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Drivers of disruption? Estimating the Uber effect☆

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ABSTRACT

A frequent belief is that the rise of so-called "gig work" has led to the displacement of workers in a wide range of traditional jobs. This paper examines the impacts of the flagship of the gig economy—Uber—on workers employed in conventional taxi services. Our analysis exploits newly collected data on the staggered rollout of Uber across metropolitan areas in the United States and a difference-in-differences design to document that incumbent taxi drivers experienced a relative earnings decline of about 10 percent subsequent to Uber's entry into a new market, while there are no significant effects on their labor supply. Additional evidence from a battery of placebo tests, event study estimates, and specifications using Google Trends data to capture differences in treatment intensity underlines these findings. A triple-differences design that compares changes among taxi drivers relative to bus, tractor, and truck drivers that were unaffected by the arrival of Uber, provides further supporting evidence that the diffusion of Uber has reduced the earnings potential of incumbent drivers in conventional taxi services in the United States.

1. Introduction

Does the expansion of the "gig economy" spell the end of traditional jobs? In recent years, this debate has centered on the impacts on the earnings and employment prospects of workers in one of the most exposed industries—taxi services—that have seen increased competition from digital ride-hailing services such as Uber. Since its inception in 2010, the spread of Uber in the United States has been fiercely opposed by taxi drivers, which has led to class-action lawsuits being filed against the company in Atlanta, Philadelphia, and Ontario. Meanwhile, the Uber platform has been rapidly adopted. As of last year, it is estimated that there were up to 500,000 active Uber drivers in the United States, which exceeds the number of traditional taxi drivers and chauffeurs (Cramer and Krueger, 2016). Yet, despite the widespread belief that Uber has reduced the earnings potential of traditional taxi drivers, there have been few attempts to empirically estimate its effects.

This paper provides the first systematic evidence on Uber's impacts on the earnings and employment of conventional taxi drivers in the United States. Exploiting the staggered rollout of the Uber platform across the 50 largest Metropolitan Statistical Areas (MSAs), which we identify from newly collected data from a variety of online sources and press materials, we analyze its impacts on incumbent drivers drawing on data from the American Community Survey (ACS) samples. As the

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timing of Uber's entry differs across metropolitan areas, the main empirical analysis takes a simple difference-in-differences approach comparing relative differences in earnings and employment of taxi drivers before and after Uber's introduction.

Our results show that Uber's entry into a new market on average led to a relative earnings decline among incumbent taxi drivers of about 10 percent. Estimated declines are largest when we restrict our sample to wage-employed taxi drivers, which excludes self-employed drivers that may have partnered with Uber after its introduction.[1] We obtain broadly similar estimates when we study the evolution of hourly earnings, which is consistent with case-study evidence of sharp reductions in capacity utilization in traditional taxi services after Uber's entry, presumably due to passengers increasingly shifting to Uber's services as they become available (Cramer and Krueger, 2016).[2] While our preferred interpretation of these estimates is that Uber's introduction has depressed the demand for conventional taxi rides, which in turn led to a reduction in earnings among incumbent drivers, an alternative explanation is that more productive drivers exited the taxi workforce to partner with Uber.[3] Yet, we find little evidence of compositional changes among drivers—in terms of, for example, age or educational attainment—after Uber's entry, which largely reduces concerns that our results simply reflect a selective exit of more productive drivers.[4]

A central concern in interpreting these estimates, however, is that Uber's choice to enter a metropolitan area may be correlated with factors that shape the evolution of earnings and employment among taxi drivers. Since Uber's strategic decisions are deliberately opaque, we provide quantitative evidence showing that the key determinant of the timing of Uber's entry is the population size of a metropolitan area, which we partly account for by focusing on the 50 largest MSAs. We also show that our estimates remain similar when we condition on broad set of controls including MSA fixed effects and linear time trends, as well as time-varying characteristics such as the mean income and population of MSAs that may be important determinants of Uber's entry. Additional estimates further reveal that there are no differences in pre-trends in earnings or employment among taxi drivers prior to entry, which suggests that Uber's rollout is seemingly random conditional on these controls.

Although our main empirical approach allows us to rule out a variety of omitted factors that may drive the relationship between the diffusion of Uber and the earnings of taxi drivers, there is a remaining concern that our estimates could reflect time-varying unobserved shocks that simultaneously encourage the entry of Uber and affect the earnings of taxi drivers. To mitigate such concerns, we exploit the fact that Uber's services are substituting for taxi drivers while leaving other types of drivers and transportation services largely unaffected as the basis for a triple-differences design. Our triple-differences estimates that compare earnings among taxi drivers relative to, for example, bus and truck drivers working within the same MSA show that relative earnings declines are similar in magnitude although they are imprecisely estimated. In a similar spirit, we provide a battery of placebo tests to show that statistically significant and negative impacts on earnings after Uber's entry are uniquely to be found among taxi drivers and not among other types of drivers, and that our baseline estimates are clear outliers compared to placebo estimates that randomizes the timing of Uber's entry across MSAs.

A broadly similar relative reduction in both total and hourly earnings suggest that the labor supply of taxi drivers changed little in response to the spread of Uber. Indeed, when examining relative changes in labor supply we obtain non-significant estimates, which is consistent with existing evidence of a relatively weak labor supply response to permanent income shocks and a small wage-elasticity among American taxi drivers (e.g., Ashenfelter et al., 2010; Doran, 2014). In conclusion, while our findings suggest that Uber has negatively affected the earnings potential of conventional taxi drivers, we do not find any evidence that it had any significant impacts on the labor supply of incumbent drivers.

Our study primarily relates to two literatures. First, analogous to the literature on deregulation, the introduction of Uber can be seen as a competing substitute service in a heavily regulated market. For example, examining the impact of the passage of the 1978 Airline Deregulation Act on earnings, Card (1998) has shown that deregulation had a negative impact on airline workers' wages. A series of studies have similarly investigated the effects of deregulation in the trucking industry on union density and wages (e.g., Belman and Monaco, 2001; Belzer, 1995; Hirsch, 1993). Work showing that Uber drivers gain from the opportunity to drive without leasing a medallion (Angrist et al., 2017), suggests that barriers to entry exist in taxi services as well. We add to this literature by examining how lower barriers to entry in the taxi industry after Uber's introduction and the subsequent growth of the driver pool has affected the earnings of incumbent taxi drivers.

Second, we add to a series of recent papers examining the economic impacts of Uber. In particular, Cohen et al. (2016) estimate the demand curve for Uber's services and calculate that the consumer surplus associated with the UberX service amounted to $6.8 billion in 2015. Beyond large benefits for consumers, survey evidence shows that Uber drivers enjoy the

[1] As noted by Hall and Krueger (2015), the Bureau of Labor Statistics has documented that 87 percent of independent contractors report self-employment in the labor surveys. However, survey evidence suggest that 61 percent of Uber drivers work full-time or part-time on another job, which implies that most of them are unlikely to appear as taxi drivers in the ACS samples (Hall and Krueger, 2015).

[2] In Uber's "home town" San Francisco, for example, the average number of rides per taxi declined by 65 percent between 2012 and 2014, which has been attributed to the increasing popularity of Uber's services (SFMTA, 2016).

[3] Existing evidence, however, suggests a relatively limited exit from conventional taxi services, which is underlined by the fact that Uber's drivers differ in several dimensions compared to the taxi driver population and that less than 20 percent of drivers reported working in transportation services prior to partnering with Uber (Hall and Krueger, 2015).

[4] One of the virtues of the Uber platform emphasized by drivers is the opportunity it provides to be self-employed (Hall and Krueger, 2015). As an additional check, we therefore also examine whether the working arrangements of taxi drivers changed after Uber's introduction, which would suggest that Uber's drivers are appearing in the ACS data. While our point estimates indicate that the share of taxi drivers that report self-employment increased after Uber's entry, these effects are small in magnitude and imprecisely estimated.

work flexibility the platform permits, while exhibiting higher hourly earnings than traditional taxi drivers (Chen et al., 2017; Hall and Krueger, 2015).[5] While these papers are concerned with Uber's drivers, our analysis instead focuses on Uber's potential economic impacts on incumbent drivers in traditional taxi services. Our study therefore relates to an influential body of work examining the earnings and labor supply decisions of taxi drivers (e.g., Ashenfelter et al., 2010; Crawford and Meng, 2011; Doran, 2014; Farber, 2005; Farber, 2015), and an emerging literature investigating how local labor markets adjust to the spread of new technologies (e.g., Autor and Dorn, 2013; Beaudry et al., 2010; Berger and Frey, 2016; Berger and Frey, 2017; Lin, 2011).[6]

The remainder of this paper is structured as follows. In the next section, we describe the construction of our dataset and provide descriptive evidence on Uber's rollout. In Section 3, we describe our empirical strategy and present our main findings, while Section 4 concludes.

2. Background and data

2.1. Background and related literature

Uber constitutes a low-cost substitute to the services provided by the traditional taxi sector. In particular, the low-end services provided by Uber are cheaper due to its efficient matching system between drivers and passengers, the absence of requirements for its drivers to obtain costly taxi medallions, and its pricing being handled by a dynamic algorithm (Cramer and Krueger, 2016). Its lower prices and the exponential growth of the driver pool has fueled the widespread belief that Uber's diffusion has significant adverse impacts on incumbent taxi drivers.

Uber' s entry into the tightly regulated market for conventional taxi services bears many similarities with episodes of deregulation in the 1970s and 1980s of the airline and trucking industries.[7] By reducing or eliminating entry barriers and liberalizing fare restrictions, the entry of new low-cost and non-union carriers posed direct challenges for incumbents in these previously highly regulated and unionized industries. Card (1998), for example, found that airline workers' wages declined after the 1978 Airline Deregulation Act and evidence similarly suggest that truck drivers saw earnings reductions as rents dissipated after the federal Motor Carrier Act of 1980 (e.g., Belman and Monaco, 2001; Belzer, 1995; Hirsch, 1993). While the introduction of Uber similarly has significantly lowered entry barriers—it only requires its drivers to pass a background check and driving record review, complete a city-knowledge test, and use a vehicle that meets a quality inspection (Hall and Krueger, 2015)—an important difference is that the taxi industry is not as unionized, which suggests that the rents accruing to incumbent workers are presumably smaller than in the airline and trucking industries prior to deregulation. All else equal, this should serve to moderate the potential wage reductions.

Although the increased competition from Uber is likely to have exerted downward pressure on capacity utilization and the earnings potential among incumbent drivers, it is less straightforward to predict their labor supply responses. An influential literature analyzes how taxi drivers adjust their labor supply in the face of income shocks by exploiting the fact that they (unlike most other workers) are typically free to choose their own working hours. Camerer et al. (1997), for example, argue that the labor supply decisions of taxi drivers in New York City (NYC) can be characterized as income targeting: a driver will work until reaching a given income target and stop working after that point (also see Crawford and Meng, 2011). Another string of papers, however, find less support for the notion that the labor supply of taxi drivers is consistent with targeting behaviour.[8] An important distinction in the empirical literature focusing on transitory earnings shocks, is that the labor supply adjustments may differ in response to more permanent changes in earnings potential. Indeed, Doran (2014) finds that NYC taxi drivers adjust their working hours to short-term shocks but not to long-term wage increases, while Ashenfelter et al. (2010) exploits two exogenous and permanent increases in fares imposed by the NYC Taxi and Limousine Commission to show that the the long-run wage-elasticity of taxi drivers is negative but relatively small in magnitude, which suggests that labor-supply adjustments are limited in the face of income shocks that extend over a longer time horizon.

Ultimately, whether Uber has adversely affected the earnings potential of incumbent drivers and how they may have adjusted their labor supply in response remains an empirical question. We next describe our data and Uber's rollout in the United States and then proceed to provide reduced-form evidence on how the diffusion of Uber shaped the evolution of earnings and employment among incumbent taxi drivers.

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[5] Cramer and Krueger (2016) provide a potential explanation for the higher hourly earnings of Uber drivers in documenting that they benefit from higher capacity utilization, due to the automated pricing and improved driver-passenger matching on the Uber platform.

[6] Although much of the focus in this literature has been the disruptive impacts of digital technology on the distribution of earnings, another line of work has emphasized that the diffusion of new technologies does not necessarily lead to employment reductions (e.g., Basker et al., 2015; Bessen, 2015; Graetz and Michaels, 2015).

[7] Over this period, several U.S. cities including Atlanta, San Diego, and Seattle also experimented with deregulating the taxi sector by removing entry barriers, licensing systems, and fare restrictions.

[8] Farber (2005) uses data on NYC taxi drivers to show that the daily income target effects are small and that the stopping behavior of drivers is most affected by cumulative hours worked during a day, while Farber (2015) uses complete records on all taxi drivers in NYC between 2009 and 2013 showing that the estimated labor supply elasticities are most often positive.

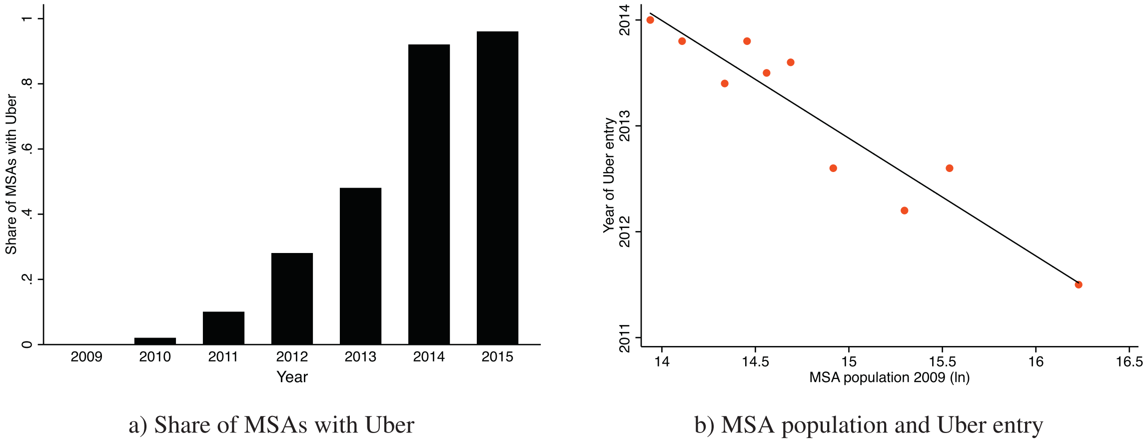

Fig. 1. Uber's rollout in the United States.
Notes: Fig. (a) shows the share of MSAs where Uber had entered between 2009 and 2015 among the 50 largest MSAs that constitute our sample; and (b) shows a binned scatterplot of the year of Uber entry and the *ln* population across MSAs, where we group the data into 10 equal-sized bins and plot the mean year of entry vs. the mean *ln* population within each bin, while also showing a fitted OLS regression based on the underlying (ungrouped) data. We exclude the two MSAs in our sample where Uber had not entered by the end of 2015. Information on Uber's entry is based on data collected from a variety of online sources and press materials described in the main text.

2.2. Uber's rollout: data and descriptive evidence

Our dataset is constructed by combining individual-level data drawn from the 2009–2015 ACS samples—consisting of annual 1-in-100 samples of the U.S. population—with newly collected information on the diffusion of Uber across MSAs obtained from a variety of online sources.[9] We begin by identifying the year and month in which Uber was introduced in each MSA from official press releases that report the date of entry into a new market, which we use to create a dummy variable taking the value 1 starting in the year when Uber was introduced in a metropolitan area and 0 for all other years.[10] Although our data precisely reflect the entry of Uber into a new market, an obvious drawback is that it does not allow us to identify the number of drivers or ridership in metropolitan areas, meaning that we do not observe the take-up of Uber's services. As an alternative measure of Uber's penetration, we therefore rely on differences in the relative search intensity for "Uber" using MSA-level data obtained from Google Trends, which is highly correlated with the number of active Uber drivers per capita in a MSA (Hall et al., 2017). For each MSA and year, the relative search intensity for "Uber" is normalized so it takes the value 100 in the first week of 2016 in San Francisco.

After Uber's launch in San Francisco in 2010, it diffused rapidly across the metropolitan areas included in our sample as shown in Figs. 1 and 2.[11]A central assumption in our subsequent analysis is that Uber did not deliberately target locations that experienced differential trends in terms of earnings or employment in the taxi sector. To enhance our understanding of what drove the timing of its rollout, we proceed to model the year of Uber's entry as a function of MSA characteristics to examine which, if any, observable factors are correlated with its introduction. Table 1 presents results from regressing the year of Uber's entry on a range of MSA characteristics. While column 1 shows that Uber was more likely to enter early on in metropolitan areas with a higher initial (2009) share of foreign-born taxi drivers, the estimates in columns 2 and 3 show that this link vanishes once we control for a wider range of MSA characteristics measured either in the initial year of our sample or when averaged over the pre-Uber period. In fact, the single most important factor that seems to have determined the timing of Uber's entry is the population size of a metropolitan area, with larger MSAs experiencing earlier entry; the population of MSAs can account for roughly 40 percent of the variation in Uber's entry in a bivariate regression (see Fig. 1 b). In our view, the evidence that Uber's entry decision mainly seems to have been determined by the size of MSAs rather than particular features of their local taxi markets suggest that we can think of the entry of Uber as plausibly random conditional on MSA fixed effects and additional controls.

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[9] Our main source of information is Uber's "newsroom" (https://newsroom.uber.com/), which we complement with additional online sources such as blogs, newspapers, and Wikipedia to verify the date of introduction in each MSA. Data from the ACS is obtained from IPUMS (Ruggles et al., 2010).

[10] As we identify the month and year in which Uber entered a new market we let the treatment indicator take the value 1 if Uber was active for the majority of the months in that year in a given MSA.

[11] We restrict our analysis to the 50 largest MSAs (using the 2013 definitions of metropolitan areas from the U.S. Office of Management and Budget) that constitute our main sample throughout the paper. Although results remain similar when including all MSAs in the analysis, we prefer to focus on the 50 largest MSAs due to the small number of taxi drivers being available in the ACS samples for smaller MSAs. Our focus on this subsample of MSAs is further motivated by the findings below that Uber specifically targeted larger cities during their initial rollout, which presumably serves to limit systematic differences between treatment and control groups.

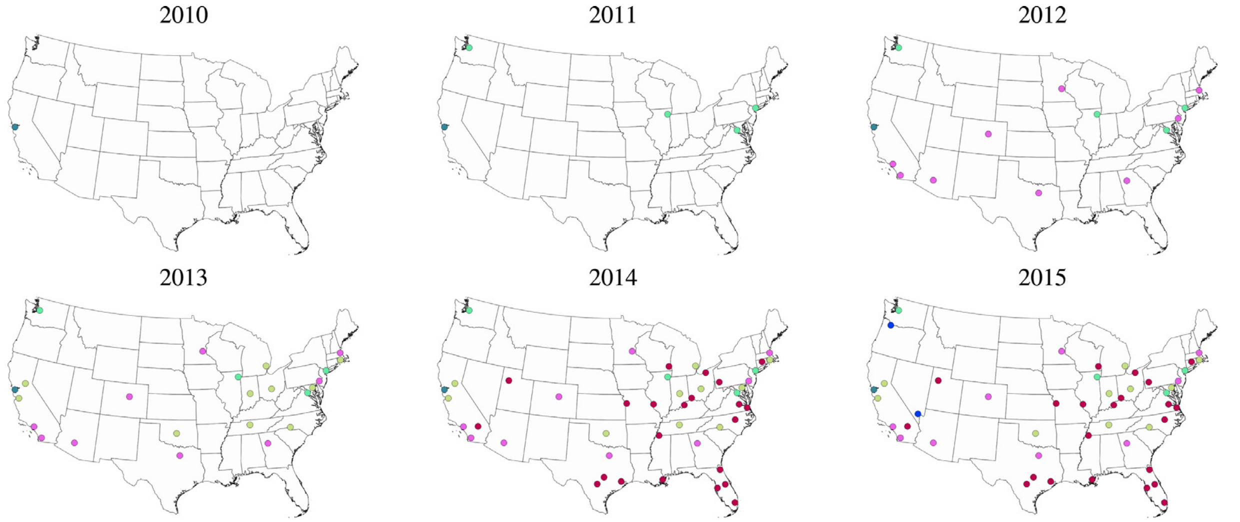

Fig. 2. The spatial diffusion of Uber in the United States.
Notes: These figures show the introduction of Uber across the 50 largest MSAs between 2010 and 2015 based on data collected from a variety of online sources and press materials described in the main text

Table 1
What determined Uber's entry?

	Outcome: year of Uber entry		
	(1)	(2)	(3)
Taxi sector characteristics			
Share in taxi services	106.269	74.804	87.673
	(153.990)	(55.525)	(81.468)
Share female drivers	0.472	−0.943*	1.781
	(0.795)	(0.518)	(2.235)
Share foreign-born drivers	−2.459*	−0.440	−0.297
	(1.262)	(0.927)	(1.118)
Share low-educated drivers	0.243	−0.607	0.840
	(0.835)	(0.623)	(1.517)
Share non-Hispanic white drivers	−0.041	−0.365	−0.344
	(1.094)	(0.812)	(1.072)
Share self-employed drivers	0.068	1.138	1.999
	(1.208)	(0.917)	(1.974)
Mean earnings (*ln*)	−0.427	0.133	1.379
	(0.584)	(0.451)	(1.129)
MSA characteristics			
Population (*ln*)		−1.148***	−1.084***
		(0.200)	(0.273)
Mean earnings (*ln*)		−2.054	−4.314*
		(1.931)	(2.194)
College share		−9.776**	−5.204
		(3.892)	(5.041)
Share aged <40		−4.721	−5.910
		(3.787)	(4.648)
Unemployment rate		6.824	−1.094
		(5.869)	(6.634)
Mean year of entry	2013	2013	2013
Characteristics measured in	2009	2009	Pre-Uber
Observations	48	48	48
R-squared	0.236	0.709	0.690

Notes: This table reports results from cross-sectional OLS regressions where we regress the year that Uber entered a MSA on a range of initial MSA characteristics measured in 2009 (columns 1 and 2) or averaged over the years prior to Uber's entry into a MSA (column 3). We exclude the two MSAs in our sample where Uber had not entered by the end of 2015. Robust standard errors are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To identify the impacts of Uber on incumbent drivers, we proceed to match the information on Uber's rollout to individual-level information on taxi drivers in MSAs drawn from the ACS 2009–2015 samples. Taxi drivers are reported in the occupation "Taxi Drivers and Chauffeurs" (#9140) under the OCC2010 occupational classification scheme, which we for brevity refer to as "taxi drivers" throughout the paper. We observe a total of 15,800 taxi drivers in our sample, with a mean (min/max) of 45 (2/746) drivers across MSA-years.[12] We calculate the earnings and employment of taxi drivers for each MSA and year separately for all drivers and for the subgroup of wage-employed drivers (to omit potential Uber drivers) in a sample restricted to non-institutionalized civilian adults (aged ≥ 16) that have non-zero labor-supply weights.[13] We estimate the labor supply of taxi drivers by the product of mean hours and weeks worked multiplied by respondents' weights that we scale to full-time/full-year equivalents. Driver earnings are computed as the hours-weighted mean *ln* (hourly) earnings. Our main earnings measure is based on income earned from wages or a person's own business (reported as INCEARN in the ACS samples). As a complementary measure, we also calculate similar measures using each respondent's total pre-tax wage and salary income (INCWAGE), which excludes potential income streams from Uber.[14]

Averaged across the MSAs in our sample, the exponentiated hours-weighted mean *ln* (hourly) earnings is $22,392 ($11.04) and $23,170 ($11.54) in 2009 and 2015 respectively, which suggests that mean earnings have remained relatively stable over the sample period despite the widespread diffusion of Uber. While we cannot directly compare the earnings of taxi drivers in our sample with Uber's drivers, it is informative to note that Hall and Krueger (2015, Table 6) estimates that in the 20 market areas they study, the mean earnings per hour among Uber's drivers was about $19.20, which is substantially higher than the mean earnings observed among drivers in our sample as well as that of Hall and Krueger (2015).[15] Although direct earnings comparisons are complicated by the fact that drivers that have partnered with Uber are not reimbursed for outlays on gasoline or insurance while conventional drivers may partly offset such expenses, it suggests that Uber's drivers exhibit higher hourly earnings than conventional drivers.

3. Empirical strategy and results

To identify the impact of Uber on earnings and employment, we exploit its staggered spatial and temporal introduction across MSAs in a difference-in-differences framework. Our baseline regressions compare changes in areas where Uber was introduced relative to areas that did not gain access to the Uber platform:

$$y_{it} = \alpha_i + \vartheta_t + \delta Uber_{it} + \gamma \mathbf{X}_{it} + \varepsilon_{it} \tag{1}$$

where the dependent variable y is typically the mean *ln* earnings or *ln* labor supply among taxi drivers in MSA i and year t. The main variable of interest is *Uber*, taking the form of a dummy variable that switches to 1 in the year when Uber arrives in a MSA and takes the value 0 for all other MSAs and years. As we lack information on the take-up of Uber's services, the estimates of δ should be interpreted as intent-to-treat estimates. As described above, in some specifications we also exploit information on the relative search intensity for "Uber" using data from Google Trends to allow for differences in treatment intensity across MSAs.For the statistical inference, we cluster standard errors at the MSA-level to account for potential heteroscedasticity and within-MSA correlation over time (Bertrand et al., 2004).

All specifications include a full set of MSA fixed effects (α_i) to account for MSA-specific and time-invariant factors that may be correlated with Uber's rollout. Additional estimations also include linear MSA-specific time trends to account for potential trend differences in the evolution of earnings and employment across MSAs, thus taking into account that Uber may have targeted locations with a rising demand for point-to-point transportation services and to reduce concerns that the estimated impacts of Uber are conflated with pre-existing trends.[16] As the demand for taxi services is highly elastic, we always include a full set of year fixed effects (ϑ_t) to account for national variation s in taxi earnings and employment that may be related to business cycle fluctuations and national income growth. Finally, we also control for time-varying MSA characteristics ($\mathbf{X_{it}}$), including age groups, earnings, college shares, population, the share of females in the labor force, as well as the unemployment rate to account for factors that may be correlated both with the rollout of Uber and the demand for taxi services.

Although MSA fixed effects, linear trends, and the set of time-varying control variables are likely to absorb a wide set of potentially omitted factors that may be correlated with Uber's rollout, there is still concern that the earnings of taxi

[12] Our main results reported below remain similar when we trim the sample to exclude MSA-years that fall below the 5th or 10th percentile of the number of drivers observed in the ACS samples (these results are available upon request).

[13] Wage employment corresponds to workers answering yes to the question "was this person an employee of a private for profit company or business, or of an individual, for wages, salary, or commissions?" while self-employment corresponds to those workers that answered yes to the statement that the worker in question was "self-employed in own incorporated/not incorporated business, professional practice, or farm". The prevalence of self-employed drivers prior to the arrival of Uber relates to the practice of taxicab owners to lease their vehicles to individual drivers beginning in the 1970s, which became independent contractors under federal law (see, for example, Occhiuto (2017)). Across the MSAs included in our sample, roughly three-quarters of drivers report wage employment over the sample period.

[14] All nominal incomes are converted into 2015 USD using the Personal Consumption Expenditure Price Index provided by Bureau of Economic Analysis.

[15] The 20 market areas studied by Hall and Krueger (2015) are: Atlanta, Austin, Baltimore, Boston, Chicago, Dallas, Denver, Houston, Los Angeles, Miami, Minneapolis, New Jersey, New York City, Orange County, Philadelphia, Phoenix, San Diego, San Francisco, Seattle, and Washington, D.C., which significantly overlaps with the 50 MSAs included in our sample.

[16] We return below to explicitly examine pre-trends in an event study framework and provide additional evidence above that few (observable) labor or taxi market characteristics can predict the timing of Uber's entry.

Table 2
Earnings of taxi drivers after Uber's introduction, 2009–2015.

	Outcome: mean *ln* earnings/wage income					
	Panel A. Mean earnings			Panel B. Mean wage income		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample: All drivers					
$Uber_{it}$ (=1)	−0.110**	−0.123**	−0.140**	−0.145***	−0.155***	−0.185***
	(0.053)	(0.053)	(0.059)	(0.053)	(0.054)	(0.067)
	Sample: Wage-employed drivers					
$Uber_{it}$ (=1)	−0.154***	−0.168***	−0.183***	−0.130**	−0.142**	−0.155**
	(0.054)	(0.056)	(0.065)	(0.055)	(0.057)	(0.064)
MSA and year FE?	Y	Y	Y	Y	Y	Y
Additional MSA controls?	N	Y	Y	N	Y	Y
MSA x linear time trend?	N	N	Y	N	N	Y
Observations	350	350	350	350	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the mean *ln* earnings (panel A) and *ln* wage income (panel B) for all (upper panel) and wage-employed (lower panel) taxi drivers respectively. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

drivers evolved differently in MSAs where it was introduced due to unobserved time-varying factors. To address this issue, we deploy a triple-differences (i.e., difference-in-differences-in-differences) design. We compare differences in earnings of taxi drivers relative to workers in other transportation occupations in the same MSA and examine these differences before and after Uber's introduction. The triple-differences regressions take the following form:

$$y_{it}^T - y_{it}^O = \alpha_i + \vartheta_t + \delta Uber_{it} + \gamma \mathbf{X}_{it} + \varepsilon_{it} \tag{2}$$

where $y_{it}^T - y_{it}^O$ corresponds to the difference in the mean *ln* earnings of taxi drivers (T) and those employed in other transportation occupations (O) while the other notation is as described above. As the basis for our triple difference analysis we focus on five alternative transport occupations as comparison groups for taxi drivers: (1) "Bus and Ambulance Drivers and Attendants"; (2) "Locomotive Engineers and Operators"; (3) "Motor Vehicle Operators, All Other"; (4) "Industrial Truck and Tractor Operators"; and (5) "Driver/Sales Workers and Truck Drivers". For brevity, we refer to these occupational groups simply as "bus drivers", "locomotive operators", "motor vehicle operators", "tractor operators", and "truck drivers" throughout the paper. Importantly, since the identifying variation is solely derived from changes among taxi drivers *relative* to changes among other types of drivers in the same MSA, this accounts for a variety of local shocks that may affect the demand for transport services and that may also be correlated with Uber's rollout.

3.1. Main results

3.1.1. Uber's impact on the earnings of taxi drivers

Table 2 presents estimates of Eq. (1) documenting that Uber's entry into a new market is associated with a relative reduction in earnings among incumbent drivers. In the upper panel, we present estimates where the outcome is the mean *ln* business and wage income (panel A) or the mean *ln* wage income (panel B) among all taxi drivers. Columns 1 and 4 report the baseline estimates only conditioning on MSA and year fixed effects, which imply that the earnings of taxi drivers decreased by about 10–13 percent (or 0.110 and 0.145 log points respectively) after Uber's entry into a MSA relative to the earnings of taxi drivers elsewhere with both estimates being highly statistically significant. A concern with these estimates, however, is that they may reflect other time-varying determinants of earnings that may be correlated with Uber's entry thus implying that these changes may have been observed even in the absence of Uber's introduction.

As a first step to try to rule out such alternative explanations, columns 2 and 5 include a set of time-varying MSA-level controls: mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, and 40–54 with ≥ 55 as the omitted group). Although these additional covariates directly control for many factors that may affect the relative earnings evolution of taxi drivers, our estimated impact of Uber remains similar in magnitude and statistical significance. While this goes some way in alleviating concerns that time-varying MSA characteristics are correlated with Uber's entry and affect the relative earnings of taxi drivers, it may still be the case that Uber targeted MSAs with a different long-term trend in the evolution of taxi earnings. To account for the fact that changes in areas where Uber was introduced may reflect pre-existing differential trends in earnings, we also include linear MSA-specific time trends in columns 3 and 6. Estimated relative changes increase in absolute magnitude after conditioning on both MSA-level controls and trends and remain highly statistically significant, which suggests that Uber's introduction may have lowered average earnings of incumbent taxi drivers by up to 13–17 percent (or 0.140 and 0.185 log points respectively).

Table 3
Hourly earnings of taxi drivers after Uber's introduction, 2009–2015.

	Outcome: mean *ln* hourly earnings/wage income					
	Panel A. Mean hourly earnings			Panel B. Mean hourly wage income		
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample: All drivers					
$Uber_{it}$ (=1)	−0.099*	−0.108**	−0.116*	−0.135**	−0.142***	−0.162**
	(0.051)	(0.050)	(0.059)	(0.053)	(0.052)	(0.065)
	Sample: Wage-employed drivers					
$Uber_{it}$ (=1)	−0.118**	−0.127**	−0.125*	−0.094	−0.101*	−0.097
	(0.057)	(0.057)	(0.068)	(0.060)	(0.060)	(0.071)
MSA and year FE?	Y	Y	Y	Y	Y	Y
Additional MSA controls?	N	Y	Y	N	Y	Y
MSA x linear time trend?	N	N	Y	N	N	Y
Observations	350	350	350	350	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the mean *ln* hourly earnings (panel A) and *ln* hourly wage income (panel B) for all (upper panel) and wage-employed (lower panel) taxi drivers, respectively. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Although the majority of Uber's drivers have another full- or part-time job and therefore are unlikely to report themselves as self-employed taxi drivers in the ACS data (Hall and Krueger, 2015), these estimates may still to some extent be affected by the fact that a small share of drivers' earnings accrue from Uber. To examine this possibility, we next restrict our sample of taxi drivers to the wage-employed in the lower panel of Table 2, to reduce concerns that self-employed taxi drivers in the ACS data partly correspond to drivers that have partnered with Uber.[17] Across all specifications reported in columns 1–6 there exists a precisely estimated relative reduction in earnings also among wage-employed taxi drivers. A broadly similar, or slightly larger, reduction in earnings among wage-employed drivers reduces concerns that potential income streams from Uber are affecting our results.

A reduction in mean earnings may be driven by a decrease in hourly earnings and/or a reduction in hours worked. We return to examine changes in the labor supply of taxi drivers below and consider here the impact of Uber's entry on hourly earnings among incumbent drivers. Table 3 reports estimates of Eq. (1) where the outcome is the mean *ln* hourly business and wage income (panel A) and mean *ln* hourly wage income (panel B) respectively. Again, we present our baseline estimates only conditioning on MSA and year fixed effects as well as including the full set of MSA controls and linear MSA trends to account for changes and trends that may affect the earnings potential for taxi drivers. Estimates presented in the upper panel in columns 1–3 suggest that the hourly earnings of taxi drivers fell on average about 9–11 percent (or 0.099 and 0.116 log points respectively) after Uber's entry into a MSA, which are typically statistically significant at least at the 10-percent level of significance. As shown in columns 4–6, the estimated reductions in hourly wage income are somewhat larger consistent with the results reported above. Again, we also present estimates when we restrict the sample to wage-employed taxi drivers in the lower panel, which constitute a group that arguably would have remained unaffected by the potentially positive effects of partnering with Uber. Although the estimates are somewhat more imprecise, they consistently suggest that hourly earnings declined among taxi drivers after Uber's entry.

Overall, these results strongly suggest that Uber's diffusion has led to a reduction in the earnings potential of incumbent taxi drivers. We proceed in the next section to analyze Uber's impact on the labor supply of incumbent drivers and then show that alternative empirical designs lend further support to our interpretation of the results reported in this section.

3.1.2. Uber's impact on the labor supply of taxi drivers

Although we have documented that incumbent taxi drivers experienced relative reductions in earnings after Uber's entry into a new market, these estimates remain silent regarding the potential impacts on their labor supply. Table 4 presents estimates based on Eq. (1) where the outcome is the *ln* labor supply for all taxi drivers (panel A) and among wage-employed drivers (panel B) respectively. To account for the fact that changes in taxi employment in MSAs where Uber was introduced may reflect differential trends in the evolution of transportation services, we again present specifications also including linear time trends and the full set of MSA-level controls.

[17] Unfortunately, the sample of self-employed taxi drivers is to small to obtain meaningful estimates but estimated changes in earnings among self-employed drivers in the ACS samples are typically small, negative, and not statistically significant.

Table 4
Labor supply of taxi drivers after Uber's introduction, 2009–2015.

	Outcome: *ln* labor supply					
	Panel A. All drivers			Panel B. Wage-employed drivers		
	(1)	(2)	(3)	(4)	(5)	(6)
$Uber_{it}$ (=1)	−0.022	−0.028	0.004	−0.092	−0.101	−0.076
	(0.062)	(0.066)	(0.081)	(0.079)	(0.077)	(0.098)
MSA and year FE?	Y	Y	Y	Y	Y	Y
Additional MSA controls?	N	Y	Y	N	Y	Y
MSA x linear time trend?	N	N	Y	N	N	Y
Observations	350	350	350	350	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the *ln* labor supply of all (panel A) and wage-employed (panel B) taxi drivers respectively. Additional MSA-level controls include mean *ln*earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5
Compositional changes among taxi drivers after Uber's introduction, 2009–2015.

	Outcome: share of taxi drivers...					
	Aged < 40 (1)	Female (2)	Foreign-born (3)	No college (4)	Non-Hispanic white (5)	Self-employed (6)
$Uber_{it}$ (=1)	−0.031	0.030	0.057	−0.052	−0.053	0.054*
	(0.032)	(0.028)	(0.040)	(0.032)	(0.045)	(0.032)
MSA and year FE?	Y	Y	Y	Y	Y	Y
Additional MSA controls?	Y	Y	Y	Y	Y	Y
MSA x linear time trend?	Y	Y	Y	Y	Y	Y
Observations	350	350	350	350	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the share of taxi drivers that is aged below 40, female, foreign-born, not college educated, non-Hispanic white, and self-employed respectively. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Estimates in columns 1–3 are consistently close to zero in magnitude and are not statistically significant. Columns 4–6 report similar estimates when only focusing on wage-employed drivers that omits potential (self-employed) Uber drivers that report taxi driver as their main job. Although point estimates are larger in absolute terms, the estimates are again not statistically significant. Thus, while the results in the previous section show that Uber's entry lowered the earnings of incumbent taxi drivers these estimates suggest it had no statistically significant impacts on their labor supply, though the confidence intervals include both positive and relatively large negative effects among wage-employed drivers.

Although our estimates suggest that there are no significant changes in the labor supply of taxi drivers after Uber's entry, it is possible that this masks compositional changes in the taxi workforce. If more productive drivers exited the driver pool after Uber's introduction (perhaps to partner with Uber) that could lead to mechanical reductions in earnings if the workers remaining in conventional taxi services are of lower quality.[18] To further reduce concerns that our findings are driven by compositional changes, we examine this possibility by analyzing differences in the characteristics of drivers before and after Uber's entry.

Table 5, columns 1–5, presents estimates of Eq. (1) where the outcome is the labor supply-weighted share of drivers that is aged below 40, female, foreign-born, not college educated, and non-Hispanic white respectively. Broadly, these characteristics are motivated by the findings of Hall and Krueger (2015, Table 1) that Uber's drivers are more likely to be female, highly educated, to identify as non-Hispanic whites, and younger than conventional taxi drivers. None of the estimates are statistically significant at conventional significance levels and they are all close to zero in magnitude, which suggests limited compositional changes after Uber's entry.[19] In column 6, we examine changes in the share of drivers that report self-employment after Uber's introduction. While the point estimate is positive, it is relatively small and imprecisely

[18] However, it is useful to note that Hall and Krueger (2015) documents that less than 20 percent of drivers that were working prior to partnering with Uber worked in transportation services and that less than a third had worked as a driver at some point in their career, which suggests a relatively limited transition from conventional taxi services to Uber.

[19] An important caveat when interpreting these results, however, is that the relatively small number of observations in the ACS samples introduces noise into the estimated shares. However, the (non-)results are similar in an unbalanced panel that excludes MSA-years that fall below the 5th or 10th percentile of the number of drivers observed (these results are available upon request).

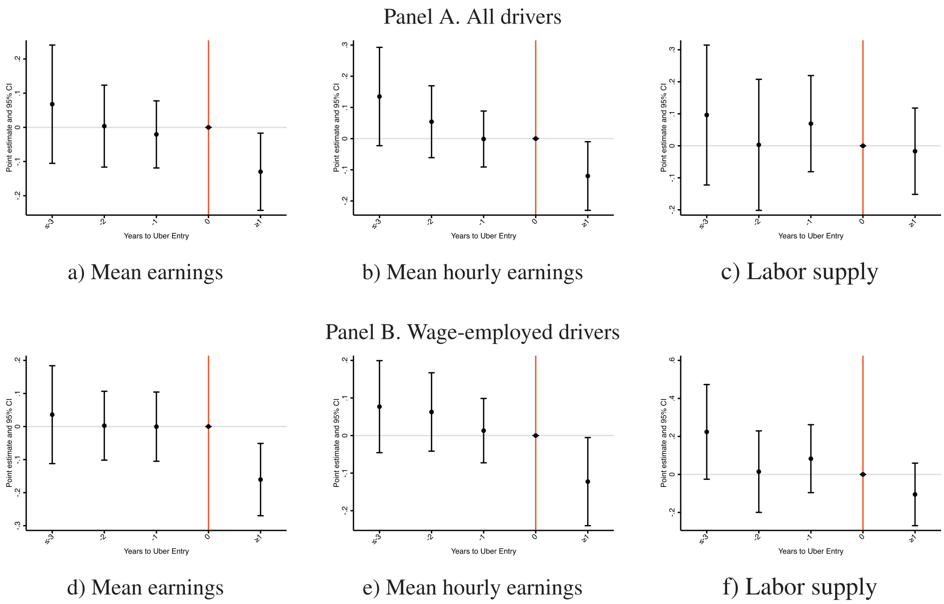

Fig. 3. Event study estimates: earnings and employment of taxi drivers before and after Uber's introduction, 2009–2015.
Notes: These figures present event study estimates where the impact of Uber entry is allowed to vary from three years (or more) prior to its introduction to one year (or more) after its introduction on the mean *ln* earnings, mean *ln* hourly earnings, and *ln* labor supply among all drivers (panel A) and wage-employed drivers (panel B) respectively. All specifications include MSA and year fixed effects. Each circle corresponds to a point estimate, while bars denote 95-percent confidence intervals

estimated thus suggesting that Uber's expansion is not reflected in a significant increase in the share of self-employed drivers. Overall, the results reported in this section suggest that there are no significant changes in the labor supply of taxi drivers nor in terms of the composition of the taxi workforce after Uber's entry, although the absence of longitudinal data on individual drivers makes it challenging to fully rule out such changes.

3.2. Additional estimates and robustness checks

Our estimates consistently suggest that Uber's entry led to relative declines in earnings among incumbent taxi drivers and in this section we provide additional estimates to bolster our interpretation of these results. First, we show that there is no evidence of differential pre-trends in earnings or employment prior to Uber's entry. Second, we show that our estimates remain similar when we use a triple-differences design exploiting within-MSA differences in earnings for taxi drivers *relative* to earnings in other transport occupations. Third, we show that our estimates remain qualitatively similar when using data from Google Trends to capture differences in treatment intensity across MSAs. Lastly, we provide evidence from a battery of placebo tests to show that the estimated relative declines in earnings after Uber's introduction are uniquely to be found among taxi drivers and not among workers in other broadly similar transport occupations that presumably remained unaffected by Uber's entry.

3.2.1. Pre-existing trends

A common threat to the validity of difference-in-differences estimates is that treatment effects may reflect pre-existing differential trends. To assess whether there exists differential trends in earnings and employment prior to Uber's entry, Fig. 3 presents event study estimates where we add leads to our baseline models used above allowing the "impact" of Uber to vary in each year from at least three years prior to entry. As shown in panels A and B, there are no significant differences in the evolution of earnings or employment prior to Uber's introduction in a MSA thus suggesting that the parallel trends assumption is not violated. Furthermore, the estimates also suggest that there is a sharp drop in relative earnings after Uber's entry consistent with our difference-in-differences estimates above. While the fact that the earnings and employment of taxi drivers in MSAs where Uber entered did not develop differently prior to its introduction largely reduces concerns that our findings are driven by pre-existing trends, we cannot completely rule out that Uber's entry is correlated with a time-varying and unobserved factor that also affected incumbent drivers. We next provide additional estimates to further reduce such concerns.

3.2.2. Triple-differences estimates

As discussed above, an empirical concern with our identification strategy is that changes in earnings may be correlated with unobserved time-varying factors that are also correlated with the introduction of Uber. While the evidence of no dif-

Table 6
Earnings of taxi drivers after Uber's introduction, 2009–2015: Triple-differences estimates.

	Outcome: mean *ln* (hourly) earnings for taxi drivers – mean *ln* (hourly) earnings for occupation listed below				
	Bus drivers (1)	Locomotive operators (2)	Motor vehicle operators (3)	Tractor operators (4)	Truck drivers (5)
	Panel A. Mean earnings				
$Uber_{it}$ (=1)	−0.131**	−0.161	−0.188	−0.104	−0.123**
	(0.064)	(0.136)	(0.159)	(0.068)	(0.060)
	Panel B. Mean hourly earnings				
$Uber_{it}$ (=1)	−0.109	−0.130	−0.120	−0.089	−0.111*
	(0.067)	(0.143)	(0.132)	(0.065)	(0.059)
MSA and year FE?	Y	Y	Y	Y	Y
Additional MSA controls?	Y	Y	Y	Y	Y
MSA x linear time trend?	Y	Y	Y	Y	Y
Observations	350	295	336	350	350

Notes: This table reports OLS estimates of Eq. (2) where the outcome is the difference in the mean *ln* earnings (panel A) or *ln* hourly earnings (panel B) of taxi drivers and (1) "Bus and Ambulance Drivers and Attendants"; (2) "Locomotive Engineers and Operators"; (3) "Motor Vehicle Operators, All Other"; (4) "Industrial Truck and Tractor Operators"; and (5) "Driver/Sales Workers and Truck Drivers" respectively. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

ferential pre-trends, the robustness of the results to controlling for both time-varying MSA factors and MSA-specific linear trends, as well as the finding that Uber's rollout seems to have mainly been driven by a sequential establishment starting with the largest MSAs goes some way in reducing concerns of unobserved shocks that are correlated with Uber's entry, we here provide further evidence from a triple-differences design. As unobservable shocks are likely to affect other transportation occupations in a similar manner and since Uber's services are mainly restricted to taxi rides, we exploit the evolution of earnings in other transport-related occupations as the basis for a difference-in-differences-in-differences framework.[20]

Table 6 reports the triple-differences estimates obtained from Eq. (2) where the outcome is the difference in the mean *ln* earnings of taxi drivers and the mean *ln* earnings of bus drivers, locomotive operators, motor vehicle operators, tractor operators, and truck drivers respectively. As shown in panel A, the estimated impact of Uber's entry on the relative earnings of taxi drivers is negative and roughly of a similar magnitude compared to the baseline estimates reported in Table 2 although they are typically imprecisely estimated. Panel B reports estimates from Eq. (2) where the outcome is instead differences in mean *ln* hourly earnings, which again are consistent with our baseline difference-in-differences estimates in Table 3 documenting a negative impact on incumbent taxi drivers though these effects are also estimated with less statistical precision. An estimated negative impact of Uber on incumbent taxi drivers also when measured relative to the evolution of earnings in other transport-related occupations in the same MSA, however, further reduces concerns that our findings are driven by local time-varying shocks to workers in transportation services that are correlated with the rollout of Uber.

3.2.3. Treatment intensity: Google Trends data

A potential drawback with our empirical approach is that it does not take into account the *intensity* of treatment. While differences in the extent to which Uber is adopted across MSAs is likely to be highly endogenous, we here provide additional evidence showing that the relative declines in earnings are more pronounced in MSAs where Uber was presumably adopted more intensively. Specifically, we use data from Google Trends on the search term "Uber" that capture relative differences in the intensity of online searches for Uber in each year and MSA. We take logs of this search intensity index to reduce the highly skewed distribution of search intensities, as well as to facilitate the interpretation of the estimates as elasticities.

Table 7 presents estimates from Eq. (1) where we replace our treatment indicator with the *ln* search intensity from Google Trends, while controlling for the full set of MSA controls and linear trends. Columns 1 and 3 document the negative elasticity between mean earnings and search intensity, which is evident both in the sample of all and wage-employed drivers although both estimates are relatively imprecise. Columns 2 and 4 show that this negative elastisticity is also evident when using mean hourly earnings as the outcome. Overall, these estimates suggest that a 10 percent increase in search intensity for "Uber" is associated with about a 1.2–1.5 percent decrease in mean (hourly) earnings, which bolsters our findings above of a relative reduction in earnings after Uber enters a MSA.

3.2.4. Placebo tests

As a final check of our results, we provide evidence from two sets of placebo tests. First, we exploit the fact that if our estimates are reflecting the impact of Uber rather than some omitted factor, then we should not see similarly timed relative

[20] Recall that by comparing relative differences in the earnings among taxi drivers relative to, for example, bus or truck drivers before and after the introduction of Uber, we exploit variation that stems from differences *between* similar transport occupations *within* the same MSA, which thus directly controls for a wide variety of time-varying shocks that affect the local transportation sector in similar ways.

Table 7
Earnings of taxi drivers after Uber's introduction, 2009–2015: Google Trends.

	Outcome: mean *ln* (hourly) earnings			
	Panel A. All drivers		Panel B. Wage-employed drivers	
	Mean earnings (1)	Mean hourly earnings (2)	Mean earnings (3)	Mean hourly earnings (4)
$Google\ Trends_{it}$ (*ln*)	−0.123*	−0.117*	−0.117*	−0.151**
	(0.067)	(0.059)	(0.059)	(0.057)
MSA and year FE?	Y	Y	Y	Y
Additional MSA controls?	Y	Y	Y	Y
MSA x linear time trend?	Y	Y	Y	Y
Observations	350	350	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the mean *ln* (hourly) earnings of all (panel A) and wage-employed (panel B) taxi drivers respectively and the main right-hand side variable is the *ln* search intensity for "Uber" based on Google Trends data for each MSA. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 8
Placebo tests: earnings in other transport occupations after Uber's introduction, 2009–2015.

	Outcome: mean *ln* (hourly) earnings					
	Taxi drivers (1)	Bus drivers (2)	Locomotive operators (3)	Motor vehicle operators (4)	Tractor operators (5)	Truck drivers (6)
	Panel A. Mean earnings					
$Uber_{it}$ (=1)	−0.140**	−0.009	0.032	0.049	−0.037	−0.018
	(0.059)	(0.030)	(0.126)	(0.144)	(0.031)	(0.019)
	Panel B. Mean hourly earnings					
$Uber_{it}$ (=1)	−0.116*	−0.007	0.037	0.002	−0.028	−0.005
	(0.059)	(0.035)	(0.117)	(0.101)	(0.025)	(0.019)
MSA and year FE?	Y	Y	Y	Y	Y	Y
Additional MSA controls?	Y	Y	Y	Y	Y	Y
MSA x linear time trend?	Y	Y	Y	Y	Y	Y
Observations	350	350	295	336	350	350

Notes: This table reports OLS estimates of Eq. (1) where the outcome is the mean *ln* earnings (panel A) and *ln* hourly earnings (panel B) of taxi drivers and (2) "Bus and Ambulance Drivers and Attendants"; (3) "Locomotive Engineers and Operators"; (4) "Motor Vehicle Operators, All Other"; (5) "Industrial Truck and Tractor Operators"; and (6) "Driver/Sales Workers and Truck Drivers" respectively. Additional MSA-level controls include mean *ln* earnings, the share of workers with a college degree, the female share of the labor force, *ln* MSA population, the unemployment rate, and the share of the labor force that falls in four age categories (16–25, 26–39, 40–54, and ≥ 55). Standard errors clustered at the MSA-level are reported in parentheses. Statistical significance is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

shifts in earnings among drivers working in related sectors that remain unaffected by the services provided by Uber. Second, we randomize the observed distribution of Uber's entry dates across MSAs to show that our obtained estimates are clear outliers relative to the distribution of placebo treatments.

Table 8 presents estimates of Eq. (1) where the outcome is the mean *ln* earnings (panel A) or hourly earnings (panel B) of taxi drivers, as well as bus drivers, locomotive operators, motor vehicle operators, tractor operators, and truck drivers respectively. Column 1 presents the baseline estimated impact of Uber on the (hourly) earnings of taxi drivers for comparison, which is negative and statistically significant at least at the 10-percent level. However, estimated impacts on earnings in all other transport-related occupations in columns 2–6 are typically close to zero in magnitude and are never statistically significant. A unique association between Uber's entry and a relative decline in the earnings of taxi drivers in our view strongly support a causal interpretation of our main results.

Fig. 4 shows the distribution of placebo estimates from randomly assigning the year of Uber entry for each individual MSA drawn from the actual distribution of entry dates in our sample. We randomize the entry dates 100 times and estimate our baseline difference-in-differences specification in Eq. (1) using each of these alternative treatment distributions. Each figure reports the distribution of these placebo estimates for mean *ln* earnings and hourly earnings respectively and for each group of drivers. Also shown is each corresponding difference-in-differences estimate using the *actual* year of Uber entry from Tables 2 and 3, which shows that they are all clear outliers relative to the distribution of the placebo estimates: at most three percent of the placebo estimates are larger in (absolute) magnitude than the corresponding actual estimate. Overall, this exercise lends further support to our interpretation of our main result that Uber's entry into a MSA led to a reduction in the earnings potential of incumbent taxi drivers.

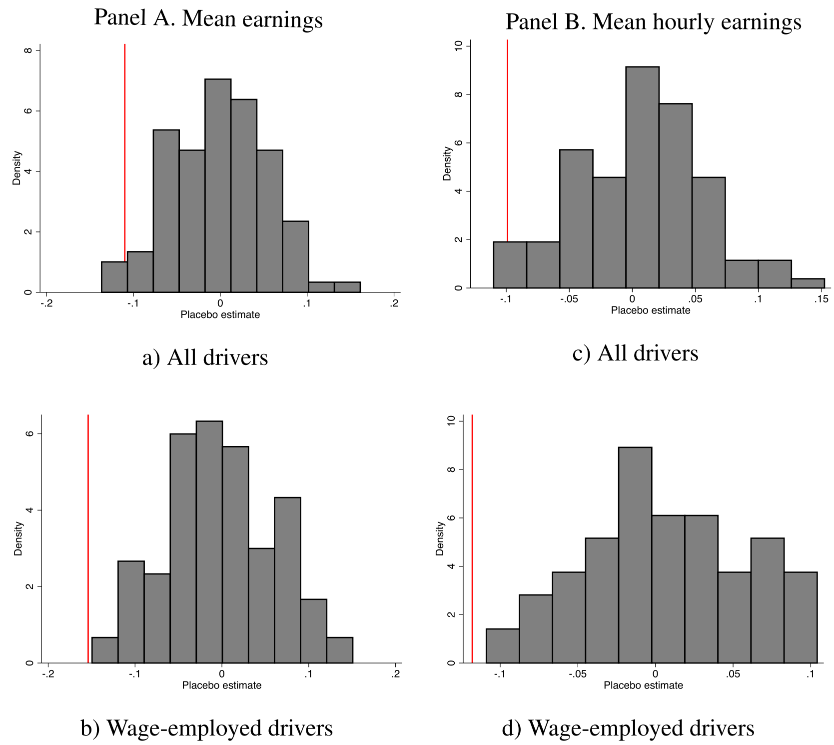

Fig. 4. Randomized placebo estimates: earnings of taxi drivers after Uber's introduction, 2009–2015.
Notes: To construct these figures we randomly assign the year of Uber entry for each individual MSA drawn from the observed distribution of entry dates across MSAs in our sample and repeat this exercise 100 times. We then estimate Eq. (1) using these placebo treatments and report the distribution of these estimates for each outcome and driver group in the figures. Also depicted (as a red solid line) are our corresponding baseline estimates from column 1, panel A and B, in Tables 2 and 4, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Conclusions

This paper provides the first systematic evidence of Uber's impact on traditional taxi services by exploiting new data on Uber's staggered rollout and information on the earnings and employment of taxi drivers across metropolitan areas in the United States. Using a variety of empirical strategies, we document that Uber's entry into a new market led to a relative reduction in (hourly) earnings of incumbent taxi drivers, which is consistent with case-study evidence suggestive of a decline in capacity utilization in response to increased competition from Uber. However, although there is a widespread belief that the diffusion of Uber has led to worsened employment prospects for taxi drivers, we find no statistically significant effects on their labor supply nor on the composition of the driver pool in terms of, for example, age or educational attainment.

Although our analysis is not intended to identify the aggregate impacts of the gig economy, it provides compelling evidence that while the spread of digital technologies may have adverse effects on the earnings of incumbent workers, such distributional impacts are not necessarily associated with worsened employment prospects in traditional jobs. Moreover, while Uber has expanded rapidly in recent years, the overall size of the gig economy remains small. In 2015, the share of workers providing services through online intermediaries, such as Uber and Task Rabbit, still accounted for a meagre 0.5 percent of the US workforce (Katz and Krueger, 2016). However, to the extent that our results can be generalized to other sectors, the continued expansion of the gig economy into a wider range of occupations and industries is likely to cause increased disruption to the livelihoods of incumbent workers.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2018.05.006.

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