Spillover Effects of The Gig Economy:

How Uber Drives Earnings and Employment[*]

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November 2022

Preliminary and incomplete.

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ABSTRACT

The rise of the gig economy—that is, firms which connect consumers with workers via websites and apps – has led to popular debate on the future nature of work and pushed academics to question whether gigs will overtake traditional employment. Meanwhile less than 2 percent of U.S. workers participate in gig work. Yet by disrupting existing industries and providing a uniquely flexible form of work, the gig economy's effect might extend beyond this relatively small group of workers and have spillover effects on workers in traditional jobs. In this paper, I estimate the effects of gig work on the earnings and employment of workers outside the gig economy. To do so, I exploit the staggered roll-out of Uber across the U.S. I find the arrival of Uber led to an 8.7 percent decline in employment among taxi drivers, consistent with the complementary nature of taxi and Uber services. However, I find that the arrival of Uber leads to a 5.5 percent increase in employment, an estimated 3.2 million additional jobs per year, across all industries. I examine two potential mechanisms behind these broad effects on employment: Uber's effect on competing and complementary product markets and the role of gig work as a novel outside option to workers.

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I. INTRODUCTION

The gig economy—that is, firms which connect consumers with workers via websites and apps – has been the focus of both popular debate and academic research. In the business community, reports from financial institutions and consulting groups provide firms strategies to retain workers interested in gigs (Metlife 2019) and guidelines for employers on how to adapt to the growing gig economy (Manyika et al. 2016). In the media, journalists assert the persistent rise of gig work (Henderson 2020) and have spotlighted gig work and independent contracting as key issues regarding the 'future of work' (Ng et al. 2021). Academic studies have sought to understand the *direct* effect of this new, flexible form of labor on the workers engaged in it, including studies of individual costs and benefits of participating in the gig economy (Mas and Pallais 2017; Chen et al. 2019), as well as the influence of gig work on household finances (Garin et al. 2020; Koustas 2018; Farrell, Greig, and Hamoudi 2019; Jackson 2020) and formal labor force participation (Jackson 2020).

Despite this growing fixation, the actual size of the gig economy is quite small; less than 2 percent of the workforce participates in gig work (Farrell, Greig, and Hamoudi 2019). Such low engagement raises questions about the magnitude of the gig economy's economic significance. However, it is plausible that the rise of gig work has had broader *indirect* effects on the labor markets of traditional workers, beyond any direct effect on the relatively small set of workers engaging in the gig economy. For example, the gig economy upended some product markets while potentially complementing others, and it has created a new, more flexible outside options for many workers; both of these forces could affect employment and wage dynamics in traditional work arrangements – that is, jobs in which workers are employed directly by the firm, are paid a wage or salary, have predictable work schedules and earnings, and an expectation of continued employment (as defined by Abraham et al. (2021)).

In this paper, I use the staggered rollout of Uber across the U.S. to identify the spillover effects of the gig economy on the employment and earnings of traditional workers. In many ways, Uber marks the start of the gig economy – the early success of Uber lead to the development of other gig firms seeking to "uberize" other industries with over 100 firms in the U.S. launching themselves as the "Uber for X" (Madrigal 2019)—making its entry an ideal setting to examine the spillover effects of the gig economy more broadly.

Uber's sequential entry into cities and towns across the U.S. provides a framework for identifying the average treatment effects of Uber entry on employment and earnings. I determine the dates of Uber entry by supplementing data collected by Teltser, Lennon, and Burgdorf (2021) and Hall, Palsson, and Price (2018) with local news reports and Uber press releases. Uber entered New York City in 2012 and continued to spread across the country into 2020. To measure earnings, hiring, separation, and employment, I use data from the Quarterly Workforce Indicator Series from 2008-2019 which provides quarterly industry level aggregates by gender, education level, age, race, and CBSA. By examining trends in both hires and separations, I can discern job churn – worker movement between jobs.

Using Uber's staggered entry across cities as an empirical strategy hinges on the identifying assumption that Uber's decision to enter cities was independent of underlying changes in the earnings and employment of workers. Uber reports that the *level* of population was the primary driver in decisions to enter one city over another (Hall, Palsson, and Price 2018), and when I predict Uber entry in my data, I find population to indeed be the greatest predictor of Uber entry. Still, even if the assumption of Uber entry being exogeneous to changes in employment and earnings is satisfied, a standard two-way fixed model is likely to yield a biased estimate of Uber's treatment effect if the effect of Uber on the formal labor market is not constant over time. I therefore adopt the approach from Callaway and Sant'Anna (2021) to estimate average treatment effects by groups who receive treatment simultaneously.

I first consider the effect of Uber's entry on employment and earnings in the taxi industry. Since Uber was seen as a substitute for standard taxis, standard economic theory would predict that Uber's arrival would reduce demand for taxis, and thus reduce employment and earnings of taxi drivers via Marshall's Law of Derived Demand. Thus, I first examine the effects on employment and earnings in the taxi industry as a check on the validity of my research design. I find the arrival of Uber is associated with an 8.6 percent ($p < 0.05$) decline in total employment and a 13.7 percent ($p < 0.01$) decline in hiring. There is no detectable effect on earnings, though this could be due to a compositional effect if less-productive taxi drivers exit the industry.

On the other hand, Uber might have been complementary to other industries, in particular bars and restaurants. Prior research shows that the presence of Uber is associated with greater alcohol consumption and higher profits in drinking establishment (Teltser, Lennon, and Burgdorf 2021) which in turn should lead to greater employment and earnings. Following the arrival of Uber, employment increases 1.5 percent in bars and restaurants. Additionally increasing hiring and separations after Uber entry suggest greater job churn. Workers in bars and restaurants also experience a 1.7 percent increase in earnings after Uber entry - consistent with prior evidence. These findings, along with the taxi industry findings, provide support for my research design which can then be extended across all industries.

I then estimate the effect of Uber's entry on employment and earnings for all other industries except taxis, bars, and restaurants. I find employment increases, on average, 5.5

percent following the arrival of Uber while hires and separations both increase 6.2 percent. This translates to 3.2 million additional jobs per year across the U.S. following the arrival of Uber. Alternatively, an estimated YYY people engage in the gig economy per year.

What explains these broader positive spillover effects? One possibility is that Uber's arrival was complementary to a broader set of industries beyond bars and restaurants. While I am unable to parse out each industry that is solely impacted via their product market, I can consider an industry in which there is very low likelihood of product market effects: namely, manufacturing. Given that the manufacturing sector produces primarily nontradeable goods – the product market of the industry is unlikely to be affected by changes to local product demand. However, in the manufacturing industry, I continue to find positive effects on hiring and separations. Thus, it is unlikely that Uber's positive spillover effects on employment and earnings are due purely to the product demand channel.

An alternative channel for through which Uber may change employment and earnings is via its effect on workers' labor supply. The arrival of Uber, and the gig economy more broadly, presents workers with a new outside option to current employment. For some workers, Uber is a viable substitute for their current employment; in this case, workers can bargain with employers for better wages or leave their current job to drive for Uber.

To identify any potential effect on employment due the expansion of workers' outside options, I examine industries in which a relatively high proportion of workers concurrently work in the gig economy. By isolating such industries, I can compare the effect of Uber on workers whose outside option it most likely affects– those in the 'concurrent' grouping – with those less likely to be affected – all other industries. Using data from the Survey of Household Economic Decision-making, I identify four industries in which 10 percent or more of the gig worker sample are concurrently employed: retail, healthcare, education, and professional services (see table 2). In the concurrent group, the arrival of Uber is associated with greater employment, hiring, and separations suggesting greater job churn.

These findings provide new evidence of the gig economy's influence beyond workers directly engaged. Researchers examining the broader effects of the gig economy, or Uber specifically, have found effects on a range of outcomes including public transportation (Hall, Palsson, and Price 2018), alcohol consumption (Teltser, Lennon, and Burgdorf 2021), drunk driving (Greenwood and Wattal 2017), entrepreneurial activity (Burtch, Carnahan, and Greenwood 2018), and economic development (Gorback 2020). Burtch, Carnahan, and Greenwood (2018) find the rise in gig work is associated with declining entrepreneurial activity by examining changes to Kickstarter campaigns and self-employment rates in response to Uber entry, but there is yet to be estimates on how Uber entry influences traditionally employed workers. Gorback (2020) examines how Uber changes economic activity within cities finding that platform entry led to increased restaurant creation and higher housing prices in previously inaccessible neighborhoods compared to neighborhoods more accessible by public transportation. The gig economy has the latitude to influence housing markets, and Gorback's findings support my proposed mechanisms for changing employment. Lastly, much research has also examined how gig work influences the financial lives of gig workers (Garin et al. 2020; Koustas 2018; Farrell, Greig, and Hamoudi 2019; Jackson 2020), yet by looking at employment and earnings outside the gig economy, I demonstrate how gig work influences far more than the 1.6 percent of workers it engages (Abraham et al. 2021).

As states continue to grapple with how to regulate the gig economy and protect workers, it is important for policymakers to understand the potential ripple effects on traditionally employed workers. Policies that seek to categorize gig workers as employees rather than independent contractors change not only the quality and pay of gig work itself, but also the value of a gig job as an outside option. My findings suggest that the more workers perceive gig jobs as high quality, the greater positive effects on employment and job churn. As more workers seek jobs with greater flexibility, the gig economy creates both new job opportunities and greater movement within industries via job churn. Findings of greater job churn, while suggestive of a healthier labor market, may imply less job stability among workers or workers having new options within their industry and the potential for a position that better suites their needs in terms of wage, flexibility, and other benefits.

II. DATA

A. UBER ENTRY DATA

Following prior research on Uber entry, I measure Uber's entry into the market with the entry of UberX rather than the original "Uber" which required drivers to drive a black town car rather than using their own vehicle. I supplement data collected by Teltser, Lennon, and Burgdorf (2021) on UberX's arrival to a region with local news reports on UberX to determine the date of entry for 338 Core Based Statistical-Areas (CBSA).

Teltser, Lennon, and Burgdorf's data on Uber entry were collected by examining press releases, Uber's blog, and social media announcements; I collected supplementary data for entry after 2017 in the same fashion. Hall, Palsson, and Price (2018) compare entry dates to Google Trend data on searches for "Uber" to determine if entry is representative of Uber's penetration into local markets. They find entry dates and Google Trend data to be very highly correlated and align with data on number of rideshare drivers (Bivens et al. 2014). I focus my analysis on first entry of UberX into each region to mark the start of the gig economy and do not use information on subsequent withdrawals and reentries.

B. Quarterly Workforce Indicator Series (QWI)

To estimate the role of Uber in formal labor markets, I utilize the Quarterly Workforce Indicator Series (QWI) which captures information on 95 percent of all private sector jobs. This series is derived from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata and sources job and employee data from unemployment insurance data, the Quarterly Census of Employment and Wages, Business Dynamic Statistics, and the American Community Survey. In these data, a job is defined as a unique connection between an individual and a single firm. Jobs are aggregated to the establishment level by geography, industry, and demographic information.

For this project, I use QWI data at the industry group and educational attainment level. Industry group is defined by 4-digit NAICS codes to allow for the identification of the taxi industry. Educational attainment is defined as less than a high school degree, high school or equivalent, some college or associates degree, and bachelor's degree or more. Geographically, the data are at the Core Based Statistical-Areas (CBSA) which consist of both Micro and Metropolitan Statistical Areas; regions are defined as areas with at least one urban cluster (with population of at least 10,000) and surrounding commuting zones. I restrict the data to 2008-2019 providing 48 periods of analysis. Thus, my data are at the industry, education, CBSA, quarter level.

To determine Uber's impact on various industries, I first isolate the taxi and drinking establishment industries. The taxi industry is defined as NAICS sector "Taxi and limo service (4853)" while drinking establishments includes "Restaurants and other eating places (7225)" and

"Drinking places (7224)". I also exclude "Agriculture, Forestry, Fishing and Hunting", "Mining, Quarrying, and Oil and Gas Extraction", and "Public Administration" from my analysis.

The QWI provides the following outcomes of interest: average monthly earnings, new hires, separations, and earnings of new hires. Average monthly earnings are estimated by aggregating full quarter earnings of individuals matching job history and demographic groupings and dividing by three. Earnings are broken down by full quarter employees and new hires and converted to real 2019 dollars. New hires include all jobs that were initiated in a given period including recall hires, new hires, and hires that did not work the full quarter. Separations – whether voluntary resignations or involuntary firings – are measured as jobs which continued from the previous quarter and were ended in the given quarter. Descriptive statistics for all four outcome measures by education level and industry groupings can be found in table 1. Given that the QWI data are drawn from unemployment insurance, employment and earnings of Uber drivers are not included in these aggregates as Uber drivers are not considered as employees as of 2019 and therefore do not qualify for unemployment insurance (Wiessner 2018; Ruckstuhl 2021).

C. Survey of Household and Economic Data

To identify from which industries gig workers are most likely to be coming to the gig economy and/or in which gig workers are concurrently employed, I use data from the Survey of Household and Economic Data (SHED) which provides extensive data on participation in various types of informal work – from childcare services to driving with Uber – starting in 2016, in addition to questions on formal employment. Table 2 lists industries in which over 4 percent of gig workers were concurrently or formerly employed for survey respondents from 2016-2019. I categorize industries in which gig workers are likely to participate as those with 10 percent or more reported participation: health care and social assistance, educational services, retail trade, and professional, scientific, and technical services.

III. METHODS

This study provides evidence of the broader effect of the gig economy using Uber's arrival to a region as a proxy for the start of the gig economy. Rather than relying on the start of Uber's black car services, I use the start of UberX services to approximate the initiation of the gig economy. UberX started as an alternative to Uber's black car service providing drivers with the option to use their personal vehicles, and it is the form ridesharing takes on today.

To identify how the arrival of Uber impacted the employment and earnings of workers outside the gig economy, I exploit the staggered rollout of UberX across the U.S.

Prior work using Uber's roll-out as a strategy for identification have utilized two-way fixed effect models that control for time and individual fixed effects, but the staggered rollout of Uber creates bias in estimating the average treatment effect of Uber's arrival (de Chaisemartin and D'Haultfœuille 2022). To produce unbiased results in the two-way fixed effect model, I would need to assume that the treatment (Uber's arrival) effects are constant over time. The rise in popularity and increasing notoriety of Uber over the course of the treatment period makes this assumption unrealistic, furthermore the treatment effects are likely to differ in the large cities that received treatment early from the smaller areas who were introduced to Uber later. It is very unlikely that the effect of Uber being present in New York City in 2016 is the same as the effect of Uber's entry into Helena, MT in 2016.

To avoid bias arising from staggered treatment, I estimate average treatment effects by groups, g, who receive treatment simultaneously (Callaway and Sant'Anna 2021):

$$Y_{i,g,t} = \alpha_g + \gamma_t + \beta_{g,t} Uber_{g,t} + \epsilon_{i,g,t}$$

Where $Y_{i,g,t}$ is my outcome of interest at time *t* for CBSA-industry-education level, *i,* which is first exposed to UberX in period *g;* α_g are group fixed effects for all CBSAs into which UberX enters at year-quarter, *g;* γ_t are year-quarter fixed effects; $Uber_{g,t}$ is an indicator of UberX's entry; and $\epsilon_{i,g,t}$ is the error associated with CBSA-industry-education level, *i,* in group *g* at time *t*. To account for the large variation in the size of labor markets across CBSAs, I weight estimates by the total employment level in each CBSA, industry, education group in Q1 of 2008, and I cluster standard errors by CBSA.

Primary findings for this paper are determined based on two aggregations of the coefficient of interest, $\beta_{g,t}$. $\beta_{g,t}$ estimates the effect on *Y* of Uber's entry on group *g* at time *t*. In section 4 and 5, I present the aggregated group-time treatment effects which are the average of group specific treatment effects across all groups; this aggregate has comparable interpretation to the standard average treatment on the treated (ATT) as it is the average effect of Uber's entry across all treatment groups. I also aggregate group-time treatment effects by length of exposure to produce event study graphs. These dynamic treatment effects estimate the effect of Uber's arrival on a given group relative to the point of entry and capture how treatment effects differ by the length of exposure.

In order for this model to identify the effects of Uber, I must make the following assumptions:

1. *Exogeneity of Uber Entry*

To estimate unbiased treatment effects, the timing of Uber entry must be independent of earnings and employment. According to Uber, the order of the rollout was primarily determined by city size with a few exceptions for cities near Palo-Alto (Teltser, Lennon, and Burgdorf 2021). To test this relationship in my data, I regress date of Uber entry on CBSA characteristics and the outcomes of interest. Table 3 displays the results of this exercise with independent variables standardized to allow for comparing the size of coefficients. Population, household income, and percent of CBSA with a bachelor's degree are the largest predictors of Uber entry.

2. Parallel trends

Next, I assume parallel trends in employment and earnings measures:

$$E\left[Y_t(0) - Y_{t-1}(0)\middle|\, G_g = 1\right] = E\left[Y_t(0) - Y_{t-1}(0)\middle|\, D_s = 0, G_g = 0\right] a.s.$$

Trends in the absence of treatment for group *g*, $G_g = 1$, must equal trends in the absence of treatment, for groups other than *g*, $G_g = 0$, who are yet to receive treatment, $D_s = 0$. That is, there would exist common trends in employment and earnings across groups had Uber never entered. While there are differences across CBSAs that influence trends in employment and earnings, group fixed effects capture the time invariant characteristics that may differ across group and influence trends. Localized shocks to labor markets could create a violation of this assumption, but graphs of dynamic treatment effects, presented fully in section 6 and 7, show little evidence of pre-trends.

3. Treatment Anticipation

I assume that there is limited treatment anticipation. While the primary model of this paper assumes no treatment anticipation, full results of anticipation tests can be found in table A1. Given the consistency of my estimates with no anticipation, 1 quarter, and 2 quarters, this assumption is quite reasonable.

4. Irreversible treatment

I assume that treatment is irreversible – once a CBSA is exposed to UberX, the effects are permanent. While UberX has stopped and restarted in various jurisdiction due to legal challenges, other gig economy firms that proceeded Uber were not subject to the same legislation therefore I would not expect the effects of Uber's entry to be reversable.

LIMITATIONS

One limitation to using the QWI for this analysis is the lack of data on hours worked. Workers may be working greater hours, but we can only capture changes to employment or earnings. Thus, positive effects on earnings may reflect higher wages or more hours worked per month. To address this concern, I estimate changes to employment and hours worked using data from the American Community Survey. My findings from the ACS are consistent with the QWI and are presented in full in section \robust.

IV. LABOR MARKET EFFECTS OF UBER ENTRY: BASELINE ESTIMATES

In this section I present estimated effects of Uber on employment and earnings in the taxi industry, bars and restaurants, and across all other industries. Employment and earnings in both the taxi industry and bars and restaurant move as hypothesized following Uber's arrival; all outcomes declining in the taxi industry and increasing in bars and restaurants following Uber's arrival. Findings from both industries provide support for my model, lending credence to the estimated effect of Uber entry across all industries. The average effects of Uber entry across all industries are strongly positive suggesting the much broader labor market implications of Uber and the growth of the gig economy.

A. DIRECTLY COMPETING INDUSTRIES: TAXIS

1. Theory

For industries in direct competition with gig platforms, such as the taxi industry, the arrival of new firms with very low production costs puts added pressure on existing firms to reduce overall costs. New alternatives to taxi cabs reduce overall demand for taxis resulting in lower output prices and, in turn, lower demand for taxi drivers. As fewer cabs are needed to meet consumer demand, theories of derived demand imply that firms would reduce employment following the drop in output prices. I predict that this reduction in demand for drivers will be observable in the data as lower earnings, as drivers pick up fewer fares, and/or lower total employment, as taxi firms reduce the number of drivers.

2. Findings

Panel A of table 4} displays the group-time average treatment effects of Uber on employment and earnings in the taxi and limousine industry. Uber's arrival led to an 8.7 percent decrease in employment ($p < 0.05$) with a 13.7 percent decline in hires ($p < 0.01$). Simultaneously, separations decreased 12.6 percent ($p = 0.104$) while the arrival of Uber led to a 2.4 percent decrease ($p = 0.27$) in average monthly earnings for workers in the taxi industry. Insignificant effects on earnings are likely due to the lowest earning employees being the first to separate from their taxi firm leaving a greater proportion of high earners.

Figure 1 displays the dynamic treatment effects of Uber graphing changes in outcomes by quarters since Uber's entry. Panel A displays how average changes to employment increased relative to Uber's entry; the effect of Uber on employment in the taxi industry is not only persisting over time but increasing. Panel B tells a similar story for changes to hires while declines in separations (panel C) are more delayed. For earnings, the event study (panel D) shows initial positive changes to earnings that only drop below zero one year after Uber entry. This initial rise is likely due to the changing composition of workers as mentioned above.

Ultimately, these findings on Uber's effect on employment and earnings in the taxi industry are consistent with the hypothesis that Uber displaces taxis.

B. Directly Competing Industries: Bars & Restaurants

1. Theory

Not all industries see the arrival of Uber as new competition; for some, Uber complements the goods and services they provide spurring demand. These complementary sectors benefit from the arrival of gig firms allowing, or even requiring, them to increase labor expenditures to meet increased demand. One such industry in which Uber has had complementary effects is the bar and restaurant industry. Prior work finds the presence of Uber is associated with greater alcohol consumption and greater spending at drinking establishments, and Uber has a positive effect on the earnings and employment of workers at drinking establishments (Teltser, Lennon, and Burgdorf 2021). My work expands and supports these findings using updated difference in difference techniques and expanding the geographic scope.

2. Findings

Panel B of table 4 presents the treatment effects of Uber entry for workers at bars and restaurants. For these workers, the arrival of Uber resulted in a 1.6 percent increase ($p = 0.24$) in employment. While employment remained somewhat stable, hires increased by 4.0 percent ($p < 0.1$) and separations increased by 4.2 percent ($p < 0.01$). Comparable increases in hires and separations suggest greater job churn – workers leaving positions in favor of better employment opportunities within the industry. This is supported by greater earnings in bars and restaurants following Uber's entry; earnings increase 1.7 percent ($p < 0.05$) following the introduction of Uber.

Figure 2 presents the dynamic treatment effects of Uber on earnings and employment. Panel A displays the treatment effect of Uber on employment in bars and restaurants by quarters since Uber entry. While the aggregate effect is small, changes to employment increase slightly the longer Uber is in a CBSA. Panels B and C graph hires and separations, respectively, both showing similar patterns as employment – the effects of Uber increase over time. For earnings in bars and restaurants, as with in the taxi industry, changes to earnings don't take on a clear pattern until a year after Uber entry.

These findings are comparable to prior research on alcohol consumption and profits at drinking establishment following the arrival of Uber (Teltser, Lennon, and Burgdorf 2021)[‡].

C. All Other Industries

In panel A of table 5, I present average treatment effects of Uber entry for all other industries combined. Across all other industries, employment increases 5.5 percent ($p < 0.01$), on average, following Uber's arrival which translates to 1,780 more people employed, on average. Hires and separations also increase 6.3 percent ($p < 0.01$) and 6.2 ($p < 0.01$), respectively. Uber's entry leads to minimal increases in earnings across all industries – a 0.64 percent increase ($p = 0.16$), on average. Once again, I find evidence of greater job churn alongside increases in employment suggesting a healthy labor market where workers are able to move within the market to find optimal employment.

Figure 3 graphs the dynamic treatment effects of Uber entry in all other industries. All four panels show no changes prior to Uber's entry – an indication that no pre-trend is driving these findings. As found in the taxi industry and bars and restaurants, changes to employment, hires, and separations increase over time, as seen in panels A, B, and C, respectively.

[‡] Teltser, Lennon, and Burgdorf (2021) report over double the increase in total earnings (3.7 percent), and a 3.5 percent increase in employment.

V. Potential Mechanisms Behind Broader Labor Market Effects of Uber

In this section I explore the potential mechanisms through which Uber can impact employment and earnings across all industries. I first consider if widespread increases to product demand could be driving increasing employment. Then, I test if Uber as a new outside option to workers is playing a role.

A. Product Demand

One potential mechanism through which Uber may be influencing employment is via much broader product demand. Beyond influencing bars and restaurants, Uber has been found to have a positive effect on housing prices and restaurant creation (Gorback 2020). Extensive work demonstrates that rising housing prices are linked with increased consumption (Aladangady 2017; Browning, Gørtz, and Leth-Peterson 2013) which suggests a potential cascading effect on demand, particularly on industries selling nontradeable goods and services.

To determine if changes to employment across all industries following the introduction of Uber is due solely to increased demand, I consider the effects of Uber entry on workers in the manufacturing industry. Rather than attempting to parse out each industry in which product demand may increase after Uber, I consider manufacturing as a falsification test. The manufacturing industry produces tradeable goods and therefore should not be influenced due to changes in local demand. Thus, any changes to employment or earnings in response to Uber entry in the manufacturing industry are likely to be driven by an alternative mechanism.

Average effects of Uber entry on employment and earnings in the manufacturing industry are presented in panel B of table 5. The arrival of Uber resulted in little change in total employment - 1.0 percent ($p = 0.66$) increase, on average. Hires increase 6.7 percent ($p = 0.12$), on average, following the arrival of Uber while separations increase 4.6 percent ($p = 0.22$).

Lastly, earnings decline 1.3 percent (p = 0.12) in the manufacturing industry following Uber entry. While statistically insignificant, the magnitude of changes to hires and separations are comparable, if not greater, then changes found in the bar and restaurant industry. These findings suggest that changes to product demand are unlikely to be the whole story behind average employment across all industries increasing following the introduction of Uber.

B. Uber as an Outside Option

1. Theory

For workers in industries whose product market is not directly impacted by the arrival of the gig economy, the effect of Uber on such workers is theoretically ambiguous. As a new outside option, gig work has the potential to directly increase worker bargaining power. Below, I elaborate on how I expect employment and earnings to change in response to gig work as a new outside option.

For many workers, the arrival of gig work presented an enticing new employment option as either a substitute for or an addition to current employment.

Just as Uber competes with and complements various industries, gig work can function as both a competitor and complement for existing employment. The flexible hours and low barriers to entry make gig work attractive to a broader spectrum of workers – both those who substitute away from worse employment options and those who earn more in their primary occupation. Workers are drawn to gig jobs for flexible hours, low search costs, and/or the nature of the work (Mas and Pallais 2017, 2020). The introduction of a new outside option, such as Uber, has the ability to influence both separations and earnings in other industries (Caldwell and Danieli 2021). Thus, on the one hand, Uber expands workers' outside options resulting in either greater earnings or more separations. On the other hand, gig work provides workers with a new moonlighting option which may encourage workers to forgo costly job search and remain primary occupations thereby keeping employment stable. Regardless of whether workers use Uber as a substitute or complement for their current employment, recent work valuing outside options demonstrates that workers with better outside options are compensated at a higher rate (Caldwell and Danieli 2021; Schubert, Stansbury, and Taska 2022; Beaudry, Green, and Sand 2012).

For workers earning more in their current occupation than they could in the gig economy, gig work provides a new moonlighting option. Rather than being a potential replacement for current work, gig work functions as a complement to existing employment. This is the case for the majority of gig workers – from 2007 to 2016, over half of gig workers had a primary occupation outside the gig economy (Collins et al. 2019). Standard theories of moonlighting suggest that workers choose to take on additional labor when they are unable to work their preferred number of hours in their primary position – they are hours-constrained (Shishko and Rostker 1976; Conway and Kimmel 1998). Historically, over 30 percent of workers desire more hours than they are currently offered (Kahn and Lang 1991). The flexible nature of gig work provides moonlighting options that were previously unavailable to hours-constrained workers. In the absence of viable moonlighting options such as gig work, hours-constrained workers are more likely to separate from their primary occupation in favor of work that offers greater earning potential (Shishko and Rostker 1976). With the availability of gig work, workers may forego costly job search for higher paid position in favor of moonlighting. Therefore, we would observe fewer separations following the arrival of Uber. Workers whose consumption needs are not met with current employment, either due to low wages or hour constraints, supplement income with gig work. Thus, these effects are likely to be most pronounced in industries in which workers are concurrently employed or arriving to the gig economy from.

For those who consider gig work a viable substitute for current employment, the effect of Uber would depend on individual worker's bargaining power (Lachowska et al. 2022). Those with greater bargaining power, typically those with less standardizable occupations (Cahuc, Postel-Vinay, and Robin 2006) and typically higher income, can leverage the new outside option for higher wages. Those with less bargaining power, typically workers with lower wages and more standardizable occupations, are more likely to be subject to wage posting rather than bargaining – workers choose between the wage offered and finding alternative employment without the ability to bargain (Lachowska et al. 2022). Therefore, workers with less bargaining power would be more likely to leave their position in favor of better paid gig work while those with more bargaining power can negotiate for better wages.

Since gig workers make up a small percentage of the total workforce, industries in which gig workers are concurrently employed are most likely to be influenced by the arrival of Uber. In order to determine which industries, I looked towards the Survey of Household and Economic Data (SHED) which asks respondents about gig involvement and multiple job holding. I find the industries most likely for gig workers to be concurrently employed in are "Health Care and Social Assistance", "Educational Services", "Retail Trade", and "Professional, Scientific, and Technical Services"[§]. Using this group of industries where workers are most acutely affected by Uber entry, I have the greatest likelihood of detecting changes to earnings and employment driven by worker decision-making in response to the arrival of the gig economy. I then compare these 'concurrent' industries to all other industries less the taxi industry and bars and restaurants.

[§] See table \shed

2. Findings

Panel A of table 6 presents aggregated group-time treatment effects of Uber entry for industries in which gig workers are likely to participate – retail, health care and social services, educational services, and professional, technical, and scientific services. Panel B presents treatment effects of Uber entry for all other industries less the taxi industry and bars and restaurants – this grouping is referred to as 'nonconcurrent' industries.

For workers in these concurrent industries, the arrival of Uber led to a 4.1 percent ($p < 0.01$) increase in employment alongside 4.0 percent increase ($p < 0.01$) in hiring and 4.1 percent increase ($p < 0.01$) in separations. Greater job churn supports theories of workers responding to a new outside option. With work in the gig economy available to cover any potential breaks in employment, workers have the ability to trade up for better employment. Effects on earnings are minimal and the direction in which earnings change following Uber's entry is dependent on the inclusion of retail trade.

Figure 5 shows the dynamic treatment effects of earnings and employment in concurrent industries. Panel A, which graphs changes to employment by quarters since Uber entry, shows steady increases in the effect of Uber on employment the longer Uber is present. Changes to hires and separations also persist over time, as seen in panels B and C, with the magnitude stabilizing a year after Uber entry.

Contrary to my hypothesis, there are strong effects on employment in nonconcurrent industries following the arrival of Uber. As seen in panel B of table 6, Uber led to a 7.8 percent ($p < 0.1$) in employment in nonconcurrent industries – greater than the average effect across all industries. The magnitude on increases to hires and separations in nonconcurrent industries are over twice the magnitude of changes in concurrent industries.

VI. Robustness Checks

A. Anticipating Uber Entry

To ensure that my results are not biased due to firms or workers anticipating the arrival of Uber, I estimate treatment effects accounting for 1 quarter of anticipation and 1 year of anticipation. Complete results can be found in appendix \anticipation and table A1.

B. Alternative Data: American Community Survey

To see if my results hold across data source, I run the same analysis using the American Communities Survey (ACS). I aggregate the yearly individual level data up by industry and CBSA to estimate average income, probability of being employed, and probability of working last week. Results of this analysis can be found in appendix \acs along with a full description of the methods used.

[add taxis & bars]

Panel A of table A2 displays treatment effects across all industries. On average, Uber is associated with a 1.7 percentage point ($p < 0.01$) increase in the probability of working and a 1.5 percentage point ($p < 0.01$) increase in the probability of working last week. The arrival of Uber is also associated with an 18.3 percent ($p < 0.01$) increase in earned income. Among workers in the manufacturing industry (panel B of table A2, Uber is associated with a 0.8 percentage (p =) point increase in the probability of working and a 1.5 percentage point increase in the probability of having worked last week. Changes to earnings are comparable to all industries, yet highly significant in the manufacturing industry. As with the QWI, effects in the manufacturing industry suggest product demand is not solely responsible for changes seen across all industries.

In concurrent industries, panel A of table A3, Uber entry corresponds to small increases in the percent of people working and probability of working last week. Earned income increases

11.7 percent ($p < 0.05$) following the arrival of Uber for workers in concurrent industries. As with the main findings, effects are much greater in nonconcurrent industries.

While the available outcomes in the ACS do not correspond perfectly to the QWI, increases in the percent of people working and earned income are consistent with my main results.

VII. Heterogeneous Treatment Effects

In this section, I investigate the potentially heterogeneous effects of Uber on earnings and employment. On one dimension, I consider how the introduction of Uber may differentially impact workers of differing gender identities or education levels. On another dimension, I examine differing effects by prevalence of public transportation and timing of Uber entry.

A. Group-Time Treatment Effects

While Uber entered larger cities first, awareness and usage of Uber increased tremendously over the study period which can impact both product markets with which Uber competes and worker decision-making. Figures X through Y graph the average effects on employment, hires, separations, and earnings by date of Uber entry.

Taxi industry

No clear trend is visible for earnings as seen in panel D of figure A1.

Bars and restaurants

Panel A of figure A2 graphs average changes to employment by quarter of Uber entry and shows that areas where Uber entered prior to 2015 have more positive employment effects than later areas. While effects on separations are relatively consistent over entry date, separations were more likely to increase following Uber entry in areas where Uber arrived earlier. Trends in changes to earnings over entry date, panel D of figure X, follow a slight but similar pattern – more positive effects in earlier entry areas.

All industries

Figure A3 shows the average effects of Uber entry on employment, hires, separations, and earnings across all industries. In panel A, changes to employment appear slightly greater in cities where Uber entered earlier, but no clear trends are found in panels B and C for hires and separations. Lastly, no clear pattern arises by entry date in average effects on earnings, panel D.

Concurrent industries

Among industries in which gig workers are likely to work concurrently, a more substantial trend over entry date is observed in panels A of figure A4. In panel A, effects on employment decline by entry date before stabilizing around zero around 2015 entries. Similarly, there are greater effects on hires and separations for areas where Uber entered prior to 2014. No clear trend is observed in earnings by entry date.

D. Differential Effects by Gender

When considering the differential effects of Uber on the employment and earnings of women, it is important to recognize the small number of female drivers and their lower earning potential. While Uber drivers are more likely to identify as female than taxi drivers and chauffeurs, the vast majority of drivers identify as male. According to survey data from 2012-2014, 13.8 percent of Uber drivers identify as female (compared to 8 percent of taxi drivers and chauffeurs) (Hall and Krueger 2018). Furthermore, women earn less than men while driving for Uber which is attributed to women driver's unwillingness to drive in areas with higher crime and areas with more bars and restaurants. On average, men earn 7 percent more than women (Cook et al. 2018).

With fewer women driving for Uber and lower average earnings, effects on earnings and employment driven by worker decision-making are unlikely to be found among women.

Results

Table A4 presents group-time treatment effects of Uber by gender in columns A and B. While the magnitude of changes to all outcomes are consistently less for women than men, there are still significant effects on employment and earnings for women contrary to my hypothesis.

C. Differential Effects by Educational Attainment

The gig economy is likely to impact workers of differing education levels via two channels. First, the majority of Uber drivers have not attended any higher education institutions (Hall and Krueger 2018) implying workers with less than a college degree are more likely to consider Uber as a viable employment option. Thus workers with less than a college degree are more likely to make employment decisions with Uber and other gig work in mind. Second, as a proxy for income level, educational attainment can determine the level of bargaining power workers hold in their current employment. Those with greater bargaining power, typically those with less standardizable occupations (Cahuc, Postel-Vinay, and Robin 2006) and typically higher income, can leverage the new outside option for higher wages. Those with less bargaining power, typically workers with lower wages and more standardizable occupations, are more likely to be subject to wage posting rather than bargaining – workers choose between the wage offered and finding alternative employment without the ability to bargain (Lachowska et al. 2022). Therefore, workers with less bargaining power – lower educational attainment – would be more likely to leave their position in favor of better paid gig work while those with more bargaining power – higher educational attainment – can negotiate for better wages.

Results

I break educational attainment into two groups – workers who attended some college or less schooling and workers with a college degree or more. Results can be found in table A4.

When examining the average effect of Uber entry across all industries, unlike with taxis and bars and restaurants, the effects on employment and earnings of workers with and without a college education are substantial. As seen in table A4, for workers without a college education, the arrival of Uber results in a 6.5 percent ($p < 0.01$) increase in employment, 8.6 percent ($p < 0.01$) increase in hires, and 7.6 percent ($p < 0.01$) increase in separations, on average. Those with a college degree experience 4.7 percent ($p < 0.01$) greater employment, and 4.8 percent ($p < 0.01$) increase in hires and separations following Uber entry. These findings show that effects are greater among workers with less education – those more likely to drive for Uber, yet more highly educated workers also experience rising employment and job churn following Uber entry.

D. Effects by Public Transit

Across regions the role Uber plays in any given transportation system depends greatly on the existing public transit infrastructure. Prior research finds that Uber functions as a complement to the average public transportation system in the U.S. (Hall, Palsson, and Price 2018). As such, Uber can expand workers commuting zone.

To determine how Uber's impact on employment and earnings differs by availability of public transportation, I use data from Federal Transit Authority on passenger trips in 2008. I divide my sample of 371 CBSAs into high and low ridership regions based on the median passenger trips recorded in 2008.

Findings

Table A4 presents aggregated group-time treatment effects by public transit usage in columns E and F. Employment increases 2.8 percent ($p < 0.01$) in high ridership areas and 4.5 percent ($p < 0.10$) in low ridership areas, on average, following Uber's arrival while changes to hires and separations are similar across ridership level. Earnings increased 1.5 ($p < 0.01$) and 0.7 ($p < 0.01$) percent in high and low ridership areas, respectively, after Uber entry. Greater changes to employment in low public transit regions may suggest that the complementary effects of Uber and public transit impact worker's commuting zones more in low ridership regions.

VII. Conclusion

Summary

Limitations

Implications for Policy

Implications for Future Research

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IX Tables & Figures

Table 1. Descriptive Statistics

	Taxi & Limos	Bars & Restaurants	All	Manufacturing	Concurrent Industries	Nonconcurrent Industries
Employment	804	13,953	34,802	31,007	49,062	24,179
	(873)	(17,598)	(48,313)	(34,223)	(62,137)	(32,552)
Observations	33,867	200,875	1,231,788	73,032	291,970	996,018
Hires	158	3,610	4,350	2,106	5,055	3,551
	(192)	(4,219)	(6,276)	(2,417)	(6,363)	(6,237)
Observations	27,170	190,155	1,187,548	72,599	290,739	934,597
Separations	85	1,693	2,282	1,463	2,972	1,634
	(90)	(2,030)	(3,060)	(1,691)	(3,704)	(2,337)
Observations	24,648	177,954	1,162,784	71,960	287,647	902,900
Monthly Earnings	2,302	1,743	4,410	5,216	4,174	4,959
	(1,708)	(414)	(2,823)	(2,312)	(2,123)	(3,293)
Observations	37,856	200,050	1,232,622	72,964	291,780	999,361

Source: Quarterly Workforce Indicator Series, 2008-2019.

Notes: Mean outcomes across industry, CBSA, and year. Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services; nonconcurrent industries are all other industries.

Table 2. Industry of Primary Occupation for Workers Engaged in Gig Work

NAICS Industry	Percent
Professional, Scientific, and Technical Services	16.3%
Health Care and Social Assistance	11.8%
Retail Trade	10.1%
Educational Services	10.0%
Transportation and Warehousing	8.8%
Finance and Insurance	5.8%
Other Services (except Public Administration)	4.8%
Information	4.5%
All else (12 industries)	27.9%
Observations	602

Source: Survey of Household and Economic Data, 2016-2019.

Table 3. Predicting Uber Entry

Variables	(1) Date of Uber Entry	(2) Uber Entry (0/1)
Log population, 2010 (z)	-170.4***	0.00722
	(33.67)	(0.00673)
Log pop change 2000-2010 (z)	-70.94**	-0.00274
	(30.79)	(0.00277)
Pct Bachelor's degree (z)	-83.67**	0.0196
	(35.66)	(0.0145)
Average age (z)	49.13**	0.00299
	(21.21)	(0.00303)
Log household income (z)	-90.90**	-0.0125
	(40.53)	(0.00977)
Unemployment rate (z)	-72.26***	0.0106
	(26.77)	(0.00832)
Log average monthly earnings (2019 $) (z)	23.34	-0.0162
	(37.76)	(0.0139)
Log employment (z)	-21.36	0.0136
	(258.3)	(0.0880)
Log hires (z)	99.38	0.0241
	(373.7)	(0.0356)
Log separations (z)	-133.9	-0.0248
	(434.6)	(0.0862)
Constant	20,138***	0.991***
	(26.51)	(0.00618)
Observations	217	219
R-squared	0.501	0.056

Notes: Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: Uber Entry Data; American Community Survey, 2008-2019; Quarterly Workforce Indicator Series, 2008-2019.

Table 4. Group-time Treatment Effects of Uber Entry in Taxi Industry & Bars and Restaurants

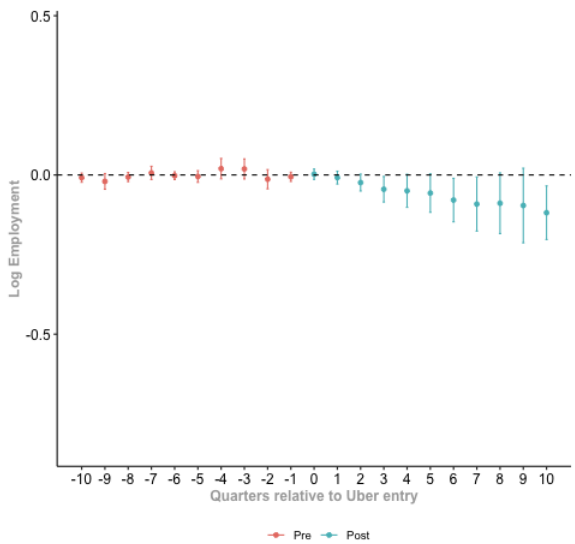
	Log total employment		Log hires		Log separations		Log monthly earnings	
A. Taxi and Limo								
Uber	-0.0865	**	-0.1365	***	-0.1255		-0.0242	
	(0.0438)		(0.0506)		(0.0771)		(0.0219)	
Observations	25,056		10,560		6,864		34,512	
CBSA*education level	522		220		143		719	
B. Bars and Restaurants								
Uber	0.0155		0.0404	*	0.0421	***	0.0174	**
	(0.0132)		(0.0221)		(0.0147)		(0.0074)	
Observations	189,312		150,144		129,792		191,088	
Industry group*CBSA*ed. level	3,944		3,128		2,704		3,981	

Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019.

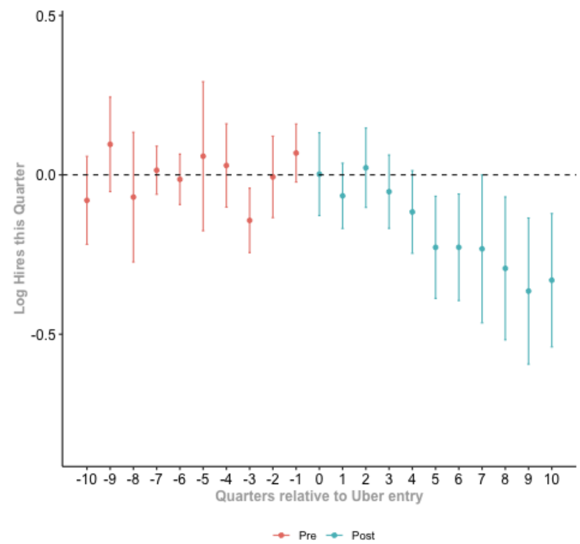
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1. Dynamic Treatment Effects of Uber Entry in the Taxi & Limousine Industry

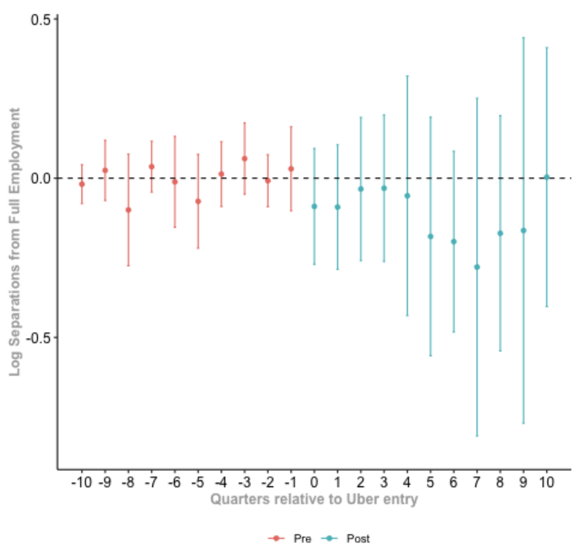
(a) Employment by length of exposure



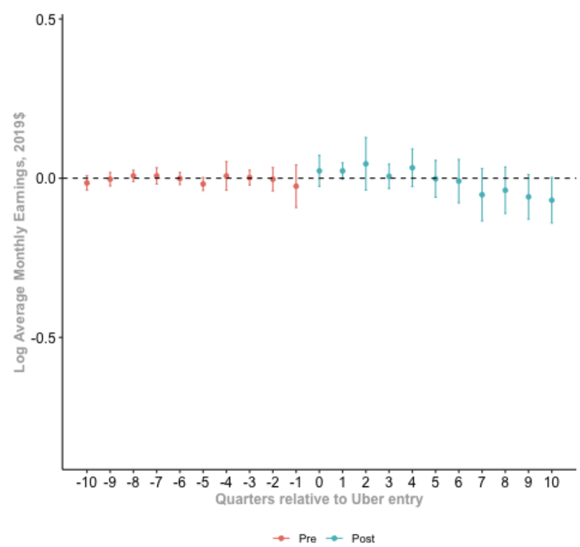
(b) Hires by length of exposure



(c) Separations by length of exposure



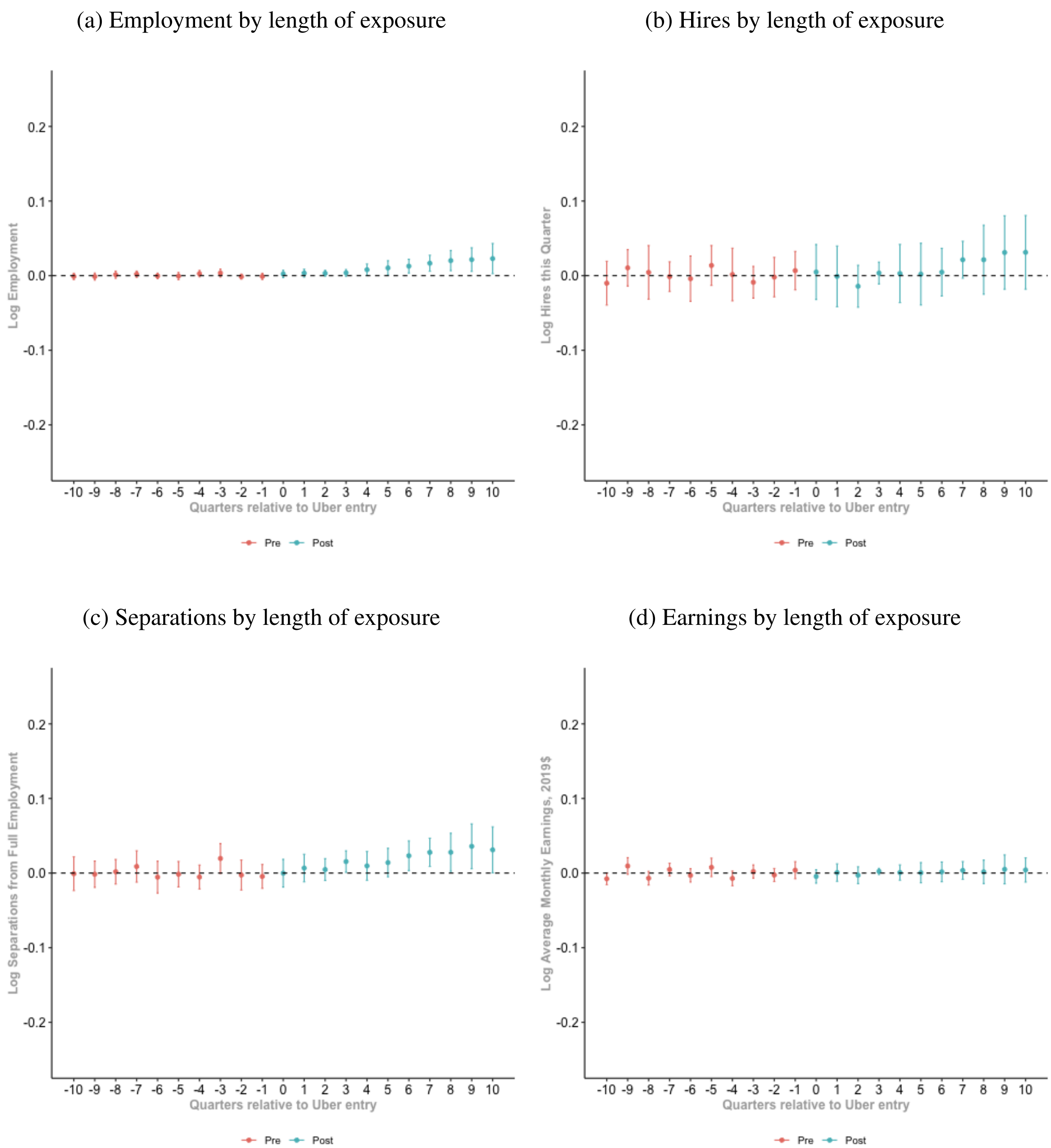
(d) Earnings by length of exposure



Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

Figure 2. Dynamic Treatment Effects of Uber Entry in Bars and Restaurants



Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

Table 5. Group-time Treatment Effects of Uber Entry in All Industries & Manufacturing

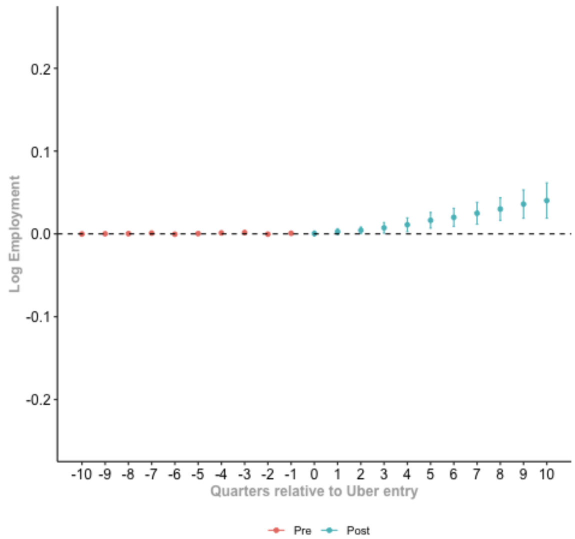
	Log total employment		Log hires		Log separations		Log monthly earnings
A. All Industries							
Uber	0.0552	***	0.0628	***	0.0624	***	0.0064
	(0.0209)		(0.0196)		(0.0177)		0.0045
Observations	1,180,560		1,055,184		1,000,080		1,024,080
Industry group*CBSA*ed. level	24,595		21,983		20,835		21,335
B. Manufacturing							
Uber	0.0095		0.0670		0.0461		-0.0130
	(0.0217)		(0.0430)		(0.0375)		(0.0084)
Observations	70,272		67,440		66,432		60,672
Industry group*CBSA*ed. level	1,464		1,405		1,384		1,264

Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019.

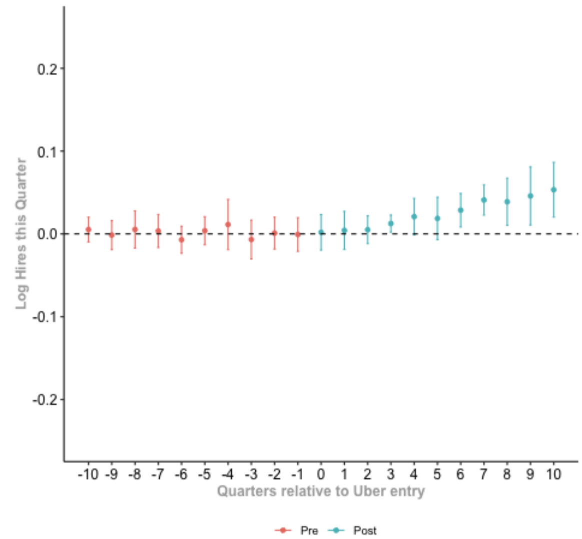
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 3. Dynamic Treatment Effects of Uber Entry in All Industries

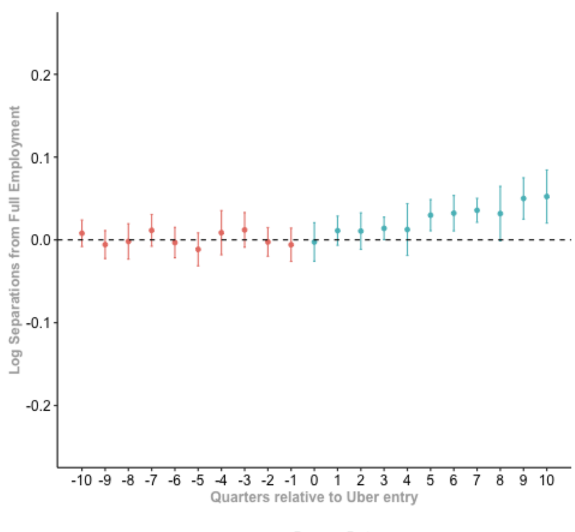
(a) Employment by length of exposure



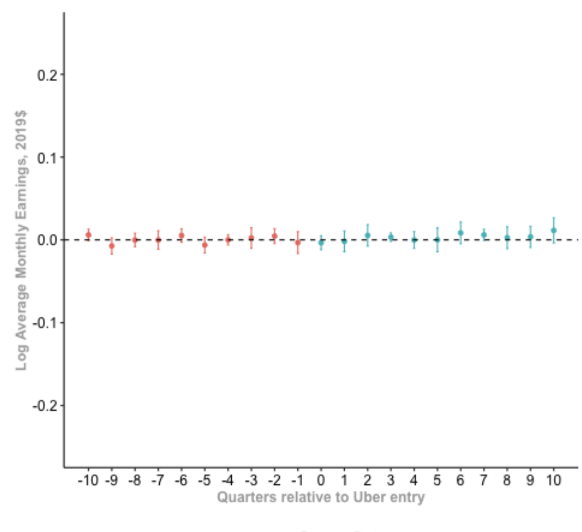
(b) Hires by length of exposure



(c) Separations by length of exposure



(d) Earnings by length of exposure

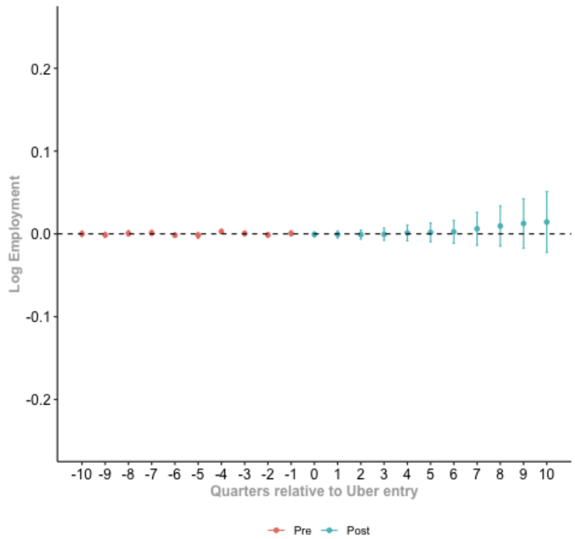


Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

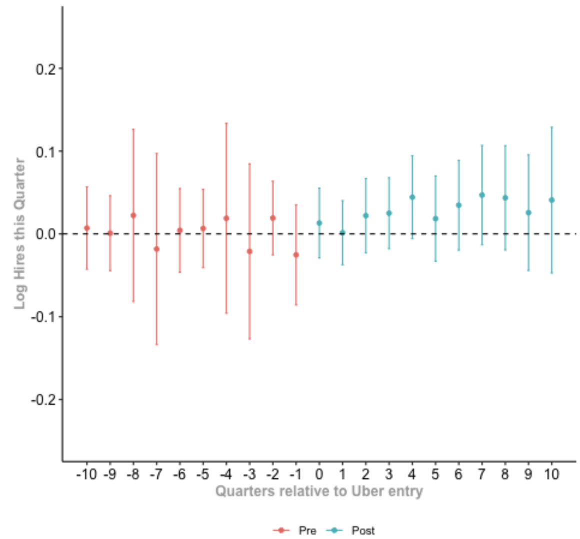
Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

Figure 4. Dynamic Treatment Effects of Uber Entry in Manufacturing

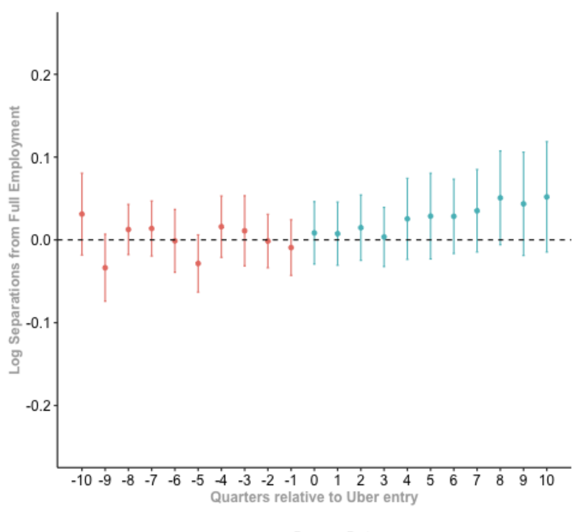
(a) Employment by length of exposure



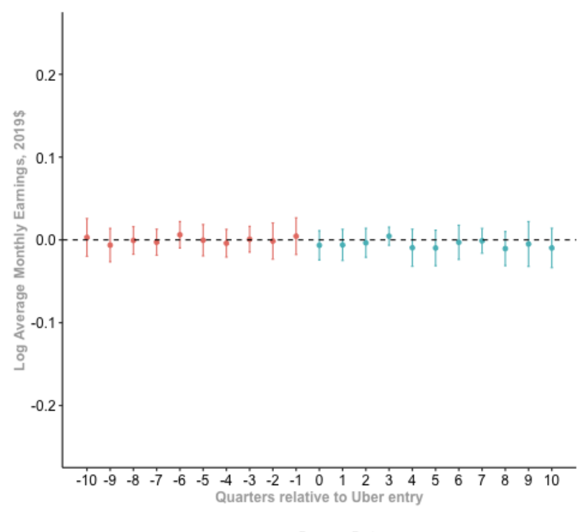
(b) Hires by length of exposure



(c) Separations by length of exposure



(d) Earnings by length of exposure



Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019
Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters

Table 6. Group-time Treatment Effects of Uber Entry in Concurrent & Nonconcurrent Industries

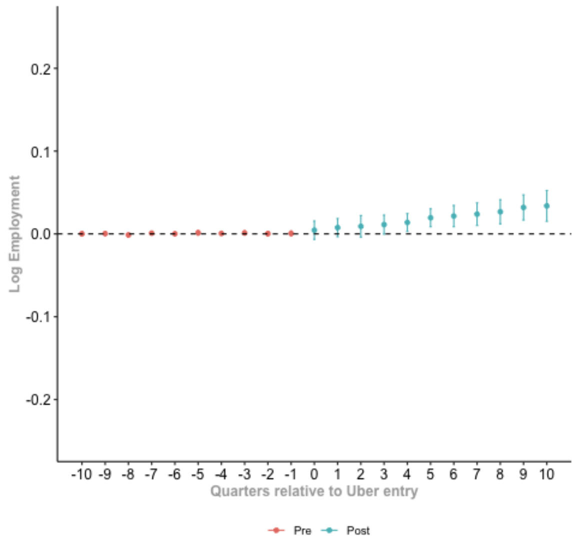
	Log total employment		Log hires		Log separations		Log monthly earnings
A. Concurrent Industries							
Uber	0.0407	***	0.0396	***	0.0414	***	0.0032
	(0.0089)		(0.0148)		(0.0124)		(0.0054)
Observations	280,368		274,608		265,536		242,592
Industry group*CBSA*ed. level	5,841		5,721		5,532		5,054
B. Nonconcurrent Industries							
Uber	0.0784	*	0.0911	***	0.0887	***	0.0111
	(0.0412)		(0.0275)		(0.0326)		(0.0069)
Observations	947,184		776,592		710,448		828,864
Industry group*CBSA*ed. level	19,733		16,179		14,801		17,268

Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019.

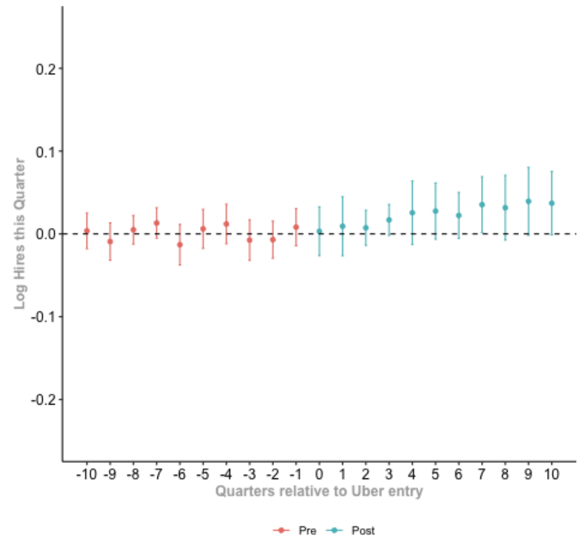
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services; nonconcurrent industries are all others. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 5. Dynamic Treatment Effects of Uber Entry in Concurrent Industries

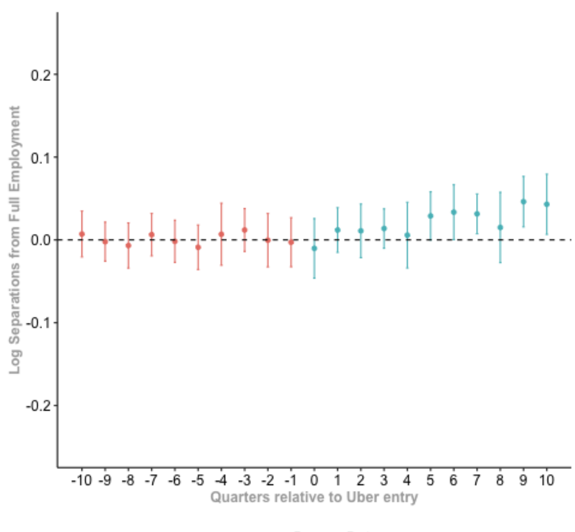
(a) Employment by length of exposure



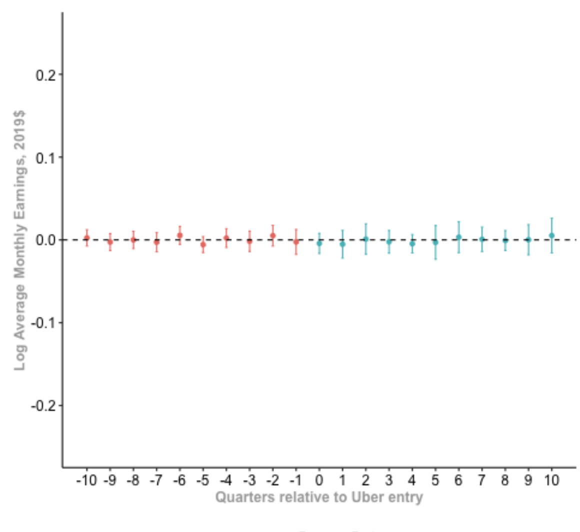
(b) Hires by length of exposure



(c) Separations by length of exposure



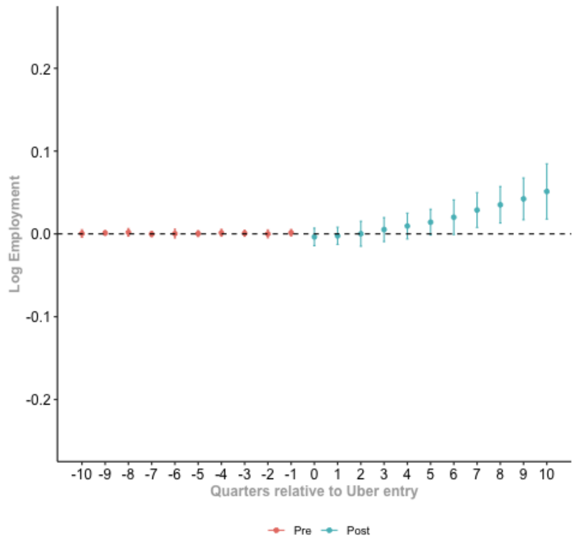
(d) Earnings by length of exposure



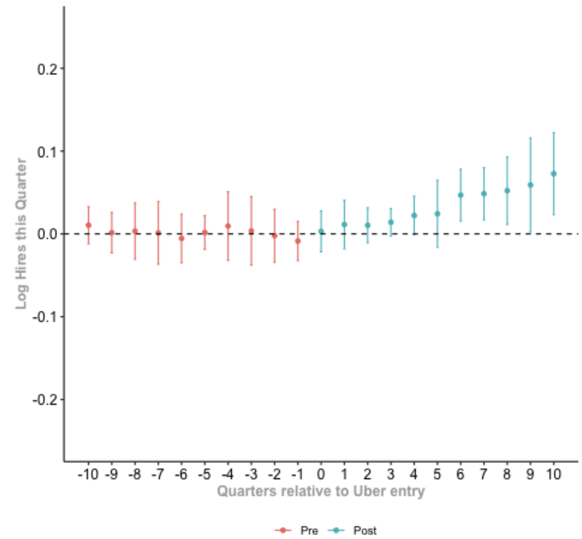
Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019
Note: Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services. These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

Figure 6. Dynamic Treatment Effects of Uber Entry in Nonconcurrent Industries

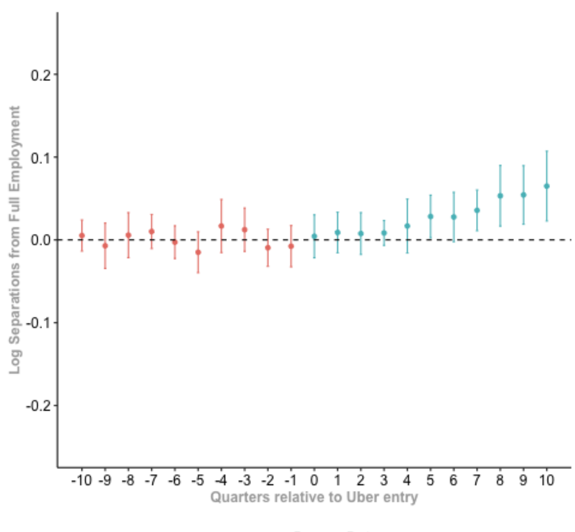
(a) Employment by length of exposure



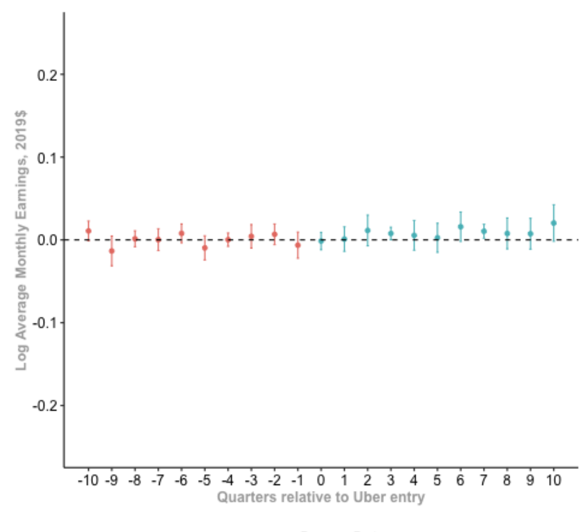
(b) Hires by length of exposure



(c) Separations by length of exposure



(d) Earnings by length of exposure



Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019
Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

A Appendix: Tables & Figures

Appendix Table A1. Group-time Treatment Effects of Uber Entry with Anticipation

Sample = All industries	Log total employment		Log hires		Log separations		Log monthly earnings	
A. Anticipation = 1 quarter								
Uber	0.0584	***	0.0719	***	0.0577	***	0.0034	
	(0.0200)		(0.0194)		(0.0170)		(0.0055)	
Observations	1,367,952		1,187,088		1,107,696		1,192,800	
Industry*CBSA*education level	28,499		24,731		23,077		24,850	
B. Anticipation = 2 quarters								
Uber	0.0599	***	0.0716	***	0.0563	***	0.0099	*
	(0.0193)		(0.0194)		(0.0180)		(0.0059)	
Observations	1,367,952		1,187,088		1,107,696		1,192,800	
Industry*CBSA*ed. level	28,499		24,731		23,077		24,850	

Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019.
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A2. Group-time Treatment Effects of Uber Entry in All Industries & Manufacturing

	Working	Worked last week	Log earned income	
A. All Industries				
Uber	0.0171	0.0154	0.1831	
	(0.0044)	(0.0053)	(0.0403)	
Observations	2,304	2,304	2,304	
Industry*CBSA	192	192	192	
B. Manufacturing				
Uber	0.0079	0.0150	0.1864	***
	(0.0093)	(0.0137)	(0.1145)	
Observations	2,304	2,304	2,304	
Industry*CBSA	192	192	192	

Source: Uber Entry Data; American Community Survey, 2008-2019.

Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA in 2008. Earned income is in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A3. Group-time Treatment Effects of Uber Entry in All Concurrent & Nonconcurrent Industries

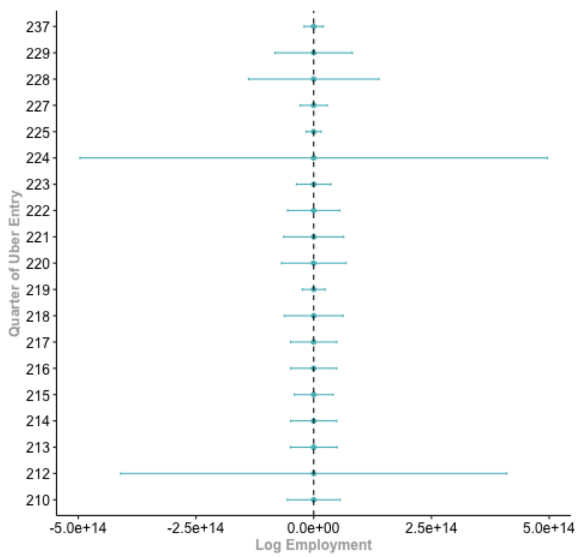
	Working		Worked last week		Log earned income	
A. Concurrent Industries						
Uber	0.0054		0.0089		0.1166	
	(0.0046)		(0.0042)		(0.0478)	
Observations	2,304		2,304		2,304	
Industry*CBSA	192		192		192	
B. Nonconcurrent Industries						
Uber	0.0239	***	0.0183	***	0.2062	***
	(0.0040)		(0.0045)		(0.0398)	
Observations	2,304		2,304		2,304	
Industry*CBSA	192		192		192	

Source: Uber Entry Data; American Community Survey, 2008-2019.

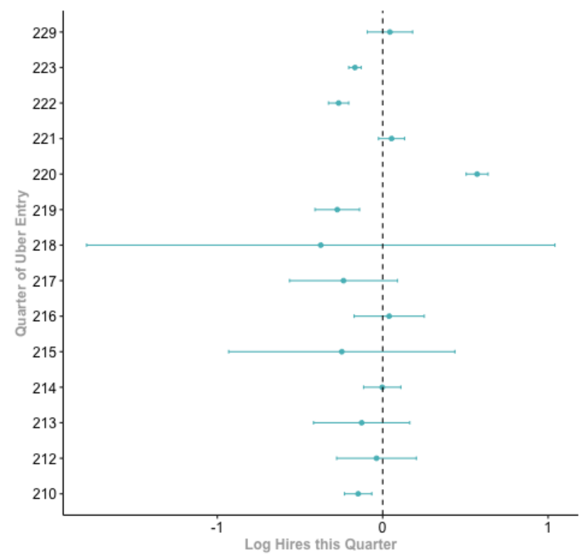
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA in 2008. Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services; nonconcurrent industries are all others. Earned income is in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figure A1. Group Treatment Effects of Uber Entry in the Taxi & Limousine Industry

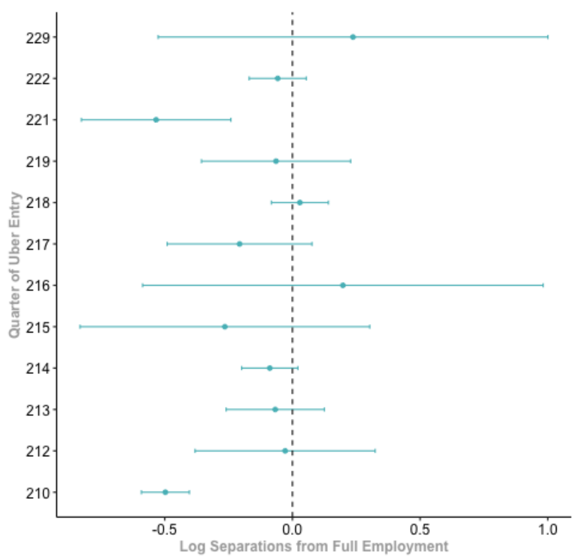
(a) Employment by quarter of Uber entry



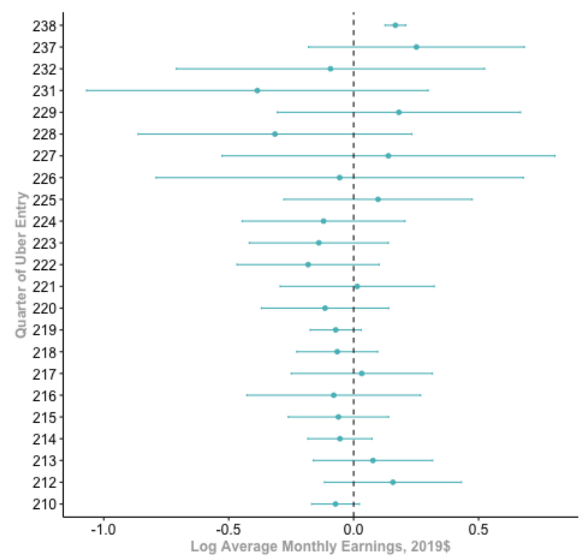
(b) Hires by quarter of Uber entry



(c) Separations by quarter of Uber entry



(d) Earnings by quarter of Uber entry

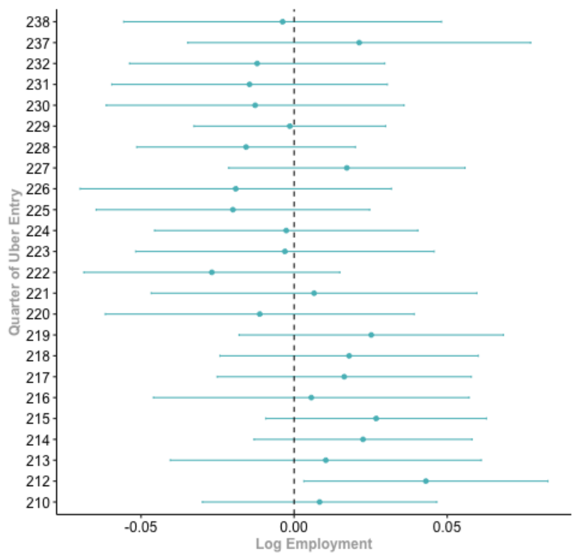


Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

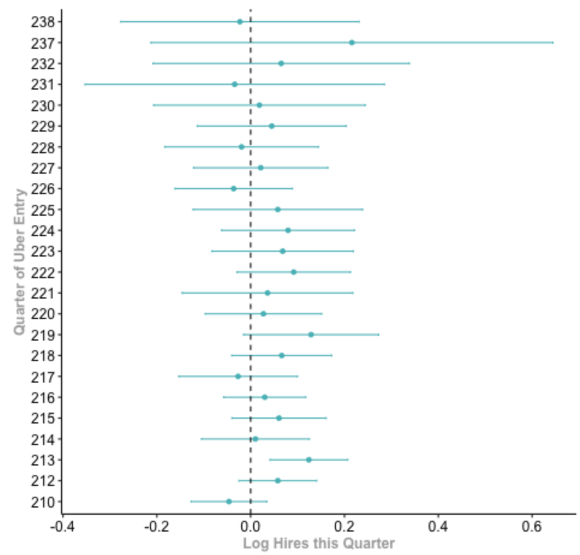
Notes: These figures present treatment effects of Uber entry aggregated by quarter of Uber entry.

Appendix Figure A2. Group Treatment Effects of Uber Entry in Bars & Restaurants

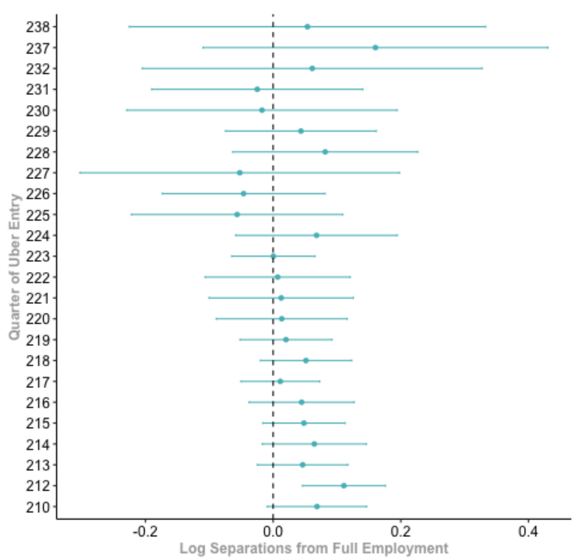
(a) Employment by quarter of Uber entry



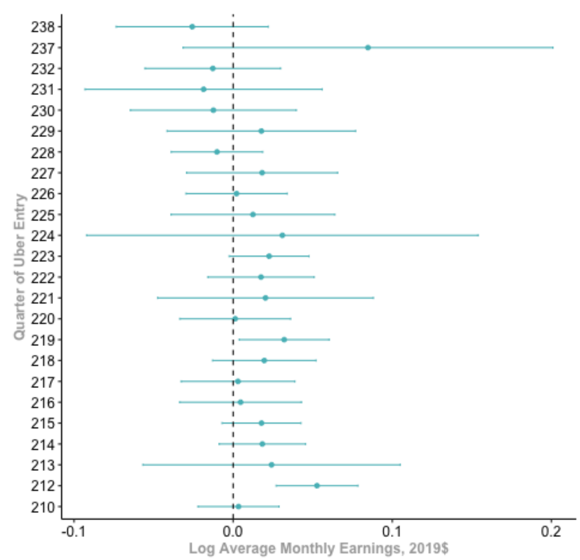
(b) Hires by quarter of Uber entry



(c) Separations by quarter of Uber entry



(d) Earnings by quarter of Uber entry

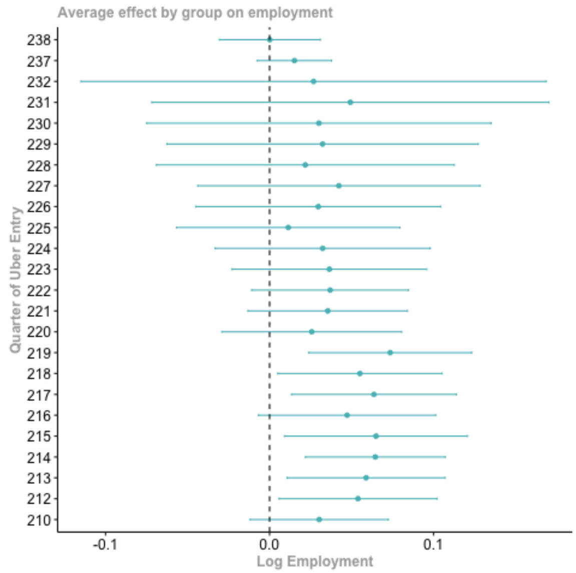


Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

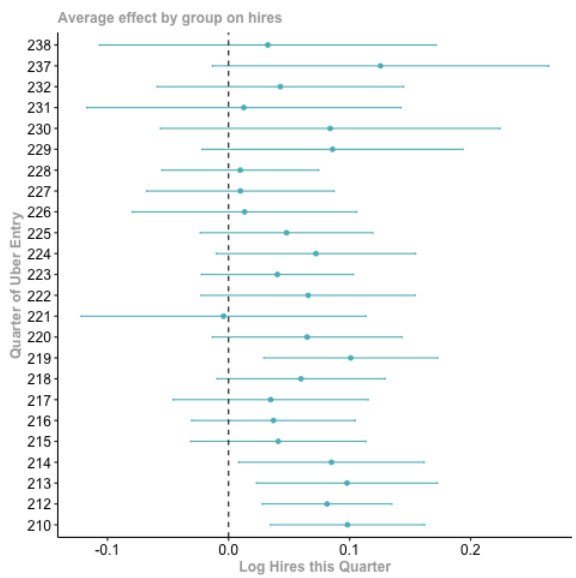
Notes: These figures present treatment effects of Uber entry aggregated by quarter of Uber entry.

Appendix Figure A3. Group Treatment Effects of Uber Entry in All Industries

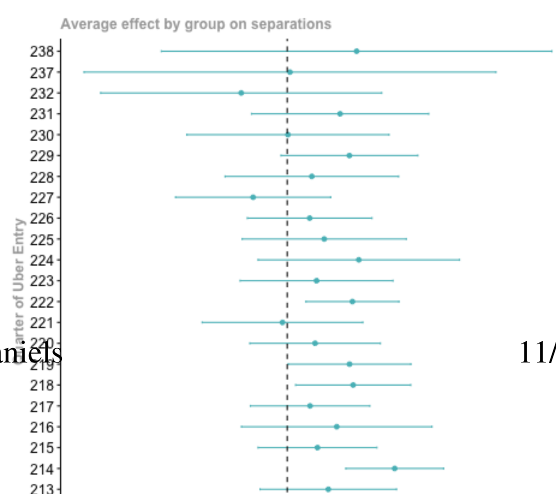
(a) Employment by quarter of Uber entry



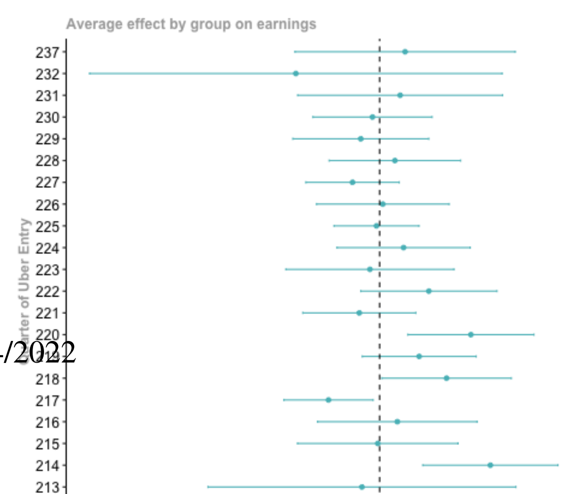
(b) Hires by quarter of Uber entry



(c) Separations by quarter of Uber entry

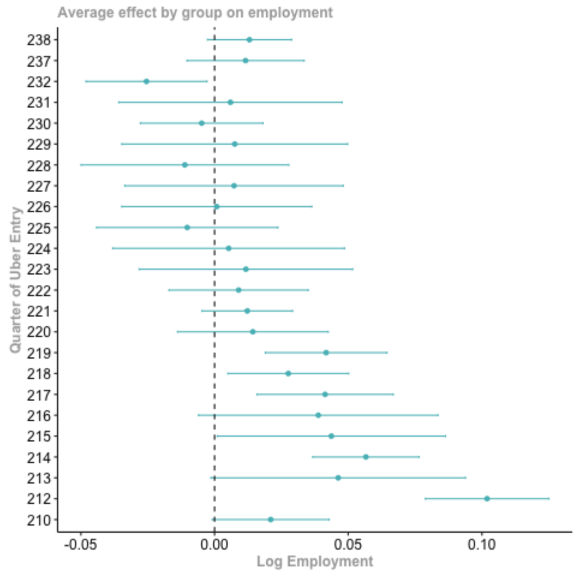


(d) Earnings by quarter of Uber entry

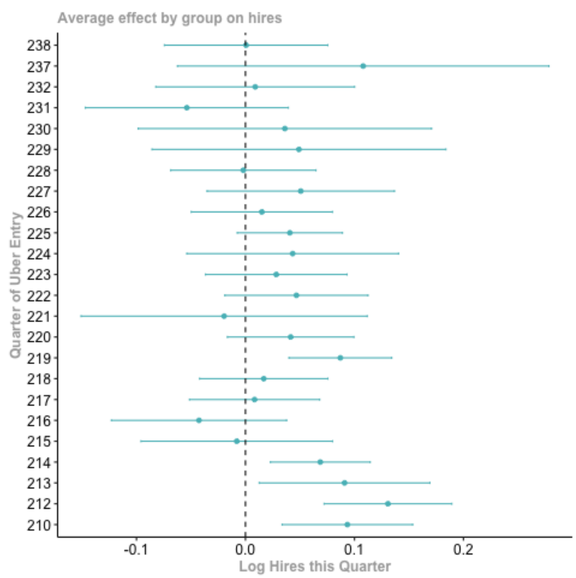


Appendix Figure A4. Group Treatment Effects of Uber Entry in Concurrent Industries

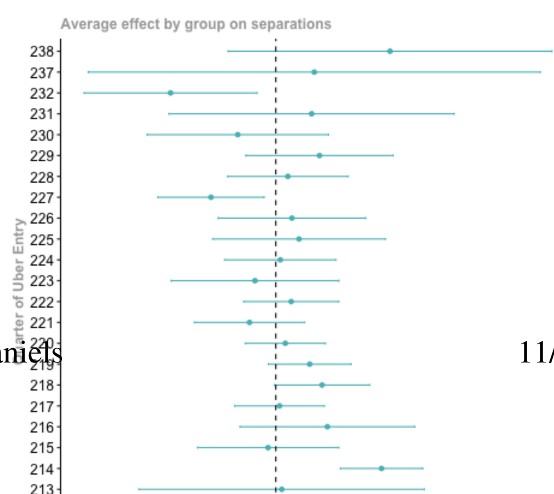
(a) Employment by quarter of Uber entry



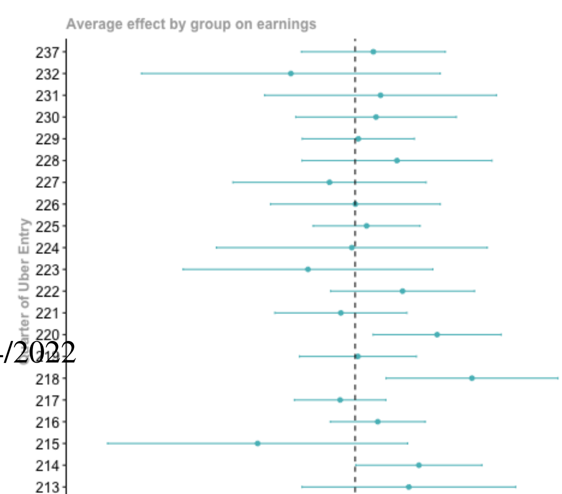
(b) Hires by quarter of Uber entry



(c) Separations by quarter of Uber entry



(d) Earnings by quarter of Uber entry



Appendix Table A4. Heterogeneous Group-time Treatment Effects of Uber Entry in All Industries

	Men		Women		<College education		College degree of more		Low public transit		High public transit	
A. Log total employment												
Uber	0.0613	***	0.0557	***	0.0650	***	0.0468	**	0.0453	*	0.0281	***
	(0.0193)		(0.0165)		(0.0201)		(0.0186)		(0.0238)		(0.0045)	
Observations	667,392		649,968		1,025,856		341,712		731,472		539,680	
Industry*CBSA*ed. level	13,904		13,541		21,372		7,119		15,239		13,492	
B. Log hires												
Uber	0.0886	***	0.0752	***	0.0855	***	0.0483	***	0.0606	***	0.0647	***
	(0.0249)		(0.0161)		(0.0208)		(0.0156)		(0.0144)		(0.0113)	
Observations	600,384		572,160		891,264		294,912		600,192		497,080	
Industry*CBSA*ed. level	12,508		11,920		18,568		6,144		12,504		12,427	
C. Log separations												
Uber	0.0721	***	0.0649	***	0.0762	***	0.0481	***	0.0568	***	0.0446	***
	(0.0231)		(0.0124)		(0.0181)		(0.0138)		(0.0146)		(0.0084)	
Observations	532,848		504,624		832,704		274,992		541,440		480,000	
Industry*CBSA*ed. level	11,101		10,513		17,348		5,729		11,280		12,000	
D. Log monthly earnings												
Uber	0.0126		0.0087	*	0.0157	**	0.0165	**	0.0154	***	0.0077	***
	(0.0083)		(0.0045)		(0.0072)		(0.0068)		(0.0049)		(0.0029)	
Observations	680,736		663,072		1,036,848		345,648		742,368		543,040	
Industry*CBSA*ed. level	14,182		13,814		21,601		7,201		15,466		13,576	

Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019. Federal Transit Authority, 2008 Transit Operating Statistics.

Notes: This table presents aggregated group-time treatment effects weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$