Gig Work and Education Decisions: The Effect of Uber on College Enrollment and Attainment

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Abstract

The emergence of the gig economy in the past decade has offered many individuals a new type of work relationship that is both more flexible and more precarious. This paper seeks to understand whether the availability of Uber impacted college enrollment and attainment in the past decade. Uber may be a compliment to education, being flexible and thus more compatible with academic schedules, or it may induce individuals to substitute to working Uber full time. The net effect depends on the relative magnitudes of these effects, making it ultimately an empirical question. Using a staggered difference-in-difference regression, I exploit variation in Uber entry timing across metropolitan areas to examine the net effect of Uber availability on college enrollment and graduation rates. Using the Integrated Postsecondary Education Data System (IPEDS), I find evidence that Uber entry caused full time enrollment at community colleges to decline by 5% and 2-3 year graduation rates to decline by 0.8%. I also use data from the American Community Survey to analyze the mechanisms for this effect. I find no evidence that Uber entry significantly altered incomes of either individuals in school or those without a college degree. Two remaining potential mechanisms are that Uber's flexibility decreases the opportunity cost of enrollment without increasing income by allowing individuals to better optimize their time or that Uber increases family incomes and induces younger college students to substitute from community college to a 4-year college.

JEL Codes: I2, I23, J24, J8, O33
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1 Introduction

Over the past decade, the rapid rise of flexible alternative work arrangements has broadened the traditional understanding of work. This so called "gig economy" has grown from almost nothing in 2012 to nearly 1.9 million workers by 2016 (Collins et al. 2019). The flexibility of gig work is facilitated by online platforms that connect workers and customers to perform tasks ranging from therapy to grocery delivery. As policy-makers continue to grapple with weighing the benefits and downsides associated with gig work, it is important to understand its potential impacts on postsecondary educational outcomes. Since traditional work often conflicts with academic schedules, gig work, due to its flexibility, offers a potential way to lower the opportunity costs of education. At the same time, many types of gig work, like Uber and Doordash, do not require a higher degree, and therefore may reduce the relative payoff to receiving an education. This paper seeks to shed light on this open empirical question by analyzing how the growth of Uber in the past decade has impacted postsecondary educational outcomes in the United States.

The literature on gig platforms, of which Uber is emblematic, has primarily focused on consumer and worker welfare. Although consumer welfare analyses have typically yielded favorable evaluations, papers studying how gig work impacts worker's labor decisions are more ambiguous. Positive findings include Chen et al. 2019 who finds workers receive large utility benefits from the flexibility of Uber work and Koustas 2018 who finds that individuals are better able to smooth consumption after gig work becomes available. Other assessments are not as favorable, such as Jackson 2020 who finds that individuals who take up gig work during unemployment spells have lower long-run incomes and Burtch, Carnahan, and Greenwood 2018 who finds that measures of entrepreneurial activity decline after gig work becomes available. This paper adds to the literature on labor decisions by studying gig work's impact on human capital investment decisions. Although qualitative research from sociology has provided anecdotal evidence on this topic, to my knowledge no empirical analysis has been done.

I use data from the Integrated Postsecondary Education Data System (IPEDS) to run a staggered difference in difference regression on enrollment and attainment measures at the institution level. IPEDS provides annual data on enrollment and attainment for the universe of US postsecondary institutions that are disaggregated by student type (full/part time), race, and gender. IPEDS also provides detailed data on institutional characteristics including public/private control, geographic location, and programs offered.

Following the empirical strategy of many Uber related papers, I leverage the differential timing of Uber entry into US metropolitan areas from 2010-2017 as my source of exogenous variation. My identifying assumption is that, conditional on my controls, parallel education trends exist between places Uber does and does not enter. At the aggregate level, I find no evidence of Uber impacting enrollment, as measured by annual enrollment and entering class enrollment, and no evidence of Uber impacting attainment, as measured by completion rates and cohort graduation rates. However, when looking specifically at public 2-year colleges (community colleges) and 4-year colleges (bachelors colleges), Uber seems to decrease enrollment at community colleges and increase enrollment at bachelors colleges. Furthermore, when focusing on community colleges, which predominately enroll students at the margin of work and school, I find statistically significant results that full time enrollment decreases by around 5% after Uber entry. This is a significant portion of total US enrollment as community colleges make up almost 50% of US postsecondary enrollment. However, Uber does not appear to affect the enrollment of part time students at community college. As for attainment, I find that the 2-3 year graduation rate at community colleges drops by 0.8% after Uber entry but no change in the 2-year graduation rate, meaning that the fraction of transfers or dropouts increases for those graduating on longer timelines. Additionally, I also use data from the American Community Survey (ACS) to examine what potential mechanisms explain this effect. I find no evidence that Uber impacted incomes of students or non-degree holders, eliminating a personal income mechanism as an explanation for the results. However, the evidence is consistent with changes in family incomes and/or the benefits of flexibility driving students to switch from community college to 4-year programs, leading to lower enrollment and graduation rates.

This paper also contributes to a literature on the determinants of educational decisions. Understanding how labor market changes affect educational decisions is the topic of papers like Cascio and Narayan 2015, who looks at the impact of fracking jobs on high school enrollment, and Charles, Hurst, and Notowidigdo 2018, who looks at the impact of the 2000s housing boom on postsecondary enrollment and attainment. As the percentage of students concurrently working while studying increases, evidence on the potential detrimental effects is important for guiding work-study programs and employment policy. Papers by Stinebrickner and Stinebrickner 2003 and Triventi 2014 find evidence that working while enrolled negatively impacts academic outcomes. Understanding how Uber, which is both a low skill labor shock and flexible work option, impacts educational outcomes sheds additional light on the determinants of education decisions.

Section 2 provides a review of the literature on gig work and determinants of educational outcomes. Section 3 builds a theoretical framework for understanding the important mechanisms through which Uber may impact educational decisions. Section 4 summarizes the data sources used in this paper and section 5 covers the methodology. Section 6 presents the findings and robustness checks. Section 7 discusses potential mechanisms. Section 8 concludes and proposes future areas of inquiry.

2 Literature Review

This paper lies at the intersection of research on the gig economy and on determinants of educational outcomes. Both broad literatures provide important context on the motivations and results of this paper.

2.1 Gig Economy

Research on the gig economy broadly concerns issues of measurement and welfare. The nebulous definition of gig work and the variety of forms it may take makes measuring the number of gig workers in the US difficult. National surveys like the Bureau of Labor

Statistic's (BLS) Current Population Survey and the RAND American Life Panel suffer from measurement error since survey respondents often misinterpret questions on gig work status. RAND estimated that gig workers made up 0.5% of all US workers in 2015, while the BLS estimated that number to have grown to 1% in 2017. Collins et al. 2019 provides a non-survey measure by using the universe of tax returns to observe whether individuals receive any income from online gig platforms. They estimate that online platform employment grew rapidly from almost nothing in 2012 to 1.9 million by 2016. As comparison, in 2018, around 1.3 million retail workers were employed by grocery stores.[1] However, the majority of these workers use gig work as a supplement to other forms of income, with the majority making less than $2,500 annually from gig work.

The gig economy's growth has not been equal across demographics, as gig workers are primarily male, young, urban, and educated. The gig working population is overwhelmingly male (70% compared to 50.5% for wage workers). The age distribution is also similarly skewed, with the bulk of workers being in the age range 20-35, peaking at age 30 and declining thereafter (Collins et al. 2019). This may be driven by demographics from large gig platforms like Uber. Hall and Krueger 2018 survey Uber drivers and find that 86.2% of Uber drivers are male and 49% are aged 18-39. Additionally, the Uber work force is more diverse than the general working population, with only 40% of Uber drivers being white, compared with 55.8% for all workers. Lastly, gig work is heavily skewed towards urban areas and gig workers tend to have higher levels of education than the general workforce.

Overall, gig work as it stands is not a replacement for traditional work, but a flexible supplement that is skewed towards young, urban, educated males. The gig economy's growth in the past decade, paired with increasing digitization and decentralization of work during the COVID-19 pandemic, make understanding the welfare implications of gig work, for both workers and consumers, more important than ever. To understand gig work, researchers often use Uber, the largest and one of the earliest gig platform, as a case study.

1. Bureau of Labor Statistics, "Retail Jobs Among the Most Common Occupations", https://www.census.gov/library/stories/2020/09/profile-of-the-retail-workforce.html, accessed 4/3/22

Uber, founded in 2009, is synonymous with the rise of gig work and the subject of much of the literature surrounding its welfare implications. Uber connects consumers and drivers through its mobile platform, using matching algorithms and instantaneous price adjustments to provide a more efficient transportation service relative to traditional taxis (Cramer and Krueger 2016). Based out of San Francisco, Uber ramped up expansions within the US and internationally, launching across major US cities in 2011. Over the span of the next 5 years, Uber expanded across the US, launching more products like UberPOOL, a cheaper carpool ride option, and Uber Eats, a food delivery service. The number of Uber drivers nearly doubled every six months from the middle of 2012 until 2015 when Uber hit nearly half a million driver-partners in the US (Hall and Krueger 2018). Uber's rapid growth was not without controversy and was met with resistance by taxi cab drivers, city regulators, and Uber drivers themselves. Controversy surrounding the safety of Uber, the labor categorization of Uber drivers as independent contractors, and exploitative aspects of Uber work have driven policy debates on questions of how to regulate gig work.

Welfare analyses on Uber have yielded varied results. For consumers, Uber provides tangible benefits in availability, price, and traffic safety. Cohen et al. 2016 use price data and a regression discontinuity design based on the rounding of surge prices and finds that for each dollar spent by consumers on Uber, $1.60 of consumer surplus is generated. Cramer and Krueger 2016 find that the capacity utilization ratio (ratio of hours with a passenger to hours worked) is on average 30% higher for Uber drivers than taxi drivers. Dills and Mulholland 2018 find that for each quarter Uber is present in a county, Uber reduces vehicle fatalities by 0.2%. For workers, Uber provides flexible work that may help individuals smooth consumption but lacks the legal protections and predictable earnings of traditional work arrangements. Chen et al. 2019, using data on Uber driver schedules and surge prices, estimate that the weekly surplus of hourly scheduling flexibility is $154, compared to $49 when only daily scheduling flexibility is allowed. Koustas 2018 uses personal finance data to find that the elasticity of consumption spending to income falls by 80% for individuals who work, meaning individuals are better able to smooth consumption when gig work is available. Fos et al. 2019 uses data from a credit company to find that individuals with gig work available are less likely to turn to unemployment insurance, rely less on debt, and pay bills on time more often. However, the decrease in income volatility afforded by flexible gig work may come at the expense of lower net income, especially for rideshare drivers since expenses like car maintenance, gas, insurance, and data fees are not compensated for (Daniels and Grinstein-Weiss 2019).

In focusing on the welfare of Uber drivers themselves, it becomes apparent that gig work may also indirectly impact individuals' labor decisions and outcomes with respect to job search, entrepreneurship, or human capital investment. These decisions share many key characteristics, namely they involve a large upfront investment in exchange for future benefits. For example, finding the right job may take a longer time and individuals who are financially constrained may settle for a lower quality job due to shorter search time. Jackson 2020 looks at the unemployment job search process and finds that individuals who had gig work available in the short run are better able to smooth income during unemployment spells, but in the long run have annual incomes significantly lower ($4,000) than those who did not have gig work available. She theorizes this could be because individuals with gig work available procrastinate on their job search or have less time to put into their job search, resulting in worse outcomes. A similar pattern is observed with respect to local entrepreneurship. Burtch, Carnahan, and Greenwood 2018 find that measures of entrepreneurship decline when gig work is made available in an area. The mechanism of this finding appears to be that lower quality entrepreneurs substitute to gig work instead. In both cases the availability of gig work changes the way individuals make decisions about long term labor decisions. Gig work seems to both induce delays in the timing of the investment decision (in the case of job search) and also induce individuals to self-sort into different professions based off of individual characteristics (in the case of local entrepreneurial activity).

Although there has been no economic research yet on the impact of gig work on education, there is qualitative interview-based research in sociology on the topic. These papers not only motivate the need for an empirical understanding of how working Uber has impacted education decisions, but provide anecdotal evidence of the potential mechanisms. For example, in Robinson 2017, a student, Joy, describes how the lack of flexibility in her previous job interfered with her studies. “I had a test, and I was just going to get my boss to give me a week off, and they just flipped out. And it was such a hassle because I needed time to study”. Another student, Aristides, was “studying to become an electrician” and was persuaded to drive Uber by his uncle, another Uber driver, who said “he could make money to pay off his classes”. Peticca-Harris, deGama, and Ravishankar 2020 write on the theme of Uber being convenient for individuals in periods of transition. One interviewed student, Dhaval, who gave up his job as a security guard to go back to school, says “Uber is just right for me because I’m studying on the side. I’m looking for some other job, a professional career.” This sociological research paints a picture of student Uber drivers valuing the flexibility, income, ease of access, and lack of commitment in gig work. This aligns with findings that the majority of Uber drivers use gig work as a supplement to other forms of income. The reviews are not all positive however, and many drivers lament the lack of job protections, the unpredictable wages generated by the dynamic pricing algorithm, and the burden of a laundry list of associated expenses, from gas and vehicle maintenance to data costs and car insurance.

2.2 Economics of Education

Although the effects of Uber on education have not been researched specifically, there exists a vast literature on how outside labor options impact education decisions, including opportunity costs, credit constraints, and concurrent employment effects. The primary framework for understanding education decisions in economics is human capital theory based on the work of Becker 1962 and Mincer 1958. This model breaks down the effect of Uber on education in terms of changes to the opportunity cost of education and changes to the relative education wage premium. With this framework, research has found that labor market changes, particularly increases in the wage of low skill labor, can increase the opportunity cost of education, leading to lower enrollment. Relaxing the basic assumptions of human capital theory allows us to consider two additional mechanisms. If we relax the assumption of perfect credit markets, Uber may relieve credit constraints by providing short run consumption support, making college less costly without the aid of credit markets. If we allow for students to work during school, then Uber may take away time from studying or engaging in the school community, worsening academic outcomes.

2.2.1 Labor Market Shocks and Education

Based off the basic human capital theory models, it is intuitive that changes in the labor market will impact both the relative wage premium of education and the opportunity cost of education. Black, McKinnish, and Sanders 2005 look at the coal boom in the 1970s that prompted an expansion of low skill work in rural Appalachian areas with large coal reserves. They find that a 10% increase in the earnings of low skill workers decreased high school enrollment rates by as much as 5-7%. Atkin 2016 finds similar results when studying expansions in export-manufacturing in Mexico in the 1980s to 2000s, namely that for every 25 jobs created, one student dropped out of school at grade nine. Atkin 2016 also examines which sectors have large effects on education outcomes and finds that dropout is driven most by sectors that only require a high school degree, have high wage premiums, and arrive in locations with large youth populations at crucial decision ages (high school graduation age).

Although most papers agree on the negative enrollment effects of low skill labor shocks, it is unclear through which mechanism (decreasing relative wage premia or increasing opportunity costs) these effects happen, and what predicts what mechanism dominates. For instance, Cascio and Narayan 2015 look at the expansion in fracking and find that without fracking, teen male dropout rates would be 1 percent lower. They attribute this effect mainly decreases in the relative payoff to a high school degree compared to non-skilled fracking jobs. They support this with evidence that the majority of male teens who do end up dropping out are not looking for jobs which runs contrary to the opportunity cost theory.

2.2.2 Credit Constraints

The basic human capital theory model also implies that constraints in credit will lead to underinvestment in human capital, a result that worsens inequalities as lower income individuals often end up being credit constrained and unable to borrow to finance investing the optimal amount in human capital. At the postsecondary level, Carneiro and Heckman 2002 find that when looking at the 1980s, credit constraints are negligible (affecting at most 8% of the population) and the relevant margin is early childhood investments. They argue this is because after controlling for observables, wealth no longer is predictive of college enrollment. Instead, they attribute the relationship between family income and college enrollment to more long-run family effects. Lochner and Monge-Naranjo 2012 review the literature on credit constraints and education and find that although small in the 1980s, as the cost and return to college education skyrocketed into the 2000s, so did the number of constrained individuals in the United States. Youth from higher income families are 16% more likely to attend college, even after controlling for achievement. Although there are government programs and private credit markets designed to alleviate this constraint, since government programs do not provide loans for non-tuition related expenses, credit constrained individuals may be more consumption constrained during college, thus leading to increased dropout. However, Stinebrickner and Stinebrickner 2008, using detailed survey data from a small liberal arts college (Berea College), find that credit constraints explain at most 30% of dropout. Although this indicates that the majority of dropout is caused by other reasons, 30% of dropout being caused by credit constraints is still economically significant.

2.2.3 Working During School

If we relax the assumption in the basic human capital theory model that schooling and employment are mutually exclusive, we can analyze the effect of working while in school on academic achievement and outcomes. There are two forces in tension with one another. First, employment may help relieve credit constraints, improve consumption during college, and lower the opportunity cost of attending college, making individuals more likely to attend and complete college. At the same time, employment might eat up time used to study, engage in the school community, and attend classes, worsening academic achievement and resulting in decreased earnings prospects after school. Riggert et al. 2006 reviews the broader social science research on working during school. They find that due to the rising costs of enrollment, the number of individuals working while in school has increased substantially in the United States. In 1998, for students aged 16-24, 66% of individuals at 2-year institutions (associates colleges) worked, while 51% of individuals at 4-year institutions (bachelors colleges) worked.

Neyt et al. 2019 reviews the economic research on the effects of working during school on educational outcomes. They describe a zero-sum framework that assumes time spent working substitutes for time spent studying rather than time spent on leisure or other activities. Overall, evidence supports this zero-sum framework since most papers find that increases in hours worked lead to worse academic outcomes and increased dropout. For instance, Stinebrickner and Stinebrickner 2003 find that increasing the amount worked by 1 hour a week lowers that semester's GPA by 0.162. Similar findings are found by Triventi 2014 when looking at first-year students in Italy, where work delays individuals' academic progression, the most so for high workload students who work 35+ hours a week.

2.2.4 Community Colleges

It is crucial to note that these effects are not homogenous across institution types, and differentially affect students at public 2-year college programs. Often known as community colleges, these colleges aim to increase access to college education and teach students college preparatory material or technical skills. Community colleges often have an open admissions policy, little to no tuition, and flexible class schedules for full time and part time students (Kane and Rouse 1999). In 2010, community colleges made up nearly 44% of total undergraduate enrollment, with around 30% of that enrollment being full time students and 70% being part time (Ma and Baum 2016). Demographically, community colleges disproportionately serve minority, first-generation, low income, and adult students. Additionally, a large fraction of community college students work while enrolled, with 36% of students working part time and 33% of students working full time. The cost of attendance is substantially lower than that of 4-year colleges, with the average net cost of attendance price being $7,230 in 2015-2016. Lastly, although community college students are less likely to borrow (possibly since more students choose to work more instead of borrowing more), community college students are disproportionately likely to default on student loans, with nearly 19% defaulting on loans within 3 years, compared to just 6% defaulting in the private 4-year sector (Ma and Baum 2016).

Some research has been done to look specifically at the impacts of low skill labor shocks on students at 2-year institutions. Charles, Hurst, and Notowidigdo 2018, look at the impact of housing price bubbles in the 2000s and their impact on local labor markets and education. They find that the housing boom reduced college enrollment and attainment, an effect concentrated at two-year colleges. They attribute this to an increase in the opportunity cost of college since the housing boom increased employment and wages of individuals without a college degree without increasing the returns to college education. Darolia 2014 looks at differential effects of working on educational outcomes and finds that increases in work hours only lead to detrimental effects for full-time students at 4-year institutions, while part-time students and students are 2-year institutions show negligible effects. Lee 2020 looks at changes in the minimum wage across state boundaries and finds that a 10% increase in the minimum wage decreases the enrollment of part-time students at community colleges by 5-6%. This suggests that part time community college students are more at the margin of choosing between work and education.

To summarize, the literature on the determinants of educational decisions in an investment framework predict that as outside labor options increase in pay or availability (particularly low skill labor options), the opportunity cost of education increases, leading to lowered enrollment. This is particularly salient for community college students who are most at the margin of choosing between work and school. At the same time, work interacts with education beyond an investment framework, helping credit constrained individuals to finance their education and impacting the amount of time students have for their academics.

3 Theory

The theory of human capital has many important lessons for understanding and cataloging the potential mechanisms through which Uber may impact education. The most studied of these mechanisms is education as human capital investment, where individuals tradeoff between the opportunity costs and relative payoffs of education. Uber may alter both the opportunity costs and relative payoffs of education through changing both the payoffs while enrolled and the payoffs of non-skilled labor. Understanding these basic mechanisms will allow us to build a more complex model that incorporates individual characteristics and selection between 2-year and 4-year programs. This will give us an underlying theory to interpret our empirical results and hypothesize what mechanisms drive those results.

3.1 A Basic Model of Human Capital Investment

Following the basic model of human capital investment, consider an individual choosing between attending school or not attending school. In this simple two period model I will assume there is no discounting between the two periods. The payoff to attending school is w_e, the payoff while enrolled, in the first period and w_s, the skilled payoff, in the second period. The payoff to not attending school is w_n, the non-skilled payoff, in both periods. These payoffs can be understood as a function of both the wage received and the non-income factors that impact one's utility. In a simple two period model, an individual chooses to attend school if:

$$\underbrace{(w_s - w_n)}_{\text{Relative Payoff}} > \underbrace{(w_n - w_e)}_{\text{Opportunity Cost}}$$

After the entrance of Uber, all three parameters, may change (denoted by $\hat{w}_s, \hat{w}_n, \hat{w}_e$). For the purposes of modeling, I will assume that that the skilled wage is unchanged ($\hat{w}_s = w_s$) since Uber has no education requirements and has little to no wage growth over time. Uber may alter the nonskilled payoff (w_n), as Uber entry may allow non-skilled workers to supplement their hours with working Uber. Uber may also alter the payoff while enrolled (w_e), as the flexible nature of Uber work may be more compatible with demanding school schedules, allow individuals to better optimize their time, or better smooth income over shocks. Taken altogether, the net effect on an individual's enrollment decision ultimately depends on the relative magnitude of both changes to the nonskilled ($\hat{w_n}$) and enrolled payoffs ($\hat{w}_e$), highlighting the need for an empirical understanding of the effects of Uber.

3.2 Flexibility

One of the most important features of Uber, and gig work more generally, is the flexibility in scheduling both the amount and timing of work. In order to understand how Uber may potentially impact the payoff while enrolled (w_e), we can not only consider the impact of wages, but the impact of flexible work scheduling on payoffs. Intuitively, Uber may increase payoffs while enrolled by being more compatible with school schedules that other forms of employment. However, many students already work part-time while enrolled, indicating that students are not completely without in school work options. In this case, Uber still can increase the payoffs while being enrolled without offering higher wages than other work options. This can come about in two ways. First, all else equal, flexible work allows individuals to adjust their working hours to better smooth their income across periods. Second, individuals would be able to better optimize their time between working and studying depending on shocks to their marginal utility of time spent working or studying.

First, consider a student decision maker choosing how much time to work during the school year, divided between a present (t) and future period (f) . The student has risk averse preferences, and has allocated a total of N hours to working across both periods. Students experience a random income shock in the future modeled by γ.[2] For example, unexpected medical bills would be a negative income shock, and unexpected pay raises

2. I assume that $\gamma > -f$ to avoid complex solutions.

would be a positive income shock. The student's preferences can be described by

$$u(t, f) = \sqrt{t} + \sqrt{f + \gamma}$$

The student then chooses between two work options for the semester, a traditional employment option where they first decide their hours for the present and future, and then they learn their value of γ, or a flexible employment option where they are able to first learn their value of γ, and then decide how to allocate their time. Regardless of the utility function, the flexible option is weakly preferable for individuals with diminishing marginal utility of wealth since they are then able to smooth their income between periods.

Second, consider a related problem, where a student decision maker is choosing to allocate N total hours between working (w) and studying (s). Time spent working and studying both have diminishing marginal utility, and studying can be more or less important depending on an unknown shock. This models periods of the semester (midterms, finals) where the marginal utility of time spent on schoolwork increases temporarily. Although assignment due dates are known ahead of time, the exact time needed for a project or exam often isn't fully known until studying. This will also be modeled by a random shock σ that takes on some positive value. For example, a busy week with many exams corresponds to an increase in the marginal utility of time spend studying (high σ). The student's preferences can be described by

$$u(w, s) = \sqrt{w} + \sigma\sqrt{s}$$

Once again, the student chooses between a traditional and flexible work option where the key difference is that the flexible option allows for the student to choose w and s after σ is revealed. Again, we see that Uber, a flexible option, would yield greater utility by allowing individuals to make time allocation decisions after receiving more information about the relevant factors.

This simple model of flexibility gets at the crux of what makes gig work different from other traditional work arrangements. In this model, individuals are "risk-averse" with respect to their allocations across today/future and work/school. The flexibility of Uber thus functions as a sort of insurance that gives individuals more certainty by being able to adjust to unknown shocks. Past research has shown that changes in wages impact educational outcomes, but gig work changes not only wages, but also the way in which work is scheduled. In this sense, Uber does not need to increase the wages of enrolled or nonskilled workers to have an impact on educational outcomes, but the flexible nature of gig work itself is enough to impact the payoffs of the educational decision making process.

3.3 Extended Model with Schooling Ability and School Choice

In the basic model thus far, we have considered only enrollment and ignored heterogeneity in schooling choices and individual characteristics. Consider now an extended model that incorporates differences in schooling ability and two schooling options, a shorter degree with lower payoffs, and a longer degree with larger payoffs. This reflects real postsecondary choices between 2-year associates and 4-year bachelors programs. Furthermore, we can incorporate the flexibility benefits of Uber to understand how the payoffs of enrollment and nonskilled labor change.

In this model, individuals choose between three options: working for all periods, going to associates college and then working, or going to bachelors college and then working. Formally, let N represent the number of periods the individual exists and let t_a and t_b represent the time needed to complete an associates or bachelors degree, respectively. We will assume that $N > t_b > t_a > 0$.

The payoffs an individual receives from each of the three options depends both on the outside labor conditions and their own personal characteristics. Outside labor options determine the payoffs of all three options, while an individuals schooling ability (a) determines the relative payoff increase after receiving a degree. Note that schooling ability is not purely a measure of innate characteristics, but of socioeconomic status and the relative privileges afforded to different demographic groups. Formally, let the payoffs for an individual be described by:

$$u_i(k,a) = \begin{cases} t_b w_e + (N - t_b) w_b(a) & \text{if Bachelors} \\ t_a w_e + (N - t_a) w_a(a) & \text{if Associates} \\ N w_n & \text{if No School} \end{cases}$$

where w_e represents the payoff while enrolled, $w_a(a)$ and $w_b(a)$ represent the skilled wage for associates and bachelors graduates, respectively, and w_n represents the non-skilled wage. Furthermore, I assume that $w_a(a), w_b(a)$ are increasing, concave functions with respect to a. This reflects the fact that an individuals schooling ability increases their post-schooling wage with diminishing returns. Specifically let,

$$w_a(a) = w_n \cdot (a)^{\alpha} \qquad\qquad w_b(a) = w_a(a) \cdot (a)^{\beta} = w_n \cdot (a)^{\alpha+\beta}$$

where $\alpha, \beta \in (0,1)$ and $\alpha + \beta < 1$. I also assume that $a > 1$, ie that the skilled payoff is strictly greater than the non-skilled wage, and $w_n > w_e$, that the non-skilled wage is strictly greater than the enrolled wage. An individual chooses the option that maximizes their total utility. Thus, an individual chooses an option if and only if its utility is greater than that of the other two options. This results in three inequalities that determine an individual's schooling choice.

$$\text{Choose bachelors over associates if: } t_b w_e + (N - t_b) w_b(a) > t_a w_e + (N - t_a) w_a(a) \quad (1)$$

$$\text{Choose bachelors over no school if: } t_b w_e + (N - t_b) w_b(a) > N w_n \quad (2)$$

$$\text{Choose associates over no school if: } t_a w_e + (N - t_a) w_a(a) > N w_n \quad (3)$$

These equations can be simplified into a more intuitive relative payoff and opportunity cost comparison as we saw in the basic model.

$$\begin{aligned}
t_b w_e + (N - t_b) w_b(a) &> t_a w_e + (N - t_a) w_a(a) \\
(N - t_b) w_n a^{\alpha+\beta} - (N - t_a) w_n a^{\alpha} &> (t_a - t_b) w_e \\
(N - t_b) w_n a^{\alpha+\beta} - (N - t_b + t_b - t_a) w_n a^{\alpha} &> (t_a - t_b) w_e \\
(N - t_b) w_n a^{\alpha+\beta} - (N - t_b) w_n a^{\alpha} &> (t_a - t_b) w_e + (t_a - t_b) w_n a^{\alpha} \\
\underbrace{(N - t_b)(w_n a^{\alpha+\beta} - w_n a^{\alpha})}_{\text{rel. payoff of bachelors compared to associates}} \quad &> \quad \underbrace{(t_b - t_a)(w_n a^{\alpha} - w_e)}_{\text{opp. cost of lost associates payoffs}} \qquad (1)
\end{aligned}$$

$$\begin{aligned}
t_b w_e + (N - t_b) w_b(a) &> N w_n \\
t_b w_e + (N - t_b) w_n a^{\alpha+\beta} &> N w_n - t_b w_n + t_b w_n \\
\underbrace{(N - t_b)(w_n a^{\alpha+\beta} - w_n)}_{\text{rel. payoff of bachelors compared to non-skilled}} \quad &> \quad \underbrace{(t_b)(w_n - w_e)}_{\text{opp. cost of lost non-skilled payoffs}} \qquad (2)
\end{aligned}$$

$$\begin{aligned}
t_a w_e + (N - t_a) w_a(a) &> N w_n \\
t_a w_e + (N - t_a) w_n a^{\alpha} &> N w_n - t_a w_n + t_a w_n \\
\underbrace{(N - t_a)(w_n a^{\alpha} - w_n)}_{\text{rel. payoff of associates compared to non-skilled}} \quad &> \quad \underbrace{(t_a)(w_n - w_e)}_{\text{opp. cost of lost non-skilled payoffs}} \qquad (3)
\end{aligned}$$

The interpretation of these equations follows from our basic 2-period model from before, where for each of the three inequalities, the left hand side represents total relative payoff and the right hand side total opportunity cost. The total relative payoff in each case is the length of time one receives the payoff, multiplied by the relative payoff in one period. Similarly, the total opportunity cost is the length of time one incurs those costs, multiplied by the per period opportunity cost.

We can plot these three inequalities in order to understand, given the payoffs of each degree (α, β) and economic conditions,w_n and w_e, how enrollment choice varies with respect to individual schooling ability. Plotted below are the three conditions, with the following parameters, $N = 3, t_b = 2, t_a = 1, \alpha = \beta = 0.25$. On the y axis is a measure of the relative opportunity cost of schooling $c = \frac{w_n}{w_e}$. On the x axis is schooling ability (a). Note that we required that $a > 1$ and $c > 1$, ie. that the skilled payoff is greater than the non-skilled payoff, and that the non-skilled payoff is greater than the enrolled payoff. In this particular case, inequality (2) is never pivotal in determining an individuals decision.

Thus, I only plot inequalities (1) and (3). Here, the white region represents choosing not to enroll, the green region represents enrolling in an associates program, and the red region represents enrolling in a bachelors program. Although this is a graph for particular parameters, in general the qualitative shape of the regions holds for values of α, β such that the relative payoff of a bachelors degree does not dwarf that of a associates degree.[3]

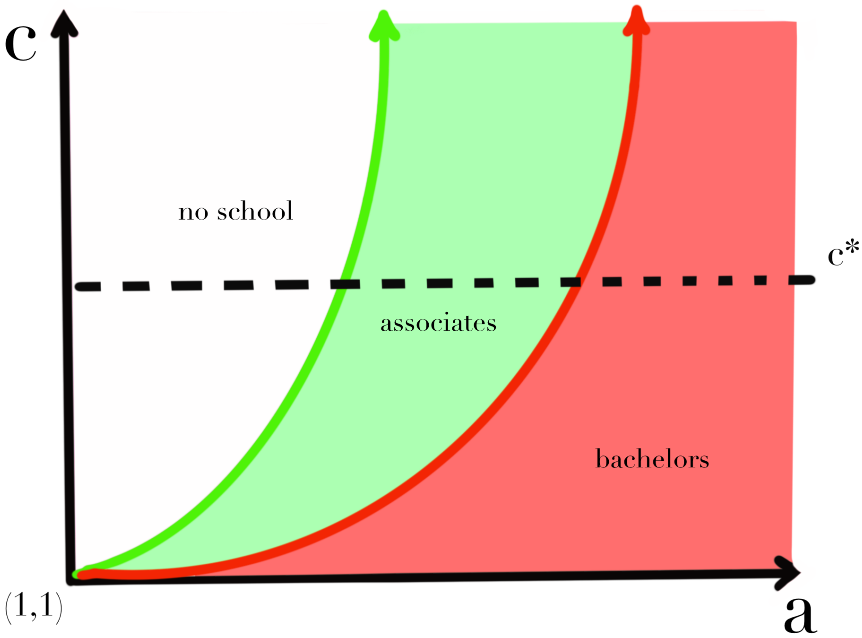

Figure 1: Enrollment decisions with schooling ability (a) on the x-axis and relative opportunity costs ($c = w_n/w_e$) on the y-axis. The red region represents enrollment in a bachelors program, the green region represents enrollment in an associates program, and the white region represents not enrolling. The dotted black line is simply a given value of c.

A few things are apparent from this graph. First, notice that when an individual has schooling ability such that there are no returns to schooling ($a = 1$), no matter the relative opportunity cost (c), individuals don't enroll since there is no payoff to schooling. Second, notice that when there are no opportunity costs to schooling ($c = 1$), all individuals enroll since there is no cost to going to school. For any given set of labor conditions c^*, individuals with high schooling ability enroll in bachelors programs, whereas individuals

3. If the payoff to a bachelors degree is much bigger than that of an associates degree, the two curves intersect, making it so that for high enough opportunity costs, associates college enrollment is 0. Real world evidence that associates college enrollment makes up nearly half of all college enrollment and that the return from associates colleges, although smaller than bachelors colleges, is still substantial, indicate that the relevant parameters for real world situations produce graphs like the one plotted in Figure 1.

with lower schooling ability either enroll in associates programs or don't enroll. Thus, for a given set of labor conditions which determine c^*, individuals will sort to different enrollment options based on their schooling ability.

These schooling ability cutoffs for different enrollment choices change with respect to the relative opportunity cost (c). Let us consider how Uber changes the parameters of this model. Uber does not impact return to education for individuals, but rather impacts their nonskilled payoff (w_n) and payoff while enrolled (w_e). If the net impact of Uber is to increase relative opportunity cost (c), potentially through increasing non-skilled payoff w_n by providing additional opportunities for non-skilled individuals, then the dotted black line c^* with shift up, increasing the schooling ability cutoffs for both associates and bachelors programs. Furthermore, the schooling ability cutoff for bachelors programs will shift more than that for associates programs. The net effect will be to decrease net enrollment, increase associates college enrollment, and decrease bachelors college enrollment. Also, the average schooling ability of associates colleges and bachelors colleges will increase, possibly leading to increased graduation rates for both.

If Uber instead decreases the relative opportunity cost (c), potentially through increasing the payoff while enrolled (w_e) by providing students with a flexible labor option, then the dotted black line c^* will shift down, decreasing schooling ability cutoffs. This shift will be greater for bachelors colleges than for associates colleges, meaning that the net effect will be to increase net enrollment, decrease associates college enrollment, and increase bachelors college enrollment. Furthermore, the average schooling ability of associates colleges and bachelors colleges will decrease, possibly leading to decreased graduation rates for both.

This model yields important testable hypotheses as to how Uber may impact enrollment and attainment. To summarize,

Table 1: Predictions from Extended Theory Model

Rel Opportunity Cost (c)	Total Enrollment	Associates Enrollment	Bachelors Enrollment	Avg Schl. Ability
↑	↓	↑	↓	↑
↓	↑	↓	↑	↓

The intution of these results stems from the decreasing returns to schooling ability. As the relative opportunity cost of schooling falls, the relative cost of bachelors colleges falls further than that of associates colleges since bachelors college individuals have higher schooling ability and thus lower marginal benefit to increased schooling ability. Thus, although the decrease in opportunity cost of schooling increases total enrollment, it also increases the relative proportion of students enrolled in bachelors programs. This theoretical result allows us to hypothesize whether Uber has increased or decreased the opportunity cost of schooling based on how total enrollment and the distribution across associates and bachelors programs has changed. As we will see, the evidence indicates that after Uber enters, associates college enrollment falls and total, as well as bachelors, enrollment increases. Additionally, we see that graduation rates at associates colleges decrease which aligns with our model of average schooling ability decreasing at associates colleges.

In order to come to these results, I made a few key assumptions to keep the model tractable and focused on human capital as investment. First, I assumed that individuals do not discount the future. This is for mathematical simplicity, as the discount rate would capture the same effect of decreasing the time one receives the payoffs to an education ($N - t_b$ or $N - t_a$). If individuals have heterogeneous discount rates however, more impatient individuals would be more likely to enroll in associates programs. Second, I assume that there are no differences in the payoff to enrollment at associates and bachelors colleges (ie, w_e is the same). In reality, bachelors colleges are often more expensive than associates programs. However, given that credit markets exist and the credit constraint literature has shown that the majority of individuals are not credit constrained, the difference in net cost of attendance can be thought of as altering the relative payoff of bachelors colleges relative to associates colleges. Third, I assume that Uber does not change the relative payoff of a college degree (ie, Uber entry does not change α, β). This is done to focus on the opportunity cost channel, and evidence that the majority of gig workers make less than \$2,500 a year indicates that gig work is a small income supplement rather than a standalone job for most people.

4 Data

For my main regression, I gather data on education outcomes between 2005-2019 from the Integrated Postsecondary Education Data System (IPEDS), data on Uber entry dates from published papers[4] and local news articles, and data for controls from various government sources.[5] For my robustness checks and regressions on mechanisms, I use the Public Use Microdata Sample (PUMS) from the 1-year American Community Surveys (ACS) from 2008-2019.[6]

The IPEDS data contains annual information on all postsecondary institutions in the United States that participate in any federal financial assistance program. This means the data covers nearly all postsecondary institutions in the United States. IPEDS contains data on institutional characteristics, such as location, private/public control, tuition, urbanization, degree-granting status, and program type. I drop institutions that are not authorized to grant degrees and that do not exist continuously between 2005 to 2019. I run regressions on samples split by two main characteristics, 1) whether the institution primarily offers 2-year or 4-year programs, and 2) whether the institution is under public or private control.

I focus on two measures of educational outcomes, enrollment and graduation rate. Enrollment is defined as the 12-month headcount from July 1st to June 30th.[7] This measure is more general than an fall entering student count since associate college programs can have open enrollment that allows individuals to enroll throughout the year. For robustness, I also include the fall entering enrollment counts as a measure of enrollment. Enrollment data is disaggregated by gender, race, undergraduate/graduate enrollment, and part/full time enrollment.

Graduation rate is defined as the percentage of individuals in a given cohort year who

4. From Hall, Palsson, and Price 2018

5. I get county population and income from the American Community Surveys, college age population from the Center for Disease control's Wide-ranging Online Data for Epidemiologic Research, regional gas prices from the U.S. Energy Information Administration, county unemployment rates from the Bureau of Labor Statistics, and county test scores from the Stanford Education Data Archive.

6. Data is accessed via census API from the tidycensus R package, developed by Walker and Herman 2022

7. Uber entry dates occur throughout the year so I define Uber as having entered in a given year if it entered before July 1st, thus ensuring that IPEDS reporting dates align with my Uber entry years.

graduate within a specific timeframe. For graduation rate within 2 or 3 years at associates colleges, disaggregated measures by gender and race are available. Since a number of years must pass until the graduation rate of a cohort is known, I focus on associates college graduation rates since the data is available from 2005-2017. For bachelors colleges, I construct a proxy for graduation rate, annual completion rate, defined as the number of degrees awarded in a given year divided by the total number of students in the entering cohort 4 years prior (2 years prior for associates colleges). Although this does not take into account how long it takes to graduate, this measure is available until 2019.

Broadly speaking, 2-year associates colleges make up around 50% of postsecondary enrollment, the rest being primarily from 4-year bachelors programs. (Figure 2). However, despite similar enrollment shares, associates colleges have significantly lower graduation rates. For example, only 22% of the 2010 entering cohort graduated in 150% of expected time (3 years) at public 2-year colleges, compared to 47% graduating in 150% of expected time (6 years) at public 4-year colleges. (Table 2). Enrollment also differs between 2-year and 4-year colleges, with community colleges averaging 12,709 students in 2010 and public 4-year colleges averaging 10,316 students. Private 2-year and 4-year colleges tend to be much smaller (2,168 and 2,439 students respectively) but have higher graduation rates. Taken altogether, community colleges enroll a substantial fraction of all postsecondary students but struggle with low graduation rates.

Data on Uber entry comes from Hall, Palsson, and Price 2018 and online sources (local news publications and Uber's company website). Uber entry dates are at the core based statistical area (CBSA) level, which are geographic regions set by the US Office of Management and Budget. I focus on a particular type of CBSA, metropolitan statistical areas (MSAs), that are economically and socially linked regions consisiting of a city and its surrounding communities. For example, Boston is part of the Boston-Cambridge-Newton MSA that includes multiple counties centered on Boston. Uber was founded in the San Francisco Bay area, and slowly expanded and entered other US metropolitan areas between 2010 to 2018. (Figure 3). Uber first targeted high population urban areas, entering areas in almost population rank order. (Figure 4). The bulk of entry occurred in

2014 when Uber received its largest influx of funding. In total there are around 300 MSA entry dates, spanning 2010 to 2018. Previously published papers provide entry dates up to 2015 and my online sources catalog entry up until 2018.

Mapping Uber entry dates provides a clearer image of Uber's entry decisions. The data show that Uber favored high density urban areas, but entered different metropolitan areas at different times, even within the same state, providing substantial variation for empirical analysis. (Figure 5)

For robustness, I use the Public Use Microdata Sample (PUMS) from the 1-year ACS to measure enrollment and attainment. This data does not break down college enrollment by college type (2 vs. 4 year), but does contain data on undergraduate enrollment. For a measure of attainment, I use the percentage of individuals who dropped out of college, defined as having an educational attainment of some college experience but no degree. The PUMS provides geographic data on respondents in the form of Public Use Microdata Areas (PUMAs). I map these PUMAS to MSA in order to link them to Uber entry data.[8] Lastly, for regressions on mechanisms I use measures of income (total income, family income, and income from wages) and work hours from the PUMS.

5 Methods

In order to identify the effect of Uber entrance on educational outcomes, I leverage variation in the timing of Uber's entrance into MSAs across the United States. My empirical strategy is a staggered difference in difference at the university level. My regression equation is specified by:

$$Y_{i,t} = \beta Uber_{i,t} + \gamma_i + \delta_{s,t} + \Phi X'_{i,t} + \epsilon_{i,t}$$

where $Y_{i,t}$ is my outcome of interest in university i in year t, $Uber_{i,t}$ is an indicator variable of whether Uber has entered the CBSA of the university i in year t, γ_i is a university fixed effect, $\delta_{s,t}$ is a state by year fixed effect, and $X'_{i,t}$ is a vector of time-

8. IPUMS staff, from https://forum.ipums.org/t/methodology-for-crosswalk-between-msas-and-2010-pumas/331, accessed 4/05/22

varying controls and baseline characteristics, namely baseline 2009 county unemployment rate and median household income time trends, regional retail gas prices, county college age (15-29) population, and county 8th grade standardized math test scores as a proxy for college readiness. My coefficient of interest is β, the change in the outcome of interest at an institution after Uber entry. Non-percentage outcomes will be in logged regressions so the interpretation of β is percent changes in the outcome variable.

The motivation for this empirical design is that Uber's temporal variation in entry provides a compelling natural experiment for study. However, Uber entry is likely endogenous with respect to my outcome variables. Therefore I must control for all relevant confounding variables. I control for all time invariant factors by using institution fixed effects. State by year fixed effects flexibly control for state level trends from state level policies that may influence both Uber entry and educational outcomes. Another concern is that Uber enters areas with better economic conditions earlier, and those same areas may have different trends in educational outcomes in the absence of Uber entry. To address this concern, I control for differential trends by baseline median household income and unemployment rate to account for potentially differing trends by economic condition. Lastly, I control for time variant factors that may introduce endogeneity. Gas prices may impact both the cost of working Uber and Uber's decision to enter an area. College age population may impact the funding of postsecondary institutions, as well as influence the available market size for Uber. College readiness of high school students may be linked to broader local policy, as well as impact the college enrollment and attainment of individuals.

Although I run this regression on the entire IPEDS sample, I focus on undergraduates at community colleges for three main reasons. First, the mission of community colleges is to provide broad access to postsecondary education, making it the most appealing to individuals at the margin of deciding whether to attend school (Kane and Rouse 1999). Second, focusing on community colleges fits my empirical strategy since enrollment is local, meaning changes in enrollment can be plausibly be linked to local changes in Uber availability. Additionally, selection biases are less prevalent since most community colleges have open admission policies and low financial costs. Third, since graduation rate data lags the current year by the expected degree time, associate college data is available up until 2017, while 4-year college data is only available up until 2014.

In order for my regression to correctly identify the effect of Uber entry on education outcomes, there must be parallel education trends between treated and untreated universities. In order to ensure this I run the regressions on increasingly specific samples, starting with all institutions and narrowing to focus on public and 2-year colleges. Since Uber was founded in the San Francisco Bay Area in 2010, I drop all observations for that MSA. Additionally, since my outcome variables are serially correlated, I cluster standard errors at the institution level (Bertrand, Duflo, and Mullainathan 2004). Lastly, much recent econometric research has shown that there are issues with the standard two way fixed effect regression when treatment is staggered and heterogeneous treatment effects exist. To address this, I use the Sun and Abraham estimator to avoid the negative weighting associated with staggered treatment and heterogeneous treatment effects (Sun and Abraham 2021).[9]

The biggest threat to identification is if Uber's entry decision is endogenous with the growth rate of education in a given CBSA. If so, my regression may incorrectly attribute findings to Uber's entry in a CBSA. However, evidence from previous papers who use a similar empirical strategy shows that this is unlikely. Hall, Palsson, and Price 2018 regress a variety of CBSA factors on Uber entry and find that Uber largely entered CBSAs in population rank order.[10] This makes sense given that population is likely most predictive of the availability of drivers and the size of the market. Additional evidence from the IPEDS dataset suggest although enrollment level is highly correlated with population, and thus Uber entry, the annual change in enrollment has little to no relationship with population. Figure 4 plots the relationship between Uber entry date and CBSA enrollment and shows that Uber entered areas in almost enrollment rank order. Although the level of enrollment is predictive of Uber entry, the annual change

9. All regressions are estimated using the fixest R package developed by Bergé 2018

10. Similar results are found by Daniels and Grinstein-Weiss 2019, Fos et al. 2019, Koustas 2018, Berger, Chen, and Frey 2018, Jackson 2020, Burtch, Carnahan, and Greenwood 2018

in enrollment has no clear relationship with Uber entry date, as shown in the second panel of Figure 4. Furthermore, examining Table 3 displays 2010 educational outcomes of community colleges by year of Uber entry. As noted before, level of enrollment is higher in the earliest entered metropolitan areas since Uber entered the largest markets first. However, looking at graduation rates, we see that graduation rates are nearly equal between all the years of entry.

As a further check on my identification strategy, I run an event study to check for pre-trends and examine the effect of Uber entry over time. This regression is nearly identical to my staggered difference in difference, except that I now include a year interaction term that indicates how many years have passed since Uber entered an area. Specifically, my event study regression equation is :

$$Y_{i,t} = \sum_{j=-5, j\neq -1}^{5} \beta_j (\text{years since Uber entry} = j) + \gamma_i + \delta_{s,t} + \Phi X'_{i,t} + \epsilon_{i,t}$$

Running this regression allows me to examine pre-trends and determine whether the parallel trends assumption holds with my given set of controls.

Lastly, I run the same staggered twoway fixed effects regression using the ACS dataset as a robustness check for the IPEDS regression and to examine potential intermediate mechanisms that drive changes in educational outcomes. The regression is specified by :

$$Y_{i,t} = \beta Uber_{i,t} + \gamma_i + \delta_{s,t} + \Phi X'_{i,t} + \epsilon_{i,t}$$

where $Y_{i,t}$ is the variable of interest, $Uber_{i,t}$ is an dummy variable of whether Uber has entered core based statistical area (CBSA) i in year t, γ_i is a CBSA fixed effect, $\delta_{s,t}$ is a state by year fixed effect and $X'_{i,t}$ is the same vector of controls as the IPEDS regression but aggregated to the CBSA level.

In order to focus on the population that is most likely to be impacted by Uber and making educational decisions, I narrow the sample to individuals aged 16-35. My primary outcome variables of interest in the ACS data are measures of income and educational outcomes. For income, I look at CBSA median personal annual income, CBSA median personal annual income from wage/salary work, CBSA median hours worked per week, and CBSA median family income. For educational outcomes, I look at the percentage of the CBSA enrolled in an undergraduate program, and the percentage of the CBSA who dropped out of college.[11]

6 Findings

6.1 Educational Outcomes

Starting at the most broad level, I look at Uber's effect on educational outcomes for all postsecondary institutions. Although there are many different types of colleges, this regression will give a sense of Uber's impact on college enrollment as a whole. Table 4 reports regression estimates for my main educational outcomes, namely annual enrollment, entering class enrollment, completions, and completion rate. It is important to distinguish between completion rates and cohort graduation rates. I construct completion rates for all institutions since cohort graduation rate data for bachelors colleges are only available until 2014. The enrollment and completions variables are logged so the interpretation of the coefficients are percent changes. I also include my full set of controls in all four regressions. The findings are not significant and do not provide evidence that Uber has a substantial impact on overall enrollment and attainment. Focusing just on the signs of the variables, we see suggestive evidence that enrollment, measured by annual enrollment and entering class enrollment, increases.

Next, I narrow the sample to focus only on public schools and split the sample by whether the college primarily offers bachelors (4-year) or associates (2-year) degrees. I focus on these samples for a couple of reasons. First, I expect Uber to impact those most at the margin of attending school and the cost of public institutions is typically lower than that of private institutions. I split the sample by bachelors and associates for a similar reason, namely that associates college are most likely to enroll students at the margin of attending college or working. Second, public institutions typically enroll a larger fraction of local individuals, both due to their size and their regional/state tuition

11. Defined as the percentage of individuals whose highest level of educational attainment is some years of college but no degree.

discounts, making these regressions less subject to measurement error that comes from student migration. The second and third panels of Table 4 report regression estimates of educational outcomes for these programs. Although the coefficients are not significant, there is a clear differential effect between community colleges and public bachelors programs. The regression is suggestive that Uber decreases enrollment at community colleges and increases enrollment at bachelors colleges, as evidenced by their differing signs. Similarly, the results suggest Uber increases completion rates slightly at public associates programs while decreasing them at bachelors programs. The differential impact on enrollment is even more apparent when looking at an event study plot of the effect of Uber over time on public associates and bachelors programs (Figure 6).

Further focusing on community colleges allows us to look at the differential effect Uber has on different types of students. Table 5 reports regressions on full/part time enrollment by age group. Looking at column (1), we see that aggregate full time enrollment at community colleges drops by about 5% after the entrance of Uber. This result is significant at the 95% level. This effect is primarily driven by decreases in younger students, with enrollment of 20-21 year olds dropping by 7.8% in column (3). Since we don't see this effect for 18-19 year olds, it suggests that students may be graduating on time more frequently, transferring more frequently, or switching to work or bachelors programs. Lastly, we see that the effect is not present for the 25 and older age group. This may be due tot he fact that older students often finance their own education and are less dependent on family contributions. When looking at part time enrollment instead, we see that there are no significant changes in enrollment at any age level. This may be due to the fact that part-time enrolled students already are scheduling their schooling around outside employment, and so the introduction of Uber doesn't significantly alter their payoffs. In a sense they are less time constrained than full time enrolled students. Looking at attainment as measured by cohort graduation rates, we find that the 2-3 year graduation rate drops by 0.8% after Uber entry in column (11). We see similar, though not significant, negative effects for 2 year and 3 year graduation rates. This indicates that although the rate of on time graduation does not seem to change, fewer students are graduating in longer timeframes, either due to dropout or transfer.

Lastly, I look to see if there are differential effects by gender and race for community colleges. Table 6 reports regression coefficients for enrollment and graduation rates grouped by gender and race. There seems to be differential effects on enrollment and attainment by gender, with the decline in female enrollment being larger than that of male enrollment in columns 1-2, and the decline in male graduation rates being larger than that of female graduation rates in columns 3-4. This may be due to the differing demographics of Uber drivers, as only around 13% of Uber drivers are female (Hall and Krueger 2018). Next, looking at enrollment by race, the effects are uniformly negative for all races aside from enrollment for hispanic students. This also may be related to the fact that the Uber workforce is more diverse than the general US population.

6.2 Robustness Checks

Looking at event study figures for these regressions allows us to confirm our parallel trends assumptions and also examine the effect of Uber over time. Figure 7 displays the event study plot for full time community college enrollment. Notice that aside from slight pretrends for students 25 and older, the parallel trends assumption seems to hold. Furthermore, the effect of Uber increases over time as we would expect. Figure 8 displays the event study plot for part time community college enrollment. Once again, there are no pretrends, confirming the parallel trend assumption, and Uber seems to never have an effect on part time enrollment over time. Figure 9 displays the event study plot for graduation rates for community colleges. There are some pretrends for graduation rates which indicate there may be additional confounding variables that I need to control for. Once again, we see that the effect of Uber on graduation rates increases over time as we would expect. Altogether, these event study plots give us more confidence in our regression results on enrollment and attainment at community colleges.

Using the ACS allows us to perform another robustness check on our earlier IPEDS regression by looking at how the percentage of enrolled undergraduates and dropouts changes after Uber entry. Although the ACS does not report enrollment by college type, it is microlevel data that gives us another measure of educational outcomes.

First, Table 7 displays regression outputs of the percentage of enrolled undergraduates and dropouts for the 21-36 year old population for each CBSA. Although the ACS is a more noisy measure of educational outcomes since we cannot control for institution level variables, it is still a useful sanity check on the results from the IPEDS regressions. Columns (4) and (5), while not significant, somewhat align with our IPEDS regressions. First, we see that the change in aggregate enrollment is small in magnitude, less than a percent, which aligns with our IPEDS estimates. Second, we see that percentage of college dropouts seems to increase, aligning with our IPEDS aggregate results that completion rates decrease.

6.3 Mechanisms

As discussed before, Uber may alter the relative payoffs and opportunity costs of education by changing the payoffs for students and for nonskilled labor. Table 7 also reports aggregate regression estimates of how Uber affects median personal income, median weekly hours, and median income from wages/salary. We see that Uber does not have a significant effect on earnings, as measured by income or wages. However, Uber does seem to decrease weekly work hours by 1%. This may be due to the flexibility of Uber allowing individuals to better optimize their time allocation between work and leisure.

Focusing on the payoffs for nonskilled labor, Table 8 reports median income measure for individuals with associates, bachelors, or no postsecondary degree. Here, though none of the earnings coefficients are significant, wages and income for non-degree holders seems to increase relative to that of associates and bachelors degree holders. This may indicate increases in payoffs for nonskilled labor, which would correspond to an increase in the opportunity costs of education. We also see that weekly work hours decrease for degree holders, by 2% for bachelors degree holders, while work hours seem to increase for non-degree holders.

Table 9 looks at changes in earnings between enrolled and non-enrolled individuals for different age groups of students. First, in panel 1 of Table 9, although not significant, median family income, defined as the total household income, appears to increase for students relative to non-students aged 21-25 (columns 1 and 4). Furthermore, personal income from wages appears to decline for students relative to non-students. This may indicate that the availability of Uber allows families to better finance their children's education, lowering their personal costs of education and thereby their opportunity costs to a degree.

This interpretation is aided by the second panel of Table 9, in which when looking at older individuals aged 31-35, family income of students does not increase relative to that of non-students. This may stem from the fact that older individuals are more likely to have to finance their own education and thus not be impacted by changes in their personal family income.

Overall, the ACS provides some reassurance about our IPEDS regressions as they align in magnitude with aggregate effects on educational outcomes. Additionally, the results do not provide much support for a personal income mechanism whereby Uber changes the wages of students and nonskilled labor. Instead, there does seem to be suggestive evidence that increases in family income for younger students may drive substitution from community colleges to four year programs.

7 Discussion

These findings indicate that Uber has a significant effect on the educational enrollment and attainment of community college students. Recall the findings from our model of education as investment with heterogeneity in schooling ability and schooling choices, namely that if the relative opportunity cost of schooling decreases, associates college enrollment decreases, total and bachelors college enrollment increases, and average ability decreases at both associates and bachelors colleges. The evidence is consistent with this interpretation as full time enrollment at community colleges decrease by 5% and 2-3 year graduation rates decline by 0.8%.[12] Furthermore, the signs of the regressions on aggregate

12. This is related to the finding from Burtch, Carnahan, and Greenwood 2018 that after Uber entry, overall entrepreneurial activity declined, but the quality of the remaining entrepreneurial ventures was higher. Here we see the opposite substitution effect, where enrollment at associates colleges declines

enrollment and bachelors college enrollment suggest that both increased. These effects all stem from a decrease in the relative opportunity cost, but Uber may alter the relative opportunity cost in a variety of ways. The regressions on ACS data allow us to better pinpoint through which potential mechanisms Uber lowers the relative opportunity cost of schooling.

First, there is little evidence that Uber lowers the opportunity cost of schooling by increasing the net wages earned by students while enrolled. The regressions on ACS data do not indicate that wages increase for enrolled students, and data on the earnings of Uber drivers indicates that the vast majority of Uber drivers make less than \$2,500 annually from the platform (Collins et al. 2019). Furthermore, if Uber were to increase net wages substantially, we'd expect both the enrollment of full time and part time students to decrease. As Lee 2020 finds, a 10% increase in the minimum wage decreased part time community college enrollment by 5-6%. The fact that we only see enrollment declines for full time students indicates that income likely is not the channel through which Uber impacts educational outcomes. Many potential mechanisms remain, but the findings align with a narrative of opportunity costs being lowered through increased family income and/or the benefits of flexibility.

If Uber increased family incomes, younger students who often have their education financed by their parents may have their opportunity cost of enrollment decrease since less time needs to be spent working to cover school expenses. This is reflected in the finding that the decreases in full time community college enrollment occur primarily for younger students. Similarly, the ACS regressions showed that family income for students aged 21-25 increased relative to non-enrolled individuals, and that increase was not present when looking at older students aged 31-35.

At the same time, Uber may decrease the opportunity cost of enrollment without actually affecting the net income a student receives by allowing students to better optimize their time and smooth over income shocks. This aligns with the finding that part time enrollment does not change at community colleges, since students who are enrolled part

because those with the highest schooling ability seem to have switched to bachelors programs.

time likely already have arranged their school and work schedules to be compatible. Put another way, full time enrolled students have less flexibility with their time, thus the introduction of some working flexibility with the availability of Uber is more impactful for full time students. Furthermore, this interpretation would be compatible with the ACS regressions indicating that Uber did not substantially change students' wages.

8 Conclusion

This paper provides some of the first empirical estimates of the effect of the gig economy on educational outcomes. Despite anecdotal evidence of students who report that the flexibility of Uber work aided their academic experience, the empirical evidence shows either no effects or negative effects on postsecondary enrollment and attainment. In particular, community colleges experience a significant decline in full time enrollment, as well as decreases in attainment as measured by completion rates and graduation rates. Furthermore, the mechanism driving this effect is likely not changes in the incomes of students or unskilled workers. The exact mechanism cannot be pinned down, but the evidence aligns with increases in family income and the benefits of flexibility decreasing the opportunity cost of college, causing higher schooling ability students to substitute away to bachelors programs. The welfare impact of this is unknown as individuals who choose not to enroll may be better off working Uber, but a cause of concern is the lack of human capital development and stagnant wage growth in Uber work. If their earnings trajectory follows that of the unemployed individuals who worked Uber in Jackson 2020, individuals may have incomes that lag those who went to school or worked traditional jobs in the long run.

These findings also contribute to research on how changes in the labor market affect educational outcomes. While past papers have focused primarily on changes in the wages or availability of work, I examine the added dimension of flexibility in work. Furthermore, this paper contributes to the literature seeking to understand the enrollment and attainment decline at community colleges in the past decade. Whereas literature has primarily focused on supply side effects like tuition increases, these findings highlight the importance of substitution between associates and bachelors colleges from changes in labor market conditions.

This paper is not without concerns, but these concerns are themselves further questions and directions for future research. For the theory model, the results depend on specific assumptions that abstract from the exact mechanism through which Uber impacts educational outcomes. Although there is little evidence to support Uber impacting educational outcomes by substantially changing the wages of either students or non-skilled workers, it does not rule out changes in family income or benefits of flexibility. Incorporating these channels directly into the theoretical model will help explain the heterogeneous effects we see between younger and older students, and full and part time community college students. Other important factors, such as heterogeneity in wealth will help understand how these educational changes differ by income, especially since associates and bachelors colleges serve socioeconomically different groups. Lastly, given that one of the primary functions of community colleges is to help students transfer to four year programs, incorporating this optionality in a theoretical model will allow for a better understanding of the differential effects of Uber on educational outcomes.

For the empirical side, this paper depends on controlling for all potential variables that impacted both educational outcomes and Uber entry decisions. Further research on the determinants of educational outcomes will allow for more potential omitted variables to be controlled for. Additionally, an important potential mechanism that is unobserved in the IPEDS and ACS data is the number of transfers from community colleges. If community college enrollment declines due to students substituting from community college to bachelors programs, it is important to understand if they substitute before enrolling or are transferring out of community colleges to bachelors programs. However, enrollment and attainment are not the only relevant educational outcomes since working while enrolled decreases academic outcomes. Although our ACS regressions didn't indcate substantial increases in work hours for enrolled students, a more detailed analysis of the working schedules of student gig workers and their ultimate labor outcomes will help further clarify the effect of Uber on educational outcomes.

Regardless of whether gig work becomes an increasingly large part of the labor market, its size today warrants a rigorous evaluation of the impacts it has on consumers and laborers. Continued research on how gig work impacts laborers' education decisions will further our understanding of new forms of work arrangements and the determinants of education decisions themselves.

Figures

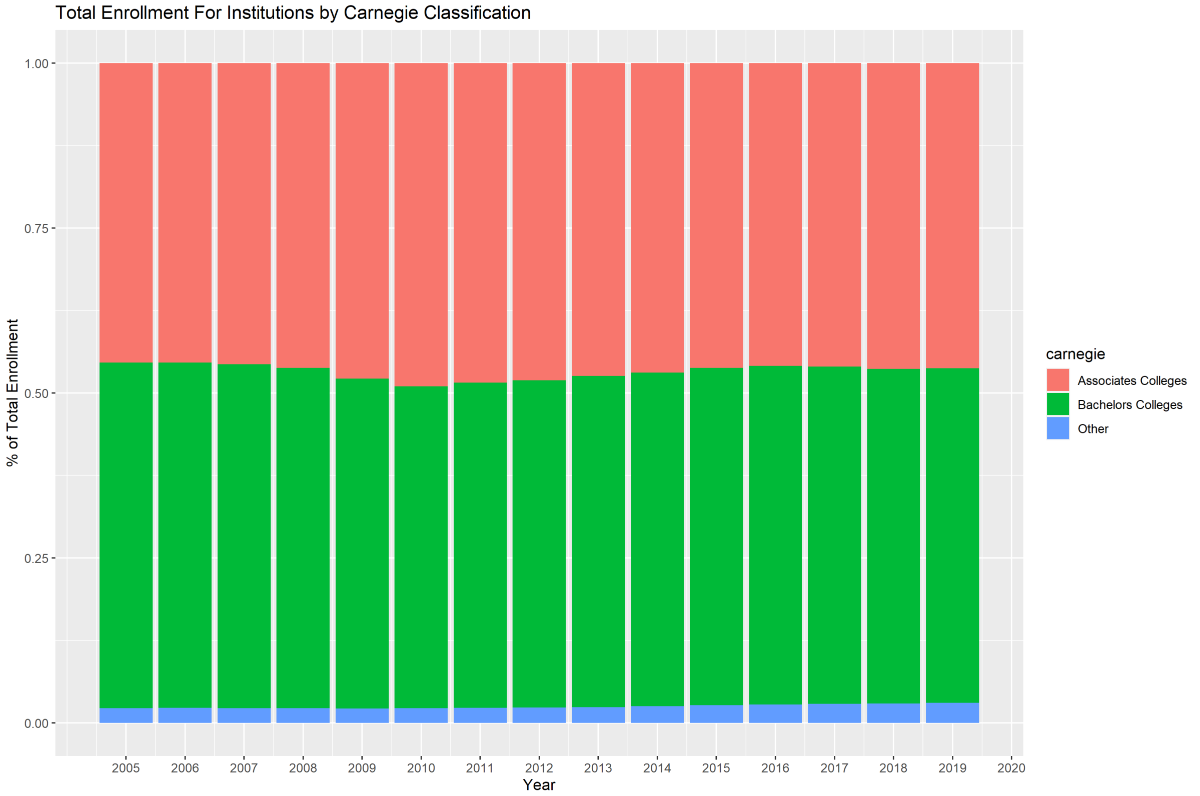

Figure 2: Total Enrollment By Institution Type

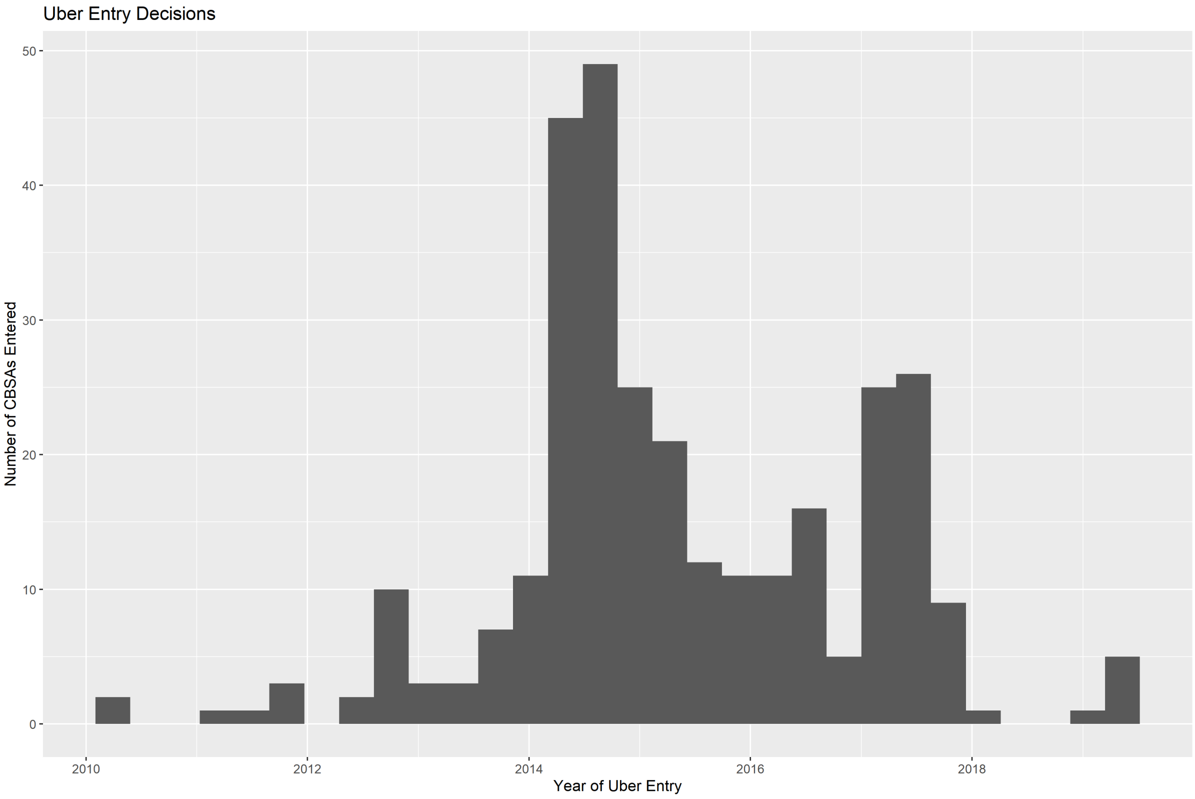

Figure 3: Uber Entry Year Histogram

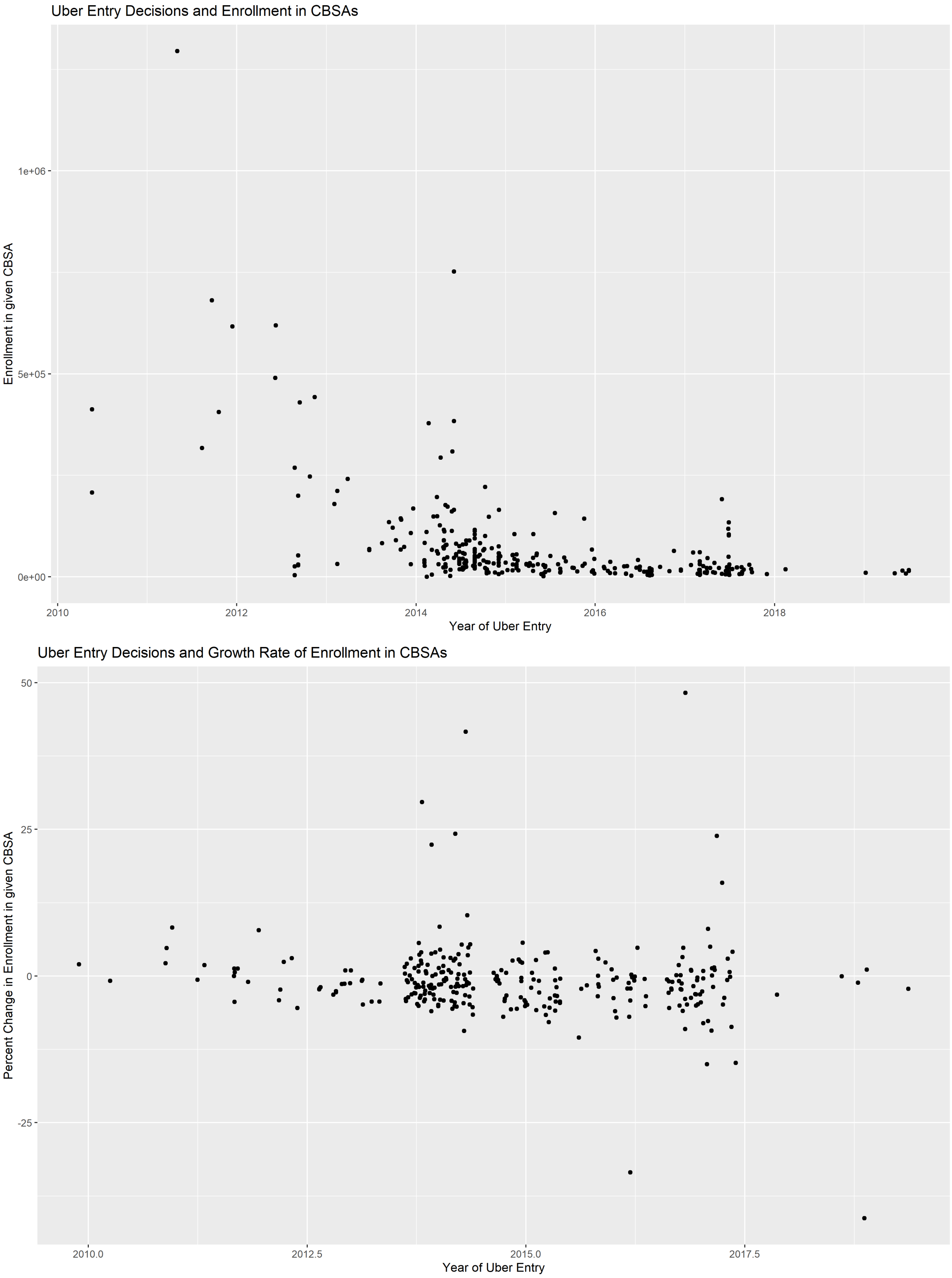

Figure 4: Uber Entry Year by Enrollment Level and Enrollment Growth

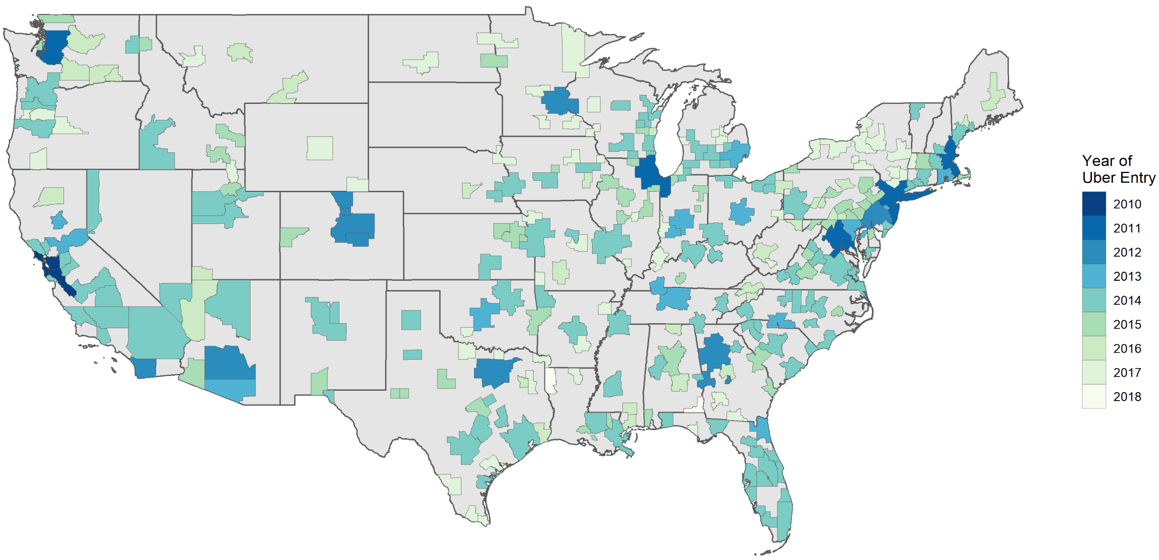

Figure 5: Mapping of Uber Entry Dates

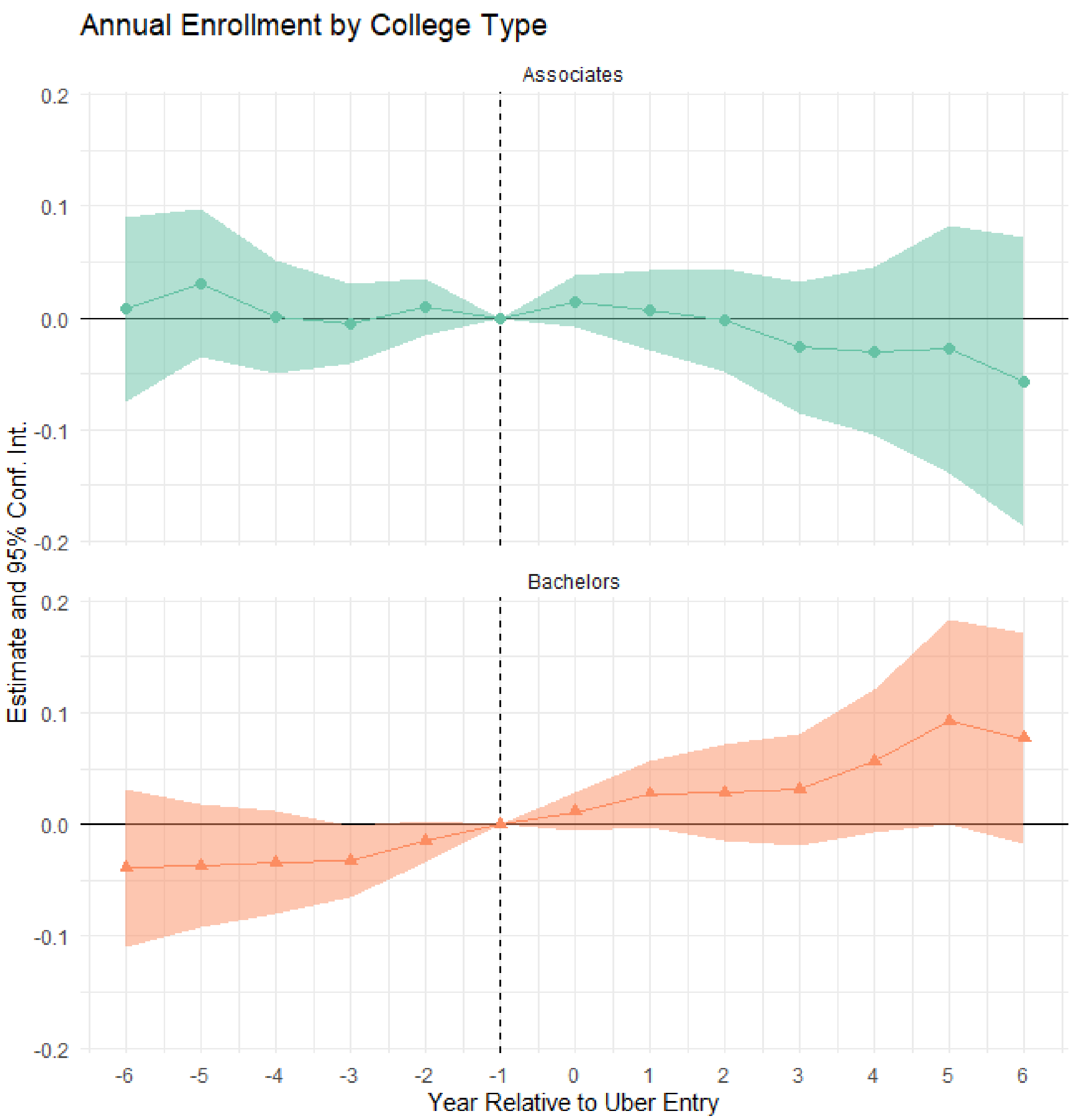

Figure 6: Annual Enrollment by Institution Type. Confidence Intervals are at the 95% level.

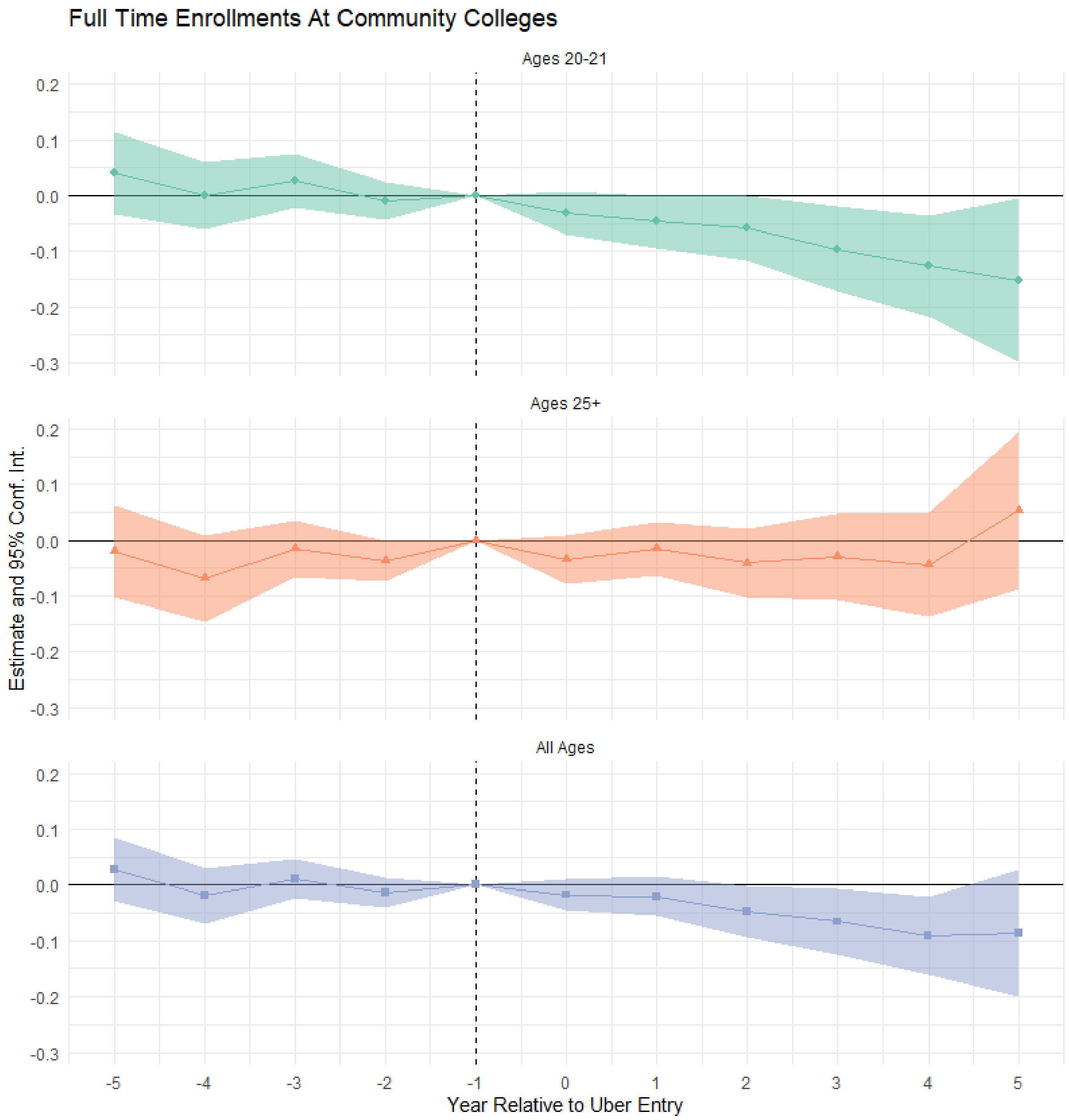

Figure 7: Full time Enrollment at Community Colleges by Age Group. Confidence Intervals are at the 95% level.

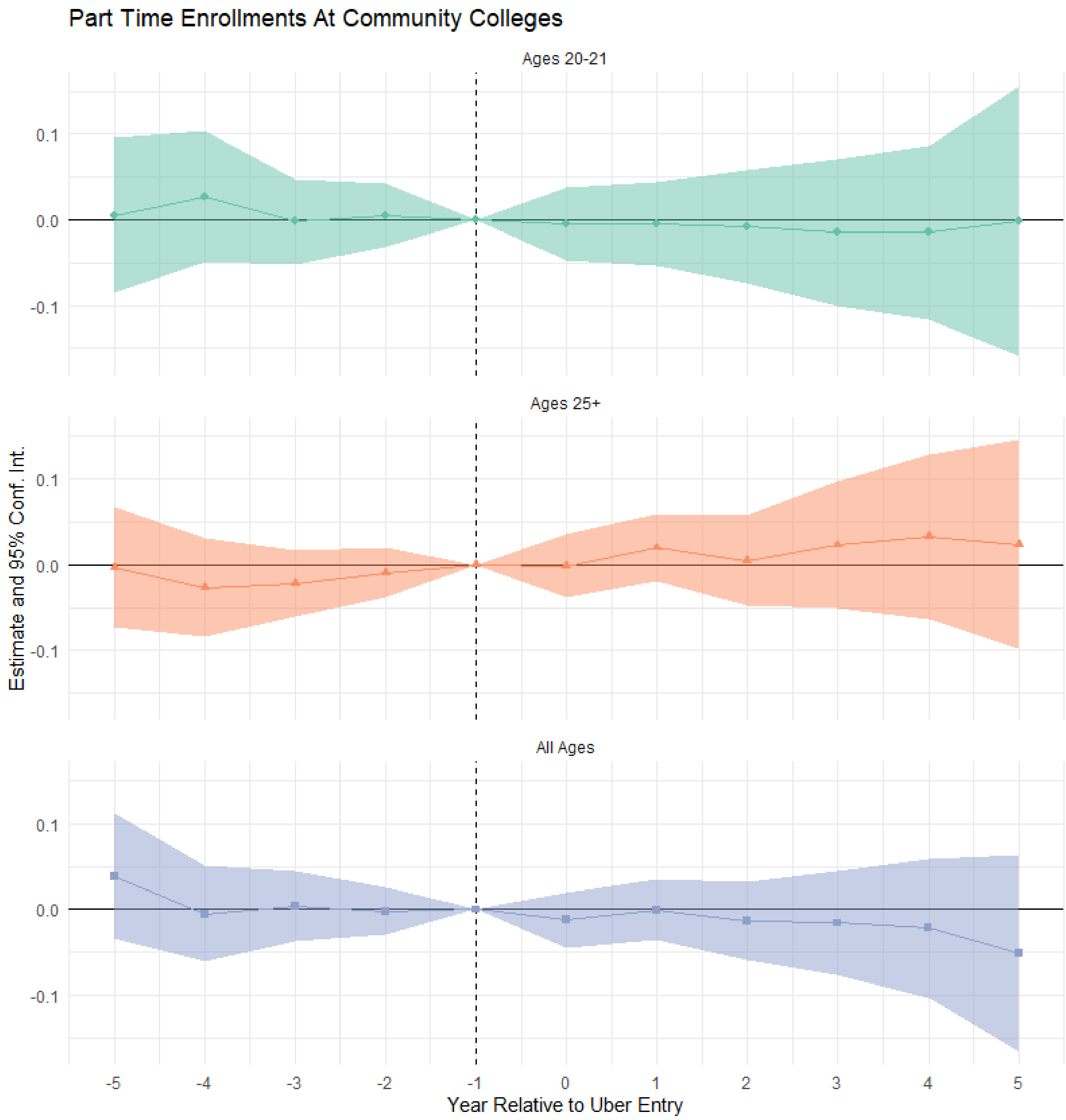

Figure 8: Part time Enrollment at Community Colleges by Age Group. Confidence Intervals are at the 95% level.

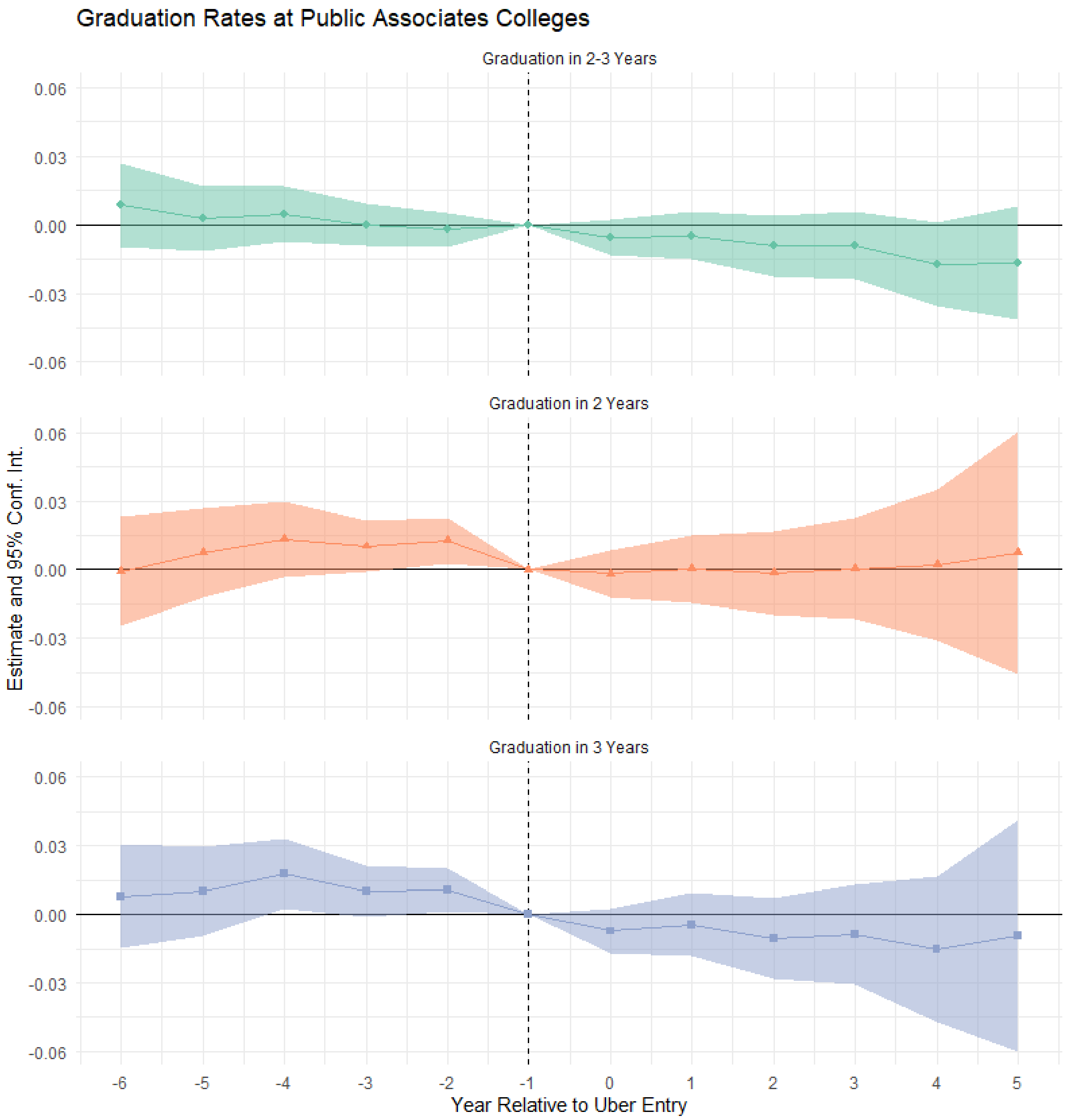

Figure 9: Graduation Rates at Community Colleges by Graduation Time. Confidence Intervals are at the 95% level.

Tables

Table 2: Summary Statistics of Undergraduate Institutions in 2010

	Private 2-Year	Public 2-Year	Private 4-Year	Public 4-Year
Enrollment	1835.01	11473.67	2408.93	9829.92
	(3094.36)	(12463.54)	(4635.68)	(9281.5)
Completions	162.44	555.5	285.89	1197.43
	(316.06)	(587.45)	(491.98)	(1677.7)
Graduation Rate in 100% of Expected Time	0.35	0.12	0.4	0.26
	(0.25)	(0.11)	(0.24)	(0.17)
Graduation Rate in 150% of Expected Time	0.46	0.22	0.53	0.47
	(0.25)	(0.12)	(0.22)	(0.18)
Graduation Rate in 200% of Expected Time	0.47	0.27	0.55	0.5
	(0.25)	(0.12)	(0.22)	(0.18)
Count	379	1015	2102	880

Notes: Standard errors are reported in parentheses. 2010 is chosen as a baseline year since it is right before Uber expands to any markets.
Source: IPEDS, 2005-2019.

Table 3: Summary Statistics of 2-Year Colleges by Uber Entry Year

Year Entry	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Never Entered
Enrollment	20317	16325	20907	17325	16686	12138	7339	8590	5167	3363	4837
	(10995)	(10026)	(13629)	(14853)	(15821)	(16974)	(4780)	(6914)	(2822)	(2870)	(3692)
Completions	474	854	746	815	829	567	462	571	350	166	280
	(267)	(615)	(479)	(686)	(872)	(524)	(330)	(450)	(153)	(128)	(202)
Graduation Rate in 100% of Expected Time	0.11	0.08	0.09	0.07	0.10	0.11	0.16	0.15	0.08	0.15	0.16
	(0.12)	(0.09)	(0.05)	(0.05)	(0.12)	(0.10)	(0.10)	(0.09)	(0.06)	(0.10)	(0.12)
Graduation Rate in 150% of Expected Time	0.25	0.19	0.19	0.17	0.19	0.20	0.24	0.24	0.12	0.35	0.25
	(0.13)	(0.10)	(0.08)	(0.08)	(0.13)	(0.13)	(0.09)	(0.10)	(0.01)	(0.19)	(0.12)
Graduation Rate in 200% of Expected Time	0.33	0.24	0.25	0.23	0.24	0.25	0.29	0.28	0.20	0.40	0.30
	(0.13)	(0.09)	(0.09)	(0.09)	(0.13)	(0.13)	(0.10)	(0.10)	(0.01)	(0.17)	(0.12)
Count	22	79	97	54	218	55	28	57	2	10	393

Notes: Standard errors are reported in parentheses. 2010 is chosen as a baseline year since it is right before Uber expands to any markets.
Source: IPEDS, 2005-2019.

Table 4: Educational Outcomes by Institution Type

Educational Outcomes:	Annual Enrollment	Entering Enrollment	Completions	Completion Rate
Model:	(1)	(2)	(3)	(4)
I. All Institutions				
Variables				
Uber	0.0203	0.0017	0.0028	-0.0011
	(0.0158)	(0.0227)	(0.0232)	(0.0020)
Fit statistics				
Observations	11,789	11,789	11,780	11,789
R^2	0.98921	0.96749	0.98018	0.93190
II. Public Bachelors Colleges				
Variables				
Uber	0.0324	0.0560	0.0053	-0.0024
	(0.0261)	(16.52)	(0.0291)	(0.0026)
Fit statistics				
Observations	2,316	2,316	2,316	2,316
R^2	0.99331	0.98415	0.99483	0.94492
III. Community Colleges				
Variables				
Uber	-0.0096	-0.0105	0.0317	0.0015
	(0.0170)	(0.0325)	(0.0328)	(0.0020)
Fit statistics				
Observations	4,016	4,016	4,012	4,016
R^2	0.98899	0.96061	0.97981	0.91643

Clustered Institution standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Models (1)-(3) are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely institution fixed effects, state by year fixed effects, baseline 2009 county unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices.
Source: IPEDS, 2005-2019.

Table 5: Full/Part Time Enrollment and Graduation Rates at Public Associates Programs

Outcome Variables:	Full Time Enrollment				Part Time Enrollment				Graduation Rate		
	all ages	18-19	20-21	25+	all ages	18-19	20-21	25+	2 Year	3 Year	2-3 Year
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Uber	-0.0508**	0.0317	-0.0777**	-0.0252	-0.0151	0.0058	-0.0089	0.0165	0.0002	-0.0085	-0.0087*
	(0.0247)	(0.0370)	(0.0308)	(0.0317)	(0.0247)	(0.0411)	(0.0344)	(0.0285)	(0.0084)	(0.0078)	(0.0050)
Fit statistics											
Observations	3,327	3,327	3,327	3,327	3,327	3,322	3,326	3,326	3,059	3,059	3,059
R^2	0.98509	0.97194	0.97863	0.97496	0.98758	0.97325	0.98587	0.98718	0.86227	0.89307	0.72113

Clustered Institution standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Models (1)-(8) are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely institution fixed effects, state by year fixed effects, baseline 2009 county unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices. *Source*: IPEDS, 2005-2019.

Table 6: Educational Outcomes by Subgroups at Public Associates Programs

	Annual Enrollment		3 Year Grad Rate		Annual Enrollment				
Subgroup:	Male	Female	Male	Female	White	Black	Asian	Hispanic	Native
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Uber	-0.0015	-0.0136	-0.0111	-0.0089	-0.0182	-0.0182	-0.0207	0.0168	-0.0757
	(0.0204)	(0.0177)	(0.0092)	(0.0090)	(0.0221)	(0.0290)	(0.0613)	(0.0394)	(0.0571)
Fit statistics									
Observations	4,016	4,016	3,059	3,059	4,016	4,016	4,014	4,010	4,012
R^2	0.98712	0.98921	0.87670	0.86188	0.97749	0.98908	0.97871	0.98552	0.95138

Clustered Institution standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Models (1),(2), and (5)-(9) are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely institution fixed effects, state by year fixed effects, baseline 2009 county unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices. *Source*: IPEDS, 2005-2019.

Table 7: Income and Educational Outcomes Regression

Dependent Variables:	Income	Weekly Hours	Wage/Salary	% Undergrad Enrollment	% College Dropout
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Uber	-0.0099	-0.0114*	-0.0258	-0.0031	0.0026
	(0.0152)	(0.0063)	(0.0186)	(0.0038)	(0.0049)
Fit statistics					
Observations	3,071	3,071	3,071	1,994	1,994
R^2	0.80125	0.58052	0.77845	0.86293	0.79798
Within R^2	0.05647	0.03846	0.05019	0.03610	0.04215

Clustered CBSA standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Models (1)-(3) are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely CBSA fixed effects, state by year fixed effects, baseline 2009 CBSA unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices.
Source: 1-yr American Community Survey, 2009-2019

Table 8: Income Measures by Highest Degree

Highest Education Level	Associates			Bachelors			No Degree		
Dependent Variables:	Income	Wage/Salary	Weekly Hours	Income	Wage/Salary	Weekly Hours	Income	Wage/Salary	Weekly Hours
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Uber	-0.0227	-0.0138	-0.0212	-0.0252	-0.0214	-0.0221**	0.0054	0.0196	0.0144
	(0.0467)	(0.0595)	(0.0190)	(0.0489)	(0.0464)	(0.0100)	(0.0223)	(0.0331)	(0.0104)
Fit statistics									
Observations	2,903	2,903	2,898	2,903	2,903	2,902	2,903	2,903	2,903
R^2	0.40455	0.37794	0.40718	0.41565	0.41875	0.39126	0.73106	0.68549	0.63712
Within R^2	0.03222	0.03363	0.05283	0.02891	0.02930	0.06972	0.03985	0.03374	0.02753

Clustered CBSA standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: All models are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely CBSA fixed effects, state by year fixed effects, baseline 2009 CBSA unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices.
Source: 1-yr American Community Survey, 2009-2019

Table 9: Income Regressions by Enrollment By Age Group

	Enrolled			Not Enrolled		
Dependent Variables:	Family Income	Weekly Hours	Wage/Salary	Family Income	Weekly Hours	Wage/Salary
Model:	(1)	(2)	(3)	(4)	(5)	(6)
I. Ages 21-25						
Variables						
Uber	0.0536	0.0177	-0.1238	-0.0076	0.0056	0.0084
	(0.0888)	(0.0467)	(0.1785)	(0.0449)	(0.0129)	(0.0389)
Fit statistics						
Observations	1,875	2,784	2,841	2,630	2,840	2,841
R^2	0.59392	0.39554	0.39486	0.57407	0.50661	0.54534
II. Ages 31-35						
Variables						
Uber	-0.1459	-0.1032	0.0287	0.0069	-0.0215**	-0.0607*
	(0.1003)	(0.0647)	(0.3652)	(0.0290)	(0.0102)	(0.0337)
Fit statistics						
Observations	2,440	2,618	2,808	2,841	2,841	2,841
R^2	0.39410	0.36672	0.33883	0.59327	0.43444	0.61075

Clustered CBSA standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Notes: All models are logged outcome variables so the interpretation of coefficients is percent changes. All models include the full set of controls, namely CBSA fixed effects, state by year fixed effects, baseline 2009 CBSA unemployment rate and median household income time trends, county college age population (15-29), county 8th grade standardized math scores, and regional gas prices.
Source: 1-yr American Community Survey, 2009-2019

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