

Drivers of Disruption? Estimating the Uber Effect*

Thor Berger

Chinchih Chen

Carl Benedikt Frey

January 23, 2017

Abstract

A frequent belief is that the rise of the “sharing economy” has led to the displacement of workers in a wide range of traditional jobs. This paper examines the impacts of the flagship of the sharing economy—*Uber*—on workers employed in conventional taxi services. Our analysis exploits the staggered rollout of Uber across U.S. cities, showing that employment of payroll taxi services if anything expanded after the introduction of the Uber platform, accompanied by a marked relative shift towards self-employment. While we find no evidence of adverse employment impacts, our estimates show that hourly earnings declined for wage-employed drivers, which were partly offset by increases in income among self-employed drivers. A triple-difference design that compares earnings and employment changes for taxi drivers relative to bus, delivery, tractor, and truck drivers that were unaffected by the arrival of Uber provides further supporting evidence that while Uber has had no negative employment impacts it has reduced the earnings potential of incumbent drivers in point-to-point transportation services.

Keywords: Digital technology; technological change; Uber

JEL: R41; O33; J23

1 Introduction

Does the expansion of the “sharing economy” spell the end of traditional jobs? In recent years this debate has centered on taxi services, where drivers have seen increased competition from digital services such as Uber. Unlike a traditional taxi business, Uber does not own any cars; instead it provides a matching platform for passengers and self-employed drivers and profits by taking a cut from each ride. Since its inception in 2010, few inventions have caused more controversy. In Europe, taxi drivers have rebelled following its introduction, and courts have banned or restricted its services. Meanwhile, in the U.S., the number of new drivers partnering with Uber has increased exponentially: while fewer than 1,000 drivers joined the Uber platform in January 2013, almost 40,000 new drivers signed up in December 2014. Case study evidence suggests that the employment effects of Uber have been pervasive: although no direct link with the arrival of Uber has been established, the average number of rides per taxi in San Francisco—Uber’s home town—declined by 65 percent between 2012 and 2014 (SFMTA, 2016). Yet, despite the ongoing debate surrounding its potential adverse labour market impacts there exists no systematic empirical evidence on its effects.

*Berger: Department of Economic History, School of Economics and Management, Lund University & Oxford Martin School, University of Oxford. (E-mail: thor.berger@ekh.lu.se) Chen: Oxford Martin School, University of Oxford. (E-mail: chinchih.chen@oxfordmartin.ox.ac.uk) Frey: Oxford Martin School, University of Oxford. (E-mail: carl.frey@oxfordmartin.ox.ac.uk). Chen and Frey gratefully acknowledges funding from Citi.

This paper provides the first systematic evidence on Uber’s impacts on earnings and employment in conventional taxi services. By exploiting the fact that the Uber platform has been rolled out in a staggered fashion across locations, we examine the impact of Uber’s expansion on workers in point-to-point transportation services across U.S. cities over the period 2009 to 2015. For our empirical analysis, we match worker-level data on taxi drivers and chauffeurs from the annual American Community Survey (ACS), consisting of 1-in-100 random samples of the U.S. population, with newly collected data on the staggered rollout of Uber across cities.

Our analysis takes a difference-in-differences approach comparing relative changes in the employment and earnings of taxi drivers in U.S. cities before and after Uber’s introduction. Although the impacts on employment are imprecisely estimated, we find little evidence to suggest that Uber’s introduction on average has led to an employment reduction in point-to-point transportation jobs. To the contrary, our point estimates consistently suggest that the labor supply of traditional taxi drivers increased in cities where Uber was introduced relative to cities where it was not, which is also evident when separately examining the labor supply of wage- and self-employed taxi drivers. Consistent with the general perception that the Uber platform has incentivized non-taxi drivers to become self-employed Uber drivers, we moreover find that the labor supply increases among self-employed drivers are substantially larger in magnitude relative to the impact on hours worked among wage-employed drivers. Taken at face value, our estimates suggest that the labor supply of self-employed taxi drivers on average increased by almost 50 percent after the introduction of Uber, which is striking especially since we inevitably underestimate the labor supply of self-employed Uber drivers.¹

Analyzing relative changes in the earnings potential of taxi drivers after Uber’s arrival we find that hourly earnings among wage-employed drivers on average declined by up to 10 percent in cities where Uber became available relative to the ones where it remained absent. Although the earnings potential of wage-employed taxi drivers fell, these declines were offset by up to 10 percent increases in hourly incomes among self-employed taxi drivers. Examining relative changes in business income yields further evidence showing that the hourly earnings declines among wage-employed drivers were offset by large increases in business incomes of those in self-employment. Our findings are thus consistent with evidence showing that Uber drivers exhibit higher earnings than conventional taxi drivers (Hall and Krueger, 2015), reflecting also the relatively high capacity utilization the Uber platform permits (i.e., in terms of increasing the share of the time a driver spends with a passenger in the car) through improved driver-passenger matching (Cramer and Krueger, 2016). The negative earnings effect on wage-employed workers further speaks to a previously documented sharp reduction in capacity utilization in traditional taxi services (e.g., SFMTA, 2016), presumably due to increased competition from Uber: while we find that taxi drivers continue to work slightly more hours, the declining number of rides per driver-hour is consistent with evidence of declining hourly earnings among wage-employed drivers.

Our estimates remain similar when controlling for differential pre-existing trends in taxi employment across cities, as well as when controlling for a wide range of city characteristics that may be important in accounting for changes in the local demand for transportation services. Lastly, a triple-difference design that compares relative earnings and employment changes for taxi drivers relative to bus, delivery, tractor, and truck drivers that were unaffected by Uber’s introduction provides additional evidence suggesting that Uber has not reduced the demand for jobs in conventional point-to-point transportation services, though it has seemingly redistributed income from the wage- to self-employed drivers.

Our study relates to several literatures. First, a series of recent papers have documented the benefits of Uber. Estimating the demand curve for Uber, Cohen *et al.* (2016) has calculated that the consumer surplus

¹Our estimates are likely to provide a lower bound since survey evidence suggest that 61 percent of Uber drivers work full-time or part-time on another job, meaning that many of them do not appear as taxi drivers in the ACS samples (Hall and Krueger, 2015).

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 work flexibility the platform permits, while exhibiting higher hourly earnings than traditional taxi drivers (Hall and Krueger, 2015). Cramer and Krueger (2016) provide an explanation for the higher incomes of Uber drivers in documenting that they benefit from higher capacity utilization. We add to this literature by examining the potential adverse economic impacts of Uber on incumbent drivers in traditional point-to-point transportation services: while our findings similarly suggest that capacity utilization among self-employed drivers increased following the introduction of Uber, we also find evidence suggesting that wage-employed drivers witnessed a decline in capacity utilization in response.

Second, an emerging literature examines the employment effects of the proliferation of new technologies. For example, Bessen (2015) shows that the aggregate number of bank tellers increased despite the diffusion of automated teller machines. Similarly, Basker *et al.* (2015) document that employment per gasoline station increased between 1977 and 1992; even as the share of stations with self-service pumps expanded from 40 to 80 percent. We build on this literature by showing that the arrival of digital technology, in terms of the Uber platform, potentially substituting for traditional taxi drivers, has not reduced employment in point-to-point transportation services. While Katz and Krueger (2016) has estimated that workers providing services through online intermediaries, such as Uber or Task Rabbit, accounted for only 0.5 percent of all workers in 2015, we examine the impacts of the sharing economy on traditional jobs in arguably the most affected industry. Doing so, we document that even in industries where the exposure to the sharing economy has been high, its employment impact has, if anything, been positive.

Third, a growing body of work examines how local labor markets adjust in response to the arrival of new technologies (Beaudry *et al.*, 2010; Lin, 2011; Berger and Frey, 2015). In particular, a number of studies document that computer technology has substituted for workers performing routine tasks, leading to downward pressure on employment and wages in routine jobs (Autor and Dorn, 2013; Berger and Frey, 2016). A subset of this literature uses variation in broadband availability across locations, to examine the causal impact on the labor market outcomes for different types of workers (Akerman *et al.*, 2015). In similar fashion, we use variation in the spread of the Uber platform across cities, to examine local labor market outcomes among taxi drivers.

The remainder of this paper is structured as follows. Section 2 describes our data sources and empirical strategy. In section 3, we discuss our findings, and provide additional robustness checks. Lastly, in section 4, we derive some conclusions and implications for policy.

2 Empirical Strategy and Data

To identify the impact of Uber on employment and wages, we exploit its staggered spatial and temporal introduction across local labor markets corresponding to metropolitan statistical areas (MSAs) across the U.S. in a difference-in-differences framework that compares changes in areas where Uber was introduced relative to areas that did not gain access to the Uber platform. Our baseline difference-in-differences regressions take the following form:

$$y_{jit} = \alpha_i + \vartheta_t + \delta Uber_{it} + \gamma \mathbf{X}_{jit} + \varepsilon_{jit} \quad (1)$$

where the dependent variable y is the log of employment or wages in occupation j 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 specific 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 has an intent-to-treat flair and reflect the extensive rather than intensive margin of the spread of Uber.

All specifications include a full set of MSA fixed effects (α_i) to account for time-invariant differences in the level and structure of taxi employment across cities. Additional estimations also include linear city time trends to account for potential trend differences in the evolution of taxi employment across cities, thus taking into account that Uber may have targeted cities with a rising demand for point-to-point transportation services, to reduce concerns that our estimated impacts of Uber is conflated with trends that existed already prior to its introduction. As the demand for taxi services is highly elastic we always include a full set of time fixed effects (ϑ_t) to account for national variations in the level of taxi employment that may be related to business cycle fluctuations and national income growth. Finally, we also control for time-varying city characteristics (\mathbf{X}_{jit}), including the unemployment rate, the share of the population with a college degree, the female population share, and age groups that may be correlated both with the rollout of Uber and the demand for taxi services.

Although city trends and the set of time varying control variables are likely to soak up much of the variation in the evolution of taxi services that may be correlated with Uber’s rollout, there is still concern that taxi employment evolved differently in cities where it was introduced due to omitted (unobserved) factors. To further address the issue of differential trends in the evolution of taxi services we deploy a triple differences (i.e., difference-in-differences-in-differences) design, where we compare relative changes in earnings and employment of taxi drivers relative to workers in other transportation occupations *within* the same city and compare how these differences evolved before and after Uber’s introduction. Our triple-difference regressions take the following form:

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

where $y_{jit}^T - y_{jit}^O$ corresponds to the difference in the log labor supply of taxi drivers (T) and other transportation occupations (O) and the other notation is as described above. Our triple difference analysis focuses on two alternative transport occupations as comparison groups for taxi drivers: (1) bus drivers; and (2) truck, delivery, and tractor drivers. Importantly, to the extent that many factors that drive earnings and employment trends within cities are likely to affect these occupations in a similar way, the estimates are solely identified from changes among taxi drivers relative to other types of drivers within the same city and how these differences evolved relative to other cities after Uber was introduced.

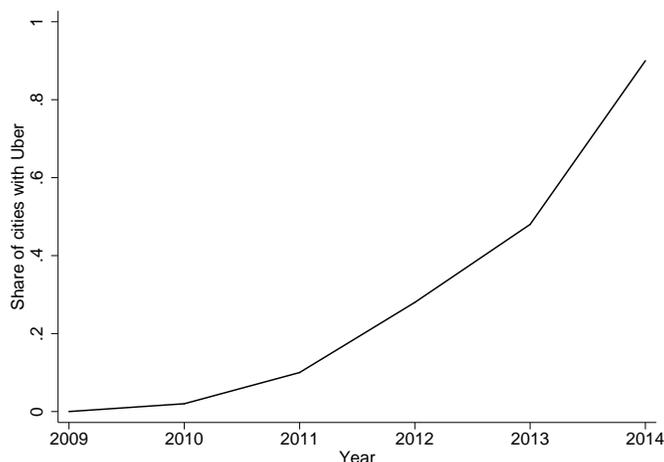
2.1 Data

We construct our dataset by combining individual-level data drawn from the American Community Survey (ACS) samples that consists of a 1-in-100 national random sample of the U.S. population with newly collected information on the diffusion of Uber across U.S. metropolitan areas obtained from Uber.

First, we identify the year and month in which Uber was introduced in each MSA from a variety of sources outlined in the Appendix, which we use to create the *Uber* variable described in the previous section. Uber was introduced in San Francisco in May 2010 and expanded rapidly across major U.S. cities starting in 2011. As shown in Figure 1, more or less all major cities had gained access to Uber’s services as of last year.

Second, we match the information on Uber’s rollout to worker-level information on taxi drivers in U.S. MSAs drawn from the ACS samples. Taxi drivers are reported in the occupation “Taxi Drivers and Chauffeurs” (#9140) under the OCC2010 occupational classification scheme in the ACS samples, which we for brevity refer to simply as “taxi drivers” throughout the paper. For each MSA we calculate the total employment of taxi drivers, as well as the number of taxi drivers that are in self- and wage-employment respectively among working-age and non-institutionalized civilian adults.² As noted by Hall and Krueger

²Wage employment corresponds to workers answering yes to the question “Was this person an employee of a private for



Notes: This figure shows the share of the 50 largest US MSAs where Uber was present between 2009 and 2015.

Figure 1: Uber’s rollout across U.S. Metropolitan Areas, 2009-2015.

(2015), the Bureau of Labor Statistics has documented that 87 percent of independent contractors report self-employment in the labor surveys and that nearly 40 percent of Uber’s driver-partners do not have another job, which suggests that the available information on self-employment among taxi drivers in the ACS samples can be used to assess Uber’s impact on the employment type of taxi drivers.

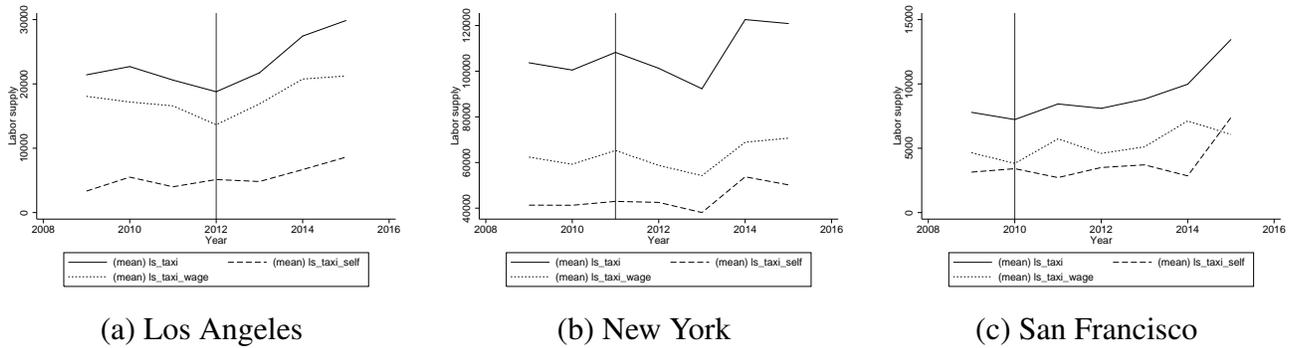
Our sample is restricted to those workers that have non-zero and positive labor supply weights and income, which is further restricted to workers making at least 25 percent of the prevailing federal minimum wage. We calculate employment by first creating labor supply weights that are based on the weights supplied in the ACS samples multiplied by the product of average hours worked and the average number of weeks worked.³ We impute the average number of hours and weeks worked by assuming that a driver works the median number of hours where these variables are reported in bins.

To calculate the earnings and incomes of taxi drivers we compute the hours-weighted mean log wage in taxi and related drivers’ occupation as well as total earnings. Our main earnings measure is based on the nominal business or wage income for the previous year (reported as INCEARN in the ACS samples). As two complementary measures of income among the wage- and self-employed we also calculate each respondent’s total pre-tax wage and salary income and the total pre-income-tax business income, which corresponds to the amount earned after business incomes have been subtracted from gross receipts (IN-CWAGE/INCBUS). All nominal incomes are converted into 2015 USD using the Consumer Price Index adjustment factors provided by IPUMS. To ensure a sufficient number of observations of taxi drivers, we finally restrict our analysis to the 50 largest U.S. MSAs.⁴

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?”.

³Alternative specifications instead examine the *share* of self-employed taxi drivers, which is simply defined as the share of self-employment in total taxi employed so that 1-the self-employed share equals the share in wage employment.

⁴Although results remain similar when including all MSAs in the analysis, which are available upon request, 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.



Notes: These figures show the evolution of taxi employment in three US MSAs before and after Uber’s introduction, which is denoted by a vertical solid line. Each figure reports the total labor supply for taxi drivers (solid line) as well as for wage-employed (short-dashed line) and self-employed drivers (long-dashed line), which is calculated by using the weights supplied in the ACS samples multiplied by the product of average hours worked and the average number of weeks worked among taxi drivers in each MSA.

Figure 2: Employment of taxi drivers before and after Uber’s introduction, 2009-2015.

3 Results

3.1 Employment impacts of Uber

Figure 2 shows the evolution of taxi employment broken down by type of employment for three MSAs: Los Angeles, New York, and San Francisco with a solid vertical line denoting the year in which Uber was introduced in each MSA. As is evident from these figures it is not obvious how Uber might have influenced the evolution of taxi employment. Although the labor supply of taxi drivers was trending downwards prior to Uber’s introduction in 2012 in Los Angeles it saw a sharp upward break after its introduction, with particular growth among the wage employed that mirrored similar but less pronounced patterns in San Francisco. In New York, however, the labor supply of wage employed taxi drivers decreased substantially after the introduction of Uber in 2011 though it rebounded over subsequent years. While these figures may be informative about the evolution of taxi employment in these three MSAs, they remain silent about whether these changes were driven by Uber’s introduction or other confounding trends and whether the patterns of employment growth in Los Angeles and New York are most relevant in understanding Uber’s role in the changes in taxi employment in U.S. cities.

To that end, Table 1 presents our baseline results for employment showing that there is little to suggest that Uber has had negative and measurable effects on the employment of conventional taxi drivers. Each column of Table 1 reports estimates from equation 1 where the outcome is the log of average hours worked per week multiplied by the average number of weeks worked per year for all taxi drivers and broken down by reported wage- and self-employment respectively. As highlighted in Figure 2, however, there is a substantial difference in the evolution of taxi employment in U.S. MSAs prior to Uber’s introduction, which may confound our estimates. To account for the fact that changes in taxi employment in cities where Uber was introduced may reflect pre-existing different trends in the evolution of transportation services, we include linear time trends in and MSA-level changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Consistently across all specifications, the point estimates are positive and relatively large in magnitude; the estimate in column 1, for example, suggests that the total labor supply of taxi drivers increased by some 8 percent after Uber’s introduction relative to other MSAs.

Table 1, panels B and C, breaks down changes in the labor supply of taxi drivers by their employment

Outcome: *ln* Labor supply for taxi drivers

	Panel A. Total employment			Panel B. Wage-employment			Panel C. Self-employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Uber (=1)	0.078 (0.070)	0.092 (0.079)	0.092 (0.079)	0.043 (0.082)	0.066 (0.095)	0.066 (0.095)	0.352 (0.241)	0.387 (0.325)	0.387 (0.325)
MSA FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y
MSA x linear time trend?	N	Y	Y	N	Y	Y	N	Y	Y
Additional MSA controls?	N	N	Y	N	N	Y	N	N	Y
Observations	350	350	350	350	350	350	350	350	350

Notes: This table reports OLS estimates of equation (1) where the outcome is the log labor supply of taxi drivers in each of the 50 largest US MSAs. All specifications include a full set of MSA and year fixed effects. Additional MSA controls include changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Statistical significance based on standard errors clustered at the MSA-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 1: Taxi employment after Uber's introduction, 2009–2015.

status. Again, all point estimates are positive which suggests that even among wage-employed taxi drivers the introduction of Uber had seemingly no negative impact on employment. Although the imprecision of the estimated impact of Uber on the employment of conventional taxi drivers should caution any relative comparison, the larger point estimates among the self-employed in panel C is consistent with the notion that Uber's introduction led to a relative increase in self-employment among taxi drivers. Taken at face value, these estimates suggest that the labor supply of self-employed taxi drivers increased by more than 45 percent relative to MSAs where Uber was not introduced. To shed further light on this relative shift, Table 2 presents similar estimates where the outcome variable is the *share* of taxi workers that report their employment status as self-employed. According to these estimates, the introduction of Uber led to an increase in the share of self-employed taxi drivers of some 2 to 3 percentage points.

Although these estimates consistently suggest that Uber if anything had positive impacts on employment of both conventional and self-employed taxi drivers it is important to note, however, that these estimates are associated with quite large standard errors when we cluster at the MSA-level, which means that these estimates are not typically statistically significant at conventional levels. Alternative ways to estimate the standard errors, for example using robust Huber-White errors, reduce their size and lead to an increase in the associated t -statistics. Yet, we prefer to report the most conservative (i.e., clustered at the MSA-level) standard errors.

An empirical concern with our identification strategy is that the shifts in local employment are driven by unobserved factors that vary over time and are correlated with the introduction of Uber. For example, if Uber specifically targeted cities with a growing demand for taxi services the estimates may reflect changes that would have taken place even in the absence of Uber's introduction. As unobservable factors are likely to affect other transportation occupations in a similar manner, and since Uber's services are restricted to taxi drivers, this provides a set of natural placebo occupations that we can exploit in a difference-in-differences-in-differences framework. By comparing relative differences in employment among taxi drivers relative to, for example, truck drivers before and after the introduction of Uber we exploit variation that stems from differences in employment trends *within* similar transport occupations.

Table 3 presents estimates of the baseline regressions where the outcome variable is the difference in the log of the labor supply of taxi drivers and bus, truck, delivery, and tractor drivers respectively.

	Outcome: share of self-employed taxi drivers		
	(1)	(2)	(3)
Uber (=1)	0.027 (0.020)	0.023 (0.026)	0.023 (0.026)
Additional controls?	Y	Y	Y
MSA and year FE	Y	Y	Y
MSA x linear time trend	N	Y	Y
Additional MSA controls?	N	N	Y
Observations	350	350	350

Notes: This table reports OLS estimates of equation (1) where the outcome is the share of taxi drivers that report themselves as self employed in each of the 50 largest US MSAs. All specification include a full set of MSA and year fixed effects. Additional MSA controls include changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Statistical significance based on standard errors clustered at the MSA-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2: Changes in self-employment after Uber’s introduction, 2009–2015.

Reassuringly, these estimates are similar in magnitude to those reported in Table 1, panel A, that solely relied on a simple difference-in-differences comparison across MSAs for taxi drivers. Similar employment shifts after Uber’s introduction also when compared to other transportation occupations within the same city provides further evidence that its introduction did seemingly not contribute to a decline in the employment opportunities of conventional taxi drivers.

3.2 Wage impacts of Uber

Although our results provide little support for the belief that Uber on average has reduced the employment opportunities for traditional taxi drivers, there is a remaining concern that the earnings potential among taxi drivers have worsened even if employment has been maintained.

Table 4 presents estimates of equation 1 where the outcome is the hours-weighted mean log earnings among taxi drivers (panel A) and broken down for wage- and self-employed taxi drivers respectively (panels B and C). Hourly earnings correspond to the hours-weighted mean business and wage income. The estimates include the full set of city controls, MSA and time fixed effects, and linear MSA trends in evenly numbered columns to account for MSA-level changes and trends that may affect the earnings potential for taxi drivers. The estimate for all taxi drivers and those being in wage employment (columns 1-4) suggest relative decline in real wages after Uber’s introduction, though these estimates typically have large standard errors. Among the self employed, the estimates in columns 5 and 6 are instead consistently positive, suggesting that the hourly earnings of self-employed taxi drivers increased after Uber’s introduction in contrast to the earnings of wage-employed taxi drivers. Table 5 provides further supporting evidence that instead restricts the attention to hourly business and wage earnings for self- and wage-employed drivers respectively. Again, the estimates suggest that while wage-employed taxi drivers saw relative income declines after Uber’s introduction those in self-employed saw substantial gains.

Outcome: \ln Labor supply of taxi drivers - \ln Labor supply of occupation X		
X =	Bus drivers	Truck, delivery, and tractor drivers
	(1)	(2)
Uber (=1)	0.093 (0.102)	0.091 (0.084)
Additional controls?	Y	Y
MSA and year FE?	Y	Y
MSA x linear time trend?	Y	Y
Observations	350	350

Notes: This table reports OLS estimates of equation (2) where the outcome is the log labor supply of taxi drivers relative to either bus drivers or truck, delivery, and tractor drivers in each of the 50 largest US MSAs. All specifications include a full set of MSA and year fixed effects. Additional MSA controls include changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Statistical significance based on standard errors clustered at the MSA-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 3: Changes in taxi employment after Uber's introduction, 2009–2015: Triple difference estimates.

Outcome: \ln Hourly earnings for taxi drivers						
	Panel A. Total		Panel B. Wage employed		Panel C. Self employed	
	(1)	(2)	(3)	(4)	(5)	(6)
Uber (=1)	-0.070 (0.043)	-0.067 (0.053)	-0.100** (0.046)	-0.082 (0.057)	0.099 (0.113)	0.079 (0.135)
Additional controls?	Y	Y	Y	Y	Y	Y
MSA and year FE?	Y	Y	Y	Y	Y	Y
MSA x linear time trend?	N	Y	N	Y	N	Y
Observations	350	350	350	350	330	330

Notes: This table reports OLS estimates of equation (1) where the outcome is the log of the hours-weighted mean log earnings of taxi drivers in each of the 50 largest US MSAs. All specifications include a full set of MSA and year fixed effects. Additional MSA controls include changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Statistical significance based on standard errors clustered at the MSA-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4: Changes in hourly earnings for taxi drivers after Uber's introduction, 2009-2015.

Outcome: <i>ln</i> Hourly earnings for taxi drivers				
	Wage-employed		Self-employed	
	(1)	(2)	(3)	(4)
Uber (=1)	-0.089*	-0.070	0.240	0.206
	(0.047)	(0.058)	(0.185)	(0.195)
Additional controls?	Y	Y	Y	Y
MSA and year FE?	Y	Y	Y	Y
MSA x linear time trend?	N	Y	N	Y
Observations	350	350	319	319

Notes: This table reports OLS estimates of equation (1) where the outcome is the log hourly wage (columns 1 and 2) and business (columns 3 and 4) earnings for taxi drivers in each of the 50 largest US MSAs. All specifications include a full set of MSA and year fixed effects. Additional MSA controls include changes in the share of the population with a college degree, the share employed in manufacturing, the female share, the size of the labor force, and the share of the population that falls in three age categories (16-25, 26-39, and 40-54). Statistical significance based on standard errors clustered at the MSA-level is denoted by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 5: Changes in hourly business and wage earnings for taxi drivers after Uber’s introduction, 2009-2015.

4 Conclusions

There is far-reaching concern that new technology—associated with the sharing economy—will fundamentally alter the future of work by displacing traditional jobs. This paper provides the first systematic evidence of the impact of the flagship of the sharing economy—Uber—on labor market outcomes in point-to-point transportation services across U.S. cities. We begin by showing that the number of hours worked expanded among wage- and self-employed taxi drivers alike, following the introduction of Uber. Though the impacts on employment are imprecisely estimated, the magnitude of the self-employment effect from the proliferation of Uber is significantly larger: while the labor supply of wage-employed taxi drivers expanded by up to 10 percent, self-employment surged by almost 50 percent, reflecting the general perception that many non-taxi drivers have become self-employed Uber drivers.

Turning to the Uber impact on hourly earnings, we find that wage-employed drivers experienced declining earnings following its introduction, which were in part offset by increases in hourly incomes among self-employed drivers. Our findings, in other words, vindicate survey evidence showing that self-employed Uber drivers in the U.S. typically exhibit higher hourly earnings than their counterparts (Hall and Krueger, 2015), reflecting higher capacity utilization among Uber drivers—in terms of the share of their time spent with a passenger in the car—relative to traditional taxi drivers, as documented by Cramer and Krueger (2016). While the increase in hourly earnings among self-employed drivers following the introduction of Uber lends further support to the view that Uber drivers benefit from higher capacity utilization—due to improved driver-passenger matching—we further document a decline in hourly earnings among wage-employed drivers, most likely reflecting a decline in capacity utilization in response to increased competition from Uber.

Taken together, we find little evidence of adverse impacts on labour market outcomes in point-to-point transportation services: total employment expanded in cities where the Uber platform was adopted, and earnings reductions among wage employed workers were in part offset by increases in hourly incomes among self-employed drivers. While we emphasize that our findings cannot be generalized across countries, our estimates cast doubt on efforts made—in parts of Europe and elsewhere—to ban or restrict the proliferation of Uber. Further research is required to guide policy making surrounding Uber and the

sharing economy.

References

- Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. *The Quarterly Journal of Economics*, **130**(4), 1781–1824.
- Autor, D. H. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, **103**(5), 1553–97.
- Basker, E., Foster, L., and Klimek, S. D. (2015). Customer-labor substitution: Evidence from gasoline stations. *US Census Bureau Center for Economic Studies Paper No. CES-WP-15-45*.
- Beaudry, P., Doms, M., and Lewis, E. (2010). Should the personal computer be considered a technological revolution? evidence from US metropolitan areas. *Journal of Political Economy*, **118**(5), 988–1036.
- Berger, T. and Frey, C. B. (2015). Industrial renewal in the 21st century: evidence from us cities. *Regional Studies*, pages 1–10.
- Berger, T. and Frey, C. B. (2016). Did the computer revolution shift the fortunes of us cities? technology shocks and the geography of new jobs. *Regional Science and Urban Economics*, **57**, 38–45.
- Bessen, J. (2015). *Learning by doing: the real connection between innovation, wages, and wealth*. Yale University Press.
- Cohen, P., Hahn, R., Hall, J., Levitt, S., and Metcalfe, R. (2016). Using big data to estimate consumer surplus: The case of uber. Technical report, National Bureau of Economic Research.
- Cramer, J. and Krueger, A. B. (2016). Disruptive change in the taxi business: The case of uber. *The American Economic Review*, **106**(5), 177–182.
- Hall, J. V. and Krueger, A. B. (2015). An analysis of the labor market for uber’s driver-partners in the united states. *Princeton University Industrial Relations Section Working Paper*, **587**.
- Katz, L. F. and Krueger, A. B. (2016). The rise and nature of alternative work arrangements in the united states, 1995-2015.
- Lin, J. (2011). Technological Adaptation, Cities, and New Work. *Review of Economics and Statistics*, **93**(2), 554–574.
- SFMTA (2016). Taxis and accessible services division report. Technical report, San Francisco Municipal Transportation Agency.