Spillover Effects of The Gig Economy:

How Uber Drives Earnings and Employment[1]

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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 gig work can rival traditional employment. Meanwhile less than 2 percent of U.S. workers participate in gig work. However, by disrupting existing industries and providing a uniquely flexible form of work, the gig economy might influence the labor market outcomes of many more workers than just those directly engaged. In this paper, I estimate the *indirect* effects of gig work on the earnings and employment of workers in the formal sector. 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, across all industries, I find that the arrival of Uber leads to a 5.5 percent increase in employment. This effect translates into Uber's arrival creating 4.8 million additional jobs, more than twice the number of workers directly engaged in gig work.

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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. Academic studies have sought to understand the *direct* effect of this new, flexible form of labor on the workers engaged in it. Researchers find evidence that workers engage in gig work to smooth income following unemployment spells (Garin et al. 2020; Jackson 2020), mixed evidence on preferences for flexibility among gig workers (Mas and Pallais 2017; Chen et al. 2019), and potentially worse household financial health following gig employment (Jackson 2020; Koustas 2018). In the business community, reports from financial institutions and consulting groups provide firms strategies to retain workers interested in gig work (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).

Despite this growing attention, the actual size of the gig economy is quite small; less than 2 percent of the workforce participates in the gig economy (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 consistent 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 led 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, hirings, separations, 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 Core Based Statistical-Areas (CBSA).

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 regress Uber entry timing on CBSA characteristics and labor market outcomes in my data, I find population to indeed be the greatest predictor of Uber entry. Further, none of the outcomes of interest for this paper – employment, hires, separations, and earnings – predict

Uber entry, suggesting that Uber's decision to enter a city was not based on the employment or earnings of workers. Still, even if the assumption of Uber entry being exogeneous to changes in employment and earnings is satisfied, a standard two-way fixed effect model has the potential to yield a biased estimate of Uber's treatment effect if the effect of Uber on the traditional 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 (Uber) simultaneously.

I first consider the effect of Uber's entry on employment and earnings in the taxi industry as a check on the validity of my research design. Since Uber was seen as a substitute for standard taxis, standard economic theory predicts 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. I find the arrival of Uber is associated with an 8.6 percent ($p < 0.05$) decline in total employment, a 13.7 percent ($p < 0.01$) decline in hiring in the taxi industry. There is no detectable effect on separations or earnings, though the later 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 establishments (Teltser, Lennon, and Burgdorf 2021) which in turn should lead to greater employment and earnings in drinking establishments. Following the arrival of Uber, no change in employment is detected in bars and restaurants yet increasing hirings and separations after Uber entry suggest greater job churn. Workers in bars and restaurants also experience a 1.7 percent ($p < 0.05$) increase in earnings after Uber entry, consistent with prior evidence (Teltser, Lennon, and Burgdorf 2021). These findings, along with the taxi industry findings, provide support for my research design which can then be extended across all industries.

I next estimate the effect of Uber's entry on employment and earnings for all other industries. I find employment increases, on average, 5.5 percent ($p < 0.01$) following the arrival of Uber while hires and separations both increase 6.2 percent ($p < 0.01$). The effect of Uber entry on employment, hires, and separations is small in the first quarters following Uber entry but continues to rise over time resulting in significant aggregate effects. This translates to an average 4.8 million additional jobs across the U.S. following the arrival of Uber while an estimated 1.9 million people engage in the gig economy per year.

The magnitude of the effect of Uber on total employment leads to two questions: first, what are the mechanisms driving this substantial overall impact, and second, is this the true overall effect or is the aggregate obscuring potentially heterogeneous effects of the arrival of the gig economy?

To address the mechanisms behind changing employment, I first examine how changing demand for goods and services following the arrival of Uber may influence employment. It is possible that Uber's arrival was complementary to a broader set of industries beyond bars and restaurants. Rather than parsing out all potential changes to product demand, I consider a set of industries with no plausible link to rideshare services: utilities, manufacturing, and wholesale trade. Given that the manufacturing and wholesale trade sectors produce primarily tradeable goods, and demand for utilities is very inelastic, the product market of these industries is unlikely to be affected by changes to local product demand. However, across all three industries, the arrival of Uber results in increases in employment, hires, and separations, suggesting that product demand is not the sole driver of the overall effect. 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 the gig economy may influence employment and earnings is the role of gig work as a new outside option to workers. As a viable alternative to existing employment, new forms of gig work can increase the bargaining power of workers resulting in greater earnings or separations. Alternatively, as a new moonlighting option, gig work allows workers to retain existing employment resulting in fewer separations. Given the small percentage of workers that engage in gig work, the effects of a new outside option are most likely to be detected within industries where gig workers are employed concurrently or were employed previously.

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 (SHED), 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). By comparing these 'concurrent' industries to all other industries, I find the effect of Uber entry to be positive and significant on employment, hires, and separations across both concurrent and nonconcurrent industries. Thus, more research is needed to determine whether the new option of employment in the gig economy influences worker decision-making sufficiently to result in broad increases in employment.

My estimate that Uber's entry led to 5.5 percent (4.8 million) more jobs suggests the gig economy had a substantial impact on the broader labor market, yet this average effect may obscure heterogeneous effects of the gig economy. The start of the gig economy might have differential effects on workers of different genders and education levels given that gig workers and more likely to be male and have less than a college education than the greater workforce (Collins et al. 2019; Hall and Krueger 2018). Furthermore, the introduction of an outside option has a differential impact on women's versus men's employment and earnings (Caldwell and Danieli 2021). When estimating average treatment effects by educational attainment, Uber entry results in greater increases in employment among workers with less than a college education compared to workers with a college degree or more. Additionally, I find the effect of Uber entry to be greater on men versus women on all measures of employment and earnings. While the magnitude of changes may be statistically higher for men compared to women and workers without a college degree compared to those with one, across both gender and education breakdowns, the arrival of Uber results in statistically significant *increases* in employment and earnings. These findings provide insight into the types of workers more likely to be impacted, but do not leading to conclusive evidence of heterogeneous treatment effects driving overall changes in employment.

In addition to worker characteristics, the characteristics of a CBSA may impact how the arrival of Uber influences employment and earnings of workers, in particular the availability of public transportation. The size of public transit systems change how Uber is used within a region often acting as a connector to existing transit options or a substitute for less comprehensive transit systems (Hall, Palsson, and Price 2018). To determine if the effects of Uber on employment are being driven by regions with large public transit systems, I estimate the effects of Uber entry separately for CBSAs with high versus low public transportation ridership; ridership is measured as number of passenger trips in 2008 according to Federal Transit Authority data. Results show that the effects of Uber entry on employment and earnings do not differ by level of ridership. As with estimates of heterogeneous effects by gender and education, different levels of public transit ridership are not driving the overall effect of the gig economy on employment as prior research may suggest.

These findings on the substantial effect of Uber entry on employment can be informed by existing research on the characteristics of gig workers and how workers choose to engage in gig work. Research identifying gig workers through tax filings finds that gig workers are more likely to have filed for unemployment in the year prior to earning money from a gig; this suggests that workers use gig work to fill gaps in employment (Garin et al. 2020). Building on this finding, Jackson (2020) estimates the effect of engaging in gig work to fill employment gaps on short and long run income. Individuals likely to engage in gig work have higher short-term incomes than those less likely to engage in gig work, in the long run, workers less likely to engage have higher incomes (Jackson 2020). Additionally, higher levels of debt and credit card utilization are strong predictors of driving for rideshare firms (Koustas 2018). With this picture of gig workers in mind, I consider how gig work influences far more than the 1.6 percent of workers it engages (Farrell, Greig, and Hamoudi 2019).

Existing research on the broader effects of the gig economy demonstrates how this new form of work influences individuals' personal and financial choices, but little work has considered the gig economy's potential influence on workers beyond those directly engaged. Prior research examining the broader effects of the gig economy, or Uber specifically, have found effects on a range of outcomes including complementary effects on public transportation

(Hall, Palsson, and Price 2018), increased alcohol consumption (Teltser, Lennon, and Burgdorf 2021), declines in drunk driving (Greenwood and Wattal 2017), decreased entrepreneurial activity (Burtch, Carnahan, and Greenwood 2018), and greater economic development (Gorback 2020). Declining entrepreneurial activity, as measured by examining changes to Kickstarter campaigns and self-employment rates in response to Uber entry (Burtch, Carnahan, and Greenwood 2018), supports the theory that gig work provides a new outside option that workers consider – individuals choose gig work over potentially riskier independent business endeavors. This paper is the only research to date looking at the effect of gig workers on workers not engaged in the gig economy. Additionally, researchers have examined Uber's effect on local economies: the arrival of Uber led to increased restaurant creation and higher housing prices in previously inaccessible neighborhoods compared to neighborhoods more accessible by public transportation (Gorback 2020). These findings demonstrate that the gig economy has the ability to influence both individual decision-making, in regard to both personal (alcohol consumption) and professional (starting a new business) matters, and broader product demand.

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. As more workers seek jobs with greater flexibility (Chen et al. 2019), the gig economy may create both new job opportunities and greater movement within industries via job churn. Findings of greater job churn is suggestive of a healthier labor market (Lazear and Spletzer 2012), but I am unable to determine if greater churn is good or bad for workers. More churn may imply less job stability among workers, but it can also represent workers having new options within their industry and create the potential for a position that better suits worker needs in terms of wage, flexibility, and other benefits (Tanaka, Warren, and Wiczer 2023).

This paper proceeds as follows: first, I present the data and methods employed to estimate the effect of Uber in various industries, next, I present the theoretical framework and findings for the taxi industry, bars and restaurants, all industries, and industries where gig workers are likely employed, then I provide robustness checks and heterogeneous treatment effects, and lastly, I conclude with a discussion the of the results and policy implications.

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", now known as Uber Black, which required drivers to drive a black town car rather than using their own vehicle. The introduction of UberX allowed for anyone with a license and access to a vehicle to drive for Uber and is now the default service provided. 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.

Prior research that utilizes Uber entry as an identification strategy has validated the use of press releases, local reporting, and other social media reports to determine dates of UberX entry. Teltser, Lennon, and Burgdorf's data on Uber entry were collected by examining press releases, Uber's blog, and social media announcements and document dates of Uber entry from 2009 to 2017. I update 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 up to 2020 for 338 Core Based Statistical-Areas (CBSA). 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 (Hall, Palsson, and Price 2018).

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. Agriculture and mining are excluded due to low sample size in matched CBSAs, and public administration is excluded due to the higher wage rigidity in government jobs.

The QWI provides the following outcomes of interest: employment, new hires, separations, and average monthly earnings. Employment is measured as the total number of jobs on the first day of a given quarter. 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. By estimating the effect of Uber entry on hires and separations, I can determine the amount of job churn present as a result of Uber entry. Greater job churn is associated with healthier, tighter labor markets (Lazear and Spletzer 2012). Average monthly earnings are measured by aggregating full quarter earnings of individuals matching job history and demographic groupings and dividing by three. Earnings are converted to real 2019 dollars. Descriptive statistics for all four outcome measures by 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. 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.

One concern that arises when using the roll-out of Uber to estimate changes in employment and earnings is that Uber's choice of which markets to enter was based on these very measures. 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 the comparison of the size of coefficients. Population, household income, and percent of CBSA with a bachelor's degree are the largest predictors of Uber entry. None of the outcomes of interest – employment, earnings, hires, or separations – predict Uber entry. These findings suggest that the staggered roll-out of Uber is a reasonable strategy to identify the effect of Uber on employment and earnings measures.

Prior work using Uber's roll-out as a strategy for identification have utilized two-way fixed effect models that control for time and worker or region fixed effects, but the staggered rollout of Uber has the potential to create bias in estimating the average treatment effect of Uber's arrival if treatment effects are not constant over time (de Chaisemartin and D'Haultfœuille 2022). When rollout of treatment, in this case Uber, is staggered, rather than weighting average treatment effects by the size of the group treated at a given time, two-way fixed effects models assume treatment is constant across all groups putting less weight on early and late adopters. 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 might make 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.

To avoid bias arising from staggered treatment, I estimate average treatment effects by groups, *g*, who receive treatment simultaneously, that is groups of CBSAs into which Uber entered in year-quarter *g* (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, $\beta_{g,t}$. By first estimating effects at the group-time level, I allow treatment effects to vary by group and time unlike a standard two-way fixed effect model. $\beta_{g,t}$ estimates the effect on $Y_{g,\,t}$ of Uber's entry on group *g* at time *t*. In sections IV and V, I present the aggregated group-time treatment effects which are the average of group specific treatment effects across all groups, weighted by group size. 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, the following assumptions must be met.

Assumption 1. Parallel trends

To estimate unbiased treatment effects, there must exist 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. For example, in the second quarter of 2013, Uber entered San Diego, Boston, Chicago, Seattle, and Atlanta, therefore characteristics common to these cities that may influence earning and employment trends but have not changed over time – such as progressive local politics – are differenced out. Localized shocks to labor markets could create a violation of this assumption, but graphs of dynamic treatment effects, presented fully in section IV and V show little evidence of pre-trends.

Assumption 2. Treatment anticipation

This model requires limited treatment anticipation – that is firms, workers, and policymakers did not take actions that changed employment and earnings with knowledge of Uber's impending entry. While the primary model of this paper assumes no treatment anticipation, full results of anticipation tests can be found in table B1. Given the consistency of my estimates with no anticipation, 1 quarter, and 2 quarters, this assumption is quite reasonable.

Assumption 3. Irreversible treatment

Lastly, the irreversibility of treatment is necessary to produce unbiased estimates. That is, 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, more hours worked per month, or both. 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 VI.

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. Effects in both the taxi industry and bars and restaurants move as predicted by economic theory; employment and earnings decline in the taxi industry and increase in bars and restaurants following Uber's arrival. These findings serve as a validation check on my empirical model. 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 – even if the gig economy remains relatively small, it has the ability to influence many more workers.

A. Directly Competing Industries: Taxis

1. How can Uber influence taxis?

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 in taxi industry

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, there are no detectable effects on separations or earnings. 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 estimates of declines in separations (panel C) are much noisier. 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. How can Uber influence bars and restaurants?

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 from 225 Metropolitan and Micropolitan Statistical Areas to 338 CBSAs.

2. Findings in bars & restaurants

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 which may mean greater instability for workers, but with employment growing workers may be leaving positions in favor of better employment opportunities within the industry. Regardless, greater job churn is indicative of a healthy labor market within the drinking establishment industry (Lazear and Spletzer 2012). 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[3]. 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

[3] Recall, group-time aggregated treatment effects are treatment effects aggregated at the group level while dynamic treatment effects are aggregated by quarter relative to Uber entry. See section III for more detail.

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 supported by prior research on greater alcohol consumption and profits at drinking establishment following the arrival of Uber (Teltser, Lennon, and Burgdorf 2021)[4].

C. All Other Industries

In panel C of table 4, 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 20,575 more jobs, on average in year-quarter *t* in a given CBSA. 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.

The magnitude of changes to employment following Uber entry far exceeds estimates on the size of the gig economy. While on average 1.9 million workers participate in the gig economy in a given year, the introduction of Uber is associated with 4.8 million additional jobs.

[4] 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, wholesale trade, and utilities industry. Rather than attempting to parse out each industry in which product demand may increase after Uber, I consider these industries as falsification tests. The manufacturing and wholesale trade industries produce tradeable goods, and therefore these industries should not be influenced due to changes in local demand. Furthermore, the inelasticity of demand for utilities makes it unlikely to be influenced by the arrival of gig work. Thus, any changes to employment or earnings in response to Uber entry in these industries are likely to be driven by an alternative mechanism.

Average effects of Uber entry on employment and earnings in each of these industries are presented in table 5. In the manufacturing industry, while statistically insignificant, the magnitude of changes to hires and separations are comparable to, if not greater than, changes found in the bar and restaurant industry. As seen in panel B of table 5, the arrival of Uber resulted in greater changes in total employment in the wholesale trade industry – 3.3 percent ($p < 0.05$) increase, on average. Hires increase in wholesale trade 3.8 percent ($p < 0.05$), on average, following the arrival of Uber while separations increase 4.9 percent ($p < 0.05$). As with the manufacturing industry, changes in employment, hires, and separations are not statistically significant in the utilities industry, but earnings increase, on average, 4.0 percent ($p < 0.05$) following Uber entry. 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. How can Uber influence worker's choices?

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. On the one hand, as a new outside option, gig work has the potential to directly increase worker bargaining power. On the other hand, gig work provides workers with a new moonlighting option which may encourage workers to forgo costly job search and remain in lower paid primary occupations thereby keeping earnings low and employment stable. Below, I elaborate on how I expect employment and earnings to change in response to gig work as a new outside option.

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). 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 in primary occupations thereby keeping employment stable. 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). 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). Further, 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).

Economic theory suggests that workers moonlighting in the gig economy are less likely to separate from their current employment. 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). 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 more education (Malloy 2016), 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"[5]. 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

[5] See table 2.

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.

2. Findings by industry wide gig work participation

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. Not only are these findings contradictory to my hypothesis, but they suggest that level of gig work engagement within an industry is not positively correlated with greater employment changes. Specific industries within the nonconcurrent group may be driving the effect sizes such as real estate or arts and entertainment, both of which experience large employment effects following Uber entry, suggesting the divide between concurrent and nonconcurrent industries is less meaningful than previously thought. Further research is needed to determine if there truly is no outside option effect following Uber entry.

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 and 2 quarters of anticipation. If businesses or workers make changes that impact employment or earnings in anticipation of Uber's arrival, I may underestimate the true effect of Uber entry. When I account for 1 or 2 quarters of anticipation, I find no significant differences in treatment effects. The complete results of the alternative anticipation specifications can be found in table B1.

B. Alternative Data: American Community Survey

To see if my results hold across data sources, 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 table B2 along with a full description of the methods used in appendix A.

Table B2 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 a 6.2 percent ($p < 0.01$) increase in earned income while no effect was detected on earnings in the QWI data. While the available outcomes in the ACS do not correspond perfectly to the QWI, increases in the percent of people working and earned income in all industries are consistent with my main results.

B. Multiple Hypothesis Testing

Given the large number of tests conducted in this analysis, there is concern that significant effects are spurious. To account for the number of tests, I conduct the Bonferroni adjustment in which I divide the significance level, α, by the number of tests per outcome, 6, and compare $\alpha/6$ to the p-values of each estimate. Adjusted significance levels can be found in appendix table B3. As seen in panel C, adjusting for multiple hypothesis tests does not change the significance of the effect of Uber entry on employment, hires, and separations in all industries.

IIX. 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 the 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. Figure B1 shows the average effects of Uber entry on employment, hires, separations, and earnings across all industries by group[6]. 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.

B. 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 (Cook et al. 2018). While Uber drivers are more likely to identify as female than taxi drivers and chauffeurs, over 70 percent of online platform workers identify as male (Collins et al. 2019). 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.

Table B4 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

[6] CBSAs are grouped by quarter of Uber entry. See section III for details.

are still significant effects on employment and earnings for women contrary to my hypothesis. Higher participation in gig work among men, particularly in earlier years of the gig economy, likely contributes to the greater magnitude of effects on employment and earnings for men than women. Given that the direction of effects is consistent across gender, it is unlikely that the gig economy differentially impacts employment and earnings by gender.

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 more education (Malloy 2016), 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.

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 B4.

When examining the average effect of Uber entry across all industries by education level, the effects on employment and earnings of workers with *and* without a college education are substantial. As seen in columns C and D of table B4, 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. For both workers with and without a college education, earnings increase 1.6 percent ($p < 0.05$). 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. Positive effects across education level suggest that workers with high and low levels of bargaining power are impacted by the presence of gig work.

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 338 CBSAs into high and low ridership regions based on the median passenger trips recorded in 2008.

Table B4 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.

IX. Conclusion

In this paper, I examine the potential spillover effects of the gig economy on the employment and earnings of traditionally employed workers. Using the staggered roll-out of Uber, the first major gig economy firm, I identify changes to employment and earnings that occur as a result of Uber entry. While less than 2 percent of workers in the U.S. participate in gig work, nearly 1.9 million workers (Farrell, Greig, and Hamoudi 2019), I find that the presence of the gig economy is associated with a 5.5 percent increase in employment on average across all industries, nearly 4.8 million jobs.

To determine if Uber's arrival influences workers outside the gig economy, I examine the effect of Uber on the taxi industry and drinking establishments before considering the effect of Uber entry across all industries. In the taxi industry. I find the arrival of Uber is associated with declining employment and hires while in drinking establishments, the arrival of Uber results in greater job churn and earnings. These findings are consistent with notions that Uber is a direct competitor to the taxi industry and a complement to bars and restaurants. Across all industries, I estimate a 5.5 percent ($p < 0.01$) increase in total employment, on average, following the arrival of Uber. These aggregate treatment effects translate to 4.8 million more jobs across the U.S. following Uber entry.

To understand how the gig economy could have such a large effect on employment across all industries, I consider potential mechanisms driving this change. The first mechanism I consider is product demand; the gig economy is complementary to a larger number of industries than just bars and restaurants. By examining the effect of Uber entry in unrelated industries, I can eliminate the notion that increased employment is driven solely by greater product demand. An alternative mechanism I consider is that by functioning as a new outside option to workers, gig work influences worker bargaining power and thereby employment. I find that in industries in which gig workers are more likely to engage, and thereby most influenced by Uber entry, are not experiencing greater employment or earnings compared to all other industries. Thus, it is inconclusive which mechanisms are driving the rise in employment following Uber entry.

An alternative way to make sense of such large employment effects is to consider the underlying heterogeneity that a 5.5 percent increase in employment is obscuring. I consider two characteristics of workers, gender and education level. Education and gender both influence engagement in gig work and worker responses to outside options. The effect of Uber entry on employment and earnings is greater among men than women and among workers with lower levels of educational attainment than high, but in both cases the less impacted group still experiences positive, significant changes to employment and earnings following Uber entry. While these findings provide insight into for whom the effect of Uber entry is greatest, they do not support the theory that worker heterogeneity is driving the magnitude of overall employment effects.

Beyond differential effects on workers, I consider how the characteristics of CBSAs may influence how the start of the gig economy impacts employment and earnings across industries. I estimate the effect of Uber entry among CBSAs with low versus high public transit usage and find minimal differences. In future research, differentiating CBSAs with more regulation of gig firms versus those with less regulations may provide greater insight into the heterogeneous effects of Uber entry. While this work is unable to determine whether one type of worker or CBSA characteristic is driving such large effects, it remains unlikely that Uber, as the vanguard of gig work, has such large overall effects on employment across industry.

Two questions remained unanswered: what are the mechanisms driving greater employment following Uber entry, and is the 5.5 percent increase in employment estimated a true overall effect or driven by unidentified heterogeneous effects. Analyses in this paper are unable to provide conclusive evidence of the mechanisms driving greater employment; further research is needed to decisively conclude that workers' changing choice sets are not impacting employment and earnings. Furthermore, estimates of treatment effects by gender, education level, and public transit usage support the idea that Uber entry has differential impacts, yet fails to characterize the CBSAs and workers primarily impacted by the start of the gig economy.

In order to support workers both inside and outside the gig economy, municipalities across the U.S. have passed policies regulating gig work, yet little is known about how such regulations may influence workers across all industries. The findings in this paper make clear that the presence of gig work does, on average, positively influence the employment of traditionally employed workers. Thus, policies which reduce the size of the gig economy or decrease the expected benefits of gig work may hurt more than just workers in the gig economy; these policies have the ability to stifle the broader employment effects of gig work. Policy makers seeking to improve working conditions by regulating gig work must consider both the workers directly displaced by the gig economy, such as taxi drivers, as well as the potential for gig work to increase employment more broadly. While questions remain about the mechanisms driving increases in employment in response to the gig economy and the municipality level factors that exacerbate the magnitude of employment increases, the findings of this paper highlight how interconnected the gig economy is with existing industries and therefore how regulating gig work has far broader implications than previously considered.

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XI 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)	2.3%
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	-170.4***	0.00722
	(33.67)	(0.00673)
Log pop change 2000-2010	-70.94**	-0.00274
	(30.79)	(0.00277)
Pct Bachelor's degree	-83.67**	0.0196
	(35.66)	(0.0145)
Average age	49.13**	0.00299
	(21.21)	(0.00303)
Log household income	-90.90**	-0.0125
	(40.53)	(0.00977)
Unemployment rate	-72.26***	0.0106
	(26.77)	(0.00832)
Log average monthly earnings (2019 $)	23.34	-0.0162
	(37.76)	(0.0139)
Log employment	-21.36	0.0136
	(258.3)	(0.0880)
Log hires	99.38	0.0241
	(373.7)	(0.0356)
Log separations	-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: All predictors standardized to mean 0. 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

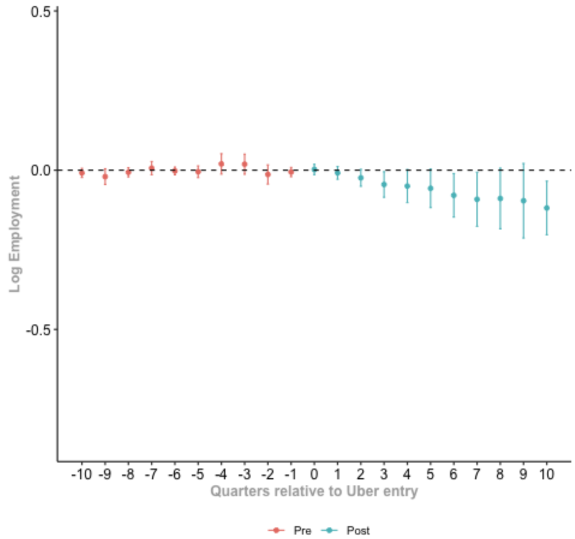
	Log total employment		Log hires		Log separations		Log monthly earnings	
A. Taxi and Limo								
Uber	-0.0865	**	-0.1365	***	-0.1255		-0.0242	
	(0.0438)		(0.0506)		(0.0771)		(0.0219)	
Observations	25,056		10,560		6,864		34,512	
CBSA*education level	522		220		143		719	
B. Bars and Restaurants								
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	
C. 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	

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

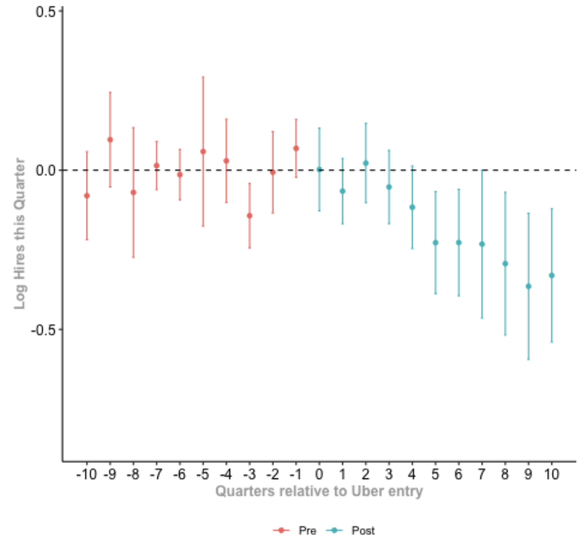
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

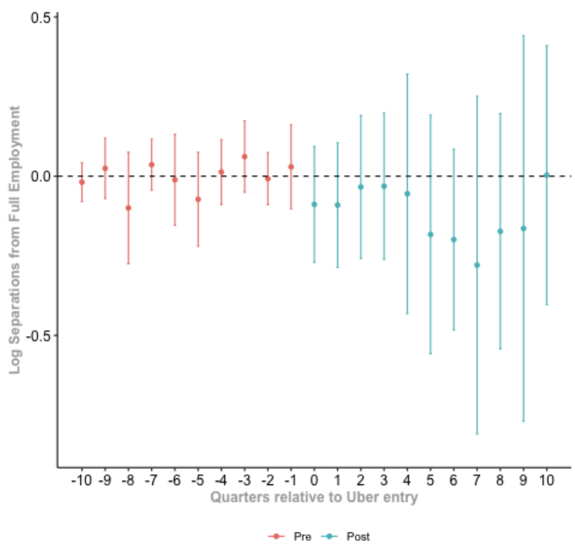
(a) Employment by length of exposure



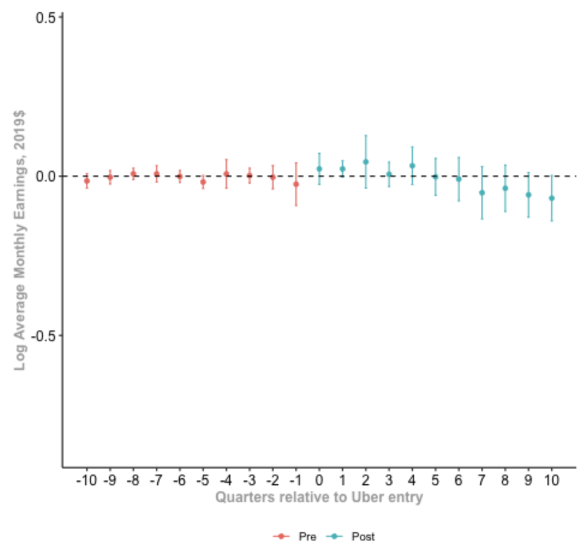
(b) Hires by length of exposure



(c) Separations by length of exposure



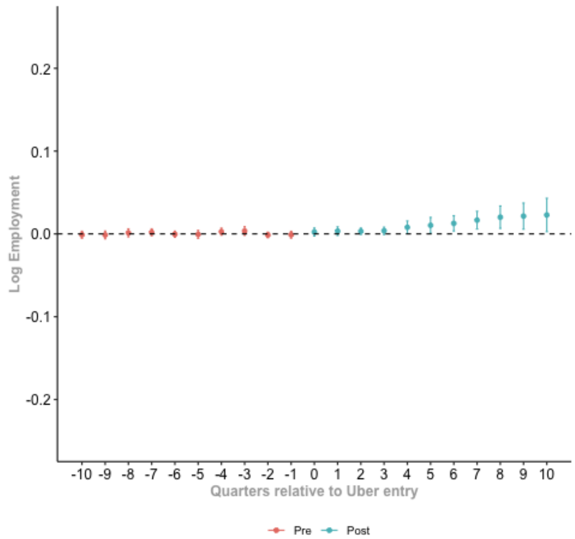
(d) Earnings by length of exposure



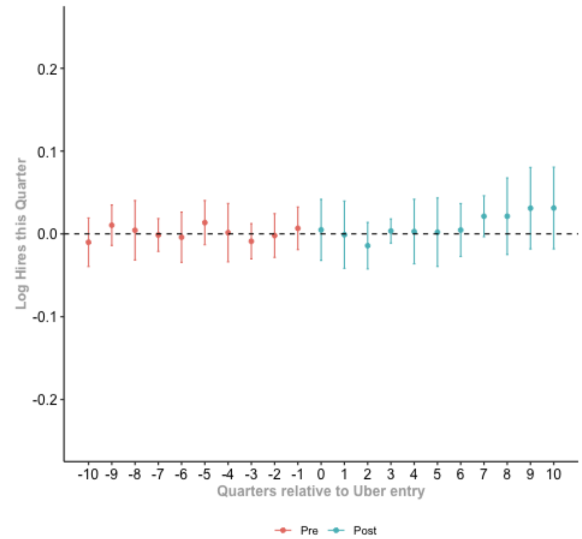
Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019
Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

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

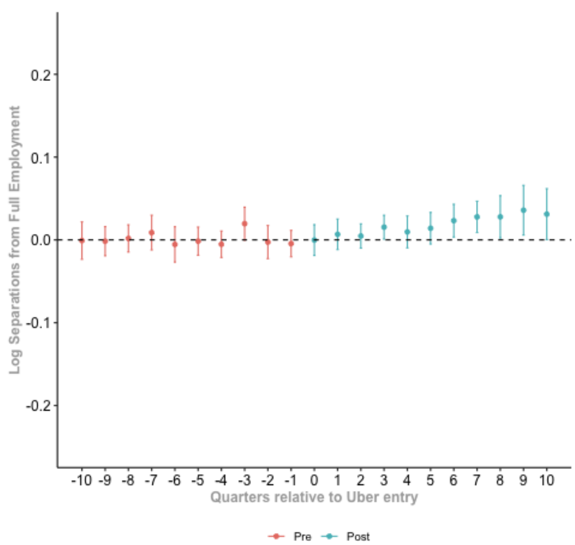
(a) Employment by length of exposure



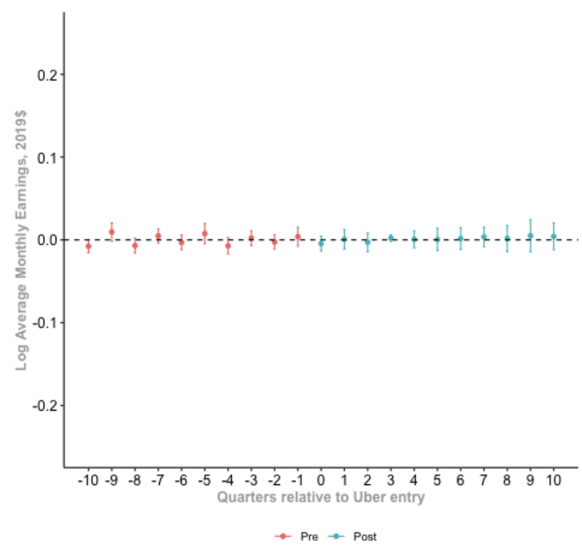
(b) Hires by length of exposure



(c) Separations by length of exposure



(d) Earnings by length of exposure

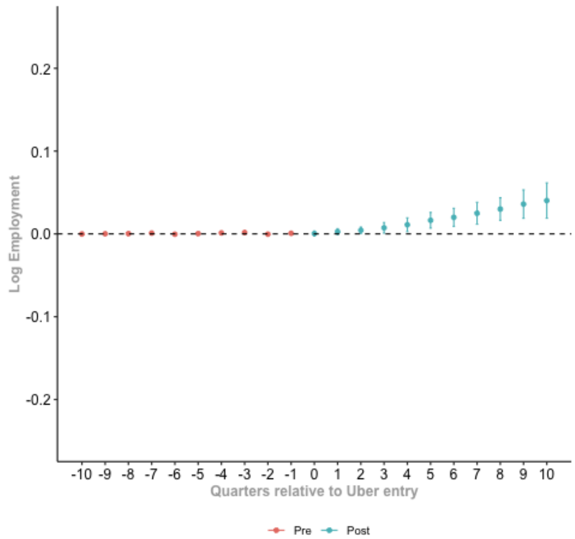


Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

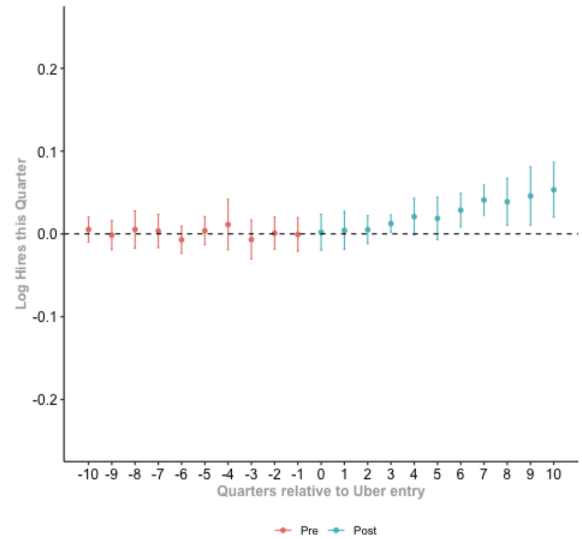
Notes: These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

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

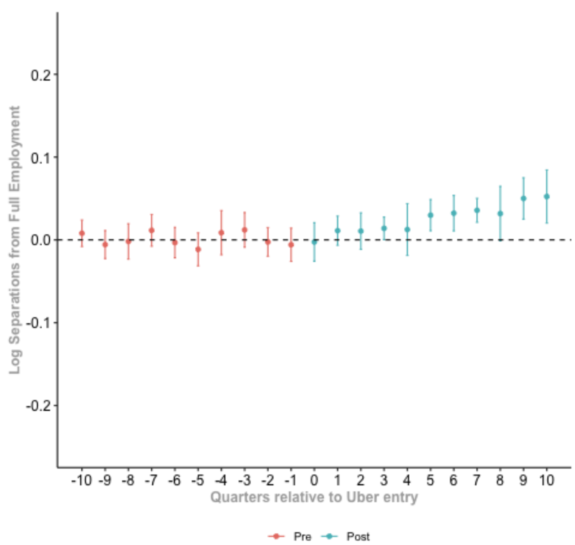
(a) Employment by length of exposure



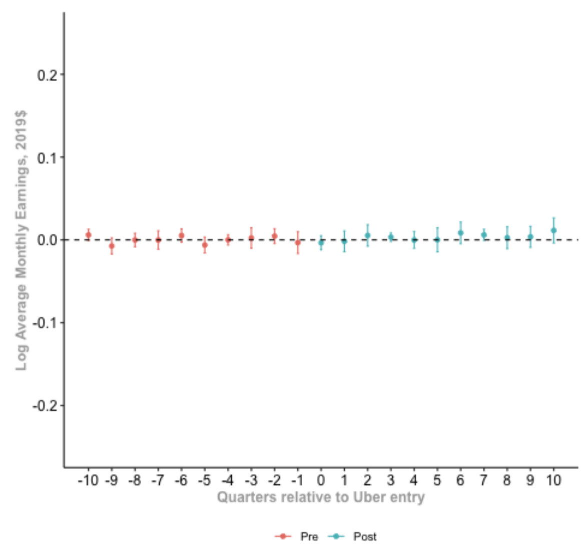
(b) Hires by length of exposure



(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.

Table 5. Group-time Treatment Effects of Uber Entry in Unrelated Industries

	Log total employment	Log hires	Log separations	Log monthly earnings
A. 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
B. Wholesale Trade				
Uber	0.0328 **	0.0384 **	0.0487 **	0.0025
	(0.0152)	(0.0212)	(0.0239)	(0.0088)
Observations	70,272	65,760	62,208	60,672
Industry group*CBSA*ed. level	1,464	1,370	1,296	1,264
C. Utilities				
Uber	0.0704	0.0647	0.1836	0.0403 **
	(0.0710)	(0.1575)	(0.1638)	(0.0174)
Observations	64,944	22,368	18,816	57,408
Industry group*CBSA*ed. level	1,353	466	392	1,196

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; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

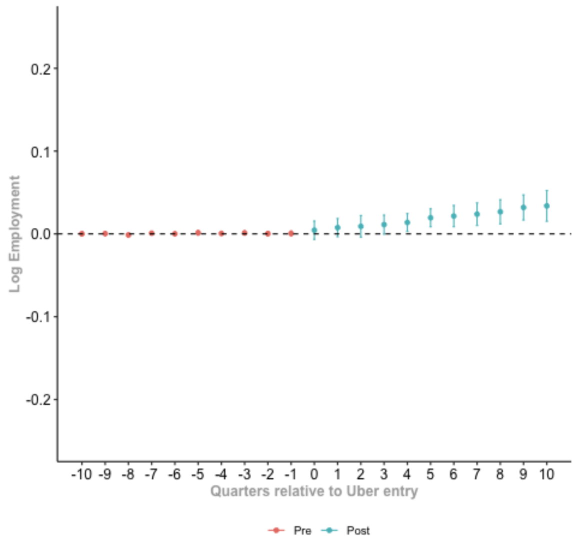
	Log total employment		Log hires		Log separations		Log monthly earnings
A. Concurrent Industries							
Uber	0.0407	***	0.0396	***	0.0414	***	0.0032
	(0.0089)		(0.0148)		(0.0124)		(0.0054)
Observations	280,368		274,608		265,536		242,592
Industry group*CBSA*ed. level	5,841		5,721		5,532		5,054
B. Nonconcurrent 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.

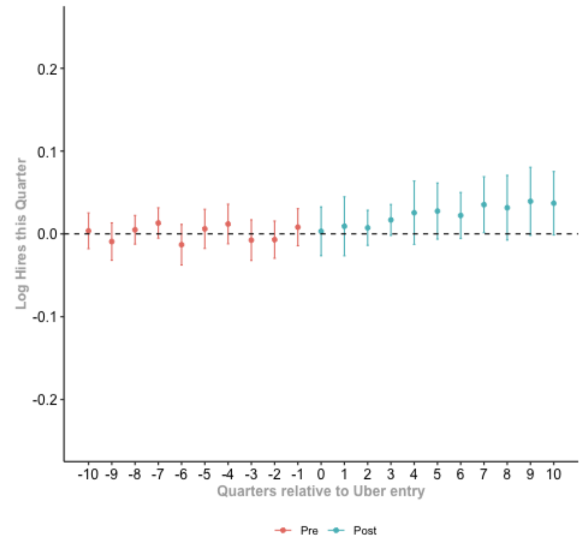
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services; 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 4. Dynamic Treatment Effects of Uber Entry in Concurrent Industries

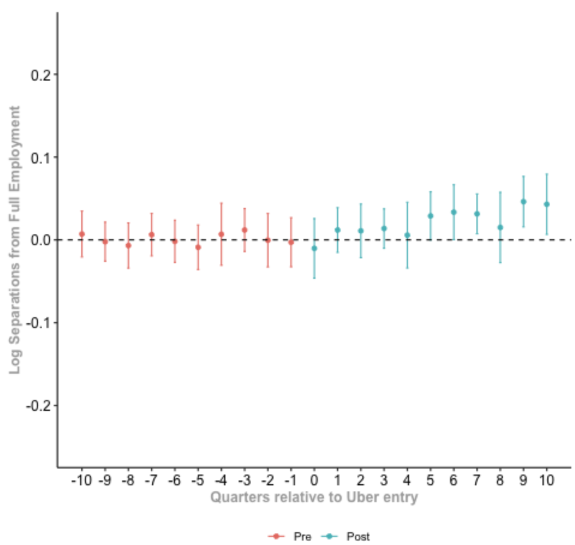
(a) Employment by length of exposure



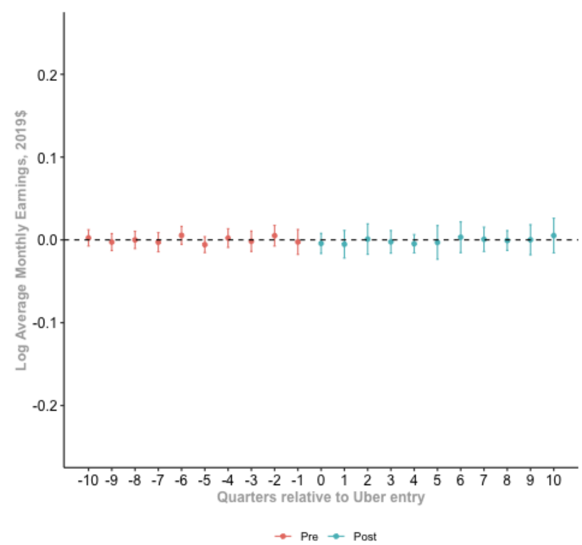
(b) Hires by length of exposure



(c) Separations by length of exposure



(d) Earnings by length of exposure

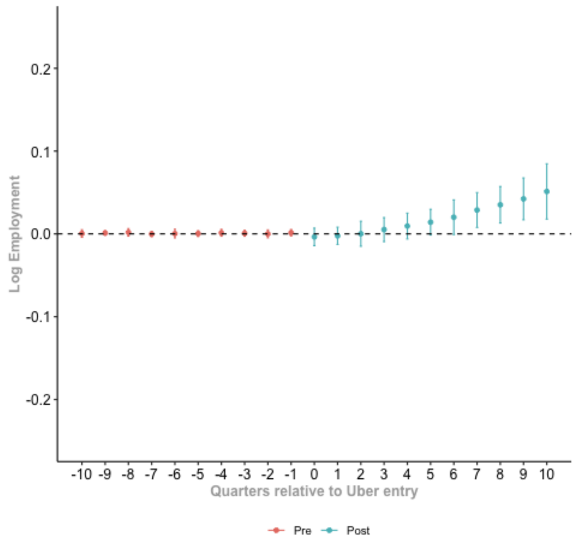


Source: Uber Entry Data; Quarterly Workforce Indicator Series, 2008-2019

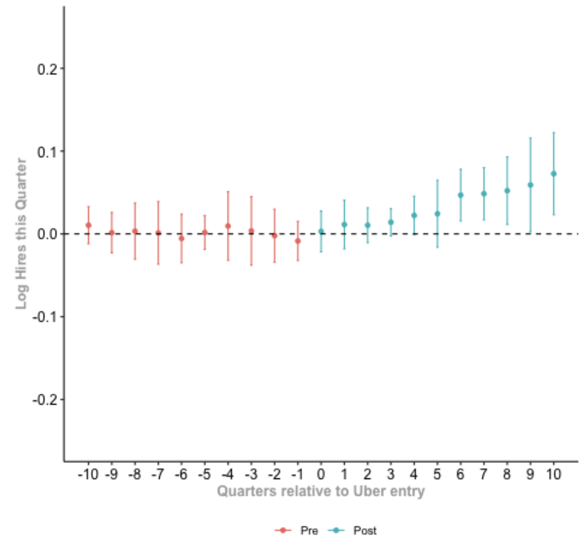
Note: Concurrent industries include retail, health care and social services, educational services, and professional, technical, and scientific services. These figures display the point estimates and 95% confidence intervals of the effect of Uber entry aggregated by quarters relative Uber entry.

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

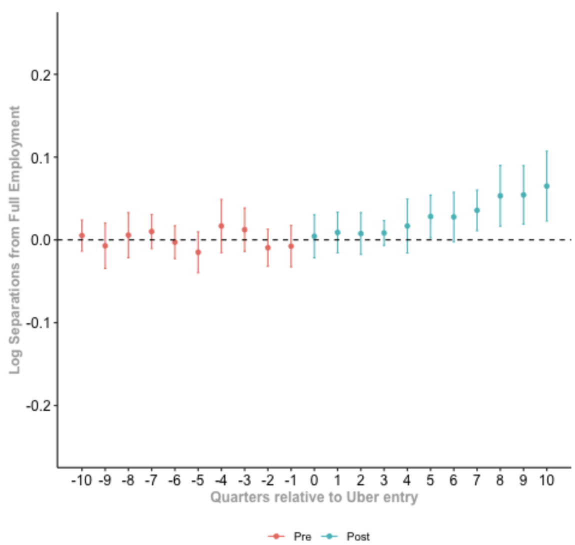
(a) Employment by length of exposure



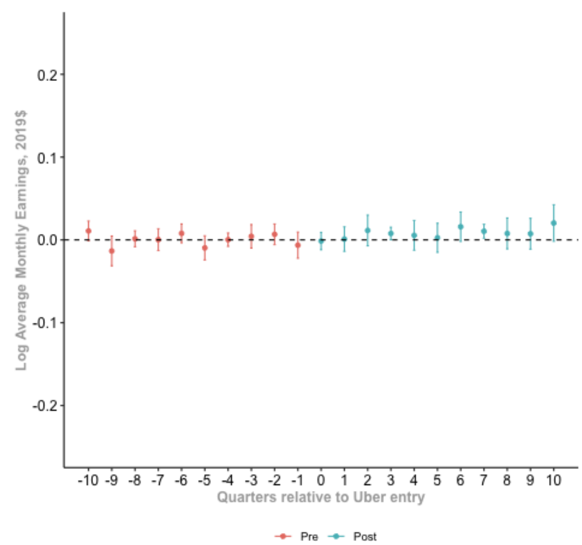
(b) Hires by length of exposure



(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.

Appendix A: Employment and Earnings in the American Community Survey

To determine if my findings of Uber's relationship with total employment as measured at the firm level is consistent with individual reports of employment, I estimate the effect of Uber entry in the American Community Survey (ACS). Below I outline the specific ACS data I use and the methods employed.

The ACS is a nationally representative survey administered by the United States Census Bureau annually. In this work, I use data from the 2008 – 2019 ACS 1-year samples which ask questions on employment, earnings, and industry of occupation. I match these data to Uber entry dates by metropolitan area – matching a total of 232 MSAs. I consider three outcomes of interest: percent of respondents currently employed, percent of respondents who worked for pay last week, and average pre-tax wage and salary income.

To determine the average effect of Uber entry, I again estimate average treatment effects by group where groups are defined by MSAs into which Uber enters in the same year. Individual level observations are aggregated up to the MSA-industry level. I first estimate

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

where $Y_{i,g,t}$ is my outcome of interest at time *t* for MSA-industry, *i,* which is first exposed to UberX in year *g;* α_g are group fixed effects for all CBSAs into which UberX enters at year, *g;* γ_t are year fixed effects; $Uber_{g,t}$ is an indicator of UberX's entry; and $\epsilon_{i,g,t}$ is the error associated with MSA-industry, *i,* in group g at time *t*. I weight estimates by ACS person weights adjusted for MSA and industry size, and I cluster standard errors by MSA. Aggregated group-time treatment effects, the average of group specific treatment effects across all groups, for each outcome of interest can be found in table B2.

B Appendix: Tables & Figures

Appendix Table B1. 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 B2. Group-time Treatment Effects of Uber Entry in All Industries

	Working		Worked last week		Log earned income	
Uber	0.0171	***	0.0154	***	0.0623	***
	(0.0044)		(0.0053)		(0.0117)	
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 B3. Bonferroni Adjustment: Group-time Treatment Effects of Uber Entry

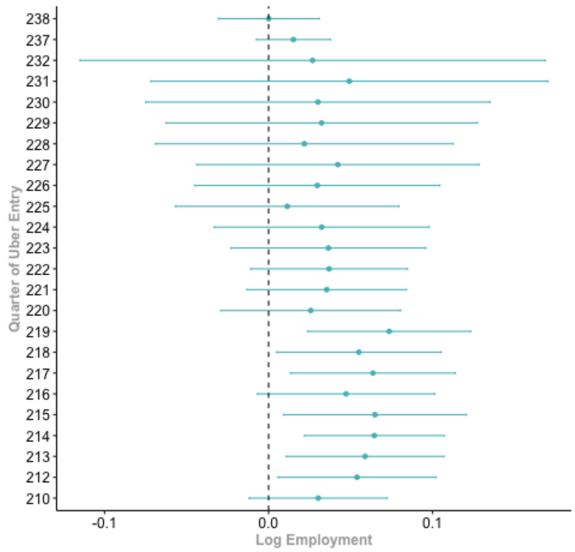
	Log total employment	Log hires	Log separations	Log monthly earnings
A. Taxi and Limo				
Uber	-0.0865	-0.1365 **	-0.1255	-0.0242
	(0.0438)	(0.0506)	(0.0771)	(0.0219)
Observations	25,056	10,560	6,864	34,512
CBSA*education level	522	220	143	719
B. Bars and Restaurants				
Uber	0.0155	0.0404	0.0421 **	0.0174
	(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
C. 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
D. 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
E. 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
F. 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.

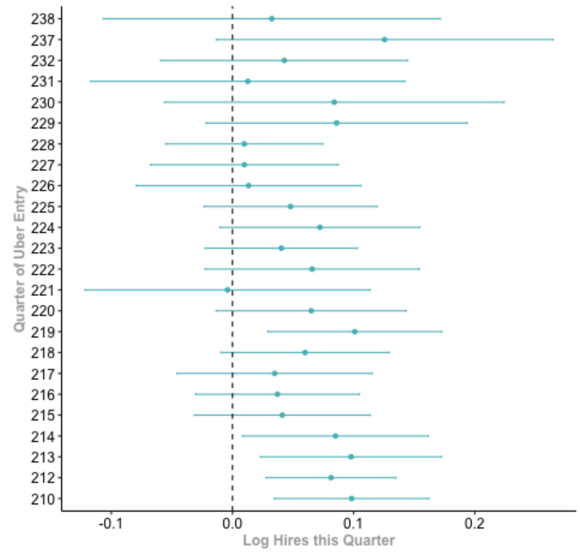
Notes: This table presents aggregated group-time treatment effects by industry weighted by total industry employment in CBSA and education group in 2008. Earnings are in real 2019 dollars; standard errors clustered by CBSA in parentheses; * $p < 0.017$, ** $p < 0.008$, *** $p < 0.002$

Appendix Figure B1. Group Treatment Effects of Uber Entry in All Industries

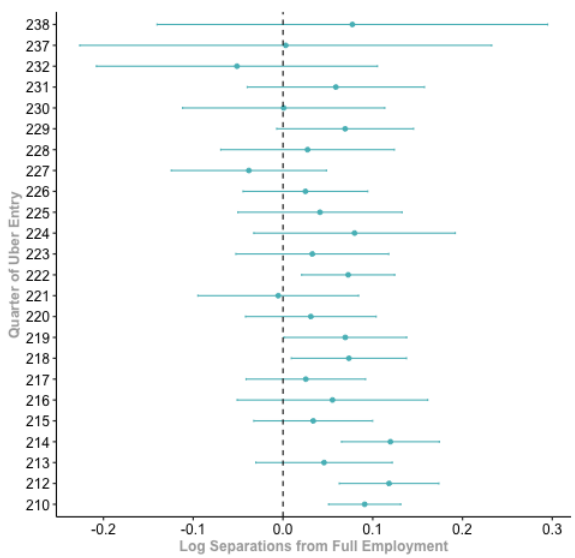
(a) Employment by quarter of Uber entry



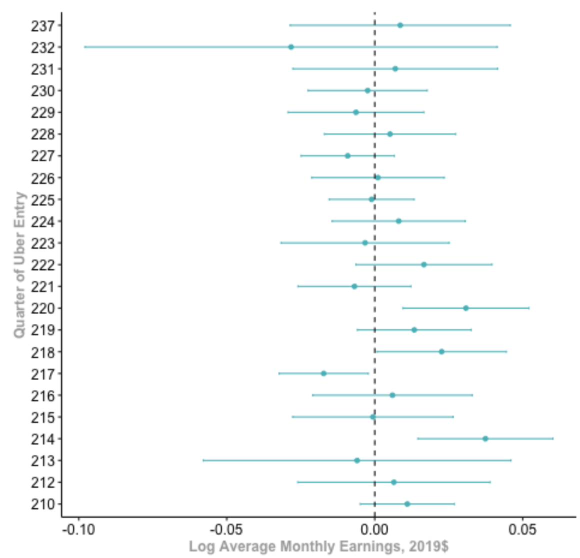
(b) Hires by quarter of Uber entry



(c) Separations by quarter of Uber entry



(d) Earnings by quarter of Uber entry



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. Quarters are expressed as numerical values where 210 = quarter 3 of 2012 and 238 = quarter 3 of 2019.

Appendix Table B4. Heterogeneous Group-time Treatment Effects of Uber Entry in All Industries

	A		B		C		D		E		F	
	Men		Women		<College education		College degree or 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; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$