upon graduating from ASU online, suggesting a large (ex-ante) value-added assessment of the program; (2) students' reported likelihood of enrolling in a bachelor's degree is positively impacted by the flexibility in the learning and working environments, with the former (that is, learning environment flexibility) being particularly valued; and (3) almost half of the students were not attending any higher education institution prior to enrolling in ASU online education, suggesting the program draws in students who otherwise would not have pursued a college education.

Taken together, our results are quite reassuring. They strongly indicate that flexibility in learning and working environments eases many of the frictions associated with performing these activities simultaneously, providing a suitable path for many (low-income, low-socioeconomic background, or older) students who work to pay their way through an increasingly expensive college education. Finally, our findings suggest that combining flexible work and learning formats constitutes a promising avenue for allowing workers to up-skill without incurring significant short-term costs.

The rest of the paper is organized as follows. Section 2 describes the institutional details concerning the ASU-Uber partnership, while Section 3 describes the data. Section 4 presents a simple analytical framework. Section 5 describes the empirical strategy. Section 6 quantifies key trade-offs associated with working while attending college. Section 7 further characterizes the cost of performing working and learning activities simultaneously. Section 8 discusses the role of flexibility. Section 9 shows how work and study effort measures impact academic performance. Section 10 explores the scope of this uniquely flexible work-study program to expand the demand for higher education. Finally, Section 11 concludes.

2 Institutional Details: The ASU-Uber Partnership

Beginning in the fall semester of 2018, ASU and Uber initiated a partnership to make higher education more accessible to drivers who consistently use the Uber application. This partnership established that Uber will cover the tuition of drivers anywhere in the US who have completed at least 3,000 rides and maintain an Uber Pro Gold, Platinum, or Diamond status.[6] With the guarantee of tuition coverage, participants have several options to choose from in furthering their education. The first and most relevant for this paper is the option to earn credits toward an undergraduate degree. Alternatively, participants may take non-degree enrichment entrepreneurship or English language competency courses (though we do not focus on these short programs). These alternatives provide a lower commitment option to drivers who want to invest in their skills but do not want to commit to a degree program.

Qualifying Uber participants pursuing an undergraduate degree at ASU have over 140 degree programs to choose from. The courses are offered following the standard university calendar, which includes full-term courses (Session C) and half-term courses that run through the first half (Session A) or second half (Session B) of the term. However, within a course, students have considerable flexibility when they watch lecture videos and, depending on the course, additional flexibility in completing assignments and taking exams. Ultimately, the exact level of flexibility depends on the course and instructor preferences: some courses may allow students to access problem sets or exams at any time, whereas others may only allow access in given weeks or days around assignment due dates.[7] Though the degrees are all

[6] The program also extends to beneficiaries of the drivers, such as a spouse, child, sibling, or parent. However, our analysis focuses only on drivers. Approximately 30% of the program participants are family members of the Uber drivers.

[7] Though not directly observable in the data, our sense from discussions with online instructors is that most courses fall into the latter category, where instructors allow students to access new materials within a given week around a deadline.

through the ASU Online program, ASU does not distinguish between in-person and online degrees on a student's transcript or diploma. Thus, the ASU-Uber partnership provides an especially valuable opportunity for many Uber drivers.

While the qualifying restriction of completing at least 3,000 rides might appear quite daunting, this number is attainable for many drivers, even for those working part-time. For example, the Uber-students in our sample complete an average of roughly 43 weekly trips when they are not actively enrolled in classes. At that rate, drivers would surpass the necessary 3,000 trips in less than a year and a half, and even a more casual driver who completes only 30 trips per week would surpass the qualification in under two years. As of May 2023, the threshold was adjusted to 2,000 trips, though we do not have data for this period. Once this goal is met, drivers must also have reached either Uber Pro Gold, Platinum, or Diamond. To first achieve Gold status, a driver must meet a location-specific point goal, have an average star rating of 4.85 or greater, and have a cancellation rate (conditional on trip acceptance) of under 4 percent.[8] Once one of these different Uber statuses has been attained, the driver must continue to reach their location-specific point total, receive a minimum star rating of 4.75, and maintain a cancellation rate below 10 percent in order to keep their Uber Pro status. The Uber Pro Gold, Platinum, or Diamond status must be held in three-month periods, such that the activity in the previous three months determines the status in the current period.[9]

[8]The specific particulars of the point-based goals depend on location, but we can provide some general insights. These points are earned through the completion of rides, with the number of points awarded per completed trip being one or more, contingent upon the time of day and other factors. In most areas (with some exceptions), drivers must accrue between 200 and 600 points within a three-month time frame to sustain their status. As an illustrative example, assuming a midpoint target of 400 points and 1.5 points per trip, our rough calculations suggest that drivers would need to complete less than 21 trips each week to meet this goal.

[9]The following link https://uber.asu.edu/ provides further details concerning the program's characteristics.

3 Data Description

Our analysis is based on three innovative data sources. Firstly, data provided by Arizona State University enables us to monitor the interactions of Uber-students and their classmates with each course's online platform on a weekly basis. This includes their performance in weekly assignments and overall course outcomes. Secondly, we utilize data from Uber, which encompasses all drivers participating in the ASU-Uber partnership, excluding family members. These data also include a subset of eligible drivers for the ASU-Uber program who chose not to enroll. Notably, this data set represents student-drivers nationwide, not just those residing in Arizona. Additionally, we have access to data on market-level demand in each driver's local labor markets. We merged these two data sets at the individual-week level. For our empirical analysis, we omitted the peak period of the COVID-19 outbreak, as the pandemic significantly disrupted Uber activities. Consequently, our sample spans from August 2018 to March 2020, and from August 2021 to December 2021. Our primary findings remain qualitatively similar when the analysis is confined to the pre-COVID-19 period.

Finally, in November 2023, we conducted a survey among (currently enrolled) Uber-students and a random subset of their classmates to augment the data from the ASU and Uber platforms. This survey gathered a host of additional information of interest, including allocation of time in activities beyond the platforms, expectations regarding labor market and graduation outcomes, and preferences for flexible education and learning formats. Unfortunately, the survey data cannot be integrated with the Uber and ASU data sets.[10]

In the remainder of this section, we provide summary statistics and highlight significant features of each data set. Appendix A offers additional details on the construction of the samples and specific variable definitions.

[10]Moreover, the merged sample from the ASU and Uber data does not fully overlap with the survey sample, as the latter includes students enrolled at ASU in November 2023.

3.1 ASU Data

The first data set we employ in our analysis comes from students enrolled in online undergraduate programs at ASU. Since the degree programs available to drivers in the ASU-Uber partnership are all operated through ASU Online, the students primarily interact with the course and materials through Canvas, an online learning management system. This program feature allows us to access students' background characteristics and track each student's activity in a given course each week. This data set includes many measures of activity on Canvas at the student-class level, such as the number of days online, number of Canvas logins, total clicks, and total minutes online during the week. In addition, we have information on each student's weekly achievement (e.g., total points earned, total points possible, assignments submitted, and assignments graded), their final course grades, field of study, and other background characteristics.

3.1.1 Characterizing ASU-Uber Students

Background Characteristics Table 1 shows background characteristics and proxies for academic preparation of Uber-students and their classmates enrolled in ASU-Online undergraduate programs. More specifically, column (1) corresponds to Uber-students, while column (2) focuses on their classmates that are not ASU-Uber program participants. Uber-students differ in multiple dimensions from their classmates. They are, on average, 14 years older, overwhelmingly male (85%), and more racially diverse. For instance, 33% of the Uber-students are black, whereas the analogous share for their peer population is only 6%. In addition, Uber-students are more likely to be first-generation (i.e., do not have a parent who graduated from college) and to reside outside Arizona. The middle panel shows that Uber-students have higher financial needs (based on FAFSA records): 49% of them are designated as "very high" financial need versus 38% of their peers; they are also more likely to be eligible for Pell Grants. The last panel shows that Uber-students have lower high school/incoming GPAs than their counterparts, are more likely to transfer from other

Table 1: Student level observables, by sample

	Uber-Students		Class Peers		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Background Characteristics					
Age	39.25	(10.029)	24.90	(7.491)	14.36***
Female	0.15	(0.361)	0.56	(0.496)	-0.41***
White	0.36	(0.480)	0.54	(0.498)	-0.18***
Black	0.33	(0.470)	0.06	(0.240)	0.27***
Hispanic	0.15	(0.353)	0.23	(0.420)	-0.08***
Asian	0.07	(0.251)	0.08	(0.275)	-0.01**
First generation	0.57	(0.495)	0.36	(0.479)	0.21***
AZ resident	0.06	(0.238)	0.52	(0.500)	-0.46***
Financial need					
None	0.01	(0.072)	0.02	(0.155)	-0.02***
Very low	0.03	(0.170)	0.08	(0.278)	-0.05***
Low	0.08	(0.269)	0.11	(0.309)	-0.03***
Moderate	0.24	(0.427)	0.20	(0.400)	0.04***
High	0.16	(0.366)	0.15	(0.354)	0.01
Very high	0.49	(0.500)	0.38	(0.486)	0.10***
Ever Pell eligible	0.50	(0.500)	0.44	(0.497)	0.06***
Academic Profile					
Incoming GPA	2.71	(0.587)	3.09	(0.621)	-0.38***
Transfer status	0.62	(0.486)	0.51	(0.500)	0.11***
Transfer credit hours	73.19	(51.549)	38.93	(39.006)	34.24***
Number of terms enrolled	3.01	(1.656)	4.64	(3.280)	-1.63***
Average credit hour load	7.95	(3.027)	8.77	(3.147)	-0.82***
STEM degree	0.40	(0.489)	0.30	(0.456)	0.10***
Observations	1540		141913		

Note: Weekly Canvas activity. "Uber-students" refers to ASU students participating in the ASU-Uber partnership. "Class peers" corresponds to students enrolled in the same classes as the Uber students. First-generation refers to students whose parents did not attend college. "AZ resident" indicates if the student is listed as an Arizona resident. Each of the financial need variables "None", "Very low", "Low", "Moderate", "High", and "Very high" indicate the financial need status of the student, which is constructed by ASU based on students' applications to federal student aid. "Ever Pell eligible" indicates if the student was ever eligible for a Pell grant. The variable incoming GPA corresponds to a student's transfer GPA or, if transfer GPA is inapplicable, high school GPA. "Transfer status" is an indicator variable denoting whether the student transferred from another higher-education institution, and "transfer credit hours" refer to the number of credit hours carried over from their previous institution. "Number of terms enrolled" denotes the number of distinct terms that the student has been enrolled in ASU courses. "Average credit hour load" reflects the student's average number of credit hours per term, and "STEM degree" indicates if the student is in a science, technology, engineering, or math degree program. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table 2: Weekly Canvas activity and outcomes, by sample

	(1)		(2)		(3)		(4)	(5)
	Uber-Students Active in Uber		Uber-Students Inactive in Uber		Class Peers		Col (1) - (3)	Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Difference	Difference
Activity								
Days connected to Canvas per course	3.57	(2.30)	3.75	(2.27)	3.48	(2.12)	0.09***	-0.18***
Clicks per course	75.97	(89.33)	79.04	(85.57)	63.94	(69.70)	12.03***	-3.07***
Hours online per course	1.57	(2.12)	1.61	(2.10)	1.25	(1.64)	0.31***	-0.04**
Outcomes								
Assignments submitted per course	1.97	(4.14)	1.99	(2.92)	2.12	(4.05)	-0.15***	-0.02
Assignment share per course (%)	90.19	(27.59)	90.55	(26.81)	91.56	(25.10)	-1.37***	-0.36
Point share per course (%)	79.40	(29.31)	80.13	(28.66)	81.16	(28.64)	-1.76***	-0.74**
Observations	43527		12201		1831331			

Note: All statistics reported in the table are at the weekly level. "Uber-Students: Active in Uber" denotes weeks in which the student shows positive driving hours and is enrolled in ASU classes. "Uber Students: Inactive in Uber" denotes weeks in which the student shows zero driving hours but is enrolled in ASU classes. "Class peers" correspond to students who are enrolled in the same classes as the Uber students. Assignment and point shares refer to the total number of assignments submitted and points earned relative to the number of assignments due and points possible, respectively. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

institutions, were enrolled in fewer terms at ASU (because the partnership is relatively new), are more likely to pursue a major in STEM, and have a lower average course credit hour load per term than their class peers.[11] In summary, the main takeaway from Table 1 is that the ASU-Uber program seems more likely to attract non-traditional students who are racial minorities, financially disadvantaged, and older.

Weekly Academic Engagement Table 2 shows weekly level proxy measures for student engagement (i.e., active days, clicks, hours online) and performance in ASU online courses. The sample is divided into three groups: Uber-students active in Uber, Uber-students inactive in Uber, and class peers, where active and inactive distinguish the weeks in which Uber-students were actively participating on the Uber platform; if they complete at least one trip during a week, they are classified as active. On average, Uber-students show a higher engagement on Canvas than their classmates. They tend to spend more days per week connected to the ASU platform, perform more clicks, and spend more time on it.[12]

[11]The five most popular majors among the Uber-students are information technology, business, liberal studies, software engineering, and psychology. According to the information provided by the College Scorecard (U.S. Department of Education), the median earnings of Arizona State University graduates four years after graduation are $70,685 for business, $101,600 for computer engineering, and $45,403 for psychology majors. There is no available information for the other two majors.

[12]Appendix Table F1 shows that our measures of online activity (i.e., days connected to Canvas, number of logins and clicks, and time spent on the platform) are highly correlated. In particular, the high correlation

Interestingly, Uber-students also slightly increase their engagement on Canvas during weeks when they are inactive on the Uber platform. Finally, students spend 1.6 hours online per course in a given week, making a total of 2.84 hours of online study activity per week when averaging across all courses and weeks.

In terms of weekly academic performance, Uber-students submit, on average, 1.97 assignments per course during active driving weeks, slightly less than their peers (2.12), representing 90.2% of the total assignments requested. They obtain approximately 80% of the total points, which is similar to the point share of their class peers (81%).[13] Finally, differences in weekly academic performance between active and inactive Uber weeks are small. To conclude, a possible concern with these data is that our various Canvas engagement variables may be incomplete measures of study time and effort. For example, time spent reading hard copies of a textbook would not be included in the measure of minutes on Canvas. However, the students' self-reported study time allocation on and off the platforms (see subsection 3.3) and the strong correlation between Canvas hours and academic performance (discussed in Section 9) suggest that our measures of study effort constitute good proxies for actual study time. Furthermore, under the assumption that the ratio of the study time allocated within and outside the ASU online platforms remains fairly stable across various weeks, our empirical methodology, which includes individual fixed effects, could further help address measurement issues.

Course-Level Academic Outcomes Table 3 shows course-level information corresponding to Uber-students and their class peers. The top panel presents summary statistics on

between hours online and clicks suggests that idle time is not likely to be an important concern when proxying study time with "hours online".

[13]The point share is determined by dividing the points earned in a course for a given week by the points possible for the student in a given course-week. Assignments submitted refer to the number of assignments the student submitted throughout the week (assignments do not necessarily need to be submitted in the week they are due). In Appendix Table F2, we provide an alternative version of Table 2 where we re-weight the control group by coarsened exact matching (see Iacus et al., 2012) on many of the observable characteristics presented in Table 1. After doing so, the Uber-students' Canvas activity measures are much more similar to the control group, suggesting that once we control for fixed observable characteristics, the Uber-students study behaviors are quite similar to their non-Uber peers.

Table 3: Course-level summary statistics, by sample

	(1)		(2)		(3)
	Uber Students		Class Peers		Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Activity					
Total hours on Canvas	14.63	(12.73)	11.47	(9.62)	3.16***
Assignments submitted	18.38	(16.89)	19.37	(17.54)	-0.10***
Outcomes					
Passed course	0.76	(0.43)	0.83	(0.38)	-0.07***
Numeric course grade	2.49	(1.66)	2.70	(1.54)	-0.21***
Observations	6591		213842		

Note: "Uber-Students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

course-level activity, and the bottom panel displays information on course academic outcomes. On average, Uber-students stay connected to Canvas fourteen hours per course (including drop-outs), where most courses last approximately seven to eight weeks; a small number of courses are 15-16 weeks long. This is roughly 3.2 hours more than their peers. Uber-students also submit a similar number of assignments throughout the course as their peers. Specifically, they submit roughly 18.4 assignments per course, whereas their classmates submit approximately 19.4. These numbers suggest that the course-level activity of Uber-students is also similar to those of their peers when considering overall course-level information.

The bottom panel of Table 3 shows that Uber-students have a 76% passing rate and average course grades of 2.49.[14] Unlike activity, these measures of academic performance are somewhat worse compared to their peers (i.e., a passing rate of 83% and an average grade of 2.70).[15] However, these differences are somewhat expected given that enrolled Uber-

[14]The average course pass rate of the Uber-students in their top 10 most popular classes is also very similar to those observed for in-person students in those same classes. If dropping out is defined as not being enrolled for two consecutive terms, we find that 29% of the Uber-students have left the program, while for in-person students, according to ASU facts (https/facts.asu.edu), the first-year retention rate is 86% (for full-time students), and the 4-year (6-year) graduation rate is 55.4% (67.6%).

[15]Appendix Table F3 also presents summary statistics regarding the progress of Uber-students and their class peers (i.e., cumulative GPA, and credits to date). Additionally, Appendix Table F4 presents the same summary statistics as in Table 3, but when we re-weight the "Class Peers" to be more similar to the Uber-

students, on average, are from less advantaged backgrounds and have substantially lower prior academic credentials. In light of the evidence presented in this table, the higher levels of engagement presented in Table 2 could be interpreted as Uber-students exerting more effort to catch up with the course material.

Overall, the main takeaway from these summary statistics is that Uber-students, despite coming from more disadvantaged backgrounds than their class peers, have only slightly lower course completion rates and grades but somewhat higher levels of engagement in learning activities than their classmates.

3.1.2 Variation in Weekly Canvas Engagement

To further characterize the variation in weekly course effort, we perform an event study style analysis focusing on Uber-student Canvas hours.[16] In particular, we analyze how study time in the different weeks of the term compares to the third week before the beginning of the academic semester.[17]

The results corresponding to eight-week-long courses (which is the modal course length) are presented in Figure 1. As expected, leading up to the beginning of the course, Canvas

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students on observables. Once re-weighting, the differences in activity across groups attenuate considerably.

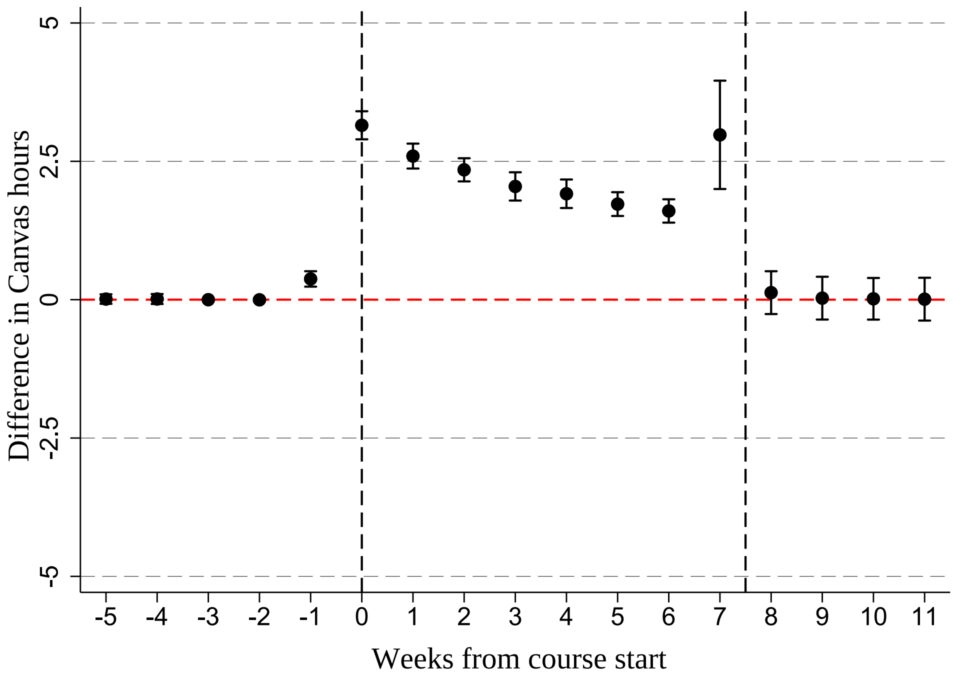
[16]This analysis only intends to show the variation in the data, so it does not constitute a proper event study analysis because we are not including a control group.

[17]We estimate a specification of the following form:

$$CourseE_{i,c,t} = \sum_{\substack{y=-5 \\ y\neq -3}}^{T} \alpha_t \mathbb{I}(t - t^* = y) + \beta_1 \sum CourseWork_{i,t,-c} + \beta_2 MarketHourlyPay_{l,t} + \\ \beta_3 Weather_{l,t} + X_{i,t}\Phi + \psi_i + \delta_m + \phi_c + \varepsilon_{i,t}, \tag{1}$$

where $CourseE_{i,c,t}$ is Canvas hours for Uber-student i, taking course c, in week t. $CourseWork_{i,t,-c}$ captures course peer activities in the other courses ($-c$) in which the student is enrolled (controlling or not for this variable provides very similar results). The vector $X_{i,t}$ includes controls for the number of course days in the week and if the week includes Christmas. ψ_i, δ_m, and ϕ_c denote individual, month-year and classroom fixed effects. $MarketHourlyPay_{l,t}$ and $Weather_{l,t}$ denote the average market-level hourly pay and second-order polynomials of rainfall and snowfall, respectively, in the labor market l for individual i in week t. $\eta_{i,t}$ corresponds to the idiosyncratic shock. Finally, $I(t - t^* = y)$ denotes indicators for the week of the course, y, where t^* is the first week of the course ($y = 0$). The excluded week is the week that is three weeks prior to the start of the course. Thus, each $\hat{\alpha}_t$ corresponds to the conditional mean of $CourseE_{i,t}$ for each week t (relative to the third week prior to the course start). Section 5 discusses the rationale for this specification. To appropriately capture the evolution of driving hours and study hours, we exclude individuals who drop out or withdraw at some point during the course.

Figure 1: Variation in study time during eight weeks courses



Notes:—OLS coefficient estimates from a version of Equation (1) where the dependent variable is hours on Canvas and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

hours are essentially zero.[18] Hours spike to roughly 3 hours per week in the first week of class but decline monotonically throughout the course until the final week, where hours on Canvas spike again. Taken together, the results presented in Figure 1 suggest that students front-load study time as they adjust to the course (and perhaps the Canvas environment) and then taper down their Canvas activity each week until the final week of the term when they increase substantially, most likely reflecting students' preparation for final exams.

3.2 Uber Data

The Uber driver data include background characteristics and individual weekly driving activity corresponding to two groups of drivers: Uber-students and a random sample of drivers that qualify to participate in the ASU-Uber partnership program but did not enroll (henceforth, Uber peers). Additionally, we have access to city-level labor market characteristics and weather conditions.[19]

3.2.1 Characterizing ASU-Uber Drivers

Background Characteristics Table 4 shows how Uber-students compare with Uber peers; Uber peers are drivers who quailify for the ASU-Uber program but do not enroll in ASU courses. Uber-students are, on average, more likely to be female and younger than their Uber peers. They are also less diverse in terms of language spoken (i.e., almost none speak Spanish) and more likely to work in Arizona than their driving counterparts (i.e., 6% vs. 2%). The bottom panel of this table also indicates that Uber-students have longer Uber tenures than their peers. In particular, they have been driving for more than 128 weeks, and during 78% of those weeks (i.e., 100 weeks), they have been active on the Uber platform. On average, they have completed more than 8,100 trips, indicating an important degree of

[18] The point estimate for the week -1 is slightly above zero because some classes allow students to access the Canvas page the week before class begins (i.e., some students have non-zero Canvas hours in week -1). This is why we set week -3 as the baseline.

[19] The drivers in our sample work in 111 distinct geographic regions/cities across the United States. Information on weather conditions was downloaded from the PRISM Climate Group at Oregon State University.

Table 4: Driver-level observables, by sample

	(1)		(2)		(3)
	Uber-Students		Uber Peers		Col (1) - (2)
	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Background Characteristics					
Female	0.15	0.353	0.10	0.300	0.05^{***}
Age†	43.74	10.68	50.63	12.83	-6.89^{***}
English	0.99	0.072	0.91	0.292	0.09^{***}
Spanish	0.00	0.051	0.07	0.254	-0.07^{***}
Ever driven in AZ	0.06	0.237	0.02	0.149	0.04^{***}
Uber activity					
Weeks in Uber data	128.91	27.568	111.75	37.757	17.16^{***}
Active weeks in Uber data (%)	0.79	0.159	0.81	0.170	-0.02^{***}
Lifetime completed trips	8118.40	4554.433	7798.29	4732.587	320.11^{***}
Lifetime average rating	4.92	0.039	4.90	0.050	0.02^{***}
Observations	1540		96513		

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Uber peers" corresponds to drivers that qualify to participate in the ASU-Uber partnership, but do not enroll in ASU courses. †Age is based on the decade of birth rather than the actual year of birth, as reported in Table 1 (this is how Uber released this information). English and Spanish refer to the primary language spoken by the driver, "active weeks" refer to weeks where driving hours were non-zero, and "lifetime" refers to the driver's entire driving history. "Lifetime average ratings" range from zero to five. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

attachment to driving with Uber. Overall, these drivers' activity levels are large enough to suggest that Uber is likely a main source of income. Finally, Uber-students have, on average, high Uber ratings consistent with the eligibility requirements of the ASU-Uber program.[20]

Weekly Driving Engagement Table 5 shows weekly summary statistics on driving engagement when Uber-students are enrolled in classes at ASU. The top panel of Table 5 shows that, on average, Uber-students work (i.e., stay connected to the Uber platform) 18.25 hours per week and complete 36.62 trips.[21] The bottom panel of the table indicates that Uber-students earn roughly $442 each week and that their earnings per trip (hour) is $12.37 ($24.26).[22] The final rows of Table 5 show that tips account for approximately 10%

[20] Our final sample of Uber drivers participating in the program is relatively small. We believe this is partly because our analysis is limited to a period when the program was less known.

[21] Note that this measure of Uber hours includes both active (i.e., driving to pick up a ride or completing a ride) and inactive (i.e., waiting for a pick up request) time. In the individual-level data, we are only able to observe total time.

[22] Analogous summary statistics for Uber peers cannot be shown as it is considered sensitive information by Uber.

Table 5: Weekly Uber-student driving activity

	Mean	Std. Dev.
Activity and trips		
Hours online	18.25	(17.29)
Completed trips	36.62	(35.74)
Uber earnings		
Weekly earnings	442.21	(461.71)
Earnings per trip	12.37	(5.67)
Earnings per hour	24.26	(9.89)
Tips per trip	1.12	(1.10)
Tips per hour	2.20	(2.25)
Average weekly rating	4.94	(0.13)
Observations	28896	

Note: Sample is limited to weeks in which drivers are enrolled in ASU classes. The variables "hours online", "completed trips", and "weekly earnings" include zeros for weeks that the drivers were inactive on the Uber platform. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

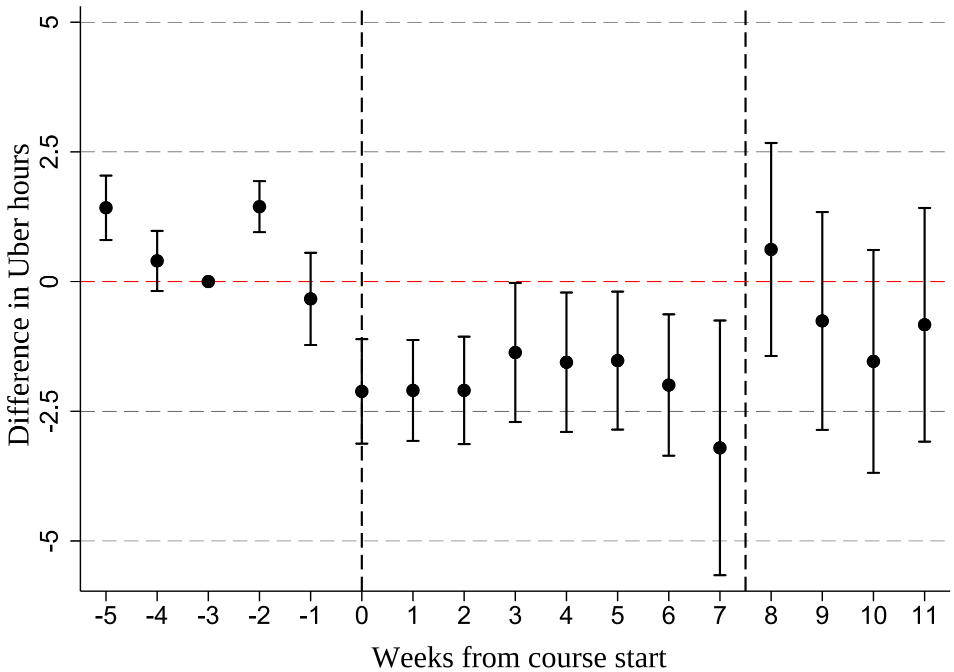
of Uber-students' earnings per trip or hour and that these drivers maintain exceptionally high ratings. To conclude, Appendix Table F5 shows the correlation between Uber activity (i.e., completed trips, time on the Uber platform) and total pay, incentive pay, and tips, indicating that hours online and completed trips are highly correlated, suggesting that idle time in the Uber platform is likely not a meaningful concern.

3.2.2 Variation in Weekly Uber Driving

As with study time, we augment the summary statistics in Table 5 by examining the evolution of driving hours throughout the course. To do this, we estimate an event-study style specification, where the baseline week corresponds to the third week before a course begins.[23] Figure 2 displays the coefficients corresponding to the week of the course on driving hours in eight-week-long courses. We find that as drivers approach the beginning of a course, their driving hours seem to slightly taper off in week -1 and then drop by roughly two hours per week once the course starts. The decline in driving hours remains fairly constant across

[23] The empirical specification follows eq. (6) described in Section 5, but replacing the covariate associated with coursework with indicators referring to the week of the semester (in a similar fashion as in eq. (1)).

Figure 2: Variation in driving hours during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is hours on the Uber platform and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

the semester, with an additional decline in hours (slightly over 2.5 hours per week) in the course's final week, which is when students prepare for exams. After the course ends, driving behavior is no longer statistically significantly different than pre-course levels. Interestingly, these results are consistent with our previous findings: we see that the increase in Canvas hours shown in Figure 1 is somewhat mirrored by a decrease in hours spent driving in Figure 2.

3.3 Survey Data

All participants of the ASU-Uber program enrolled in Arizona State University's online courses in November 2023 received an email invitation to participate in our survey. This invitation was also extended to a randomly selected, equal number of their course peers.

The survey aimed to collect data on students' demographic backgrounds, previous academic experiences, expectations for college and labor market outcomes, time allocation outside the online platforms, and their willingness to pay for flexible learning and working options. As an incentive for participation, respondents entered into a lottery, offering a chance to win one of 250 $15 Amazon gift cards or one of 10 $100 Amazon gift cards. A total of 692 students responded to the survey, including 243 Uber-students, 105 family members of Uber drivers benefiting from the program, and 344 classroom peers. We exclude the responses of family members from the analysis. The median time taken to complete the survey was 22 minutes.

Appendix Table F6 presents a comparison of the demographics and field of study between Uber-students (excluding family members) in our survey sample and those recorded in the administrative data (i.e., platform data). This comparative analysis reveals that the demographic characteristics of the two groups are similar. The primary deviation is observed in the female participation rate. However, this discrepancy arises because the survey also encompasses courier drivers, representing a more gender-balanced group.

While the primary aim of the survey was to evaluate the extent to which students value flexible learning and working formats, and to understand the program's impact on educational attainment and labor market outcomes, the survey also sought to determine the proportion of study time Uber-students spend on the platforms and whether they drive for other ride-sharing services. Survey results reveal that 77% of the Uber-students' study time is conducted on the Canvas platform, and they dedicate over 83% of their ridesharing hours exclusively to Uber. These shares are consistent with Hyman et al. (2020), which shows that less than one-third of drivers use both the Uber and Lyft platforms in Seattle. These statistics suggest a strong correlation between the students' learning time and ridesharing activities and the data captured on the platforms.

4 Analytical Framework

In this section, we lay out a simple model where agents have to balance effort between working and learning activities in a changing environment (i.e., incentives may vary across weeks). While the model is highly stylized, it provides an economic justification for our empirical specifications presented in Section 5, and it will also allow us to quantitatively characterize how performing learning and working activities simultaneously impact the marginal cost of effort of each activity (in Section 7).

Agents' Maximization Problem Equation (2) poses the problem of the agent. Individual i has linear preferences at time t (i.e., week) over earnings and academic performance, where α denotes the weight assigned to each component. Earnings are determined by the wage rate at time t and work effort (i.e., driving hours or trips completed), $w_t e_{ilt}$, while academic performance is represented by coursework grades, G_{it} (e.g., weekly college homework assignments, mid-term exams, etc.), at time t. In Equation (3), we define G_{it} as a function of individual-specific college effort, e_{ict} (i.e., study time); ability (Ab_i); and the level of difficulty of college activities (ς_t) in a given period. More formally, $G_{it} = f_i(e_{ict}, Ab_i, \varsigma_t)$. This linear specification of grades allows for (positive) complementarities in the production of grades between ability and college effort, and between course difficulty and college effort.

For an agent, exerting effort is costly and varies by type of activity, where λ_l and λ_c determine the cost associated with each type of effort. Finally, the model allows for (negative) complementarities in the cost of effort. For example, an additional working hour could be more costly (λ_{lc}) in weeks when the agent exerts more effort in college activities (e.g., driving an extra hour may be more daunting in weeks when college assignments have been more time-consuming). Finally, the additional constraints reflect basic/intuitive restrictions on α and the λs. Given these preferences, the problem of the agent is to choose the optimal vectors of effort in each activity $(\mathbf{e}^*_{ic}, \mathbf{e}^*_{il})$.[24]

$$\max_{\mathbf{e}^*_{il}, \mathbf{e}^*_{ic}} \sum_{t=1}^{T} \Big(\alpha w_t e_{ilt} + (1-\alpha) G_{it} \Big) - \lambda_l \sum_{t=1}^{T} e^2_{ilt} - \lambda_c \sum_{t=1}^{T} e^2_{ict} - \underbrace{\lambda_{lc} \sum_{t=1}^{T} e_{ilt} e_{ict}}_{\substack{\text{Neg. complementarities of effort} \\ \text{btwn. work and college activities}}}, \tag{2}$$

where

$$G_{it} = \beta_0 + \beta_1 e_{ict} + \beta_2 Ab_i + \beta_3 e_{ict} Ab_i + \beta_4 \varsigma_t + \beta_5 e_{ict} \varsigma_t + \varepsilon_{it} \tag{3}$$

$$\alpha \in [0,1]$$

$$\lambda_l \geq 0, \lambda_c \geq 0, \lambda_{lc} \geq 0.$$

Optimal Effort The solution to the agent's problem is straightforward when we specify a linear production function for grades as in Eq. (3). The first-order-conditions of the agent's problem imply that the optimal levels of work and study effort satisfy:

$$e^*_{ilt} = \frac{(\alpha-1)\lambda_{lc}[\beta_1 + \beta_3 Ab_i + \beta_5 \varsigma_t] + 2\alpha\lambda_c w_t}{4\lambda_c\lambda_l - \lambda^2_{lc}} \tag{4}$$

$$e^*_{ict} = \frac{2(1-\alpha)\lambda_l[\beta_1 + \beta_3 Ab_i + \beta_5 \varsigma_t] - \alpha\lambda_{lc} w_t}{4\lambda_c\lambda_l - \lambda^2_{lc}}. \tag{5}$$

Equations (4) and (5), while simple, are appealing and informative in several important ways. First, given that w_t and ς_t change at a high frequency in our context, incentives to exert effort on learning and working activities are likely to vary periodically. For example, as expected, the model predicts that a wage increase, $\uparrow w_t$, leads to an increase (decrease) in work (study) effort, while more demanding weeks of class, $\uparrow \varsigma_t$, lead to a likely decrease

[24] As mentioned earlier, the goal of the model is to provide a framework to guide the empirical specification. Thus, the model is simplified along several dimensions. For example, the decision of each period is treated as static in nature. Similarly, Uber earnings are taken as given, and we do not allow for the possibility that individuals may strategically decide to drive at times within the week with higher rates. The last simplification is partly also made because we only observe Uber earnings at the weekly level.

(increase) in work (study) effort.[25] The fact that, in most settings, it is not possible to directly observe effort in different activities makes our empirical context appealing to understand optimal effort decisions. Equations (4) and (5) also clarify that the solution to an agent's maximization problem only depends on exogenous variables that are independent of the agent's choices. This shows that it would be inconsistent with this type of economic model to empirically specify individual work effort as a function of individual college effort (regardless of the presence of instruments that could allow us to circumvent concerns of endogeneity).[26]

5 Empirical Strategy

Our baseline empirical approach has three fundamental goals. First, we intend to determine the impact of college coursework on labor supply. This will allow us to quantify the short-run opportunity costs that students face when taking classes in terms of forgone earnings. To the best of our knowledge, this is the first paper to estimate this elasticity. Second, we aim to assess the effect of labor market conditions on course engagement. While many studies have determined how working hours affect academic performance, little is known about the role of transitory changes in labor market conditions on course activity and engagement. Finally, we study the impact of work and study effort on weekly and course-level academic performance.

5.1 The Impact of Learning Activities on Labor Market Supply

We rely on weekly individual-level data on driving and college engagement to uncover the effect of overall college coursework on labor supply. Our baseline specification, which is

[25] It is expected that β_3 and β_5 are positive due to likely positive complementarities between effort and ability/college activities' difficulty.

[26] Wooldridge (2015) provides a discussion on this point. In particular, Wooldridge (2015) argues that an improper use of simultaneous equations models would be to model weekly hours spent studying and weekly hours working. Each student chooses these variables simultaneously as a function of the wage that can be earned working, ability as a student, etc. Therefore, it is incorrect to specify two equations where each is a function of the other.

motivated by Equation (4), is as follows:

$$WorkE_{i,t} = \beta_0 + \beta_1 \sum_c CourseWork_{c,t} + \beta_2 MarketHourlyPay_{l(i),t} \\ + \beta_3 Weather_{l(i),t} + \psi_i + \delta_m + \phi_b + \epsilon_{i,t}, \tag{6}$$

where $WorkE_{i,t}$ denotes work effort/labor supply for individual i in week t. In our setting, we measure work effort as either total (i.e., active and inactive) hours connected to the Uber platform or completed trips. $CourseWork_{c,t}$ corresponds to the intensity of weekly activities in course c, which is captured by the weekly average hours that course peers stay connected to Canvas. Note that we sum $CourseWork_{c,t}$ across all the courses c in which the Uber-student is enrolled in week t. $MarketHourlyPay_{l(i),t}$ denotes average active hourly pay for all drivers in week t and city l who are eligible for the ASU program but do not enroll, capturing labor market conditions at the location level.[27] $Weather_{l(i),t}$ controls for precipitation and temperature in order to account for shocks that could simultaneously affect labor supply and Uber earnings. ψ_i is an individual fixed-effect that captures driver and city-level unobserved heterogeneity.[28] δ_m is a month-year fixed effect that accounts for seasonality in the labor market and ϕ_b corresponds to fixed effects representing the bundle of courses in which the student is enrolled in each term.[29] Finally, $\epsilon_{i,t}$ represents an idiosyncratic shock.

The main coefficient of interest is β_1, which indicates how college activities impact labor market productivity/supply, characterizing short-run opportunity costs of attending college.

[27]Market level average active hourly pay is determined by dividing average total earnings by the average number of active driving hours for the peer drivers in a given city-week. In addition to active hours, we also observe average inactive hours (i.e., including idle time) on the Uber platform at the city-week level which allows us to construct a measure of market-level hourly pay that accounts for idle time. Our results are robust to using either definition of market-level pay, but we prefer active hourly pay because we think this is the more salient measure of compensation for drivers. There is substantial variation in market-level weekly hourly pay, where the standard deviation of this variable is \$5.5 in the sample. In addition, there is considerable variation across cities, as well as within cities across weeks. The standard deviation in weekly hourly pay across cities is \$4.3, and within cities across weeks is \$3.5.

[28]Individual fixed effects also serve to account for students' study time outside the ASU platform, operating under the assumption that the ratio of study time apportioned within and outside the ASU online platforms remains stable across weeks.

[29]In the data, a large proportion of students share the same bundle of courses. Moreover, we also exploit differences in the bundle of courses across semesters within individuals.

Our key identifying assumption is that once conditioning on individual, course-bundle, and month-year fixed effects, the variation in weekly Canvas activity of ASU-Online peers represents exogenous changes in college activities/tasks. Given the time spans used in the analysis, we believe the assumption of time-invariant individual characteristics is quite reasonable. Finally, given that we exploit individual-level variation within college terms, the usual concern in this literature regarding the role of pre-college enrollment disengagement effects is not likely to be relevant in our setting. We also estimate more robust specifications that include city-week fixed effects. However, such an empirical model prevents the identification of β_2.

Our estimate of β_2, while not the object of study, reflects the responsiveness of labor supply to changes in average hourly earnings across weeks at the market level. The identification of this parameter requires slightly stronger assumptions. In particular, it is necessary to impose orthogonality between unobserved factors impacting weekly city-level earnings and worker i's labor supply. The main instance in which this condition may not hold is when weather conditions (e.g., precipitation) affect both hourly pay (through demand) and the desire of drivers to spend time on the road (driving on rainy days may be more inconvenient). As a result, we have included controls for weekly average precipitation and temperature to avoid this concern.[30] The residual weekly variation in market hourly pay, after controlling for weather conditions and seasonality, is arguably coming from idiosyncratic factors. For example, one would expect the hourly pay to be higher in weeks when a city is hosting a conference or an event that brings out-of-town people into the city, increasing demand for rideshare services. This is the variation that presumably allows us to identify β_2. In fact, we check for this directly by merging local weekly-level hotel vacancy data with our main dataset. These data were obtained from the STR INC., a recognized leader in hotel indus-

[30]Though not a threat to identification per se, including student-drivers who have dropped out of their courses in our sample could complicate our interpretations of $\hat{\beta}_1$ and $\hat{\beta}_2$. As a robustness check, we also estimate our main regression specifications on a subset of the sample that excludes likely dropouts. We determine likely dropouts based on their final course grades (e.g., incomplete or withdrawals) and their activity. Specifically, if a student receives a failing grade, an incomplete, or a withdrawal *and* has a spell of inactivity for at least the final three weeks of the course, we consider them a likely dropout. Directly excluding these individuals has little effect on our coefficient estimates. See Appendix A.1 for more details on this point.

try analytics. In Appendix B, we show that the variation in market hourly pay is, in fact, (statistically and economically) significantly related to variation in local hotel vacancy data. More specifically, we find that a one standard deviation change in local hotel vacancy rates is associated with a 0.25 standard deviation change in local market hourly pay.

5.2 The Impact of Labor Market Conditions on College Effort

As with our main estimating equation for the effect of earnings and coursework on hours driving, we derive our baseline specification to identify the impact of labor market conditions and coursework on student effort from Equation (5) of the analytical model. The primary estimating equation is:

$$\begin{aligned} CourseE_{i,c,t} &= \delta_0 + \delta_1 CourseWork_{i,t,c} + \delta_2 \sum_{-c} CourseWork_{i,t,-c} \\ &+ \delta_3 MarketHourlyPay_{l(i),t} + \delta_4 Weather_{l(i),t} + \delta_5 X_{c,t} + \pi_i + \alpha_m + \rho_c + \eta_{i,c,t}, \end{aligned} \tag{7}$$

where $CourseE_{i,c,t}$ denotes course level effort of student i on class c during week t.[31] Course effort is captured by the number of weekly hours the student spends on Canvas, the weekly number of clicks, or logins in course c. $CourseWork_{i,t,c}$ measures course activities in course c captured by the number of Canvas hours, clicks, or logins of the peers in the class, while $CourseWork_{i,t,-c}$ also captures course peer activities but in the other courses ($-c$) in which the student is enrolled in. $X_{c,t}$ denotes number of course days in the week and π_i, α_m, and ρ_c denote individual, month-year and classroom fixed effects.[32] Finally, $MarketHourlyPay_{l(i),t}$ and $Weather_{l(i),t}$ have the same definition as in Equation (6). Note that this specification controls for classroom fixed effects rather than for bundle of courses, where a classroom is defined as a given course with a given instructor in a given term. $\eta_{i,t}$ corresponds to the

[31] While the previous specification relies on observations at the individual-week-level, this specification involves observations at the individual-course-week-level.

[32] We include the number of course days in the week as a control because some weeks of class (such as the first and final weeks of the course) do not start on Monday or end on Friday. As a result, Canvas activity is, in a sense, mechanically lower due to fewer days of potential activity.

idiosyncratic shock.

The parameter of interest from this empirical model is δ_3, which indicates how sensitive college effort is to labor market conditions. The implicit assumption is that conditional on the vector of fixed effects, observables, and weather conditions; we identify the reduced-form effect of Uber pay rates on course effort. As a robustness check, we implement a placebo test (in Table 7) to test for the validity of our identifying assumption.

5.3 The Effect of Labor Market Effort on Academic Performance

Finally, we study how work effort and labor market conditions impact academic performance. To this end, we propose three specifications. First, we analyze the direct effect of Uber driving hours on course grades by estimating the following equation:

$$CourseG_{i,c} = \gamma_0 + \gamma_1 f(\textstyle\sum_t WorkE_{i,t}) + \psi_i + \phi_c + \delta_{instr} + \pi_{term} + \eta_{i,c}, \tag{8}$$

where $CourseG_{i,c}$ denotes student i's final grade in course c. ψ_i, ϕ_c, δ_{instr}, and π_{term} denote individual, course (e.g., ECN 101), instructor, and term (e.g., Fall 2021) fixed effects, respectively. $WorkE_{i,t}$ denotes Uber work hours in week t, where the sum is over the total number of weeks in the academic term, and f corresponds to a flexible function. Due to the inclusion of individual fixed effects, variation in performance across academic terms (i.e., 7 to 8 weeks) identifies the effects of work effort on course grades.

A key threat to identification in the model presented in Equation (8) arises if work hours are endogenous to a student's particular ability in a course (i.e., courses in which a student is particularly capable may have high driving hours and high achievement). In order to address this concern, we adopt an instrumental variables (IV) strategy, where we instrument an individual's total driving hours throughout the course with the average market-level hourly pay for drivers who were eligible for the ASU-Uber program but did not enroll, averaged across all course weeks. The intuition of the instrument is that market-level earnings should induce variation in a given student's driving time but are otherwise exogenous to course outcomes.

Second, we assess the impact of labor market conditions on academic performance by estimating a similar specification as in eq.(8), but replacing work effort with college effort.[33] By doing so, we can combine the estimates on college effort from this specification with those obtained from eq.(7) to provide a back-of-the-envelope calculation of the effect of labor market hourly pay on academic performance through its impact on course effort. As with work effort, it is likely that study time is endogenously determined by course outcomes. Again, we account for this by instrumenting an individual student's total Canvas time throughout the course with the average total Canvas hours of their non-Uber peers.

Third, we explore how weekly effort translates into weekly course performance. To do so, we estimate versions of the following regression specification:

$$PointShare_{i,t} = \pi_0 + \pi_1 WorkHours_{i,t} + \pi_2 Weather_{l(i),t} + \pi_3 X_{i,t} + \psi_i + \delta_m + \phi_c + \varepsilon_{i,t}, \quad (9)$$

where $PointShare_{i,t}$ refers to the share of points (out of 100) that student i earned in week t relative to the total number of points they could have possibly earned; $WorkHours_{i,t}$ are the total number of hours (active and inactive) that a driver spent on the Uber platform in a week; $Weather$ denotes the standard set of weather controls; $X_{i,t}$ is a set of indicator variables that account for (i) the number of days in the course week, and (ii) an indicator if there were no possible points to earn in a given week.[34] The remaining controls: ψ_i, δ_m, and ϕ_c are individual, month-year, and classroom fixed-effects, respectively. Similarly to looking at overall course outcomes, we also investigate the role of study effort on weekly course performance by estimating a version of Equation (9), but where we include Canvas hours instead of driving hours. In both cases, we also estimate IV specifications that attempt to

[33] College effort is a mediating variable for the effect of work effort on academic performance. Therefore, the effect of work effort on academic performance once conditioning on study effort is expected to be close to zero.

[34] We code weeks with no possible points as receiving the maximum share, but the results are robust to excluding those weeks, or coding them as the minimum share.

account for potential simultaneity between work or study effort and weekly course outcomes, where we use the week-level analogs to the instruments outlined above (i.e., average market-level earnings and average peer Canvas hours for each week).

6 Results

6.1 Course Work and Labor Market Supply

Table 6 shows the estimates corresponding to Equation (6), i.e., how college activity impacts hours driven and completed trips. Columns (1) and (4) indicate that a 10% increase in average learning activities decreases average driving time or completed trips by approximately 1% (reported at the bottom of the table). Considering that, on average, peers are engaged 2.45 hours per week on the Canvas platform, our estimates imply that the average Uber-student decreases driving time by approximately 1.7 hours (-0.680 $\times$ 2.45) each week due to coursework.[35] Coupled with the fact that Uber-students earn roughly $24 per hour, we interpret these findings as suggesting that the average short-run opportunity cost of college enrollment is approximately $41 per week or $180 per month. Columns (2)-(3) and (5)-(6) show that our estimates are robust to controlling for weather conditions or city-week fixed effects.[36,37] Appendix Table F7 shows that further controlling for leads and lags of the independent variables (i.e., the prior and following weeks) does not meaningfully change the effect of study hours on work effort. This is somewhat expected, given that our baseline specifications already control for individual fixed effects.

Finally, the estimates corresponding to labor market conditions presented in Table 6 (which should be interpreted with some caution per the discussion in Section 5.1) show that

[35] Projecting peers' Canvas hours onto Uber-students' actual Canvas hours yields a coefficient close to 1.

[36] The number of observations varies slightly across columns because weather data are not available for some cities. In addition, for some city-weeks, there is only one observation; specifications with city-week FEs drop such cases.

[37] Given the city-week fixed-effects included in our specifications for Columns (3) and (6), we are somewhat limiting the level of identifying variation available. Reassuringly, though, we see that there are, on average, 26 observations in each city-week (ranging from 2 to 73 observations per city-week).

Table 6: Determinants of work effort

	(1) Work Hours	(2) Work Hours	(3) Work Hours	(4) Completed Trips	(5) Completed Trips	(6) Completed Trips
Sum of avg. study hours across all c, peers	-0.680***	-0.678***	-0.667***	-1.283***	-1.279***	-1.311***
	(0.071)	(0.072)	(0.100)	(0.146)	(0.146)	(0.205)
Market level active hourly pay, currently elig.	0.122**	0.132**	-	0.351**	0.381**	-
	(0.051)	(0.051)		(0.112)	(0.113)	
Obs.	27475	27404	26265	27475	27404	26265
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Course Bundle Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓		✓	✓	
Weather controls		✓			✓	
City-Week FE			✓			✓
Mean dep. var.	18.24	18.21	18.39	36.52	36.48	36.78
Market level active hourly pay, peers	33.62	33.61		33.6	33.6	
Sum avg. study hours all c, peers	2.45	2.45	2.46	2.45	2.45	2.46
Mean hourly earnings	24.23	24.22	24.38	24.23	24.22	24.38
Mean pay-per-trip	12.37	12.37	12.46	12.37	12.37	12.46
Elasticity w.r.t. peer coursework	-0.091	-0.062	-0.089	-0.086	-0.086	-0.088
Elasticity w.r.t. peer earnings	0.225	0.244		0.323	0.351	

Note: The dependent variables for Columns (1) to (3) and Columns (4) to (6) are weekly work hours and weekly completed trips, respectively. The variable "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. The variable "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Elasticities are calculated by multiplying the relevant coefficient estimates by the ratio of mean peer coursework or market-level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

a $1 increase on average hourly pay increases average weekly Uber hours by 0.122 hours (i.e., 7.3 minutes) or 0.35 trips per week.[38] If we consider that the average *active* hourly pay of drivers that do not attend ASU is $33.60, and that the average weekly driving time among Uber-students is 18.24 hours, then a 10% increase in average hourly pay leads to an increase in driving time (trips) of roughly 2.3% (3.2%). Caldwell and Oehlsen (2022) finds that the Frisch elasticity for Uber male drivers (our sample is overwhelmingly male) is 4%, which is higher than the elasticity we estimate. However, two reasons could explain the differences in findings. First, Caldwell and Oehlsen (2022) estimates labor supply elasticities using random variation generated by an experiment that allowed drivers to work for one week with 10-50% higher earnings per trip. Given that the experiment explicitly highlighted the possible gains from additional driving hours, we expect drivers to be more responsive in their labor supply in this context. Second, our sample of drivers tends to have a stronger attachment to work (i.e., they consistently drive more hours per week than the average Uber driver), likely making them less responsive to changes in market hourly pay.[39]

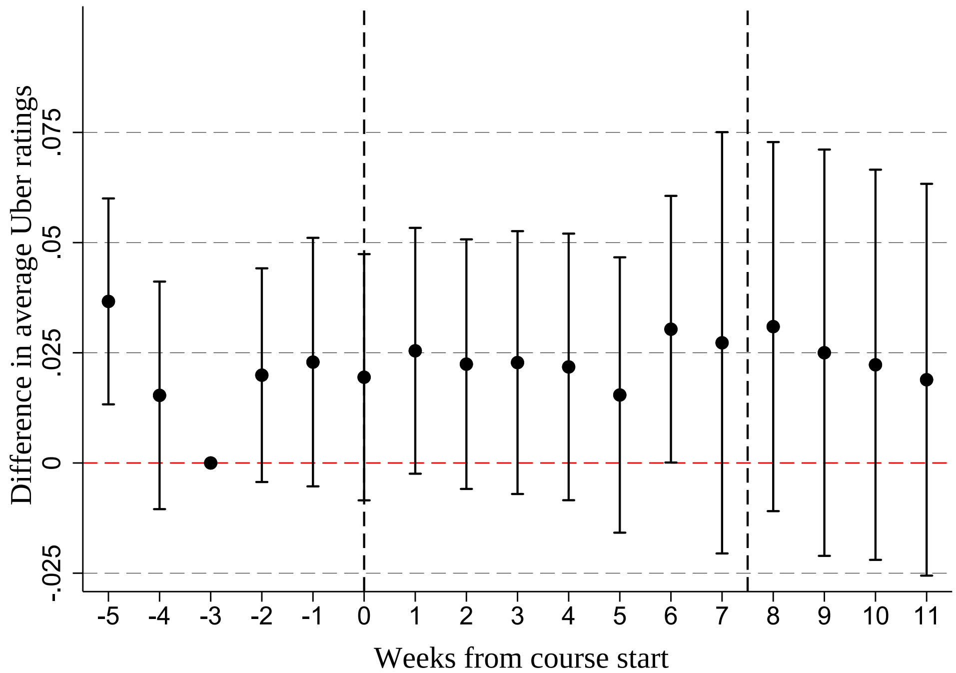
Our data also allows us to analyze whether the quality of the service that drivers offer is affected by college activities. To this end, we performed a similar event study style analysis as in Section 3.1 but included as dependent variables the ratings the drivers received from their passengers and the share of income from tips. Figure 3 shows no negative impact on ratings, while appendix Figure G1 shows a small drop in the fraction of earnings coming from tips, but the economic impact is extremely small (a decrease of 1 percentage point in the share). Thus, we conclude that college activities have no meaningful impact on the quality of service.

Overall, our findings indicate that the "short run" opportunity cost of attending college in this context is small (∼$180 per month) relative to the average earnings that Uber-students

[38] The top subfigures of Appendix Figure G2 present the distribution of the labor supply elasticity w.r.t course work and earnings (i.e., calculated based on the average course work and market-level hourly earnings of each Uber-student).

[39] This difference in labor supply elasticity does not appear to be specific to Uber drivers in the Uber-ASU program. We estimate an elasticity of 2.7% for a sample of non-ASU Uber drivers who were eligible for the program but never enrolled.

Figure 3: Variation in driver ratings during eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is average driver rating and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

make when taking classes at ASU (∼\$2,200 per month). Additionally, we do not observe any meaningful negative impact of college activities on the quality of work performed.

6.2 Labor Market Conditions and Study Effort

Table 7 presents results from estimating the effects of labor market conditions and college course demand on Uber-students Canvas hours. Evidence on how variation in weekly earnings impacts study effort is scarce. Thus, the estimates in Table 7 are unique in that they quantify the extent to which Uber-students are willing to sacrifice study time for higher income in the short run. Column (1) shows that a \$1 increase in average hourly pay decreases study hours by less than a minute, or in other terms, a 10% increase in average hourly pay leads to a decrease in study time for the mean Uber-student of approximately 1.7% per course; note that we describe the results in minutes rather than hours (which is the unit of the dependent variable) to ease interpretation. Therefore, this finding suggests that study time is not highly sensitive to changes in labor market conditions.[40] However, this result could be specific to our context, given that flexibility may allow drivers to spend more time on the Uber platform when earnings are high without meaningfully decreasing their study time. We also find that average peer Canvas hours have a nearly one-to-one relationship with Uber-student study hours, suggesting that our measure of course demand effectively captures the variation in college work across weeks.[41] Surprisingly, we do not find much evidence of crowding out between courses, given that an increase in coursework demand in other courses, $-c$, does not impact study time in course c. Column (2) performs a similar analysis as in column (1), but instead of including peer hours on Canvas, we measure coursework demand by the number of assignments in a given week in course c. Results show that having an additional assignment increases weekly average study hours in course c (i.e., 1.58 hours) by around 3% (i.e., 0.046/1.58).

Finally, Column (3) presents results from a placebo test to check the extent to which market-level hourly pay may be capturing some unobserved shock that is not captured by our controls. For example, suppose weather conditions (which we control for) simultaneously affect study hours and earnings. In that case, we should observe a mechanical correlation between Uber's market hourly pay and study hours for students who do not drive with Uber. To this end, we repeat the specification in Column (1) but on the sample of students attending ASU-Online classes but not participating in the Uber-ASU program. Reassuringly,

[40] To provide a comparison–albeit an imperfect one–to our findings, the study by Lee (2020) shows that a 10% increase in the minimum wage leads to a 5.2% decline in part-time enrollment at community colleges. However, this increase in minimum wage seemingly has a negligible and statistically insignificant impact on full-time enrollments. Contrarily, research by Alessandrini and Milla (2021) indicates that a 10% rise in the minimum wage leads to a 1% decline in post-secondary enrollments. However, this overall effect obscures substantial underlying heterogeneity. Specifically, a 10% enhancement in minimum wage is associated with a 5% reduction in university enrollments while simultaneously inducing a 6% increase in enrollments at community colleges.

[41] The bottom subfigures of Appendix Figure G2 present the distribution of course effort elasticity w.r.t course work and earnings (i.e., calculated based on the average course work and earnings of each Uber-student).

we find a coefficient of zero for these students. To conclude, Appendix Table F8 presents results where we further control for leads and lags of the independent variables to understand how this would impact the effects reported in Table 7 (i.e., current effects at time t). We find that the coefficients remain quite robust across specifications.[42]

6.3 Heterogeneous Effects

Next, we examine whether changes in coursework loads and labor market conditions lead to differential responses based on Uber-students' observable characteristics. In particular, we consider i) full-time or part-time driver status, since time constraints may be more binding for full-time drivers; ii) field of study, since certain majors may be more demanding than others; iii) gender, as prior literature demonstrates that labor supply choices may differ by the gender of the driver (Cook et al., 2021; Caldwell and Oehlsen, 2022); iv) financial need status, since labor supply may be more inelastic to changes in coursework demand for this group; v) incoming academic performance (above- vs. below-median incoming GPA), as certain students may be more responsive to coursework demands; and vi) age (under 35 vs. 35 or older), given that schedule flexibility may differ by age (because of family responsibilities etc.).[43]

Panels A and B of Table 8 present results from re-estimating equations (6) (i.e., labor supply) and (7) (i.e., study hours), respectively, but interacting the independent variables of interest with the different student observables. Column (1) of Panel A shows differential responses between full-time and part-time drivers; where we define full-time drivers as those who, on average, drive at least 25 hours per week when not enrolled in courses. We find that the labor supply of full-time drivers is more responsive to coursework activities, which is consistent with the fact that part-time drivers have more flexibility to avoid altering their labor supply in response to higher coursework responsibilities. Column (2) of Panel A also

[42] Appendix Table F9 replicates the analysis in Table 7 but weekly clicks and logins replace study hours as the dependent variables. The results across all of these models are qualitatively very similar.

[43] Slightly under two-thirds of the drivers in our estimating sample are 35 or older.

Table 7: Determinants of study effort

	Study Hours in c (1)	Study Hours in c (2)	Placebo Test (3)
Avg. study hours in c, peers	1.134***	-	1.022***
	(0.027)		(0.018)
Sum of avg. study hours in $-c$, peers	-0.009	-	-0.007***
	(0.006)		(0.002)
Assignments graded in c	-	0.046***	-
		(0.015)	
Sum of assignments graded in $-c$	-	-0.012**	-
		(0.005)	
Market level active hourly pay, currently elig.	-0.008**	-0.029***	-0.001
	(0.004)	(0.004)	(0.001)
Observations	55293	55293	555752
Individual Fixed Effects	✓	✓	✓
Classroom Fixed Effects	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓
Weather controls	✓	✓	✓
Mean dep. var.	1.58	1.58	-
Avg. study hours in c, peers	1.27	-	-
Sum avg. study hours in $-c$, peers	1.55	-	-
Assignments graded in c	-	2.21	-
Sum assignments graded in $-c$	-	2.78	-
Market level active hourly pay, peers	33.6	33.6	-
Elasticity w.r.t. peer coursework	0.912	0.064	
Elasticity w.r.t. peer earnings	-0.170	-0.617	

Note: The dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. "Assignments graded in c" and "Sum of assignments graded in $-c$" denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Column (2) are from a 2SLS specification where "Assignments graded in c" and " Sum of assignments graded in $-c$" are instrumented with the average graded assignments for non-Uber peers in c and $-c$, respectively."Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Elasticities are calculated by multiplying the relevant coefficient estimate by the ratio of mean peer course work or market level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the class level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

shows that STEM majors are more prone to reduce their working hours (compared to non-STEM majors) in response to coursework demands. In particular, STEM students' labor supply is roughly 45% more responsive to changes in college activities than non-STEM ones. This finding was expected, given that STEM majors often take more demanding courses

Table 8: Heterogeneity in the determinants of work and study hours

	Full-time driver (1)	STEM (2)	Female (3)	High-need (4)	High Incoming GPA (5)	Age $\geq$ 35 (6)
Panel A: Work hours						
Sum avg. study hours all c, peers	-0.381***	-0.360***	-0.497***	-0.554***	-0.465***	-0.489***
	(0.090)	(0.092)	(0.094)	(0.132)	(0.115)	(0.118)
Sum avg. study hours all c, peers × var. in top row	-0.237*	-0.285**	0.166	0.079	0.027	-0.005
	(0.137)	(0.136)	(0.157)	(0.144)	(0.134)	(0.132)
Observations	27404	26636	26690	27388	23902	27404
Panel B: Study hours						
Market level active hourly pay, currently elig.	-0.010**	-0.007	-0.007*	-0.011*	-0.007	-0.010*
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
Market level active hourly pay, currently elig. × var. in top row	0.006	-0.001	-0.015	0.003	-0.003	0.004
	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)	(0.006)
Observations	55293	53731	53975	55266	48263	55293

Note: This table only reports the relevant coefficients, though the specifications follow equations (6) and (7) but with the inclusion of the relevant interactions with the different subgroups. Appendix Table F10 shows all the specification coefficients. For Panel A—the dependent variable in each column is hours working on the Uber platform. "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership but not enrolled. "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. For Panel B—the dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. All specifications include multiple sets of fixed effects, second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. In Panel A, standard errors are clustered at the individual level. In Panel B, standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

(in terms of peer hours).[44] Finally, we do not find statistically significant differences in the responsiveness of work hours based on gender (Column 3), financial need status (Column 4), incoming GPA (Column 5), or age group (Column 6).[45]

Panel B of Table 8 explores heterogeneous effects on Canvas (study) hours. For the most part, we find little systematic heterogeneity in terms of how labor market conditions impact study hours. As in Panel A, the female students' study hours are more responsive to market-level hourly pay, but the estimate is not statistically significant at conventional levels.

Overall, the results presented in Table 8 demonstrate that our finding that there is a small "short-run" opportunity cost of pairing online education with gig economy work is

[44] Our estimates indicate that the return to an individual hour of time spent on Canvas is lower in terms of course grades for STEM students. Specifically, we find that the return to an hour of time on Canvas is only 70% as high compared to non-STEM students. This suggests that STEM majors need to spend relatively more time on Canvas in response to their course activities. In fact, we find that, on average, Uber and non-Uber students in STEM majors spend over two hours more on Canvas for each course.

[45] In economic terms, female students' labor supply is two-thirds as responsive as males' to coursework demands, but the estimate is not precise. The lack of statistical significance in heterogeneity by gender could be due to the small sample sizes.

consistent across individuals with a variety of observable characteristics. Moreover, the cost of schooling in terms of forgone earnings only rises when individuals enter into somewhat less flexible arrangements—specifically, when students maintain stricter driving schedules and enroll in more challenging degree programs. Therein, we believe our results highlight the viability of these flexible arrangement for non-traditional and underrepresented students.

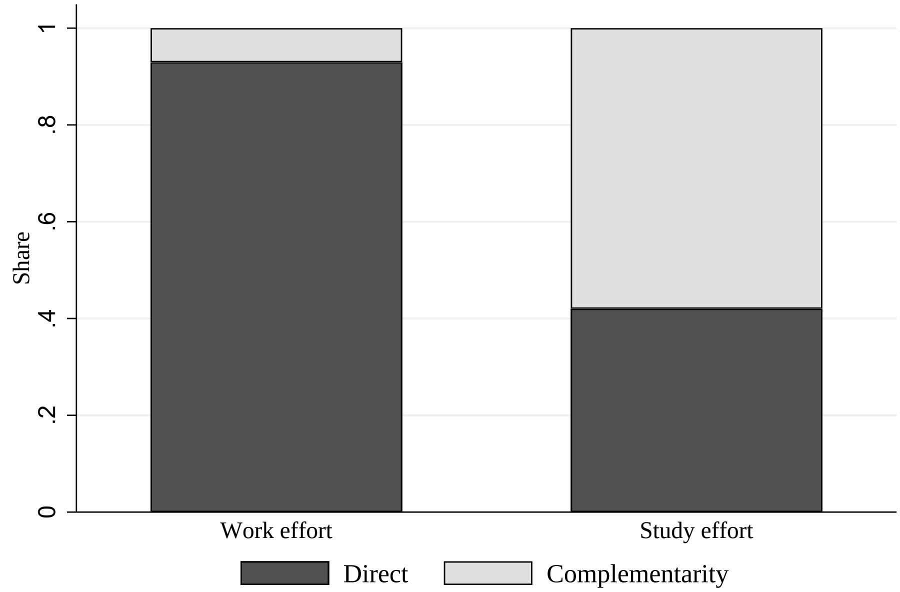
7 Decomposing the Cost of Effort

In this section, we attempt to decompose the marginal cost of study and work effort by quantifying what proportion of these costs can be attributed to (negative) complementarities arising from performing both activities simultaneously. For example, we aim to determine what share of the total weekly marginal cost of driving can be explained by school effort exerted in a given week since the cost of an additional hour of driving could be more daunting if an individual has been studying many hours during the week. To this end, we take advantage of the fact that it is possible to estimate reduced-form specifications closely linked to our analytical model's first-order conditions (presented in Section 4) and, therefore, compute the following ratios: $\frac{\lambda_{lc}}{\lambda_l}, \frac{\lambda_{lc}}{\lambda_c}$.[46] Then, we can use them jointly with the expressions for the marginal costs derived from our analytical framework to separately identify the share of the marginal cost that comes directly from exerting effort in each activity and from performing both activities simultaneously. Appendix C provides a detailed description of how we implement this decomposition.

Figure 4 presents the proportion of the marginal costs arising from complementarity effects (i.e., performing both activities simultaneously) and direct effects, where we condition on the average weekly hours of the working and learning population. The results indicate that, at the average level of work and study hours, roughly 9% of the total marginal cost of working is attributable to additional costs introduced when engaging in both activities simultaneously. Interestingly, this share is much larger for learning activities, where roughly

[46]See Equation (2) for definition of the λ's.

Figure 4: Contributions of direct effects and complementarities to marginal costs



Notes.—Each bar plot reports the share (out of 1) of the marginal cost of a given type of effort (i.e., work or study) that is directly attributable to exerting that type of effort, and that comes from the negative complementarity between exerting both types of effort simultaneously. Shares are determined at the sample average of weekly hours working and studying. For additional details on how the shares are calculated, see Appendix C.

56% of the total marginal cost is due to these negative complementarities. However, this result is mainly driven by the fact that, in our sample, Uber-students spend much more time driving rather than engaging in learning activities. Finally, we find that $\frac{\lambda_l}{\lambda_c} = 0.35$, suggesting that the disutility cost of studying is approximately three times larger than from working.

In addition to analyzing the relative shares for average work and study hours, we can also uncover their distribution based on each individual's average driving and studying behavior. Appendix Figures G3a and G3b plot the distribution of the share of marginal costs of working and studying, respectively, that is attributable to the direct costs of each activity and due to the negative complementarities across activities. These figures reflect substantial heterogeneity in the exact source of marginal costs for these two activities (driven by the combination of hours chosen), particularly for learning activities.

8 The Role of Flexibility

The large degree of flexibility in this working-learning context is a priori unique. Therefore, it is important to assess whether Uber-students exploit such flexibility when, for example, facing higher demand in course activities. Moreover, the results presented in Section 6 thus far suggest that most Uber-students face a relatively small trade-off when allocating time between school and work. One potential explanation for this is the unique flexibility of our empirical setting, especially relative to more standard work or school arrangements.

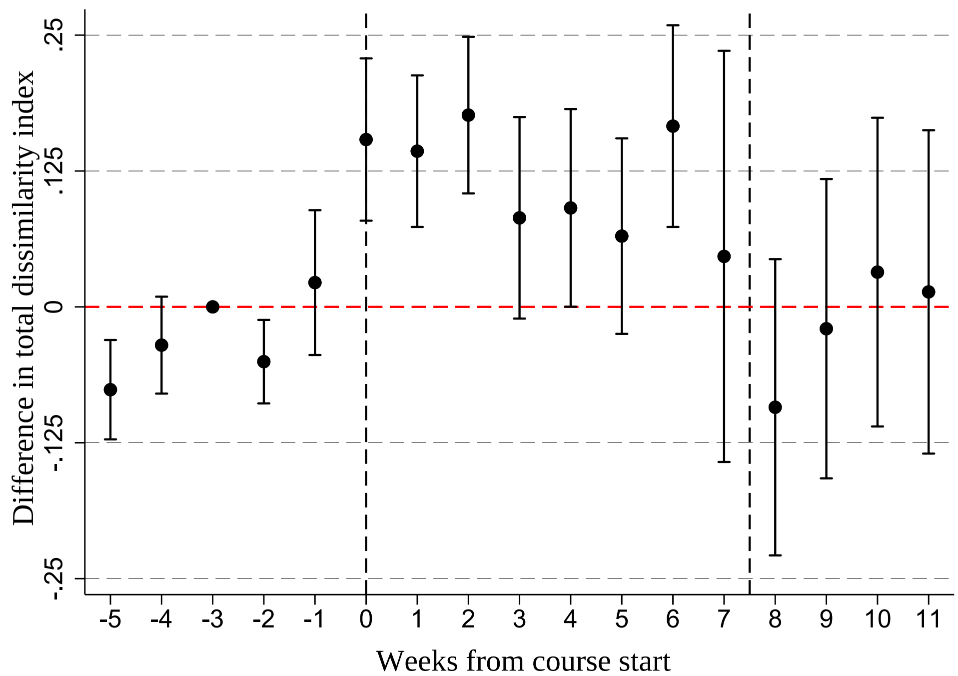
8.1 Do Drivers Adjust Working Hours in Response to College Demands?

To investigate whether Uber-students take advantage of the flexibility that gig economy work offers, we first construct a dissimilarity index that captures deviations in the driving schedules of Uber-students from their typical driving patterns when not enrolled in classes. In particular, our data allows us to observe how drivers distribute their time on the Uber platform across 28 six-hour periods in each week; for example, the first period is Monday morning from 12:00 AM to 6:00 AM and the second is Monday from 6:00 AM to 12:00 PM. We use these data to construct an index that reflects overall deviations from a driver's usual driving schedule when not enrolled at ASU. In a given week, t, Uber-student i's total dissimilarity index is equal to:

$$D_{i,t} = \frac{1}{2} \sum_{p=1}^{28} \left| \frac{\bar{m_{i,p}}}{\bar{M_i}} - \frac{m_{i,p,t}}{M_{i,t}} \right|,$$

where p refers to one of the 28 six-hour periods, $m_{i,p,t}$ is the total minutes driven in period p in week t, $M_{i,t}$ is the total number of minutes driven in week t, $\bar{m_{i,p}}$ is the average minutes driven across all p periods in non-ASU weeks (i.e., when not enrolled in classes), and $\bar{M_i}$ is the average number of minutes driven across non-ASU weeks. This index aims to capture

Figure 5: Variation within week driving flexibility for eight-week courses



Notes.—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the standardized dissimilarity index and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

changes in the distribution of hours worked across periods within the week, while accounting for the fact that total hours worked may differ substantially between ASU and non-ASU weeks. For example, $D_{i,t} = 0$ implies no change in behavior, while the maximum value in our sample of 1 suggests a fully dissimilar schedule (i.e., the distribution of hours driven in the week does not overlap with their average non-ASU schedule). In practice, for the analysis and to ease interpretation, we have standardized the dissimilarity index values.

Figure 5 presents results from a specification similar to those previously presented but using the (standardized) dissimilarity index described above as the dependent variable. Each of the coefficient estimates presented in Figure 5 should be interpreted as a percent of a standard deviation (with Week -3 corresponding to the baseline week). The more negative the standardized dissimilarity index, the less the Uber-students change their behavior driving during the class period when compared to non-enrollment periods. For example, the coefficient on the first week of courses (week zero) shows that the overall dissimilarity index increases by roughly 14% of a standard deviation for the average Uber-student. We interpret these results as indicating that within-week flexibility increases when college activities become more demanding at the beginning and end of the academic term (see Figure 1) and, as study time declines in the middle of the course, so does the value of within-week flexibility. Moreover, we calculate that the variation in the dissimilarity index shown in Figure 5 is similar in magnitude to randomly varying driver's non-course schedules by roughly 20% (see Appendix D for more details). Therefore, we conclude that the patterns in Figure 5 indicate that students do, in fact, adapt to their new schedules (i.e., finding time for their schoolwork that does not sacrifice optimal driving hours) as the courses progress.[47]

8.2 Assessing Students' Valuation of Flexible Schedules

Next, we focus on uncovering students' valuation for flexibility in learning and working schedules. To this end, our survey elicited students' likelihood of pursuing higher education under varying cost and flexibility scenarios. More specifically, the options were differentiated by three key factors: (1) the nature of the work schedule (i.e., flexible or fixed), (2) the modality of obtaining college credits (i.e., online or in-person), and (3) the annual cost of education ($0 or $6,000, with the latter reflecting approximately the regular yearly fees for an ASU working student). In the survey, students were asked the following:

"Consider the case where your education cost is [SPECIFIC VALUE HERE] per academic year. What is the percent chance (or chances out of 100) that you will enroll in the bachelor's program in each of the following four cases? When answering these questions, assume that the number of hours you work and your earnings are the same across scenarios:

[47] These event-study style coefficient estimates translate to an average treatment effect across weeks that can be summarized as follows: when the average study time of their peers increases by one hour per week, on average, drivers deviate from their typical schedule by roughly 4.1% of a standard deviation. Moreover, Appendix Figure G4 presents similar results where we construct the dissimilarity index specifically for typical peak hours periods (i.e., Friday and Saturday afternoons and nights). The results from the figure suggest that these driving behaviors during those hours are particularly likely to adjust during course weeks.

a) your work schedule is fixed and do not have flexibility AND you can take college credits toward a bachelor's degree online.

b) your work schedule is fixed and do not have flexibility AND you can take college credits towards a bachelor's degree in person only.

c) your work schedule is flexible AND you can take college credits toward a bachelor's degree online.

d) your work schedule is flexible AND you can take college credits towards a bachelor's degree in person only."

In total, each student provided eight responses (i.e., four scenarios combined with two different education costs). Table 9 summarizes the average likelihood of enrollment in each scenario, categorized by student type (Uber-students versus class peers). Uber-students, often from less privileged backgrounds, showed a greater sensitivity to education costs than their classmates, with enrollment probabilities decreasing by about 50% when costs rose from \$0 to \$6,000, irrespective of the learning and working formats. Additionally, the data reveal that flexibility in learning and working conditions significantly influences students' enrollment decisions. For instance, students reported, on average, approximately a threefold increase in enrollment likelihood when transitioning from fully rigid to fully flexible environments. Therefore, these findings strongly suggest that this sample of students places considerable value on flexible formats when considering college enrollment.

In terms of whether it is the flexibility in learning or working that matters more, the table suggests that the flexibility in learning is more valuable. For both Uber-students and their class peers, the mean likelihood of enrollment more than doubles going from in-person classes to online classes (when keeping the work schedule fixed).

In appendix E, we show how we can use this variation to recover measures of willingness to pay (WTP) using a model of expected utility for enrollment, as outlined in Aucejo et al. (2023). Two main results from the structural analysis are: (1) the WTP for flexible learning is 2-3 times as large as the WTP for flexible work schedules, and (2) given the higher expected

Table 9: Average Enrollment Likelihood by Scenario

	Uber-students	Class Peers	P-values
Enrollment likelihood with cost = $0			
Fixed work schedule x In-person Classes	30.51	32.80	0.40
Fixed work schedule x Online classes	73.12	84.92	0.00
Flexible work schedule x In-person classes	47.62	55.38	0.01
Flexible work schedule x Online classes	88.95	94.22	0.00
Enrollment likelihood with cost = $6,000			
Fixed work schedule x In-person classes	17.50	26.10	0.00
Fixed work schedule x Online classes	33.18	70.13	0.00
Flexible work schedule x In-person classes	25.51	42.82	0.00
Flexible work schedule x Online classes	43.74	78.82	0.00
Observations	243	344	

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students.

sensitivity of Uber-students to the costs of the program, their WTP for flexible (study or work) arrangements are lower than those of their counterparts.

9 Effort Measures and Academic Performance

We next examine how working hours and labor market conditions affect student performance (i.e., course grade points). Panel A of Table 10 shows results corresponding to three specifications that include individual, course (e.g., ECN 101), instructor, and term (e.g., Fall 2021) fixed effects, as described in Section 5.3. Columns (1) and (2) consider total Uber (work) hours, while columns (3) and (4) refer to specifications that flexibly account for Canvas (study) hours. The specifications in columns (2) and (4) instrument Uber-students' total hours on Uber and Canvas with the average (across weeks) market level pay for eligible drivers and average total hours on Canvas of class peers, respectively, for robustness.[48]

[48]Note that class peers do not include other drivers in the ASU-Uber program.

Table 10: The effect of work and study effort on course grades

Panel A: Final course grades				
	(1) Course Grade Points	(2) Course Grade Points (IV)	(3) Course Grade Points	(4) Course Grade Points (IV)
Total Uber hours	0.001	0.013	-	-
	(0.001)	(0.054)		
Total Uber hours^2	-0.000	-0.000	-	-
	(0.000)	(0.000)		
Total Canvas hours	-	-	0.107***	0.202***
			(0.006)	(0.027)
(Total Canvas hours)^2	-	-	-0.001***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.55	.	.64	.
Individual Fixed Effects	✓	✓	✓	✓
Course Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.		2.5		
Avg. total hours on Canvas		13.7		
Avg. total Uber hours		145.4		
Panel B: Weekly performance				
	Point Share	Point Share (IV)	Point Share	Point Share (IV)
Work hours	-0.020**	-0.614**	-	-
	(0.009)	(0.293)		
Study hours	-	-	1.338***	1.020***
			(0.231)	(0.369)
Obs.	55293	55293	55293	55293
Individual Fixed Effects	✓	✓	✓	✓
Classroom Fixed Effects	✓	✓	✓	✓
Month-Year Fixed Effects	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓
Avg. dep. var.		86.38		
Avg. study hours		1.58		
Avg. work hours		17.71		

Note: Panel A—The variable "Total Uber hours" denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. "Total Canvas hours" refers to the sum of individual Uber-student's own Canvas hours throughout a given course. Each regression model includes individual, course (e.g., ECN 101), instructor, and term fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. The model in Column (2) is estimated via 2SLS where "Total Uber hours" and "(Total Uber hours)^2 are instrumented with the average (across weeks) of average market-level pay for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where "Total Canvas hours" and "(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. Panel B—The dependent variable, "Point share", is on a scale of 0 to 100."Work hours" refers to the number of hours spent on the Uber platform in a given week, and "Study hours" denotes the number of hours a student was connected to Canvas for a given class each week. Each regression model includes individual, classroom, and month-year fixed effects. The model in Column (2) is estimated via 2SLS where "Work hours" is instrumented with the weekly average market level pay for Uber drivers eligible for the ASU-Uber program but did not enroll. The model in Column (4) is estimated via 2SLS where "Study hours" is instrumented with the average Canvas hours for non-Uber peers in the course for a given week. All standard errors are clustered at the course level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Three main takeaways emerge from these specifications. First, driving hours do not seem to impact course grades. Second, based on the estimates from the IV specification, we find that a 10% increase in the average total Canvas hours (i.e., 1.37 hours) increases course grades by 0.28 points (i.e., $1.37 \times 0.202 - (1.37)^2 \times 0.001$), approximately one-fourth of a letter grade.[49] This result indicates that Canvas hours are strongly associated with course performance, suggesting that, though imperfect, our measure of study hours is highly relevant. Finally, using these estimates, it is possible to provide a back-of-the-envelope calculation to quantify how changes in labor market conditions (i.e., market hourly pay) impact students' academic performance through a reduction in study hours. Combining the estimates from Tables 7 and 10, we find that a 10% increase in average hourly pay will only lead to a small decrease in course grade performance, roughly 0.04 grade points.[50]

In addition to the effect of effort on overall course performance, we also explore how weekly effort translates into weekly course performance. Panel B of Table 10 presents results from estimating versions of Equation (9). As with Panel A of the table, columns (1) and (2) consider total Uber hours, and columns (3) and (4) refer to specifications that account for Canvas hours. The specifications in columns (2) and (4) instrument Uber-students' weekly hours on Uber and Canvas with the average market level pay for eligible drivers and average hours on Canvas of class peers, respectively. The results in Panel B suggest that spending more hours on the Uber platform may have a small negative effect on weekly course performance, with each additional hour driving leading to a decline in the share of points earned of about 0.02 to 0.6 points (on a 0-100 scale); so the overall, impact is small in economic terms. However, consistent with Panel A, we find that more effort exerted on the Canvas platform leads to improved course outcomes at a weekly frequency.[51]

[49] We present similar results for other measures of course-level outcomes (i.e., course completion and having a passing grade) in the Appendix (see tables F11 and F12). In addition, specifications simultaneously controlling for Uber and Canvas hours provide almost identical results.

[50] From Table 7, a 10% increase in average weekly earnings of peers is \$3.36, implying a reduction in weekly study hours by 0.0269 hours (i.e., \$3.36$\times$-0.008). If we multiply this number by 7 (7 weeks is the length of a class), then the decrease in the total number of study hours for a given course is 0.1883. Finally, if we use the estimates from Table 10, jointly with 0.1883, we obtain the 0.04 point decrease in the course grade.

[51] Interestingly, when we look at the share of assignments submitted (rather than points earned), we see

In summary, the findings strongly suggest that flexible working and learning arrangements could substantially reduce the negative impact of working hours on academic performance, providing a suitable environment for many working students who intend to increase their skills.

10 Can Flexible Work-Study Programs Broaden Educational and Labor Market Opportunities?

The evidence we have presented so far indicates that formats combining flexible learning and working formats have the potential to alleviate many common challenges faced by students who are simultaneously engaged in education and working activities. However, a separate but relevant question is whether initiatives like the ASU-Uber partnership can broaden access to higher education. This is likely relevant for a growing segment of the population, specifically older individuals, looking to upgrade their skills while remaining active in the workforce.[52] To this end, we characterize who has benefited from this program by evaluating their educational experiences and assessing their expected graduation and labor market outcomes. The data collected from the student survey helps us shed light on these points.

10.1 The Potential of Flexible Work and College Programs to Increase Demand for Higher Education

As underscored in Section 3.1, the ASU-Uber program has attracted a larger share of minority, disadvantaged, and older students. However, it is yet to be determined whether these new enrollees are predominantly transfers from similar programs in other institutions, which could imply a mere reshuffling of the student population. Additionally, the implications of

no effect of driving with Uber. This may suggest that driving more hours does not lead to a decrease in completing work but may have a small effect on the quality of the work completed.

[52] Artificial intelligence is set to affect 40% of the jobs around the world (Cazzaniga et al., 2024), forcing many workers to adapt to new occupations.

such a redistribution on the overall quality of education and students' chosen fields of study remain an open question.

To assess the ASU-Uber program's impact on increasing the demand for higher education, we asked both Uber-students and their class peers about their enrollment at other institutions prior to joining ASU. Appendix Figure G5 shows that more than half—52%—of Uber-students were either not enrolled or on a break from another institution prior to joining ASU, a rate significantly higher than that of their course peers (29%). In addition, approximately half of the Uber-students who were previously enrolled or taking a leave from college were attending 2-year institutions, implying the program also facilitated the pursuit of higher-level degrees. Finally, the survey also revealed that, on average, Uber-students reported only a 37.2% likelihood of pursuing a degree in the absence of the program, suggesting an important role of this intervention in expanding access to higher education.[53]

To gain insights into the experiences of transfer students, we compared their perceptions regarding the educational quality at ASU versus their former institutions, along with examining any shifts in their chosen fields of study. Appendix Table F13 shows that 96% of Uber students considered ASU education to be either better (50%) or comparable (46%) to their prior institutions' quality, with similar perceptions also reported by their class peers. While these shares should be interpreted with caution because they are conditional on students currently enrolled at ASU Online, they suggest that Uber-students are not trading off college quality for more flexible, free education.[54]

[53]The survey asked the students: "*If you had not participated in the ASU-UBER program, what is the chance (out of 100) that you would be pursuing courses towards a bachelor's degree at ASU or elsewhere?*"

[54]We also examined whether students shifted between STEM (Science, Technology, Engineering, and Mathematics) and non-STEM fields when they transferred institutions. In this regard, the first pair of columns of Appendix Table F14 reveal that 67% (64%) of the surveyed students who were initially enrolled in a STEM (non-STEM) field of study remained in the same field when transferring institutions, while 33% (36%) changed major.

10.2 Ex-Ante Value-Added Assessment of the Program

Our concluding analysis assesses the program's potential to enhance college attainment and labor market prospects. Although we do not have data to uncover the program's value-added (given that it is relatively early to make such an assessment), we collected students' perceptions about their expected graduation rates and future income under various scenarios, allowing us to estimate the program's ex-ante value-added. Appendix Table F15 reveals that students anticipate an average graduation rate exceeding 90%. We also inquired about the expected graduation rate of transfer students had they remained at their previous institutions. Students' responses indicate a marked improvement in anticipated graduation rates due to transferring, with an increase of about 25 percentage points. As to whether these expectations will be ex-post realized is a separate question, but ex-ante these students are quite serious about completing their programs. Finally, the bottom panel of Table F15 presents the ratio of the students' projected annual income in six years, conditional on obtaining a bachelor's degree or not (i.e., dropping out of the program). On average, students foresee a 90% return from earning a bachelor's degree, highlighting the significant ex-ante value-added they attribute to the program.

In conclusion, the findings presented in this section suggest that flexible learning and working models hold significant potential for equalizing opportunities in higher education. Further research is required to comprehensively understand the impact of emerging technologies and flexible arrangements in bridging educational and labor market gaps, as well as in enhancing skills for the older working population. Nonetheless, these initial findings encouragingly suggest considerable scope for increasing access to higher education through expanding the availability of online education in tandem with the proliferation of more flexible working environments (e.g, gig economy jobs as well as more generous telework policies in traditional sectors).

11 Conclusion

This is the first study that quantifies how college activities and labor market conditions impact labor supply and effort exerted in college. Our findings indicate that frictions associated with performing working and learning activities simultaneously are small when workers participate in flexible (work and study) environments. In particular, we find that average college activities lead to an average short-run opportunity cost of only $41 per week. We also show that a 10% increase in average hourly pay decreases study time for the average Uber-student by only 2%. The small economic size of these estimates is consistent with our findings that Uber-students take advantage of their flexible context by adjusting their driving behavior when the demands of their courses increase. Finally, we find negligible effects of additional working hours on academic performance or of study hours on the quality of workplace performance, further suggesting minimal crowding-out effects in this context.

Survey findings reveal a threefold increase in the probability of college enrollment under completely flexible conditions as opposed to entirely rigid ones. This underscores the high premium students in our sample place in flexible learning environments. Additionally, our research indicates that nearly half of the Uber-students engaged in ASU's online education were not previously enrolled in any college, suggesting that the online program has effectively broadened the demand for higher education—particularly for non-traditional and underrepresented students. To conclude, while we cannot provide a welfare analysis due to the lack of data on leisure or longer-term outcomes (such as graduation or subsequent labor market outcomes), our results are encouraging. Since low-income students are more likely to work to afford an increasingly expensive college education, flexible learning and working formats could help them overcome many of the usual barriers they face when pursuing a college degree. Similarly, our findings suggest this type of flexible working-learning arrangement could also be convenient for many workers who are looking to upgrade their skills, but do not want to fully exit the labor market.

References

Alessandrini, Diana and Joniada Milla, "Minimum wage effects on human capital accumulation: Evidence from Canadian Data," 2021.

Aucejo, Esteban M, Jacob French, and Basit Zafar, "Estimating studentsâ valuation for college experiences," *Journal of Public Economics*, 2023, *224*, 104926.

Barbanchon, Thomas Le, Diego Ubfal, and Federico Araya, "The effects of working while in school: evidence from Uruguayan lotteries," *Available at SSRN 3398385*, 2020.

Beffy, Magali, Denis Fougère, and Arnaud Maurel, "The effect of part-time work on post-secondary educational attainment: new evidence from French data," 2010.

Caldwell, Sydnee and Emily Oehlsen, "Gender differences in labor supply: Experimental evidence from the gig economy," *University of California, Berkeley Working Paper*, 2022.

Cazzaniga, Mauro, Florence Jaumotte, Longji Li, Giovanni Melina, Augustus J Panton, Carlo Pizzinelli, Emma J Rockall, and Marina Mendes Tavares, "Gen-AI: Artificial Intelligence and the Future of Work," *Staff Discussion Notes*, 2024, *2024* (001).

Chen, Xianglei and Annaliza Nunnery, "Profile of Very Low-and Low-Income Undergraduates in 2015-16. Stats in Brief. NCES 2020-460.," *National Center for Education Statistics*, 2019.

Cook, Cody, Rebecca Diamond, Jonathan V Hall, John A List, and Paul Oyer, "The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers," *The Review of Economic Studies*, 2021, *88* (5), 2210–2238.

Darolia, Rajeev, "Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students," *Economics of Education Review*, 2014, *38*, 38–50.

Denes, Matthew, Spyridon Lagaras, and Margarita Tsoutsoura, "Entrepreneurship and the Gig Economy: Evidence from US Tax Returns," *Available at SSRN*, 2023.

Hyman, Louis, Erica L. Groshen, Adam Seth Litwin, Martin T. Wells, Kwelina P. Thompson, and Kyrylo Chernshov, "Platform driving in Seattle," ILR Research Report, Cornell University 2020.

Iacus, Stefano M., Gary King, and Giuseppe Porro, "Causal Inference without Balance Checking: Coarsened Exact Matching," *Political Analysis*, 2012, *20* (1), 1â24.

Kalenkoski, Charlene Marie and Sabrina Wulff Pabilonia, "Parental transfers, student achievement, and the labor supply of college students," *Journal of Population Economics*, 2010, *23* (2), 469–496.

Lee, Chang Hyung, "Minimum wage policy and community college enrollment patterns," *ILR Review*, 2020, *73* (1), 178–210.

Ma, Jennifer and Matea Pender, *Trends in college pricing and student aid 2022*, College Board, 2022.

Neyt, Brecht, Eddy Omey, Dieter Verhaest, and Stijn Baert, "Does student work really affect educational outcomes? A review of the literature," *Journal of Economic Surveys*, 2019, *33* (3), 896–921.

Papke, Leslie E and Jeffrey M Wooldridge, "Econometric methods for fractional response variables with an application to 401 (k) plan participation rates," *Journal of applied econometrics*, 1996, *11* (6), 619–632.

PRISM Climate Group at Oregon State University, https://prism.oregonstate.edu. Data created 2021-05-16. Accessed on 2022-04-14.

Saliola, Federica, Asif Mohamed Islam, and Hernan Winker, "Adapting Jobs Policies and Programs in the Face of Accelerated Technological Change," 2020.

Scott-Clayton, Judith, "What explains trends in labor supply among US undergraduates?," *National Tax Journal*, 2012, *65* (1), 181–210.

Stinebrickner, Ralph and Todd R Stinebrickner, "Working during school and academic performance," *Journal of labor Economics*, 2003, *21* (2), 473–491.

US Department of Education, "Digest of education statistics 2020," 2020.

U.S. Department of Education, National Center for Education Statistics, "Digest of Education Statistics 2020, Table 311.15," https://nces.ed.gov/programs/digest/d20/tables/dt20_311.15.asp 2020. Accessed: 3-31-2024.

Wooldridge, Jeffrey M, *Introductory econometrics: A modern approach*, Cengage learning, 2015.

A Additional Data Description

A.1 Sample Restrictions

The primary way in which we restrict our data to construct our estimation sample is to limit the weeks included in our analysis. In particular, we drop all weeks between March 16, 2020, and January 4, 2021. The motivation for doing this is that the COVID-19 pandemic and related stay-at-home orders led to a massive disruption in Uber driver activity. We include the Spring term of 2021 in our analysis because, by that point, Uber driving had picked back up to somewhat normal levels, and a large share of our sample comes from that term. In addition to dropping these observations, we also exclude "Dynamic" courses from our estimating sample. These courses are often only one week long and make up a very small share of our Uber-student sample. Besides these restrictions, we do not place any other explicit filters on our estimating sample.

For our estimation of Equation (1) (i.e., analysis of data variation), we also make additional sample restrictions. Specifically, we exclude individuals who appear to have "dropped out" during the course. As described previously, we determine likely dropouts based on their final course grades (e.g., incomplete or withdrawals) and their activity. Specifically, if a student receives a failing grade, an incomplete, or a withdrawal *and* has a spell of inactivity for at least the final three weeks of the course, we consider them a likely dropout. Though excluding these observations from our main results has little effect, they do matter in the estimation of our data variation analysis since dropouts meaningfully attenuate our estimates in weeks after they drop out (since their driving hours are relatively high and study hours relatively low due to dropping out).[55]

[55] Appendix Tables F16 and F17, present results where we re-estimate our main specifications but limit the sample by excluding likely dropouts.

A.2 Select Variable Definitions

In this subsection, we provide an overview of key variables used in our analysis. In terms of relevant measures of study effort, we directly observe the amount of time that students are connected to a course's Canvas page, as well as the number of logins and clicks that a student generates each week. To construct the measures of course demand in a given week, we calculate the average amount of time spent on Canvas by all course peers (i.e., non-Uber program participants).

For work effort/labor supply measures, we observe how much time a driver is connected to the Uber application and how many weekly trips they complete. Note that, at the driver level, we cannot distinguish between active and inactive time, where active time refers to time spent picking up and completing rides, and inactive time includes waiting for ride requests (while connected to the application). At the market level, we observe average active and inactive time connected to the Uber application for all drivers eligible for the ASU program but did not enroll. We also observe average weekly earnings for this same group. For our primary analysis, we calculate average market-level earnings (often denoted as "market level active hourly pay, currently eligible") as the ratio of average weekly earnings to average active hours for those eligible drivers who did not enroll in the program. For robustness, we also re-conduct our analysis using a measure of market-level earnings that is equal to the ratio of average earnings to average total hours (i.e., the sum of active and inactive hours). The results of the paper are both qualitatively and quantitatively consistent, regardless of the definition of market-level pay.

B Market-Level Pay and Hotel Occupancy

To understand what drives the variation in market-level pay for our main results, we collected additional data on hotel vacancies for a subset of the Uber markets. The data come from STR Inc., a hotel analytics company founded in 1985 as Smith Travel Research, the recognized leader in hotel industry analytics and provides market data, including supply, demand, and market share information on a global scale. For our purposes, STR provides comprehensive daily hotel occupancy data from 2018 to 2023 across 95 Metro Markets. Our analysis's primary variables of interest are daily occupancy rates for each market. To convert the daily occupancy data to a weekly frequency, we take the average occupancy rate from Monday through Sunday of each week. However, the results are robust to alternative constructions. We can merge data for 69 of the 111 unique Uber markets, which corresponds to roughly 94% of the observations included in the results for Table 7. With these merged data, we estimate alternative specifications of the following regression:

$$MarketPay_{lt} = \beta_0 + \beta_1 Occupancy_{lt} + \beta_2 Weather_{lt} + \psi_l + \rho_m + \varepsilon_{lt}, \tag{10}$$

where l is the labor market, t is the week, the occupancy variable is the mean from Monday through Sunday of the given week, and ψ_l and ρ_m are city and month-year fixed effects. Results reported in Table B1 show that the market-level weekly pay variable increases as the occupancy rate increases despite including a robust set of controls. To ease interpretation, note that a one standard deviation increase in the occupancy rate (17.5) leads to a 0.25 standard deviation increase in the market-level pay ($17.5 \times .073 = 1.28$ and $1.28/5 = .25$). Overall, these findings suggest that the variation in market pay we use for our analysis responds to shocks to demand.

Table B1: Relationship between Market-Level Pay and Hotel Occupancy Rate

	(1)	(2)	(3)
Hotel Occupancy Rate$_{lt}$	0.067***	0.074***	0.073***
	(0.003)	(0.003)	(0.003)
Obs.	7845	7844	7609
F-stat.	440.45	526.62	97.57
Fixed-effects	No	Yes	Yes
Precip. controls	No	No	Yes
Mean dep. var.	30.07	30.07	29.9
Std. dev. dep. var.	5.11	5.11	5
Mean occ. rate	53.53	53.53	53.48
Std. dev. occ. rate	17.62	17.62	17.5

Note: The dependent variable is market-level pay. The variable "hotel occupancy rate" denotes the weekly mean occupancy rate from Monday through Sunday. The hotel occupancy rate data come from STR Inc., a hotel analytics company founded in 1985 as Smith Travel Research. "Precip. controls" denote controls for weather conditions. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

C Decomposing the Cost of Effort

In this appendix, we provide the details corresponding to the decomposition implemented in Section 7.

Consider Equation (4) that relates the optimal work effort in a given week e^*_{ilt} to a set of structural parameters and observable data moments governing the costs and benefits of studying and working.[56] In order to map Equation (4) to the data, we re-express it as:

$$e^*_{ilt} = \frac{(\alpha-1)\lambda_{lc}\beta_1}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{(\alpha-1)\lambda_{lc}\beta_5\varsigma_t}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{2\alpha\lambda_c w_t}{4\lambda_c\lambda_l - \lambda_{lc}^2} + \frac{(\alpha-1)\lambda_{lc}\beta_3 Ab_i}{4\lambda_c\lambda_l - \lambda_{lc}^2}. \tag{11}$$

With Equation (11) in hand, we then estimate a slight variation of our primary specification in Equation (6) of the following form:

$$e_{ilt} = \gamma_0 + \gamma_1\varsigma_{it} + \gamma_2 w_{it} + \varphi_i + \vartheta_T + \varepsilon_{it}, \tag{12}$$

where e_{ilt} denotes hours worked, ς_{it} denotes course demand across all courses in week t, w_{it} is the market wage available to individual i in week t, and φ_i and ϑ_T are individual and term fixed-effects, respectively.[57] Given this setup, we assume that each of the estimands of Equation (12) corresponds to our structural parameters as follows:

$$\gamma_1 = \frac{(\alpha-1)\lambda_{lc}\beta_5}{4\lambda_c\lambda_l - \lambda_{lc}^2} \tag{13}$$

$$\gamma_2 = \frac{2\alpha\lambda_c}{4\lambda_c\lambda_l - \lambda_{lc}^2}. \tag{14}$$

A similar exercise for optimal study effort also yields a mapping from estimands of the estimating equation to the structural parameters. To be consistent with the analytical framework, we add study effort across all courses in which the student is enrolled in each

[56] The marginal benefit of studying an extra hour is the marginal improvement in grades that an hour of studying generates (weighted by $(1-\alpha)$), and the marginal benefit of working is the market wage (weighted by α).

[57] As in our previous analysis we define ς_{it} as the average study hours of course peers.

period:

$$\sum_{c}^{C} e_{ict} = \pi_0 + \pi_1 \varsigma_{it} + \pi_2 w_{it} + \varphi_i + \vartheta_T + \epsilon_{it},$$

where

$$\pi_1 = \frac{2(1-\alpha)\lambda_l \beta_5}{4\lambda_c \lambda_l - \lambda_{lc}^2} \tag{15}$$

$$\pi_2 = -\frac{\alpha \lambda_{lc}}{4\lambda_c \lambda_l - \lambda_{lc}^2}. \tag{16}$$

Though directly identifying any given structural parameter is not possible from Equations (13) - (16), we can use them jointly with the reduced-form estimates to recover the following ratios:[58]

$$-\frac{2\gamma_1}{\pi_1} = \frac{\lambda_{lc}}{\lambda_l} \tag{17}$$

$$-\frac{2\pi_2}{\gamma_2} = \frac{\lambda_{lc}}{\lambda_c}. \tag{18}$$

Finally, if we combine Eqs.(17)- (18) with the following expressions of the marginal costs of working (l) and learning (c) that are derived from our analytical framework:

$$MC_l = 2\lambda_l e_{ilt} + \lambda_{lc} e_{ict} \tag{19}$$

and

$$MC_c = 2\lambda_c e_{ict} + \lambda_{lc} e_{ilt}, \tag{20}$$

then, we can uncover the proportion of MC_l and MC_c (conditional on different levels of effort) that correspond to the direct cost of exerting each activity and of exerting both activities at the same time (i.e., complementarity costs).[59]

[58]The reduced-form coefficients (i.e., γ's and π's) are reported in Appendix Table F18. To be consistent with the fact that the first order conditions only hold at interior points, in this analysis we limit our estimating sample to individual weeks with strictly positive Canvas and Uber hours. Even though we have slightly altered our specification and our estimating sample, it is worth noting that the coefficient estimates from this specification are qualitatively and quantitatively similar to those estimated from our primary specifications and presented in Tables 6 and 7.

[59]The average study and work hours for the estimating sample in this exercise are somewhat higher than the overall sample. This is, in part, because we have dropped observations with zero hours. For reference, the average study hours for this sample is 3.38 hours per week (across all courses), and the average driving

D Interpreting the Dissimilarity Index

To help contextualize the dissimilarity index results, we first estimate the following regression equation:

$$DissimilarityIndex_{it} = \alpha_0 + \alpha_1 Class_{it} + \alpha_2 MarketPay_{it} + \alpha_3 Weather_{it} + \tau_i + \delta_m + \epsilon_{it}, \quad (21)$$

where $DissimilarityIndex_{it}$ is the standardized (mean zero, standard deviation one) dissimilarity index for person i in week t, $Class$ is an indicator for being enrolled in an ASU course, and τ_i and δ_m are person and month-year fixed effects. Thus, the coefficient of interest, α_1 reflects the average deviation from a driver's standard driving schedule across all course weeks. We estimate $\hat{\alpha}_1 = 0.26$.

Next, we find a random perturbation in non-course week driving behavior that can generate a similar point estimate. To do this, we randomly alter the driving hours of 30% of the observations by, first, drawing two random numbers between 1 and 28 (where each number corresponds to one of the 28-hour buckets for the week). We then add 10% of the given driver's average driving time to each of those buckets. To help illustrate, consider a driver that drives approximately 20 hours per week in non-course weeks. For this driver, we would add 2 hours to two different random hour bins (e.g., Monday 12 PM-6 PM and Thursday 6 AM-12 PM). Then, with this new variable, we recalculate the dissimilarity index and estimate the following regression limited to non-course weeks:

$$DissimilarityIndexRand_{it} = \beta_0 + \beta_1 Rand_{it} + \beta_2 MarketWage_{it} + \beta_3 Weather_{it} + \tau_i + \delta_m + \epsilon_{it}, \quad (22)$$

where the LHS variable is the randomized index (standardized), and $Rand$ is an indicator denoting if the observation was treated by randomization. Doing this, we estimate $\hat{\beta}_1 = 0.253$. Therefore, we interpret these results as suggesting that course demands lead to a

hours is 22.55.

similar deviation in typical driving behaviors as randomly altering non-course week driving schedules by 20%. It is worth noting that estimating a similar regression but with the true dissimilarity index on the LHS yields no relationship (as expected).

E Students' Willingness to Pay

We propose a straightforward model of expected utility for enrollment, as outlined in Aucejo et al. (2023), that allows us to derive measures of willingness to pay (WTP).[60] Consider the utility U_{is} that student i derives from enrolling under a specific state or scenario, denoted as s. This utility can be expressed as $U_{is} = u_i(X_s) + \epsilon_{is}$, where $u_i(X_s)$ represents the preferences of individual i for a set of characteristics X_s associated with scenario s. These characteristics might include factors like the mode of class delivery (in-person or online), the nature of work schedules (flexible or fixed), and the cost of education. The term ϵ_{is} captures an additional, scenario-specific component of the student's preference. We define ϵ_{is} as $\epsilon_{is} = \delta_i + \varepsilon_{is}$, where δ_i represents the unobserved, scenario-independent utility component for individual i, and ε_{is} corresponds to an idiosyncratic taste shock. In choice models, it is common to assume that ε_{is} is an independent and identically distributed (i.i.d.) Type I extreme value variable, independent of the preferences $u_i(X_s)$.[61] For estimation purposes, we assume that these errors are independent across individuals and conform to a Type I extreme value distribution. Therefore, the probability of student i choosing to enroll in college under scenario s can be modeled as:

$$ProbEnr_{is} = \frac{exp(u_i(X_s) + \delta_i)}{1 + exp(u_i(X_s) + \delta_i)}. \tag{23}$$

If we adopt a linear and separable utility specification, the utility function $u_i(X_s)$ can be parameterized as:

$$u_i(X_s) = \alpha_1 \cdot OnlineClass_s + \alpha_2 \cdot FlexibleWork_s + \alpha_3 \cdot Cost_s, \tag{24}$$

[60] For a detailed discussion on the validity of this approach and the commonly imposed identification assumptions, see Aucejo et al. (2023).

[61] In our context, the independence of irrelevant alternatives (IIA) assumption is not a concern as students face only two options: enroll or drop out. ε_{is} represents resolvable uncertainty, meaning uncertainty due to unknown factors in the hypothetical survey scenario, which will become known at the time of actual decision-making.

where $OnlineClass_s$ and $FlexibleWork_s$ denote indicators for online classes and flexible work schedules in scenario s, while $Cost_s$ refers to the student-specific university fees outlined in the scenario.

We estimate this model using the fractional response approach (Papke and Wooldridge, 1996), which accommodates dependent variables within the 0 to 1 range. This method is particularly effective for handling data extremes (0 or 1 values) and is robust in the presence of censored data. The model's parameters are estimated using a quasi-maximum likelihood approach, with the Bernoulli log-likelihood function defined as:[62]

$$l_{is}(\alpha, \delta) = ProbEnr_{is} \log \left(\frac{\exp(u_i(X_s) + \delta_i)}{1 + \exp(u_i(X_s) + \delta_i)} \right) + (1 - ProbEnr_{is}) \log \left(1 - \frac{\exp(u_i(X_s) + \delta_i)}{1 + \exp(u_i(X_s) + \delta_i)} \right). \tag{25}$$

Since the model parameters do not have a direct economic interpretation, we calculate the willingness-to-pay (WTP) for online learning as follows:

$$WTP_{OnlineClass} = -\frac{\alpha_1}{\alpha_3} \tag{26}$$

Similarly, the willingness to pay for flexible work schedules is determined as follows:

$$WTP_{FlexibleWork} = -\frac{\alpha_2}{\alpha_3} \tag{27}$$

Table E1 shows WTP estimates for the whole sample, Uber-students, and class peers. Results indicate that students' value for work flexibility (relative to a fixed schedule) is \$4,018, while for online learning (relative to in-person classes) is \$10,243. These estimates suggest a strong willingness to pay for flexibility in learning and working formats, though the WTP for flexible working schedules is lower than for online learning. Finally, the ratio

[62] For fractional data, the Bernoulli quasi-maximum likelihood estimator is efficient among a class of estimators that includes all quasi-maximum likelihood estimators in the linear exponential family and weighted non-linear least squares estimators.

(WTP flexible work/WTP online classes) is higher for Uber-students which is expected given that they chose to have more flexible work schedules.[63]

Table E1: WTP Estimates for Flexible Work and Learning Schedules

	N	(1) WTP Flexible Work	p-value	(2) WTP Online Classes	p-value	(3) Work/Study WTP ratio	p-value
All	692	4018*** (213)		10243*** (336)		0.39*** (0.02)	
Uber-Students	243	2685*** (234)	0.000	5893*** (271)	0.000	0.46*** (0.04)	0.088
Class peers	344	6933*** (568)		18239*** (1176)		0.38*** (0.02)	

Note: Willingness-to-pay reported in dollars per year. Standard errors in parentheses derived via delta method. The p-value denotes whether differences in WTP between groups (i.e., Uber-students vs. class peers) are statistically significant. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

[63]Survey responses indicate that Uber-students rate their work flexibility as 6.12 on average (on a scale of flexibility from 1 - not flexible at all, to 7 - extremely flexible), while their class peers rate their work flexibility as 3.85.

F Appendix Tables

Table F1: Correlations of Canvas activity measures for Uber-students

	Active days	Logins	Clicks	Minutes online
Active days	1			
Logins	0.826***	1		
Clicks	0.639***	0.756***	1	
Minutes online	0.568***	0.715***	0.847***	1
Observations	71907			

Note: Table reports correlation coefficients across each metric of weekly Canvas activity. "Active days" corresponds to the number of days in the week with non-zero Canvas activity, "Logins" refer to the number of distinct times a student logged onto the course Canvas page, "Clicks" reflect the number of distinct clicks that were made on various course page links, and "Minutes online" refer to the number of minutes the student spent on the course Canvas page. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F2: Weekly Canvas activity by student group, re-weighted control group

	Uber-Students Active in Uber		Uber-Students Inactive in Uber		Class Peers	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Activity						
Days connected to Canvas per course	3.57	(2.304)	3.75	(2.274)	3.59	(2.241)
Clicks per course	76.02	(89.370)	79.06	(85.577)	69.14	(77.842)
Hours online per course	1.57	(2.116)	1.61	(2.097)	1.39	(1.820)
Outcomes						
Assignments submitted	1.97	(4.143)	1.99	(2.920)	2.03	(3.999)
Assignment share (%)	90.18	(27.599)	90.55	(26.809)	89.93	(27.767)
Point share (%)	79.39	(29.322)	80.13	(28.662)	79.49	(29.279)
Observations	43467		12197		125649	

Note: The "Class Peers" control group is re-weighted using coarsened exact matching on observables to be more similar to the Uber-student sample. All statistics reported in the table are at the weekly level. "Uber-Students: Active in Uber" denotes weeks in which the student shows positive driving hours and is enrolled in ASU classes. "Uber Students: Inactive in Uber" denotes weeks in which the student shows zero driving hours but is enrolled in ASU classes. "Class peers" correspond to students who are enrolled in the same classes as the Uber students. Assignment and point shares refer to the total number of assignments submitted and points earned relative to the number of assignments due and points possible, respectively.

Table F3: Student degree progress by enrollee type

	Uber-Students		Class Peers		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Cumulative GPA	2.62	(1.386)	2.94	(1.091)	-0.33***
Credits to date	92.56	(54.110)	87.80	(46.490)	4.76***
Observations	1540		64248		65788

Note: Means are reported for each variable measured at the most recent term in the data for each student. "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students enrolled in the same classes as the Uber students. "Cumulative GPA" refers to the student's cumulative grade point average at their most recent observed term and "Credits to date" denotes the total number of academic credits on a student's transcript including transfer credits. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F4: Course-level summary statistics, re-weighted control group

	Uber-Students		Class Peers	
	Mean	Std. Dev.	Mean	Std. Dev.
Activity				
Total hours on Canvas	14.63	(12.734)	13.00	(11.589)
Assignments submitted	18.38	(16.892)	19.04	(17.710)
Outcomes				
Passed course	0.76	(0.427)	0.78	(0.413)
Numeric course grade	2.49	(1.664)	2.55	(1.619)
Observations	6591		14527	

Note: "Uber-Students" denotes ASU students that participate in the ASU-Uber partnership. "Class Peers" corresponds to students that are enrolled in the same classes as the Uber students. The "Class Peers" group is re-weighted by coarsened exact matching on observables to be more similar to the sample of Uber-students.

Table F5: Correlations of Uber activity measures for enrolled Uber-students

	Total pay (100s)	Incentive pay (100s)	Tips (100s)	Completed trips	Hours online
Total pay (100s)	1				
Incentive pay (100s)	0.671***	1			
Tips (100s)	0.517***	0.296***	1		
Completed trips	0.887***	0.580***	0.534***	1	
Hours online	0.840***	0.408***	0.499***	0.833***	1
Observations			22999		

Note: Table reports correlation coefficients across each metric of weekly Uber activity."Total pay" corresponds to the driver's total weekly earnings from Uber, "Incentive pay" refers to pay received due to specific incentive programs (e.g., completing a target number of trips), "Tips" reflect the weekly earnings received in formal passenger tips, and "Completed trips" and "Hours online" denote the total number of trips completed and hours spent on the Uber application, respectively. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F6: Sample comparison

	Uber-Students		**Class Peers**	
	Survey	Admin	Survey	Admin
Demographics				
Age	38.78	39.25	30.64	24.90
Female	0.37	0.15	0.62	0.56
White	0.47	0.36	0.58	0.54
Black or Hispanic	0.37	0.48	0.27	0.29
Academic Profile				
STEM degree	0.42	0.40	0.55	0.30
Observations	243	1540	344	141913

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students. "Transfer status" is an indicator variable denoting whether the student transferred from another higher-education institution and "STEM degree" indicates if the student is in a science, technology, engineering, or math degree program.

Table F7: Robustness: Determinants of work effort, leads and lags included

	(1) Work Hours	(2) Work Hours
Sum avg. study hours all c, peers	-0.668***	-0.551***
	(0.097)	(0.111)
Market level active hourly pay, currently elig.	0.217***	0.338***
	(0.051)	(0.071)
Observations	21572	22141
Individual Fixed Effects	✓	
Course Bundle Fixed Effects	✓	
Month-Year Fixed effects	✓	✓
Weather controls	✓	✓
Leads and lags of indep. variables	✓	✓
Mean dep. var.	17.75	17.78
Mean avg. study hours in c, peers	2.65	2.66
Market level active hourly pay, peers	33.1	33.7

Note: The variable "Sum avg. study hours all c, peers" is a proxy for coursework that denotes the sum of average Canvas hours of non-Uber students in each course c in which the Uber-student is enrolled. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. The specification includes multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls account for temperatures and rains/snow. A one-week lead and lag of each of the independent variables of interest are also included as controls. Column (2) does not include individual and course bundle fixed effects, given that models with lagged dependent variables can be biased when including fixed effects. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F8: Robustness: Determinants of study effort, leads and lags included

	Study Hours in c	Study Hours in c
Avg. study hours in c, peers	1.152***	1.152***
	(0.032)	(0.030)
Sum avg. study hours in $-c$, peers	0.009	0.023*
	(0.011)	(0.012)
Market level active hourly pay, currently elig.	-0.009**	-0.008**
	(0.004)	(0.004)
Observations	41989	41993
Individual Fixed Effects	✓	
Classroom Fixed Effects	✓	✓
Month-Year Fixed Effects	✓	✓
Leads and lags of indep. variables	✓	✓

Note: The variable "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in c. "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c in which the student was enrolled. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. The specification includes multiple sets of fixed effects. Weather controls account for temperatures and rain/snow. A one-week lead and lag of each of the independent variables of interest are also included as controls. Standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F9: Determinants of study effort (clicks and logins)

	Weekly clicks	Weekly logins	Weekly clicks	Weekly logins
Avg. study hours in c, peer	36.868***	2.105***		
	(5.580)	(0.596)		
Sum of avg. study hours in $-c$, peers	-0.226	-0.048		
	(0.373)	(0.038)		
Assignments graded in c			2.036***	0.220***
			(0.464)	(0.048)
Sum of assignments graded in $-c$			-0.531***	-0.036**
			(0.155)	(0.015)
Market level active hourly pay, currently elig.	-0.904***	-0.026	-1.616***	-0.068***
	(0.196)	(0.019)	(0.204)	(0.017)
Obs.	55293	55293	55293	55293
Individual Fixed Effects	✓	✓	✓	✓
Classroom Fixed Effects	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Mean dep. var.	76.79	9.01	76.79	9.01
Market level active hourly pay, peers	33.57	33.57	33.57	33.57
Avg. study hours in c, peers	1.28	1.28	-	-
Sum avg. study hours in $-c$, peers	1.55	1.55	-	-
Assignments graded in c	-	-	2.21	2.21
Sum assignments graded in $-c$	-	-	2.78	2.78
Elasticity w.r.t. peer coursework	0.615	0.286	0.059	0.054
Elasticity w.r.t. peer earnings	-0.395	-0.097	-0.508	-0.253

Note: The dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. "Assignments graded in c" and "Sum of assignments graded in $-c$" denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Columns (3) and (4) are from a 2SLS specification where "Assignments graded in c" and " Sum of assignments graded in $-c$" are instrumented with the average assignments graded by non-Uber peers in c and $-c$, respectively."Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Elasticities are calculated by multiplying the relevant coefficient estimate by the ratio of mean coursework or market-level hourly earnings to the mean of the dependent variable. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F10: Heterogeneity in the determinants of work and study hours

	Full-time driver (1)	STEM (2)	Female (3)	High-need (4)	High Incoming GPA (5)	Age $\geq$ 35 (6)
Panel A: Work hours						
Market level active hourly pay, currently elig.	0.124**	0.138**	0.177***	0.134	0.097	0.143*
	(0.057)	(0.063)	(0.057)	(0.083)	(0.071)	(0.081)
Market level active hourly pay, currently elig. × var. in top row	0.096	0.090	-0.052	0.046	0.091	0.025
	(0.112)	(0.115)	(0.109)	(0.102)	(0.106)	(0.100)
Sum avg. study hours all c, peers	-0.381***	-0.360***	-0.497***	-0.554***	-0.465***	-0.489***
	(0.090)	(0.092)	(0.094)	(0.132)	(0.115)	(0.118)
Sum avg. study hours all c, peers × var. in top row	-0.237*	-0.285**	0.166	0.079	0.027	-0.005
	(0.137)	(0.136)	(0.157)	(0.144)	(0.134)	(0.132)
Observations	27404	26636	26690	27388	23902	27404
Panel B: Study hours						
Market level active hourly pay, currently elig.	-0.010**	-0.007	-0.007*	-0.011*	-0.007	-0.010*
	(0.004)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)
Market level active hourly pay, currently elig. × var. in top row	0.006	-0.001	-0.015	0.003	-0.003	0.004
	(0.006)	(0.006)	(0.010)	(0.007)	(0.006)	(0.006)
Avg. study hours in c, peers	1.041***	1.074***	1.077***	0.978***	1.023***	1.000***
	(0.076)	(0.042)	(0.061)	(0.166)	(0.063)	(0.048)
Avg. study hours in c, peers × var. in top row	0.207*	0.156**	0.315	0.205	0.107*	0.225***
	(0.124)	(0.063)	(0.243)	(0.198)	(0.055)	(0.047)
Sum of avg. study hours in $-c$, peers	-0.006	0.002	-0.003	0.004	-0.019**	-0.009
	(0.008)	(0.008)	(0.008)	(0.018)	(0.008)	(0.008)
Sum of avg. study hours in $-c$, peers × var. in top row	-0.008	-0.027**	-0.045	-0.017	0.009	0.001
	(0.013)	(0.013)	(0.033)	(0.022)	(0.012)	(0.011)
Observations	55293	53731	53975	55266	48263	55293

Note: For Panel A—the dependent variable in each column is hours working on the Uber platform. "Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership but not enrolled. "Sum of avg. study hours across all c, peers" denotes the sum of the average hours per week that peers spent on Canvas across all courses. For Panel B—the dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. All specifications include multiple sets of fixed effects, second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. In Panel A, standard errors are clustered at the individual level. In Panel B, standard errors are clustered at the class level.*, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F11: The effect of work and study effort on course completion

	(1) Completion	(2) Completion (IV)	(3) Completion	(4) Completion (IV)
Total Uber hours	0.000	-0.001		
	(0.000)	(0.014)		
(Total Uber hours)^2	0.000	0.000		
	(0.000)	(0.000)		
Total Canvas hours			0.031***	0.072***
			(0.003)	(0.010)
(Total Canvas hours)^2			-0.000***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.38	.	.52	.
Individual Fixed Effects	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.	.81			
Avg. total hours on Canvas	13.7			
Avg. total Uber hours	145.4			

Note: The variable "Total Uber hours" denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. "Total Canvas hours" refers to the sum of individual Uber-student's own Canvas hours throughout a given course. Each regression model includes individual and course fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. Standard errors are clustered at the course level. The model in Column (2) is estimated via 2SLS where "Total Uber hours" and "(Total Uber hours)^2 are instrumented with the average (across weeks) of average market-level pay for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where "Total Canvas hours" and "(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F12: The effect of work and study effort on course pass rate

	(1) Completion	(2) Completion (IV)	(3) Completion	(4) Completion (IV)
Total Uber hours	0.000	-0.010		
	(0.000)	(0.035)		
(Total Uber hours)^2	0.000	0.000		
	(0.000)	(0.000)		
Total Canvas hours			0.033***	0.067***
			(0.002)	(0.009)
(Total Canvas hours)^2			-0.000***	-0.001***
			(0.000)	(0.000)
Obs.	4900	4900	4900	4900
Adjusted R^2	0.45	.	.58	.
Individual Fixed Effects	✓	✓	✓	✓
Class Fixed Effects	✓	✓	✓	✓
Instructor Fixed Effects	✓	✓	✓	✓
Avg. dep. var.		.75		
Avg. total hours on Canvas		13.7		
Avg. total Uber hours		145.4		

Note: The variable "Total Uber hours" denotes the total hours an Uber-student spent connected to the Uber platform throughout the course. "Total Canvas hours" refers to the sum of individual Uber-student's own Canvas hours throughout a given course. Each regression model includes individual and course fixed-effects. The sample excludes all terms that were meaningfully disrupted by the Covid-19 pandemic. Due to the inclusion of individual fixed effects, the number of observations that identify the parameters of interest is smaller when compared to the number of observations reported in Table 3. Standard errors are clustered at the course level. The model in Column (2) is estimated via 2SLS where "Total Uber hours" and "(Total Uber hours)^2 are instrumented with the average (across weeks) of average market-level pay for Uber drivers who were eligible for the ASU-Uber program but did not enroll and its square. The model in Column (4) is estimated via 2SLS where "Total Canvas hours" and "(Total Canvas hours)^2 are instrumented with the sum (across weeks) of average Canvas hours for non-Uber peers in the course and its square. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F13: Higher Education Quality Comparison - Transfer Students

	All	Uber-students	Class Peers	Diff: P-values
ASU Better Educ.	0.54	0.50	0.57	0.12
ASU Inferior Educ.	0.07	0.05	0.08	0.22
ASU Similar Educ.	0.39	0.46	0.35	0.03
Observations	423	125	256	

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students. The survey question and choices were *"How would you compare the quality of education at ASU to that of your previous institution? ASU offers a better/inferior/similar education than my previous institution."*

Table F14: Field of Study Before and After Enrolling at ASU

	Overall		Uber-Students		Class Peers	
	Major at ASU					
Major in Previous Institution	Non-STEM	STEM	Non-STEM	STEM	Non-STEM	STEM
Non-STEM	64%	36%	72%	28%	62%	38%
STEM	33%	67%	41%	59%	31%	69%
Total	51%	49%	61%	39%	48%	52%

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students. Rows conditional on sample sum 100%. For instance, among the students in our overall sample who completed the survey and had transferred from other institutions, 64% were pursuing non-STEM majors at their previous schools and continued with the same field of study after enrolling at ASU. While 36% changed from STEM to Non-STEM. STEM major is defined as students enrolled in Engineering, Technologies/Technicians, Health Professions and Related Clinical Sciences, and Sciences and Mathematics.

Table F15: Expected Graduation Probabilities and Earnings in 6 Years

	Overall	Uber-Students	Class Peers	P-values
Prob. complete studies in 6 years	0.918	0.910	0.929	0.41
Prob. complete studies in 6 years if remained at prev. college†	0.677	0.621	0.704	0.05
Expected returns from finishing the degree (ratio)	1.91	1.99	1.85	0.16
Observations	692	243	344	

Note: "Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students. "Expected returns from finishing the degree" refers to the ratio of "Expected annual income in 6 years if graduate" over "Expected annual income in 6 years if dropout today". † This probabilities are calculated conditional on students who transferred institutions.

Table F16: Determinants of work effort, excluding likely dropouts

	(1) Work Hours	(2) Work Hours	(3) Work Hours	(4) Completed Trips	(5) Completed Trips	(6) Completed Trips
Sum of avg. study hours across all c, peers	-0.686***	-0.683***	-0.677***	-1.286***	-1.280***	-1.337***
	(0.073)	(0.073)	(0.101)	(0.147)	(0.147)	(0.206)
Market level active hourly pay, currently elig.	0.108**	0.115**		0.301***	0.326***	
	(0.051)	(0.051)		(0.112)	(0.113)	
Obs.	25972	25907	24777	25972	25907	24777
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Course Bundle Fixed Effects	✓	✓	✓	✓	✓	✓
Month-Year Fixed effects	✓	✓	✓	✓	✓	✓
Weather controls		✓			✓	
City-Week FE			✓			✓
Mean dep. var.	18.01	17.98	18.19	36.09	36.03	36.38
Market level active hourly pay, peers	33.64	33.63		33.64	33.63	
Sum avg. study hours all c, peers	2.48	2.48	2.49	2.48	2.48	2.49
Mean hourly earnings	19.1	19.1	19.23	19.1	19.1	19.23
Mean pay-per-trip	9.76	9.76	9.83	9.76	9.76	9.83

Note: Columns (1) to (3) include as dependent variable weekly work hours, while columns (4) to (6) include completed trips. The variable "Sum of avg. study hours across all c, peers" denotes the sum of the average hours across courses that peers spent on Canvas per week. The variable "Market level active hourly pay, currently elig." denotes the average hourly pay of drivers (currently eligible) in a given week. Likely dropouts are excluded from the estimating sample. Additional details on how we identify likely dropouts are provided in Appendix A.1. Specifications include multiple sets of fixed effects. Course bundle fixed effects denote the set of courses taken in a given term. Weather controls account for temperatures and rains/snow. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table F17: Determinants of study effort, excluding likely dropouts

	Study Hours in c (1)	Study Hours in c (2)
Avg. study hours in c, peers	1.206***	-
	(0.027)	
Sum avg. study hours in $-c$, peers	-0.011*	-
	(0.006)	
Assignments in c	-	0.045***
		(0.015)
Sum assignments in $-c$	-	-0.012**
		(0.005)
Market level active hourly pay, peers	-0.005	-0.028***
	(0.003)	(0.004)
Observations	51385	51385
Individual Fixed Effects	✓	✓
Classroom Fixed Effects	✓	✓
Month-Year Fixed effects	✓	✓
Weather controls	✓	✓
Mean dep. var.	1.7	1.7
Avg. study hours in c, peers	1.28	-
Sum avg. study hours in $-c$, peers	1.56	-
Assignments in c	-	2.21
Sum assignments in $-c$	-	2.78
Market level active hourly pay, peers	33.58	33.57

Note: The dependent variable in each column is weekly study hours in course c. "Avg. study hours in c, peers" is a proxy for coursework that denotes the average Canvas hours of non-Uber students in course c. The variable "Sum of avg. study hours in $-c$, peers" denotes the sum of the average hours per week that peers spent on Canvas across all other courses besides c. "Assignments in c" and "Sum of assignments in $-c$" denote the number of assignments graded in course, c, and all other courses, $-c$ for a student in a given week. The results in Column (2) are from a 2SLS specification where "Assignments in c" and " Sum of assignments in $-c$" are instrumented with the average assignments submitted by non-Uber peers in c and $-c$, respectively."Market level active hourly pay, currently elig." denotes the average active hourly pay in a given week of drivers who are currently eligible for the ASU-Uber partnership, but not enrolled. Likely dropouts are excluded from the estimating sample. Additional details on how we identify likely dropouts are provided in Appendix A.1. Specifications include multiple sets of fixed effects. Weather controls include second-order polynomials in total weekly rainfall and snowfall. Each regression model also includes a flexible control for the number of days in the week for the course. Standard errors are clustered at the class level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

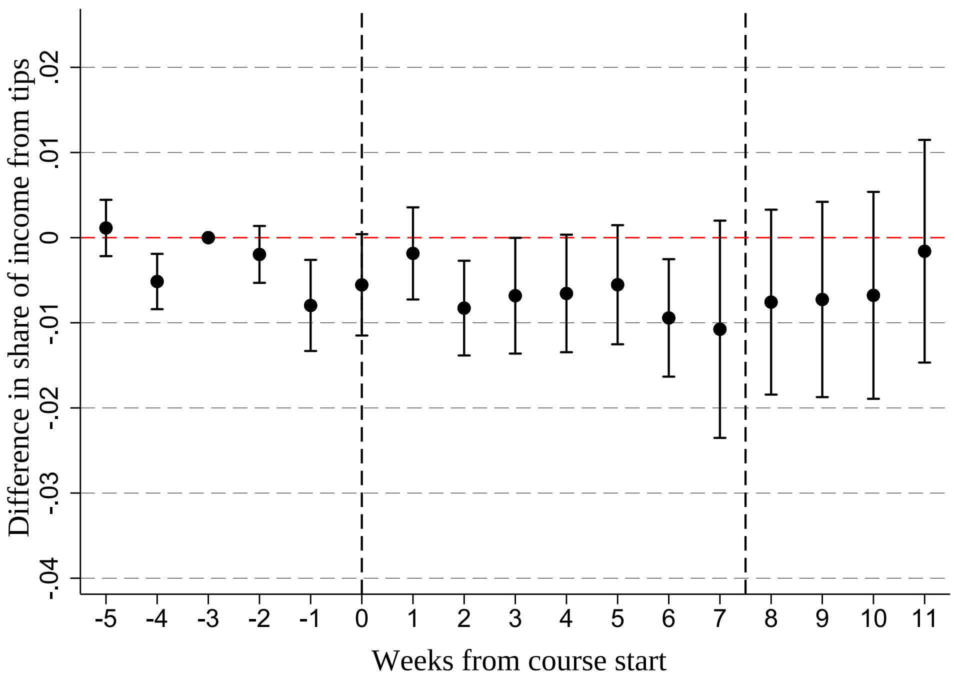
Table F18: Intermediate coefficient estimates and model parameters

	(1)	(2)
	e^*_{ilt}	e^*_{ict}
ς_{it}	-0.718***	1.311***
	(0.079)	(0.062)
w_{it}	0.064*	-0.012*
	(0.038)	(0.007)
Obs.	19050	19050
Implied λ_{lc}/λ_l	1.096	
Implied λ_{lc}/λ_c	0.381	

Note: The dependent variable Column (1) is weekly driving hours for driver i in week t and the dependent variable in Column (2) is total Canvas hours across all courses for i in t. ς_{it} is a proxy for coursework that denotes weekly Canvas hours of non-Uber peers across all of student i's courses. w_{it} denotes the average active hourly pay in a given week for drivers who are currently eligible for the ASU-Uber partnership but not enrolled in the same city as i. The estimation sample is restricted to person-weeks with strictly positive Canvas and Uber hours. Standard errors are clustered at the individual level. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

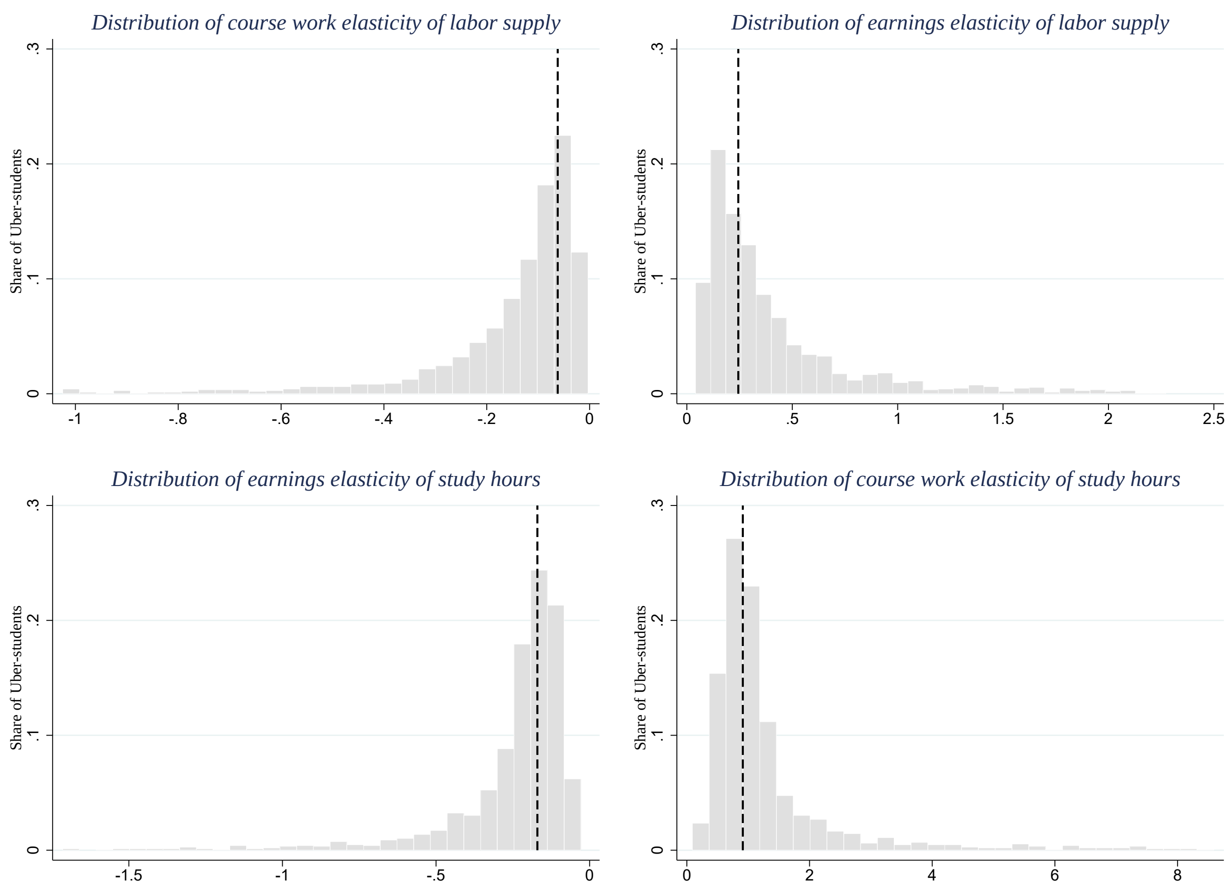
G Appendix Figures

Figure G1: Variation in the share of pay coming from tips during eight-week courses



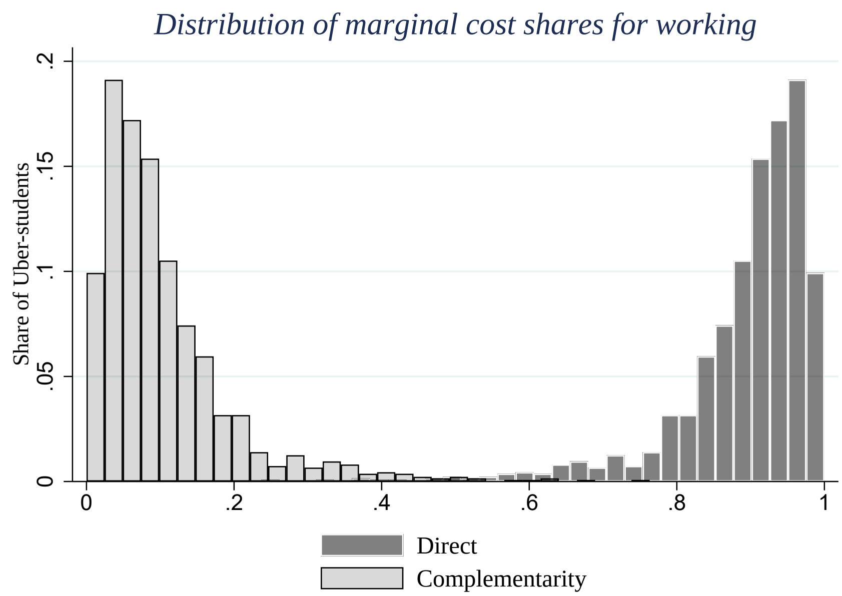
Notes:—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the share of weekly earnings coming from tips and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course. Standard errors are clustered at the classroom level.

Figure G2: Distribution of Elasticities

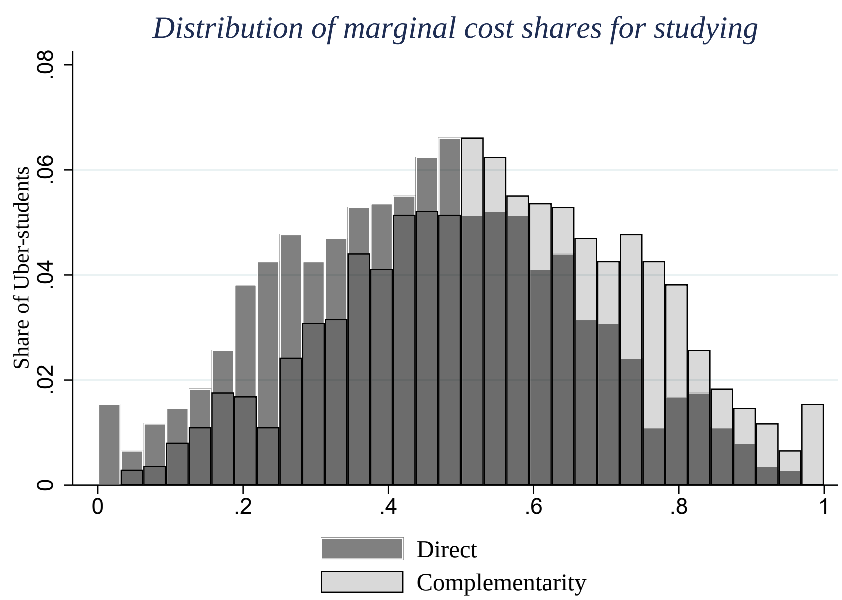


Notes:—Distribution of elasticities using individual-level means of relevant variables (i.e., average market-level pay, peer course hours, own driving, and study hours while enrolled at ASU).

Figure G3: Distribution of Direct Marginal Costs Shares for Each Activity



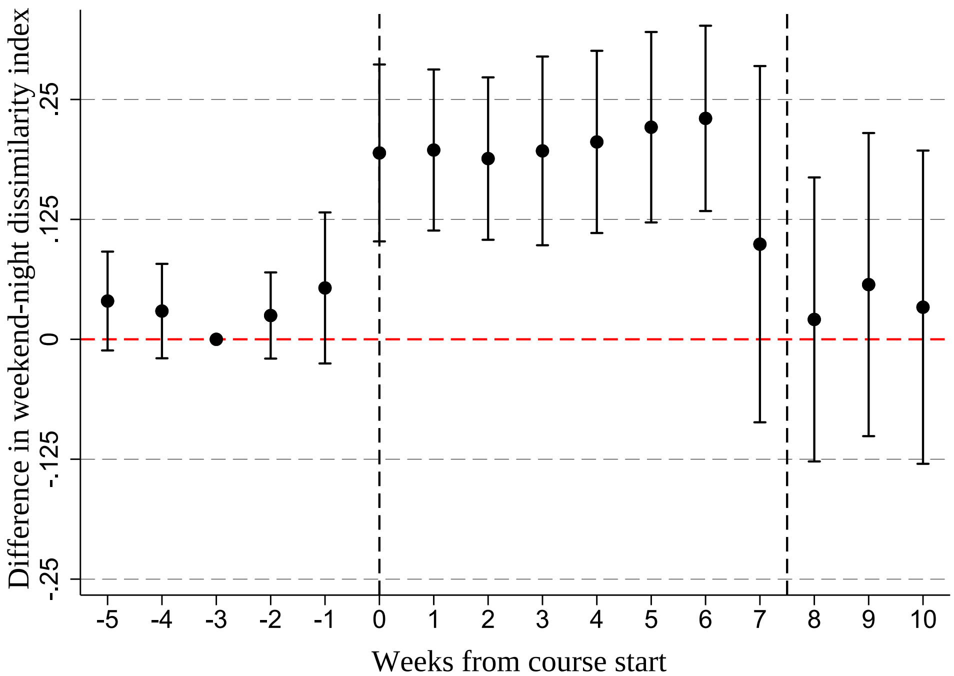
(a) Working



(b) Studying

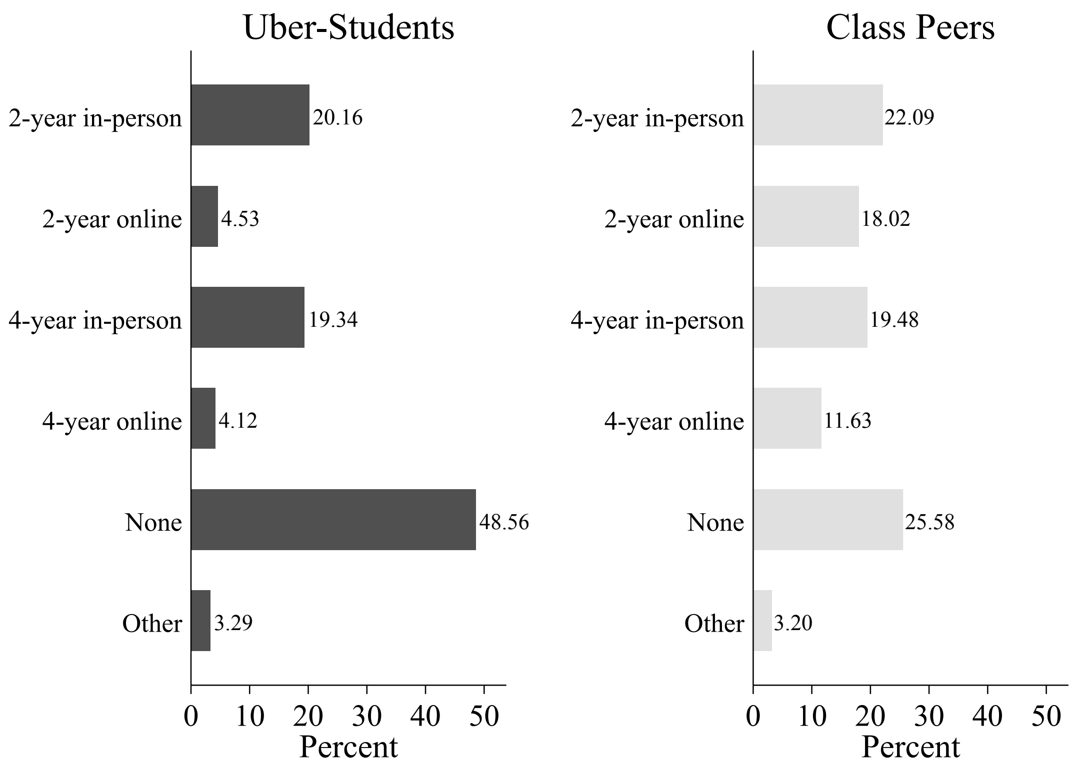
Notes:—Panel (a) plots the distribution of the share of marginal costs of working that is attributable to the direct costs of working (dark grey bar, white outline) and due to the negative complementarities between working and studying (light grey bar, black outline), and Panel (b) is analogous but for studying. A key assumption behind this exercise is that the structural parameters of our model are constant across the population but that individuals still have variation in their optimal driving behavior based on differences in earnings and course requirements. These differences yield variation in the relative contribution of direct effects and complementarities to the marginal cost of each activity.

Figure G4: Variation in flexibility on weekend nights during eight-week courses



Notes:—OLS coefficient estimates from a version of Equation (1) where the dependent variable is the dissimilarity index for share of driving hours allocated in Friday and Saturday afternoons and nights (i.e., 12:00PM-12:00AM) and 95% confidence intervals are plotted. The estimating sample excludes individuals who appear to have dropped out of the course.

Figure G5: Previous Institution Attended



Notes:—"Uber-students" denotes ASU students that participate in the ASU-Uber partnership. "Class peers" corresponds to students that are enrolled in the same classes as the Uber students. There are 243 Uber-students and 344 Class peers. The corresponding survey question is: *"You indicated that you were enrolled at another institution. Which of the following best describes your previous enrollment? I attended a 4-year/2-year public/private institution and took in-person/online classes."* We grouped the options of public and private institutions together for analysis.

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