Empowerment or Substitution? Entry of Platform-based Sharing Economy on the Local Labor Markets

Student-led Completed Research Paper

Ziru Li
Arizona State University
Business Administration, 300 E Lemon St, Tempe, AZ 85287
ziruli@asu.edu

Yili Hong
Arizona State University
Business Administration, 300 E Lemon St, Tempe, AZ 85287
ykhong1@asu.edu

Zhongju Zhang
Arizona State University
Business Administration, 300 E Lemon St, Tempe, AZ 85287
Zhongju.Zhang@asu.edu

Abstract

Digitalization has significantly changed the way individuals work for a couple of decades. The emergence and expansion of sharing economy enabled by information technology have fundamentally changed the traditional business models. In this paper, we examine the impacts of the sharing economy platforms (specifically, Uber) on labor force participation, unemployment rate, supply, and wage of low-skilled workers. Combining a data set of Uber entry time and several microdata sets, we utilize a difference-in-differences method to investigate whether the above measures before and after Uber entry are significantly different across the metropolitan areas. Our empirical findings reveal that the ridesharing platform Uber increases the labor force participation, and decreases the unemployment rate of people below poverty level. In addition, we also find evidence of a shift in the supply of labors from low-skill jobs in conventional industries to the sharing economy sector. To further access the robustness of the results, we perform additional analyses include the use of alternative measures, the relative time model and the placebo test.

Keywords: sharing economy, digital platforms, Uber, labor market, unemployment rate, labor participation

Introduction

Sharing economy platforms leverage information technology (IT) to match the supply of underutilized assets or labor (e.g., house, cars, personal time or skills) and the demand from individuals who are willing to pay for those assets or labor in a real-time manner. Despite the controversy surrounding the issues of labor exploitation in the sharing economy, its business model has disrupted many traditional industries and gained tremendous popularity over the last few years. The two leading platforms, Uber and Airbnb, are at the forefront of this phenomenon: Uber now operates in over 600 cities worldwide, and has over 16,000 employees as of 2017 (Uber Newsroom, 2017); Airbnb has over 5 million listings in 81,000 cities and 191 countries (Airbnb Press room, 2017). Underneath those numbers are millions of job opportunities. The sharing economy offers people unprecedented opportunities to work when, where, and as much as they want. According to McKinsey, roughly 162 million individuals in the United States and the European Union work in the sharing economy, equivalent to about 20% to 30% of the workforce. Katz and Krueger (2016) find that the net employment growth in the United States between 2005 and 2015 can be attributed to the rise in alternative work arrangements[1].

While empowering individuals to make money in ways and on a scale not possible before, sharing economy platforms threaten not only the disrupted conventional industries (e.g., taxis (Cramer and Krueger 2016), hotels (Zervas et al. 2015), or newspapers (Seamans and Zhu 2013)), but also other traditional businesses. Workers leave the conventional industries to work in the new economy sector in pursuit of autonomous and flexibility. Sharing economy is changing the nature of work and the structure of the economy (Kenney and Zysman 2016).

The impacts of technological change on the labor market have been a debating topic in the economics literature. While most early nineteenth-century technological innovations appear to have displaced skilled workers, in the twentieth century, technological advances favor more skilled workers (Acemoglu 2002). Sharing economy is born in the latest wave of digital innovation. Its impact on the labor market worth further exploitation. While we observed anecdotal evidence about the impact of the sharing economy on the labor market, rigorous academic research is needed to identify and quantify its net impact.

Due to the large scale and many variations of sharing economy platforms, in this paper, we focus on not the whole sharing economy but one specific sharing economy sector: ridesharing. We propose that there are two main mechanisms through which ridesharing platforms, such as Uber, can influence the local labor markets: the empowering effect and the substitution effect. On one hand, Uber is empowering millions of individuals by offering flexible and low-skill job opportunities. It provides individuals who cannot work nine-to-five jobs with a flexible option. In addition, for individuals with a low-paying full-time job, sharing economy jobs provide them with additional discretionary income. Besides, for individuals who cannot find traditional jobs in the competitive labor market, the jobs offered in the sharing economy (e.g., driver) have low skill requirements and low entry barrier, and thus serve as viable choices.

On the other hand, sharing economy is substituting low-paying jobs in traditional industries. Except for the flexible schedules, sharing economy jobs have other advantages: efficiency and higher hourly pay. Because of the advanced technology and efficient matching algorithm, Uber vehicles have higher occupancy rates than conventional cabs (Cramer and Krueger 2016). The higher capacity utilization means that Uber drivers will spend less time wandering streets searching passengers, which further means more time they are making money. Additionally, Hall and Krueger (2016) found that UberX drivers, the group most comparable to ordinary cab drivers, earned between \$16.89 and \$18.31 per hour depending on hours worked. Given the advantages listed above, individuals with low-paying jobs would be more likely to switch jobs to work in the sharing economy. In this sense, sharing economy has a strong substitution effect on those low-paying jobs with low skill requirements.

[1] defined as temporary help agency workers, on-call workers, contract workers, and independent contractors or freelancers

To empirically evaluate these effects, we collected data from multiple archival sources. Specifically, we compiled a unique data set combining Uber entry times (through comprehensive search of media reports as well as complemented with data from Uber Research), employment data and position related data from publicly-available data sources (American Community Survey, Occupational Employment Statistics and Local Area Unemployment Statistics from Bureau of Labor Statistics). We use a difference-in-differences approach to estimate the impact of Uber entry on the various labor outcomes. We find that Uber's entry into an MSA significantly increases labor participation and decreases unemployment rates of people below poverty level for that MSA. In addition, we observed that, after Uber's entry into an MSA, the employment number of low skill jobs decreases. The lower the skill level the job requires, the more the employment decreases.

This paper has significant theoretical contributions as well as practical implications. Our study belongs to growing literature on the broader societal impacts of information systems (Bapna et al. 2015, Chan and Ghose 2013, Parker et al. 2016, Rhue 2015). Specifically, we contribute the literature of sharing economy by providing evidence of the impact of sharing economy on local labor market. Prior research has primarily focused on the effect of different sharing economy platforms on the respective incumbent industries, such as the impact of Airbnb on the hotel industry (Zervas et al. 2014), the impact of Uber on the taxi industry (Wallsten 2015). This paper examines the broad impact of the sharing economy on the whole labor market and its spillover effects on low-paying jobs. Meanwhile, our paper contributes to the economics literature by adding new insights of the how this new form of digital innovation influences labors and jobs (e.g., Brynjolfsson and McAfee 2012). The results also have implications for the policy makers and the platform operators. Sharing economy has been a controversial topic, in particular for the issue around labor, such as labor safety, employee benefits. Many cities have either banned or forced Uber to close down their business due to various concerns. By revealing positive impacts of the sharing economy platforms on the U.S. labor market in terms of increasing employment, this paper suggests that policymakers should also look at the positive side(s) of the sharing economy in order to make informed decisions. On the other hand, for platform operators, it's important for them to realize these unintended positive externalities and then think about how to effectively design the platforms to enable the technological affordance that would enhance these positive externalities.

The rest of the paper is organized as follows. After reviewing the relevant literature about the sharing economy and the labor market, we develop our hypotheses. We then describe in detail the data and the econometric specifications. Next section presents our findings as well as the results of additional robustness checks. Finally, we summarize the results and the contributions.

Literature Review

Sharing Economy

There has been a long stream of research that examine the innovations of digital platforms in the Information Systems (IS) literature (e.g., Bailey and Bakos 1997; Parker and Van Alstyne 2005; Brynjolfsson et al. 2003; Dellarocas and Wood 2008; Forman et al. 2008). The traditional two-sided platforms (such as eBay, Amazon) that facilitate transactions of physical products have slowly given way to the new sharing-based platforms (such as Uber, Airbnb, TaskRabbit, Handy, Freelancer, Upwork et. al) in recent years. They are transforming industries by connecting producers with customers in increasingly innovative ways. Sundararajan (2014) argues that the sharing-based economy could potentially have significant social and economic implications, including disruption of long-standing industries (Morse 2015) and displacement of incumbents (Burtch et al. 2018; Greenwood and Agarwal 2015; Wallsten 2015; Zervas et al. 2014). Specifically, researchers find that the ridesharing platform Uber increases vehicle capacity utilization (Cramer and Krueger 2016), benefits drivers with flexible work schedule and higher hourly rate (Hall and Krueger 2016), and creates consumer surplus amounts to $6.8 billion in 2015 (Cohen et al. 2016). There are also studies that have explored the various externality effects of such sharing economy platforms (e.g., Edelman and Luca 2014; Greenwood and Agarwal 2015; Zervas et al. 2014; Li et al., 2017).

As researchers lay the ground work for examining the effects of the sharing economy on consumers and the workers, the impact of the sharing economy on the labor market still remain unclear. There is no consensus over whether these digital platforms are simply digital intermediaries or they actually increase the extent of the gig or contract work. In some cases, they are formalizing previously less organized or locally organized work. (e.g., TaskRabbit allows people to outsource small jobs and tasks to others in their neighborhood, which helps to formalize handyman services). In other cases, they are displacing or threatening existing, often regulated, service providers (e.g., Uber and Airbnb pose threat to taxis and hotel industries). Therefore, there is an ongoing debate over whether the sharing economy creates or destroys jobs (Kenney and Zysman 2016). In this study, we seek to examine the impacts of the sharing economy on the labor market from an empirical perspective.

Digital Innovation and Labor Market

The impact of technology on the labor market has been of interest to economists for as long as economics has been considered as a distinct field of study. The technological improvement of the nineteenth and the early twentieth centuries was "deskilling": it expanded the division of labor and simplified tasks previously performed by artisans by breaking them into smaller, less skill-requiring pieces (Braverman 1998). In contrast, the twentieth century has been characterized by the skill-biased technical change which favors more skilled workers, replaces tasks previously performed by the unskilled, and exacerbates inequality (Acemoglu 2002). Consistently, Brynjolfsson and McAfee (2012) argue that the rapid advancement of technology increased an economy's productive capacity but did not benefit everyone in a society automatically. The impact of digital innovation on the labor market depends on the characteristics of specific technology and specific context. It is within this research area we position our work.

Specifically, a lot of work has been done to examine how local labor markets adjust in response to the arrival of new technologies (e.g., Allred et al. 2011; Beaudry et al. 2010). Some studies (Berger and Frey 2017; David and Dorn 2013) documented that computer technology has substituted for workers performing routine tasks, leading to downward pressure on employment and suppressed wages for routine jobs. In particular, Autor et al. (2003) argue that information and communication technologies (ICT) substitute workers in performing routine tasks and complements workers in executing problem-solving, complex communication, and information-intensive tasks (often called "non-routine abstract tasks"). Besides, using data on the United States, Japan, and nine European countries from 1980 to 2004, Michaels et al. (2014) conduct an empirical study and find that industries with faster ICT growth shifted demand from middle-educated workers to highly educated workers, consistent with ICT-based polarization.[2] Akerman et al. (2015) used variation in broadband availability (provided by a public program with limited funding rolled out broadband access points) across different firms to examine the causal impact on the labor market outcomes for different types of workers and find that broadband adoption favors skilled labor by increasing its relative productivity.

The current technological change is skill-biased (Acemoglu and Autor 2011) in the sense of increasing the demand for skilled and knowledge workers in the new knowledge economy. While sharing economy is not similar to the previous technology innovation, it does not fundamentally change the way people do things but largely change the way people interact or transact. In this sense, this digital innovation does not further widen the gap of technology accessibility but narrow the gap because it makes things more accessible. Besides, sharing economy has its creative new features, as we mentioned above, freedom and flexibility, which may influence differently on labors as well as the whole labor market. Notably, no research has provided solid empirical evidence about how sharing economy influences individual labors and the labor market. The present study addresses this void.

Hypothesis Development

The Empowering Effect

With information technology, individuals gain new capabilities and channels to participate and express themselves in a networked society. This is so-called digital empowerment (Mäkinen 2006). Sharing economy is empowering those who have free time and idle assets but were excluded from the labor market. There are a few mechanisms we believe the sharing economy platforms influence the labors. First, the

[2] which is the hypothesis that information and communication technologies (ICT) polarize labor markets by increasing demand for the highly educated at the expense of the middle educated, with little effect on low-educated workers

sharing economy business models create job opportunities that are complementary to those done by labor. Those jobs tend to be flexible and autonomous in terms of work schedule, thus empowering millions of individuals (such as those who cannot work nine to five) to unlock the value of their time, skills and talent to earn a living in ways and on a scale not possible before. Additionally, even for individuals who cannot find traditional jobs in the competitive labor market, the sharing economy sector provides plenty of jobs with low skill requirements, low entry barrier, and additional discretionary income, thus serving as viable choices to work. Therefore, we hypothesize:

Hypothesis 1a: Uber's entry into a metropolitan statistical area (MSA) increases labor participation in this MSA.

Hypothesis 1b: Uber's entry into an MSA decreases unemployment rate in this MSA.

The Substitution Effect

Jobs are destroyed and replaced when technological progress causes structural changes and makes it unprofitable for existing jobs to continue operating (Mortensen and Pissarides 1998). The emergence and expansion of the sharing economy have fundamentally changed the traditional business models and threatened the conventional businesses. Utilizing the latest technology and advanced business idea, jobs in the sharing economy sector are more profitable than in traditional businesses. In the case of Uber, on the one hand, it can achieve greater efficiency. Cramer and Krueger (2016) found that Uber vehicles have higher occupancy rates than conventional cabs, a result attributable to Uber's efficient matching algorithm. Higher efficiency means a driver has more time with a fare-paying passenger in the car while he or she is working. Additionally, Uber drivers earn a higher hourly rate than traditional taxi drivers (Hall and Krueger 2016). Finally, as we discussed above, Uber provides extreme autonomy and flexibility to workers. Because of these advantages, innovative sharing-based platforms such as Uber can attract labor (especially the low-skill and low-paying workers) from traditional job markets, thus decrease the labor supply for traditional firms that provide low-skill/paying jobs. Therefore, we hypothesize:

Hypothesis 2: Uber's entry into an MSA attracts low-skill workers, thus decreases the total employment of traditional low-skill jobs in this MSA.

Data and Methods

In this study, we focus on one specific sharing economy platform: Uber. So one of our variables of interest is a proxy for the usage of Uber in an urban area. We operationalize this variable by capturing the entry time of Uber into an MSA. We collected Uber start date of Uber service for 280 areas, 19 of which do not have Uber. The below table shows the distribution of Uber entry year.

We use a natural experiment approach to empirically examine the impact of Uber on labor markets within the United States. This research design offers us an important advantage: Since the time of Uber entry into various urban areas is different, we can use a multi-site entry difference-in-differences (DID) method to investigate whether the labor market measures before and after Uber entry are different across different metro areas (Angrist and Pischke 2008). This data structure further enables us to include location and time fixed effects, which effectively control for static heterogeneity across locations, as well as any unobserved temporal trends or shocks (e.g., seasonality). Below, we will discuss the details of our data source, data generation process, and empirical models.

Labor Participation and Unemployment Rate

We collected monthly labor participation and unemployment rate data (seasonally adjusted) from the Local Area Unemployment Statistics (LAUS) program. Since Uber expanded into most metro areas in the United States between 2011 and 2014, we use only the data from 2005 to September 2017 in order to balance the pre-treatment and post-treatment time periods. Table 2 provides the summary statistics of the LAUS data and the control variables included.

Uber Entry Year	Areas
2011	4
2012	10
2013	9
2014	104
2015	63
2016	29
2017	42
No Uber Service	19

Table 1. Distribution of Uber entry year

Variable	Definition	Mean	Std.Dev.	Min	Max
1. CLF	Civilian Labor Force	367,063	826,925	24,659	1.006e+
2. EM	Employment	343,427	773,021	22,778	9.629e+
3. UNEM	Unemployment	23,636	57,824	1,025	873,714
4. UR	Unemployment Rate	6.489	2.762	2.050	28.95
Control Variables					
5. GDP	GDP	43,670	131,265	1,731	1.657e+0
6. PIpa	Personal Income per	38,301	8,689	17,917	118,295
7. pop	Population	797,139	1.937e+0	53,989	2.015e+

Note: 1. Level of analysis is MSA-Year
2. $Unemployment\ Rate = Unemployment/Civilian\ Labor\ Force$

Table 2. Summary Statistics of LAUS data

The econometric model for testing hypothesis 1a and 1b is shown in (1) where i represents a metropolitan area, t is the time period, θ_i is the area fixed effects, γ_t is the time fixed effects, δ is the coefficient of Uber entry, λ is a vector of the coefficients for the control variables, ε_{it} is the error term. For labor participation, we expect δ is significantly positive. For un-employment rate, we expect δ is significantly negative.

$$DV(LAUS)_{it} = \alpha + \delta * UberEntry_{it} + \lambda * Controls_{it} + \theta_i + \gamma_t + \varepsilon_{it} \qquad (1)$$

Total Employment and Wage

We test our second set of hypotheses using data from the Occupational Employment Statistics (OES), which contains employment and wage estimates annually for over 800 occupations. The survey participants are exclusive “employees”. It is worth to note that OES is employer/payroll survey, which is different from the household survey. For household survey, if a person did any work for pay or profit during the reference period (whether that be wage and salary employment, self-employment, independent contractors, etc.), she is counted as employed. So Uber driver would fall into this category. That is different from the employer/payroll surveys that count only those who were on employer payrolls during the reference period. In that case, an independent contractor like an Uber driver would not be counted. So using the employer/payroll survey, we can investigate the spillover effect of Uber on other traditional low-skill jobs.

Additionally, the Bureau of Labor Statistics uses the Standard Occupational Classification (SOC) code, which is used by federal statistical agencies to classify workers and jobs into occupational categories. We use this code to integrate the OES data with the Dictionary of Occupational Titles (DOT) data that is produced by the Department of Labor to define over 13,000 different types of work. The DOT data was created by job analysts who visited thousands of US worksites to observe and record the various types of work, and what was involved. The data set provides intensity measures of different skills for occupations. Autor (2003) developed three measures (abstract, routine, and manual scores) to represent the high, medium and low skill intensity of each job. We adopt the “manual score” for low-skill jobs in this research.

Variable	Definition	Mean	Std.Dev.	Min	Max
A_Wage	Mean annual wage	48573.8	27651.79	16540	271760
H_Wage	Mean hourly wage	23.43	13.30	7.95	130.65
Tot_Emp	Total employment	1315.39	4298.75	30	230910
Abstract	Task abstract score	3.073	2.27	0.042	8.18
Routine	Task routine score	3.97	2.19	1.25	8.64
Manual	Task manual score	1.071	1.17	0	6.17
RTI	Routine task-intensity	1.186	1.79	-2.11	7.97

Table 3. Definition and Summary Statistics of OES data

Table 3 provides the summary statistics of the variables in the OES data. The econometric model we use to test our second set of hypotheses is given in Equation (2) where i represents a metropolitan area, j represent a job, t is the time period. Specifically, we control for the MSA effect, and MSA specific time trends. For wage, we expect the coefficient for Task Manual Score λ to be negative (for a job, the lower the skill, the higher the manual score is) and the coefficient of the interaction term β to be significantly positive. For total employment, we expect β to be significantly negative.

$$DV(OES)_{ijt} = \alpha + \delta * UberEntry_{it} + \lambda * TaskManualScore_j + \beta * UberEntry_{it} * TaskManualScore_j + \emptyset * Controls_{it} + \theta_i + \gamma_t + \varepsilon_{ijt} \quad (2)$$

Main Results

Effects on Labor Participation and Unemployment Rate

Main Results

Table 4 presents the estimates of the model (1). As we have controlled for the two way fixed effects, the time-invariant confounding factors have been considered by the model. As to the time-variant factors, we include GDP, Population and Per capita personal income (dollars) as our control variables. The dependent variable "civilian labor force" is log transformed. It can be seen that the coefficient of Uber entry is significantly positive for labor force participation but nor significant for either the unemployment rate or the unemployment rate of people below poverty level.

DVs	ln(CLF)	UR	UR_BP
Uber Dummy	0.009***	-0.131	-0.741
	(0.003)	(0.088)	(0.570)
ln(pop)	0.863***	4.948***	19.934
	(0.048)	(1.223)	(14.097)
ln(PIpa)	0.046	-3.080*	-6.234
	(0.031)	(1.578)	(9.938)
ln(GDP)	0.095***	-4.869***	-12.875**
	(0.022)	(0.818)	(5.337)
Observations	3,324	3,324	1,967
R-squared	0.620	0.825	0.387
Number of MSAs	277	277	281
Time period	2005-2016	2005-2016	2011-2016

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. Main Results of Model (1) using LAUS data

An Alternative Measure for Uber Entry

It should be noted that we used Uber entry time to proxy for the implementation of Uber service in our estimates of model (1). Uber entry may not reflect the actual usage of its service in an area and hence its impact on labor market could be confounded. In order to alleviate this concern, we use the number of Uber searches on Google Trends as an alternative measure of its popularity in a certain geographic region. More specifically, we retrieved the Google Trends search history of the keyword combination "Uber" + "name of the urban area." There is, however, a potential issue with the search volume on Google Trends. Before Uber actually entered an urban area, the search volume is generally not zero in most urban areas. The non-zero search volume could represent some expectations and curiosity but not the actual Uber usage. We addressed this problem by multiplying it with the Uber entry dummy variable and created a new variable: Uber usage. Table 5 presents the results of our analysis using Uber usage. The results are very consistent with the main analysis.

DVs	ln(CLF)	UR	UR_BP
Uber Use	0.002***	-0.010	-0.049
	(0.001)	(0.016)	(0.085)
ln(pop)	0.868***	4.832***	18.696
	(0.046)	(1.224)	(14.059)
ln(PIpa)	0.048	-3.061*	-6.499
	(0.031)	(1.578)	(9.962)
ln(GDP)	0.094***	-4.881***	-13.335**
	(0.022)	(0.823)	(5.324)
Observations	3,324	3,324	1,960
R-squared	0.620	0.825	0.384
Number of MSAs	277	277	281
Time period	2005-2016	2005-2016	2011-2016

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Main Results of Model (2) with Alternative Measure

Relative Time Model

In order to evaluate the parallel time trend assumption, which is a very important assumption of DID model. We use the relative time model. As discussed by Angrist and Pischke (2008), the chief assumption of the DID estimation is that there is no pre-treatment heterogeneity in the trends between treated and untreated groups. If trends in the dependent variable are heterogeneous over time, this presents a problem, because it implies that the untreated group cannot serve as a valid control, i.e. reflection of what would have happened in the absence of treatment. Extensively used in extant literature (Autor 2003; Bapna and Umyarov 2015; Chan and Ghose 2013; Greenwood and Agarwal 2015), this estimation incorporates a second set of time dummies that indicate the chronological distance between an observation period t, and the timing of treatment in the metropolitan area i. Thus, this approach not only allows us to ensure that there is no pretreatment heterogeneity between the treated and untreated metropolitan areas, it also lets us determine how long it takes for significant effects to manifest following treatment. Our final model specification is expressed in Equation (3).

$$LaborParticipation/UnemploymentRate_{it}$$

$$= \alpha + \sum_{i=-4}^{4} \delta_i * T_i + \lambda * Controls_{it} + \theta_i + \gamma_t + \epsilon_{it} \qquad (3)$$

In this model, T_i represents relative time dummy, δ_i represents the coefficients for those dummies. We omitted the entry year as the baseline time period. As before, there are two kinds of time fixed effects in our model: a year fixed effect, and an area fixed effect.

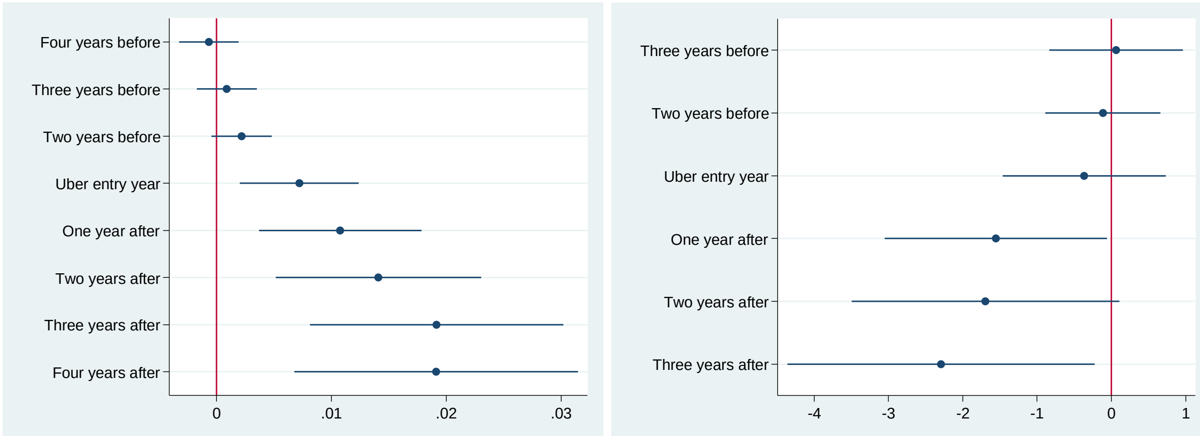
Table 6 presents the results of the relative time analysis. The three columns are for labor force participation, unemployment rate and unemployment rate of people below the poverty level respectively. We can see that none of the models exhibits a statistically significant pre-treatment trend. For labor force participation, as shown in column 1, the Uber effect becomes significant since Uber entry and increases as the year goes by. The second column is for the unemployment rate, we can see that the effect becomes significant until two years after Uber entry. That could be the reason why do not observe the effect when we conduct the basic DID model. Since for UR_BP, the time span is much shorter (2011-2016), we only include three time periods before and after Uber entry, as shown in column 3. We see that the negative effect of Uber X entry on the unemployment rate of people below poverty level becomes stable and significant roughly one year after implementation,

Figure 1 shows the marginal effect of relative time dummy in two models (for civilian labor force and unemployment rate of people below poverty level). The trend is more intuitive in this figure. We can capture the trends more easily. Broadly speaking, these estimates provide strong and significant evidence that the entry of sharing economy platforms positively associates with labor participation and negatively associates with the unemployment rate of people below poverty level in the metropolitan statistical areas. We accept Hypothesis 1a and partially accept Hypothesis 1b.

DVs	ln(CLF)	UR	UR_BP
Four years before	-0.000	0.041	-
	(0.002)	(0.059)	-
Three years before	0.001	0.046	0.063
	(0.002)	(0.063)	(0.457)
Two years before	0.002	0.030	-0.114
	(0.002)	(0.063)	(0.394)
One year before	Omitted		
Uber entry year	0.007***	0.014	-0.364
	(0.003)	(0.070)	(0.558)
One year after	0.011***	-0.122	-1.556**
	(0.004)	(0.103)	(0.760)
Two years after	0.014***	-0.270**	-1.695*
	(0.005)	(0.134)	(0.915)
Three years after	0.019***	-0.373*	-2.293**
	(0.006)	(0.190)	(1.052)
Four years after	0.019***	-0.415*	-
	(0.006)	(0.219)	-
ln(pop)	0.860***	5.091***	20.960
	(0.048)	(1.214)	(14.005)
ln(PIpa)	0.047	-3.036*	-6.048
	(0.031)	(1.559)	(9.943)
ln(GDP)	0.094***	-4.819***	-12.410**
	(0.022)	(0.813)	(5.358)
Area fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	3,324	3,324	1,967
R-squared	0.621	0.827	0.388
Number of MSAs	277	277	281
Time period	2005-2016	2005-2016	2011-2016

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Relative Time Model Using LAUS Data



(a) ln(CLF) **(b) UR_BP**

Figure 1. Plots of Coefficients Using Relative Time Model (LAUS data)

Competitive Effects of Lyft

As we mentioned, the paper focuses on one sharing economy platform: Uber. Uber has its uniqueness and specialty comparing to other sharing economy platforms. Since the impact of sharing economy platforms on the labor market are based on the nature and characteristics of the jobs. Therefore, our findings may not directly apply to other sharing platforms without further consideration. However, there are other ride-sharing platforms, which are based on the same business model, typically Lyft. Since Lyft is a very similar ride-sharing platform as Uber in terms of the platform mechanisms and the jobs it provides, we should see similar results as we can observe from Uber. We collected data of Lyft entry time manually. In most cities, Lyft follows Uber and enters city by city. We check our data. We have Lyft entry record of 139 areas. Lyft enters 27% of areas in the same year with Uber and enters 98.5% of areas after Uber entry year. Hence, there is a strong correlation between Uber entry and Lyft entry. In this sense, we may not include both entry dummies at the same time. When evaluating the Lyft effect, we just use the Lyft entry dummy and exclude the Uber entry dummy. The results are as shown in Table 7. We can see that for the civilian labor force, Lyft also has a significant positive effect. In the model without control variables, the Lyft effect is almost the same as Uber's. In the model with controls, the Lyft effect is smaller than Uber's. For the unemployment rate of people below poverty level, the effects are not significant. These results check our expectation: Lyft has a similar but smaller effect. On the one hand, Uber and Lyft are based on the same business model. They both provide flexible jobs with low entry barrier. Hence Lyft could have similar empowerment effect. On the other hand, Uber has a much larger scale than Lyft. The effect may not be as significant as Uber's.

DVs	ln(CLF)	ln(CLF)	UR_BP	UR_BP
Lyft Dummy	0.025***	0.010***	-0.871	-0.446
	(0.006)	(0.004)	(0.539)	(0.557)
ln(GDP)		0.096***		-7.163
		(0.033)		(5.397)
ln(Pop)		0.892***		-11.084
		(0.063)		(14.854)
ln(paPI)		0.037		-8.508
		(0.051)		(8.362)
Observations	2,106	1,944	1,148	1,148
R-squared	0.236	0.674	0.472	0.480
Number of MSAs	162	162	164	164

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7. Robustness Check with Lyft Dummy

Random Implementation (Shuffle) Tests

To address the potential issue for false significance in our estimates as a result of spurious relationships, we conducted a systematic placebo test of our results using a permutation approach suggested by Abadie et al. (2010). Specifically, we first deleted all the observations that belong to the post-treatment period and only keep those pre-treatment periods. This leaves us 2802 observations with 277 urban areas. On the subsample data set that consists only of pre-treatment observations, we created a pseudo (placebo) Uber entry time variable. The value of the pseudo Uber entry time for each urban area in the subsample was obtained by using a random number generator between 2005 (the beginning year of our sample) and the actual Uber entry year for that urban area. We then estimate a standard DID model (i.e., an Uber presence dummy) with time and location fixed effects. We store the coefficient of this pseudo-treatment and replicate the procedure 1,000 times. We compare the actual treatment against the mean and standard deviation of the pseudo-treatments as shown in Table 8. We can see that the probability of a similarly sized coefficient appearing purely by chance for Uber X is exceptionally low ($p < 0.001$). Besides, for the two models, the estimated placebo coefficients are insignificantly different from zero, suggesting correlation within the county-quarter has been accounted for.

	Placebo Coefficient Mean	Placebo Coefficient Std.Dev.	Uber Dummy Coefficient	Z score	P value
ln(CLF)	0.0011	0.0025	0.009***	3.16	p < 0.001
UR_BP	0.0249	0.0641	-0.990*	-15.8s	P < 0.00001

Table 8. Results of the Placebo Tests

Effects on Total Employment and Wages

Main Results

Table 9 presents the results of the model (2) and model (3). There are three hierarchies in our dataset: job, MSA and year. Specifically, we control for job fixed effect, area fixed effect, year fixed effect, and area-specific trend and use robust standard errors. There are missing values for employment and wage variables for different positions in different years and in different areas. Therefore, the data completeness for different variables is different and the panel is unbalanced. That is why we observe different numbers of total observations in two columns. In column 1, we note that the coefficient estimate for Uber entry dummy is statistically significant and positive, but it is not significant for the RTI variable. In addition, the interaction term (Uber * RTI) for total employment is significantly negative. This result highlights that for low-skill jobs, Uber entry significantly reduces the employment number. The marginal effect of Uber entry dummy at different values of RTI is shown in Figure 2(a). We see that for the positions with RTI around and greater than 4, the Uber effect is significantly negative. Specifically, for jobs with the RTI at around 4, Uber entry reduces the employment number by 2%; for jobs with the RTI at around 5, Uber entry reduces the employment number by 2.8%; for jobs with the RTI at around 6, Uber entry reduces the employment number by 3.6%; for jobs with the RTI at around 7, Uber entry reduces the employment number by 4.4%; for jobs with the RTI at around 8, Uber entry reduces the employment number by 5.2%. The results for low-income jobs are shown in Table 20 column 2 and Figure 2(b). We can see that Uber entry significantly reduces the employment number for low-income jobs. For jobs with ln(annual wage) of 10, Uber entry reduces the employment number by 5.8%; for jobs with ln(annual wage) of 9, Uber entry reduces the employment number by 15%.

An Alternative Measure for Uber Entry

As before, we use search volume on Google Trend multiplied by Uber entry dummy to serve as an alternative measure for Uber entry. The estimates are presented in Table 10; the marginal effects are displayed in Figure 3. The results again reveal that after Uber enters an MSA, it significantly reduces the employment number of low skill jobs and low-income jobs. We accept hypothesis 2.

DVs	ln(Tot_Emp)	ln(Tot_Emp)
Uber Dummy	0.013**	-0.974***
	(0.005)	(0.126)
RTI	-0.001	
	(0.001)	
ln(A_Wage)		-0.055*
		(0.031)
Uber Dummy * RTI	-0.008***	
	(0.002)	
Uber Dummy * ln(A_Wage)		0.092***
		(0.012)
Observations	277,931	283,527
Area fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Job fixed effect	No	Yes
Area specific trend	Yes	Yes
Number of MSAs	288	288
R-squared	0.4851	0.8878

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9. Main Results of Model (3) Using OES data

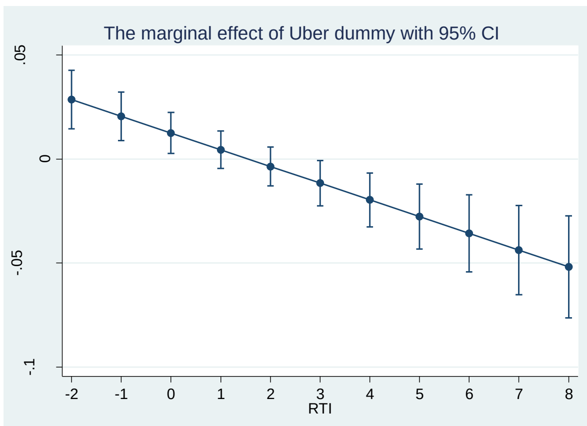


Figure 2. The marginal effect of Uber entry as the task manual score changes

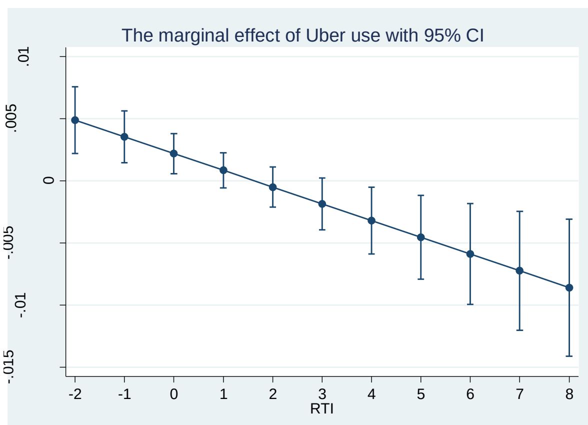


Figure 3. The marginal effect of Uber entry on the marginal effect of task manual score

DVs	ln(Tot_Emp)	ln(Tot_Emp)
Uber use	0.002***	-0.225***
	(0.001)	(0.030)
RTI	-0.003*	
	(0.002)	
ln(A_Wage)		-0.053*
		(0.031)
Uber use * RTI	-0.001***	
	(0.000)	
Uber use * ln(A_Wage)		0.021***
		(0.003)
Observations	277,931	279,037
Area fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Job fixed effect	No	Yes
Area specific trend	Yes	Yes
Number of MSAs	288	288
R-squared	0.4851	0.8887

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10. Using Google Trend as the proxy for Uber entry

Discussion and Conclusion

Sharing economy represents a new type of business model based on the efficient matching of underutilized resources (such as time, space, labor) with demand from entities that are willing to pay a price for temporary access (instead of ownership) to these resources. In the last few years, digital platforms to facilitate this matching process have sprung up in many business domains. While there has been evidence of tremendous opportunities and positive effects associated with the phenomenon, opponents argue that work arrangements in the sharing economy are only contractual and temporary, often times designed to avoid proper employment regulations. This study adds to the ongoing debate by providing positive evidence of sharing economy platforms on the U.S. labor market.

In this study, we focus on the impacts and implications of the sharing economy business models on the U.S. labor market. Specifically, we examine how Uber's entry into a geographic region influences some of the key indicators of the labor market in that area including civilian labor force participation, unemployment rate, total employment and wage for low skill jobs in conventional businesses. Using data from multiple sources, we are able to tease out the underlining mechanisms that drive our story. Exploiting a multi-treatment, difference-in-differences specification around the entry of ridesharing platform Uber, we find consistent evidence of a positive effect of Uber entry on the labor force participation and a negative effect of Uber entry on the unemployment rate. Moreover, we find evidence that Uber has a substitution effect on the low-skill jobs in conventional businesses. The results reveal that Uber attracts workers from low-skill positions in traditional industries. These findings point to a promising future that can be brought about by the sharing business models on the overall health of the labor market.

Our work contributes to the blossoming literature on the broader societal impacts of information systems (e.g., Bapna et al. 2016) by providing comprehensive positive evidence of sharing economy on the labor market. We investigate the overall effect and the spillover effect by demonstrating two mechanisms sharing economy have on the labor market: empowerment and substitution. To the degree that much of this work is designed to inform policy, either through a change in the broad understanding of digital phenomena (Burtch et al. 2016; Greenwood and Agarwal 2015; Greenwood and Wattal 2015), or by highlighting the differential effects which accrue to different groups (Rhue 2015), our work highlights the need to continue down the important path of providing robust empirical evidence which informs extant debate. Besides, this paper also adds some insights about the impact of digital innovation on the labor market. Sharing economy platforms have experienced a meteoric rise in recent years, and are projected to grow rapidly in the near future. This trend has been the latest and non-negligible revolution. Findings of the how this new form of the business model based on digital innovation influences labor participation and workers can be a significant contribution to this research area.

This research also has significant practical implications. It provides some positive evidence on sharing economy platforms, which will either informs the extant debate or informs policy makers. Our rigorous empirical analysis provides additional evidence that sharing economy platforms could actually be part of a solution to unemployment in metropolitan areas. The expansion of sharing economy faces tremendous challenges over the last few years. As discussed earlier, many cities have either banned or forced Uber to close down their business due to various concerns. Our results show that policymakers should also look at the positive side(s) of the sharing economy in order to make informed decisions.

This work is, of course, subject to a number of limitations, which offer potentially fruitful avenues for future work. First, as mentioned above, this paper focuses on one sharing economy platform: Uber. Uber has its uniqueness and specialty comparing to other sharing economy platforms. Since the impacts on the labor market are based on the nature and characteristics of the jobs. So our findings may not directly apply to other sharing platforms without further consideration. Additionally, because the sharing economy is a relatively new phenomenon, we are unable to examine the longer term consequences of Uber's entry on the labor market. Future work using more extended panel data is worth to pursue.

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