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The Empowering and Competition Effects of the Platform-Based Sharing Economy on the Supply and Demand Sides of the Labor Market

Ziru Li[a], Yili Hong[b], and Zhongju Zhang[a]

[a]W.P. Carey School of Business, Arizona State University, Tempe, AZ, USA; [b]C.T. Bauer College of Business, University of Houston, Houston, TX, USA

ABSTRACT

The sharing economy has fundamentally changed the way many individuals work. In this paper, we study the impact of the entry of a major ridesharing platform into U.S. Metropolitan Statistical Areas (MSAs), on the supply and demand sides of the labor market. Leveraging the difference-in-differences (DID) research design and a data set combining multiple U.S. Census archival sources, we exploit the variation in labor market metrics before and after Uber's entry into the MSAs. Our empirical findings reveal that the introduction of the ridesharing platform has an empowering effect on workers (the supply side of the labor market) and a competition effect on traditional jobs (the demand side of the labor market). Specifically, Uber's entry into the MSAs increases labor force participation, decreases the unemployment rate of residents living below the poverty level, and improves the employment and financial status of low-income workers. In addition, Uber's entry reduces the employment number and increases wages of conventional low-skill and/or low-wage jobs. This paper provides empirical evidence of the impact of a digital sharing economy platform on the labor market and suggests that policymakers and platform operators should account for this broader impact when they devise policies and make strategic decisions.

KEYWORDS

Sharing economy; labor market; two-sided platforms; empowering effect; competition effect; ridesharing platforms; market entry; traditional jobs; low-wage jobs

Introduction

Sharing economy platforms leverage information technology (IT) to re-distribute unused or under-utilized assets (e.g., time, vehicles, property) to individuals who are willing to pay for the services offered through such assets. The sharing economy business models leverage innovative digital solutions, such as the Internet or mobile phones, to match the supply and the demand of on-demand services. The sharing economy model has disrupted well-established business models in several industries. Despite the controversy surrounding such platforms, they have grown quickly and gained increasing popularity in the past decade. The two leading platforms, Uber and Airbnb, are at the forefront of this phenomenon. Uber operates in over 700 cities worldwide and has had over 22,000 employees as of 2019 [41]. Airbnb has over 5 million listings in 100,000 cities and 220 countries [5].

CONTACT Yili Hong yilihong@uh.edu C. T. Bauer College of Business, University of Houston, 4750 Calhoun Rd, Houston, TX 77204

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Underneath those numbers are millions of job opportunities. The sharing economy offers individuals unprecedented opportunities to work whenever, wherever, and for as long as they want. A 2016 McKinsey report [35] estimated that roughly 162 million individuals in the United States and the European Union work in the sharing economy, accounting for approximately 20 to 30 percent of the workforce. Katz and Krueger [31] pointed out that net employment growth in the United States between 2005 and 2015 can be attributed to the rise of alternative work arrangements.[1]

Although there is ample anecdotal evidence about the sharing economy's effect on the labor market, rigorous academic research is much needed to quantify its effects in a comprehensive fashion. This question belongs to the broader research area that studies the influences of technological change on the labor market, a topic of historical importance in the literature. Most technological innovations in the past centuries appear to have displaced skilled workers and increased unskilled workers' tasks. In contrast, more recent technological innovations appear to have displaced unskilled workers and increased skilled workers' tasks, thereby exacerbating inequality [3]. Additionally, cascading digital innovations have changed the nature of work and the structure of the economy [32]. Extending this line of research, we examine the staggered entry of the ridesharing platform Uber—a prominent example of the sharing economy—into U.S. Metropolitan Statistical Areas (MSAs) to quantify the sharing economy's effect on the supply and demand sides of the labor market.[2] In particular, we propose two effects through which Uber's entry into the MSAs can influence the labor market: the *empowering effect on workers* (supply side) and the *competition effect on traditional jobs* (demand side).[3]

On the supply side, ridesharing platforms *empower* millions of workers by offering job opportunities as drivers; and such jobs have low entry barriers but offer real-time flexibility. The drivers benefit from the ridesharing platform's flexibility and autonomy, which allows them to work according to their own schedules.[4] For example, the platform provides a flexible option for individuals who cannot work nine-to-five jobs, such as college students, stay-at-home mothers, and individuals who have another job. Moreover, individuals who are financially struggling have attractive options to supplement their income. Individuals who cannot find traditional jobs in the competitive labor market may also consider jobs in the sharing economy owing to its low skill requirements and low entry barrier, such as the lack of a medallion system. While the ridesharing service is a considered a substitute for the conventional taxi service, this research is designed to capture ridesharing's impact on the overall labor participation and the unemployment rate from a broader perspective, rather than examining its specific impact on the taxi industry.

On the demand side, ridesharing platforms attract workers from conventional low-skill and low-wage positions, exerting a *competition effect* on labor supply. Working as a driver for ridesharing platforms has other advantages besides flexibility and autonomy. Ridesharing vehicles have a higher capacity utilization rate, which can reduce idle time for drivers searching for customers, leading to additional time to earn money compared with taxi drivers [19]. Hall and Krueger [28] mentioned that UberX drivers earn between $16.89 and $18.31 per hour. Given such advantages, individuals with low-paying jobs in sectors such as retail and fast food preparation are likely to switch to the sharing economy sector, leading to a shortage of labor supply for certain industries that hire workers with low-skills at low hourly rates.

To operationalize this study, we examine the *empowering effect* of ride-sharing platforms on workers from two perspectives. From the macro perspective, we examine the unemployment rate and labor force participation on the MSA level. From the household perspective, we examine the household median income, the number of households below the poverty level, and the number of households with no workers. These measures allow us to gain insights into the employment and financial status of workers. To examine the *competition effect* on traditional jobs, we analyze the impact of platform entry on the employment number of low-skill and low-wage positions in conventional industries. In terms of econometric identification, we leverage the staggered entries of Uber into different MSAs to explore its effect on labor outcomes. Given that the entry of Uber into metro areas is temporally and geographically staggered, we use a difference-in-differences (DID) design to control for time-invariant, location-specific heterogeneity and broad macroeconomic trends, which may otherwise influence our results.

We find that Uber's entry into an MSA significantly increases labor participation and decreases the unemployment rate of individuals below the poverty level from the macro perspective. From the household perspective, Uber's entry increases household median income and decreases the percentage of households below the poverty level, as well as households receiving food stamps and that have no working members. We also demonstrate the competition effect on traditional jobs by revealing evidence that the employment number of low-skill jobs decreases upon Uber's entry into an MSA. The lower the skill level a job requires, the further the employment rate decreases. We conduct several robustness checks, such as alternative measures, a relative time model, and a placebo test, to further validate our findings.

This work provides several important contributions to the literature, industry practice, and policymaking. While prior research has primarily focused on the effects of sharing economy platforms on respective conventional industries, our study provides robust empirical evidence of the sharing economy's broad impact on both the supply and demand sides of the U.S. labor market. These findings offer insights for policymakers and platform operators. Despite the beneficial effects of the sharing economy business model on the labor market, we must also be mindful of the unintended externalities associated with digital platforms and examine how these platforms can be effectively designed to enable greater technological affordance. For example, the sharing economy has attracted much controversy on whether the sharing economy workers should be classified as employees or independent contractors. The dispute on the status of sharing economy workers involves several related discussions regarding labor safety and employee benefits.

The rest of this work is organized as follows: After reviewing relevant literature on the sharing economy and labor markets, we discuss theoretical underpinnings of the empowering and the competition effects. The data and methods section provides details of our data and econometric models, followed by the results section as well as additional robustness checks. Finally, we conclude and discuss our study's implications and limitations.

Literature Review

A long stream of research in the information system literature (e.g., [22, 30]) has examined the innovations of digital platforms. In recent years, sharing-based platforms, such as Uber, Airbnb, and Task Rabbit, have transformed industries by connecting producers with customers with innovative two-sided platform business models. Sundararajan [40] pointed out that the sharing-based economy could potentially have significant social and economic implications. Such changes to the economy can disrupt long-standing industries and displace incumbent sectors [19, 27, 42, 44].

Many papers explored consumer surplus [18], social welfare [12, 43], and various externality effects [15, 26, 33] of sharing economy platforms. Researchers also delved into the unique features associated with the business model of on-demand ridesharing platforms, such as flexibility, surge pricing, and commission-based compensation models. For example, Angrist et al. [8] assessed the compensation model of ridesharing platforms and found that ridesharing drivers gain considerably from the opportunity to drive without leasing. Hall and Krueger [28] revealed that independent workers drive for Uber largely due to the flexibility offered. Chen et al. [16] estimated the driver surplus generated by this flexibility and concluded that Uber drivers benefit significantly from real-time flexibility. Guda and Subramanian [25] studied the surge pricing strategy in on-demand marketplaces and offered insights for effectively managing on-demand service with independent workers. We summarize the literature to date on sharing economy platforms in Table 1. Although researchers have established the groundwork for the sharing economy's impact on consumers and workers, its effects on the labor market remain unclear. This study seeks to address this research gap by examining the sharing economy's effects on the labor market using an empirical approach.

Technology's impact on the labor market has historically been a topic that attracted the interest of many economists. The main technological improvement in the past centuries was "deskilling." Such development expanded the division of labor and simplified tasks previously performed by artisans by breaking them into simpler, less skill-intensive work [14]. By contrast, the 21st century has been characterized by skill-based technical changes that favored skilled workers who replaced unskilled ones, thus exacerbating inequality [3]. Technological change has also been demonstrated to have had a negative creative destruction effect on employment [4, 39]. There is substantial evidence that the automation of a range of low-skill occupations has contributed to further income inequality [11, 36]. As artificial intelligence assumes tasks previously performed by workers, many people recently expressed concerns about the future of work. Acemoglu and Restrepo [2] found that the introduction of robots has a negative effect on employment and wages.

We position our work within this research stream and highlight the significant implications of the sharing economy on the labor market. The effects of digital innovation on the labor market depend on the characteristics and the context of technology [3]. Based on the sharing economy's features, we argue that innovative, sharing-based business models offer workers unique features, which affect the labor market significantly. Specifically, we propose two mechanisms through which sharing economy platforms affect the two sides of the labor market: the *empowering effect* on workers (supply side) and the *competition effect* on traditional low-skill and low-wage jobs (demand side). On the one hand, sharing economy platforms empower low-skill and low-income workers with flexible job opportunities that have low entry barriers. On the other hand, sharing economy platforms compete for low-skill labor with other companies.

Table 1. Literature review of sharing economy platforms.

Paper Title	Authors and Publish Year	Platform	Topic
Reducing discrimination with reviews in the sharing economy: Evidence from field experiments on Airbnb	Cui et al. (2020) [20]	Airbnb	How to reduce discrimination with reviews
Using big data to estimate consumer surplus: The case of Uber	Cohen et al. (2016) [18]	Uber	Analyze demand elasticities and calculate consumer surplus
Your Uber is arriving: Managing on-demand workers through surge pricing, forecast communication, and worker incentives	Guda and Subramanian (2019) [25]	Uber	Analyze the surging pricing strategy
Disruptive change in the taxi business: The case of Uber	Cramer and Krueger (2016) [19]	Uber	Compare capacity utilization rate of UberX drivers with that of taxi drivers
An analysis of the labor market for Uber's driver-partners in the United States	Hall and Krueger (2018) [28]	Uber	Analyze the labor market for Uber's driver-partners
The value of flexible work: Evidence from Uber drivers	Chen et al. (2017) [16]	Uber	Estimate the value of real-time flexibility
Uber vs. Taxi: A Driver's Eye View	Angrist at al. (2017) [8]	Uber	Evaluate economic value of ride-hailing job opportunities
Social Impacts			
Paper Title	Authors and Year	Platform	Outcome Variable
Can you gig it? An empirical examination of the gig economy and entrepreneurial activity.	Burtch et al. (2018) [15]	Uber	Entrepreneurial Activity
The Competitive Effects of the Sharing Economy: How Is Uber Changing Taxis	Wallsten (2015) [42]	Uber	Taxi Consumer Complaints
The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry	Zervas et al. (2017) [46]	Airbnb	Hotel Revenues
Platform Competition in the Sharing Economy: Understanding How Ride-Hailing Services Influence New Car Purchases	Guo et al. (2019) [26]	Didi & Uber	New Car Purchases
Is Uber a Substitute or Complement for Public Transit?	Hall et al. (2018) [27]	Uber	Use of Public Transit
Drivers of disruption? Estimating the Uber effect	Berger et al. (2018) [13]	Uber	Cab Industry

Theory

Supply-Side Empowering Effect

Empowerment, which first appeared in the World Bank's *World Development Report*, refers to "the enhancement of an individual or group's capacity to make choices and transform those choices into desired actions and outcomes" [45]. Given the advances of IT and its ever-expanding influences on individuals, its empowering effect has been defined as *digital empowerment*. In digital empowerment, individuals gain new capabilities and channels to participate and express themselves through IT in a networked society [34]. The sharing economy is driven by digital innovation, and the unique business model brings significant benefits.

The most important feature of on-demand ridesharing jobs is flexibility, which refers to the ability to adapt work schedules to the demands of everyday life. Such jobs have no minimum hour requirements and only modest constraints on maximum hours. A survey[5] revealed that flexibility is a big motivating factor for Uber drivers. Specifically, 88 percent of drivers started working with Uber because it fit their lifestyles, rather than being their only option. Chen et al. [16] estimated flexibility's real value for Uber drivers and found that it brings twice the surplus they would obtain in less flexible arrangements. Another feature of such jobs is their low entry barrier. In the traditional taxi industry, drivers in large American cities must own or lease medallions, a transferable permit, to obtain the right to drive. Medallions are expensive due to their limited quota. However, on-demand ridesharing platforms let individuals drive private vehicles during their spare time with no required taxi medallion permit. Therefore, there is minimal to no fixed cost to the drivers to start working as a ridesharing driver. The compensation scheme is proportional to the drivers' earnings. Many jobs in the on-demand ridesharing sector require little skill. Therefore, the entry barrier for ridesharing jobs is relatively low in terms of initial investment and skill requirements. Nevertheless, working for ridesharing platforms is not feasible for everyone. There are various requirements for both the workers and their vehicles. For example, Uber requires a background check for prospective workers. We list the requirements and explain the process in the Online Supplemental Appendix B.

Given these features, two groups of workers are empowered by the availability of on-demand ridesharing jobs. First, ridesharing platforms empower those who are not in the workforce due to either inflexible schedules or low capability. The sharing economy provides flexible job opportunities for many individuals, such as stay-at-home parents, retirees, students, and those with disabilities, for whom the conventional routines of nine-to-five jobs are not an option. The availability of flexible and self-directed options can boost participation among the unemployed [35]. By contrast, ridesharing jobs have low skill requirements. For many low-skill workers, participation in contingent work may be the only option in a competitive labor market. This condition introduces the first manifestation of the empowering effect, that is, improved *employment status*. Second, on-demand ridesharing empowers those who have lower-paying jobs. People can work for ridesharing platforms to supplement their income. The flexible schedule makes ridesharing an ideal part-time job for many workers. Hall and Krueger [28] indicated that approximately 80 percent of Uber drivers said they were working full- or part-time before they started driving on the Uber platform, and many keep their primary jobs. The authors learned that people work for Uber due to its flexibility, and that many Uber drivers are supplementing their income while working other jobs or while between jobs. Therefore, the second manifestation of the empowering effect is improved *financial status*.

Demand-Side Competition Effect

Technological innovation could lead to the reallocation of jobs when employment shifts between firms [37]. In certain cases, existing jobs are eliminated when technological progress causes structural changes, and continuing current operations become unprofitable. This idea is referred to in the literature as "creative destruction," in which old jobs are "destroyed" to release resources for the creation of new jobs [4]. In other cases, such technological changes induce the decline of certain sectors and the growth of others [37]. Employers in the declining sectors can migrate to the expanding ones. Job-to-job worker flows can be viewed as the outcome of a decision by certain workers to search for vacancies while still being employed [38].

The sharing economy, in certain cases, is formalizing previously less organized or locally organized work. For instance, TaskRabbit lets people outsource small jobs and tasks to others in their neighborhood, thereby formalizing handyman services. In other cases, existing and often regulated service providers are displaced and threatened. For example, Uber and Airbnb pose a threat to the taxi and hotel industries. Whether the sharing economy creates or destroys jobs remains a topic of debate [32]. As we discussed, sharing economy jobs are flexible, autonomous, and well paying. These relative advantages may attract individuals with low-skill and/or low-wage jobs to switch to positions in the sharing economy. Such a condition may cause a reduction in labor supply for low-skill jobs in traditional industries, thus employers offering traditional low-skill jobs have to compete by increasing wages. Therefore, we propose that, on the demand side of the labor market, ridesharing platforms have a competition effect on conventional jobs.

Some studies have examined the competitive effects of sharing economy platforms from the perspective of industry performance. For example, Zervas et al. [46] studied the effects of Airbnb on the hotel industry and found that increased Airbnb rentals are associated with decreased hotel revenues. Wallsten [42] reveals that as competition from ridesharing increases, taxi complaints decrease because taxi drivers exert effort to improve service quality. Berger et al. [13] find that the employment of payroll taxi services expanded after the introduction of the Uber platform. While Uber has had no negative employment impacts, it has reduced the earnings potential of incumbent drivers in point-to-point transportation services. However, there is a clear lack of academic work that considers the competitive effect on the demand side of the labor market, in the broader context of conventional industries from the labor supply perspective. The present study addresses this void.

The research framework of this study is presented in Figure 1. We investigate the empowering effect from two perspectives: the macro perspective and the household perspective, and the competition effect on employment number and wages of conventional jobs.

Data and Methods

The key independent variable of interest is the entrance of Uber into local areas. We exhaustively searched the official Uber newsroom and major news articles/reports to determine whether and when Uber had entered each MSA. Thereafter, we created a dummy for

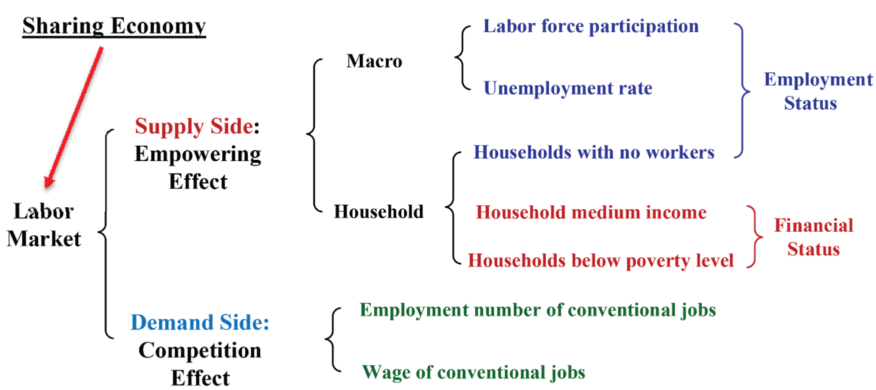


Figure 1. Research framework.

each area according to the entry time. If Uber had entered the area in the current time period, the dummy took the value of one; otherwise, it is zero. In the sample, we also have areas without Uber presence. While the analysis was conducted at a yearly level, the actual entry time is at a daily or monthly level. We use the common approach to count the entry dummy as one, regardless of whether the entry date is in January or December. Although this coding method may incur potential bias, this is not detrimental, because it will make our results more conservative which, in turn, means the actual effects may be larger than those we observed. For example, in areas where Uber entered in December, the impact may not show up in that year. Besides, to check for robustness, we adopted Uber usage based on Google search trend data as an alternative measure for Uber entries. We observed consistent results. We included the list of MSAs in our data sets and the range of the Uber entry time for those areas in Online Supplemental Table A1 and Figure A1 (Appendix A).

We focused on one specific sharing economy platform (Uber) for several reasons. First, the sharing economy is large scale and has various forms. Different sharing economy platforms have different characteristics. The proposed mechanisms depend on the unique features of sharing economy jobs, such as flexibility and low entry barriers. Uber enables a flexible work arrangement and meets our definition of a sharing economy platform. Second, Uber is the largest platform in the sharing economy and a pioneer of the industry change, which has been referred to as "Uberification" or "Uberization." In 2011, Uber's service and mobile app was officially launched in San Francisco. In early 2017, Uber captured an 84 percent share of the ride-hailing market in the United States. Large platforms are preferable for our analyses because they are more likely to affect the labor market compared with smaller platforms. Third, Uber rolled out on a city-by-city basis, and the dates and locations are publicly available. Uber entered different metro areas at various points in time and this research setting allows us to adopt a quasi-experimental approach for examining Uber's effect on U.S. labor markets.

We use a multi-entry DID method to see if labor market measures before and after Uber's entry vary across different MSAs [7]. Our unit of analysis is at the MSA-year level. The U.S. Office of Management and Budget defines an MSA as a geographical region with a relatively high population density at its core and close economic ties throughout the area. Uber launches its service mostly at the city level. Only under a few circumstances does it enter a complete metropolitan area. However, we chose the MSA as the unit of analysis for two reasons. First, an Uber launch in one area means its service is legal in that location. If an area is "illegal," the company will place a "blackout" or a "block" to ensure that no rider from that area can request a driver and vice versa.[6] But this setup only affects the pick-up process; Uber drivers can drop someone off wherever they want. In areas where cities are small, most destinations are spread over several cities. The other minor issue is that the dependent and control variables included in our models are only available at the MSA level. Therefore, the Uber entry time in the center city (as defined by the Census Bureau) is used as the entry time for the corresponding MSA. Our main model specification is given by Equation (1):

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

where i represents a metropolitan area, t is the time period, is the coefficient of Uber entry, is a vector of the coefficients for the control variables, and $_{it}$ is the error. We also include the MSA fixed effect $_i$ and time fixed effect $_t$ to control for the time-invariant heterogeneity across regions and any unobserved temporal trend or shock, such as seasonality. Moreover, we conduct analysis according to different data sources to test the two effects. Each part draws on different sources of data and models, as summarized in the following two subsections. Each part has a different time span due to the varying update statuses of distinct data sources.

Supply-Side Empowering Effect

Following the previous literature [6], we adopted several measurements from different levels and domains to operationalize the empowering effect. We used two levels and seven domains to construct the measurement framework, as illustrated in Figure 1. We captured data on labor force participation and unemployment rates across MSAs at the macro level. At the household level, we leveraged the household-related measurements on median income, the percentage of households below the poverty level, and the percentage of households with no working adult. In this study, the empowering effect has two main manifestations. First, certain individuals who were not working due to capability or schedule are now employed. This scenario can be captured by the changes in labor force participation, unemployment rate, and the number of households with no working adult. Second, other individuals work as Uber drivers in addition to their primary job to supplement their income. Workers' financial status should improve if the Uber effect is sufficiently substantial; and this effect can be captured by household median income and the poverty level. These measures capture the empowerment effect in terms of the two levels (macro vs. household) and two manifestations (financial vs. employment status), which enhance the robustness of the analysis.

As previously discussed, the nature and responsibilities of ridesharing jobs have determined that the workers are mainly low-skill/low-income workers. Uber's empowering effect has the following two manifestations: unemployed people become employed, and people obtain additional income. In both scenarios, low-skill/low-income workers improve either their employment or financial status. Hence, we expect that the empowering effect mainly targets those people. One important step is to identify the low-skill/low-income group. Different rules were adopted to identify the subgroup for macro and household data due to data availability. For macro data, we retrieved the unemployment rate of people below the poverty level. At the household level, we identify people receiving food stamps. The food stamp program, currently known as the Supplemental Nutrition Assistance Program, provides food-purchasing assistance for low- and no-income people living in the United States. Recipients must meet all eligibility criteria, such as income requirements, to receive benefits. Therefore, these people may receive a strong empowering effect. For this subgroup, we captured data on household median income, percentage of households below the poverty level, and percentage of households with no working adult.

Macro Perspective

At the macro level, we focused on two domains, namely labor force participation and unemployment rate. The first set of dependent variables included the labor force participation and unemployment rate of MSA i in month t. These data were captured from the Local Area Unemployment Statistics (LAUS) program, which produces annual labor force data for different regions. Based on a national household survey, the LAUS collects information about households and the individuals living in the households. The household survey counts independent contract workers, including Uber drivers, as employed. We used these data to see if Uber causes a shift from unemployment to employment. The earliest Uber entry time in San Francisco is 2011; thus, the annual data from 2006 to 2017 are used to balance the pre- and post-treatment time periods. As Uber enters different MSAs at varying time points, the pre- and post-treatment periods cannot be perfectly balanced. We ensured that at least three pre- and post-treatment periods are present for every MSA. We leverage another table from the Census Bureau (Table S2301), which is also based on a household survey, to acquire data on the unemployment rate of people below the poverty level. This measure has been recorded since 2011, and the recent update was in 2016. These two panels are slightly different in terms of the years and MSAs included. Hence, we examined different observations in the analytical results for the two datasets. Table 2 provides the summary statistics and Online Supplemental Table A2 (in Appendix C) shows the correlation table.

Household Perspective

At the household level, we focused on three domains: household median income, percentage of households below the poverty level, and percentage of households with no working adult. We checked these measures for all households, especially for those receiving food stamps, given that Uber has a strong empowering effect on low-income households. Annual data were collected from 2005 to 2016 from the American Community Survey of 348 MSAs. These household level measures were aggregated on the MSA level. Specifically, we retrieved data on the percentage of households receiving food stamps of MSA i in month t, the household median income of all households and households receiving food stamps of MSA i in month t, the number of households with working adults (of all households and of households receiving food stamps of MSA i in month t), and the percentage of households still below poverty level (both groups) of MSA i in month . There were 332 MSAs in the dataset after merging with the Uber data. Table 3 provides summary statistics, and Online Supplemental Table A4 (in Appendix C) shows the correlation table.

Demand-Side Competition Effect

To examine *the competition effect* on the demand side, we collected a panel data on the employment number and the wage of different positions. The data was obtained from the Occupational Employment Statistics (OES) program, which is conducted by the Bureau of

Table 2. Definition and summary statistics of the macro data.[a]

Variable	Definition	Mean	Std. Dev.	Min	Max
CLF	Civilian labor force	367,063	826,925	24,659	1.006e+07
UR[b]	Unemployment rate	6.489	2.762	2.050	28.95
UR_BP	Unemployment rate of people below poverty level	26.09	8.80	2.10	62.00
GDP	GDP	43,670	131,265	1,731	1.657e+06
Income_pa	Personal income per capita	38,301	8,689	17,917	118,295
Population	Population	797,139	1.937e+06	53,989	2.015e+07

Note: [a]Level of analysis is MSA-Year. [b].

Table 3. Definition and summary statistics of the household data.

Variable	Definition	Mean	Std. Dev.	Min	Max
H_FS	Households receiving food stamps	28,492	61,332	456	992,880
P_FS	Percent of households receiving food stamps	0.12	0.05	0.01	0.42
H_BP	Households below poverty level	14.61	4.13	4.20	36.50
MIncome	Household median income	48,651	9,257	24,501	110,040
NoWorkers	Percent of households with no workers	14.82	3.87	5.60	37.60
For the households receiving food stamps (FS)					
H_BP_FS	Percent below poverty level	53.61	8.64	15.10	92.30
MIncome_FS	Median income	18,049.50	4,507.24	7,260.000	50,053.00
NoWorkers_FS	Percent of households with no workers	21.42	7.20	0	54.50
Control variables					
Households_60	Households with one or more people in the household 60 years and over/all households (percent)	34.10	5.61	18.30	58.90
Households_18	Households with children under 18 years old/all households (percent)	32.63	5.17	18.70	58.80
Households_White	Households with white alone/all households (percent)	82.67	11.05	43.900000	98.80
Households_Disable	Households with one or more people with a disability/all households (percent)	27.00	5.06	11.00	46.00

Labor Statistics and annually produces employment and wage estimates for over 800 occupations. These data offered two advantages. First, in contrast to the household survey, the OES program is based on employer/payroll surveys in which participants are exclusively "employees." In the household survey, a person is considered employed if he/she did any work for pay or profit during the reference period, whether as wage and salary employment, as self-employment, or as an independent contractor. In this sense, Uber drivers fall into this latter category. By contrast, employer/payroll surveys count only those who were on employer payrolls during the reference period.[7] In this case, an independent contractor, such as an Uber driver, would not be counted. Therefore, the overall effect of Uber on the labor market can be estimated using the household survey, and the competition effect of Uber on other traditional low-skill jobs can be examined using the employer/payroll survey.

Additionally, using this data, we identified low-skill/low-wage jobs. Since Uber mainly substitutes low-skill or low-wage jobs, one important step is to identify such positions. For low-wage jobs, the OES data have a record of the annual wage of each position over different years and MSAs, and this lets us identify low-wage occupations directly. For low-skill jobs, we adopted the routine task intensity (RTI) measure developed by Autor and Dorn [9] to measure skill intensity for each occupation. This dataset uses the Standard Occupational Classification (SOC) code, which is used by federal statistical agencies to "classify workers and jobs into occupational categories for the purpose of collecting, calculating, analyzing, or disseminating data." With this code, we can merge the OES data with the Dictionary of Occupational Titles (DOT) data, which provides intensity measures of different skills for occupations. Based on DOT data, Autor et al. [11] derived three measures to measure routine, abstract, and manual task content by occupation. Autor and Dorn [9] further combined the three measures and created a summary measure of RTI, which indicates the level of skill/intelligence a job requires. The higher the score, the more susceptible the job is to computerization. Table 4 provides the summary statistics of the variables in this dataset, and Online Supplemental Table A3 (in Appendix C) shows the correlation table.

Table 4. Definition and summary statistics of Occupational Employment Statistics (OES) data.

Variable	Definition	Mean	Std. Dev.	Min	Max
AnnualWage	Mean annual wage	48,573.80	27,651.79	16,540	271,760
HourlyWage	Mean hourly wage	23.43	13.30	7.95	130.65
TotalEmployment	Total employment	1,315.39	4,298.75	30	230,910
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	1.170	0	6.170
RTI	Routine task intensity	1.186	1.79	-2.11	7.97

The econometric models used for this section are shown in Equations (2) and (3), where i represents MSA, j represents job category, and t represents year. Specifically, we controlled for MSA fixed effect θ_i, job fixed effect ∂_j, time fixed effect γ_t, and MSA-specific time trends $t * \theta_i$. One difference is the excluded job fixed effect for Model (2), since the RTI of each position () stayed the same over different times and areas. Including job fixed effect automatically cancels out this variable in the analysis. The $Employment\ number_{ijt} = \alpha + \delta * UberEntry_{it} + \lambda * RTI_j + \beta * UberEntry_{it} * RTI_j + \emptyset * Controls_{it} + \theta_i + \gamma_t + \ t * \theta_i + \varepsilon_{ijt}$ other difference is the interaction term. In Model (2), we interacted with the Uber entry dummy with the RTI index. Higher RTI scores indicate a job comprises more routine tasks. Based on our discussion, we expected Uber's entry to decrease the employment of those positions with high RTI. In Model (3), we interacted with the Uber entry dummy with annual wage. We expected Uber's entry to decrease the employment number of low-wage jobs.

$$Employment\ number_{ijt} = \alpha + \delta * UberEntry_{it} + \lambda * RTI_J + \beta * UberEntry_{it} * RTI_j + \emptyset * Controls_{it} + \theta_i + \gamma_t + \partial_j + t * \theta_i + \varepsilon_{ijt} \quad (2)$$

$$Employment\ number_{ijt} = \alpha + \delta * UberEntry_{it} + \lambda * AnnualWage_{ijt} + \beta * UberEntry_{it} * AnnualWage_{ijt} + \emptyset * Controls_{it} + \theta_i + \gamma_t + \partial_j + t * \theta_i + \varepsilon_{ijt} \quad (3)$$

Results

Supply-Side Empowering Effect: Macro Perspective

Main Results

Table 5 presents the results of Model (2). We estimated the models using robust standard errors clustered at the MSA level. The dependent variable civilian labor force (CLF) is log transformed. The coefficient of Uber's entry is significantly positive for labor force participation and insignificant for the unemployment rate (UR). However, the Uber effect is significant on the unemployment rate of individuals below the poverty level. Given that we had obtained the variable UR_BP from a different data source, it contained a varied number of MSAs. From the datasets, we collect the other two dependent variables, namely, CLF and UR. We included different numbers of areas and observations in the analysis. Thereafter, we ran the same model with control variables, as shown in Table 6. After the two datasets were

Table 5. Main results of the macro analysis.

DVs	ln (CivilianLabor Force)	Unemployment Rate	Unemployment Rate of people below poverty
Uber Dummy	0.025***(0.005)	-0.139(0.092)	-0.990*(0.532)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of MSAs	280	280	281
Time period	2006-2017	2006-2017	2011-2016
Observations	3,640	3,640	1,967
R-squared	0.170	0.797	0.378

Robust standard errors in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1. This applies to all the tables. MSA = Metropolitan Statistical Areas.

Table 6. Main results of the macro analysis with control variables.

DVs	ln (CivilianLabor Force)	Unemployment Rate	Unemployment Rate of people below poverty
Uber Dummy	0.009***(0.003)	-0.131(0.088)	-0.741(0.570)
ln(Population)	0.863***(0.048)	4.948***(1.223)	19.934(14.097)
ln(Income per capita)	0.046(0.031)	-3.080*(1.578)	-6.234(9.938)
ln(GDP)	0.095***(0.022)	-4.869***(0.818)	-12.875**(5.337)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of MSAs	277	277	281
Time period	2005-2016	2005-2016	2011-2016
Observations	3,324	3,324	1,967
R-squared	0.620	0.825	0.387

merged with the control variable dataset, we lost several observations, as shown in the table. The Uber effect is significant for the civilian labor force, but the effects are insignificant for the two unemployment rates. Thus, Uber's entry significantly increases labor force participation in the MSA. Given the inconsistent results, we perform additional analyses for the unemployment rate.

Additional Analyses and Robustness Checks

In our analysis, the timing of Uber's service implementation was approximated by the Uber entry time. Given that people need time to familiarize themselves with the service—that is, there may be a lag between Uber's entry and its effect on the labor market—this approximation has its limitations. To address this, we identified the search volume of the keyword "Uber" in each metropolitan area on Google Trends to address this issue. Google operates Google Trends, which provides the popularity index of top search queries in Google Search across different regions. This index is widely used in the literature to track sales activities in real time, such as retail sales, automotive sales, and travel activities [17].

We retrieved the Google Trends data for the keyword "Uber" in each MSA. These search results are treated as Uber's popularity and usage levels in a metropolitan area. This finding is also justified by the significant positive correlation between the entry dummy and the Google Trends searches. Hall et al. [27] likewise found that Google searches for "Uber" are strongly correlated with the number of active drivers per capita in each market with a correlation coefficient of 0.948. A small search volume is observed before Uber's actual entry in most urban areas, which could reflect curiosity and expectation from the community but not actual usage. We employed a new variable ***Uber_usage*** to address this issue, which is the multiplication of the search volume and the Uber entry dummy variable. We reran the main model with the new measure. Table 7 shows that the analysis with ***Uber_usage*** is similar to data acquired using the original Uber entry measure.

We then used the relative time model to evaluate an important assumption of the DID model, the parallel time trend assumption. This model assumes that trends remain the same between treated and untreated groups before the treatment [7]. A problem may arise if the dependent variable shows heterogeneous trends over time. In this condition, the control group is invalid for a robust comparison. According to the extant literature, we use the relative time model to check whether a trend in heterogeneity exists before the treatment [10, 23]. The model includes a series of relative time dummies representing the time span between the current period t and the treatment period in the metropolitan area i. This method lets us not only check the trend before the treatment but also examine the appearance and dynamics of the main effect after the treatment. The econometric specification is shown as shown:

$$Labor\ Participation/Unemployment\ Rate_{it}$$

$$= \alpha + \sum\nolimits_{i=-t}^{t} \delta_i * T_i + \lambda * Controls_{it} + \theta_i + \gamma_t + \in_{it}, \quad (4)$$

where T_i represents the relative time dummy and δ_i represents the coefficients for those dummies. We omitted one year before entry as the baseline time period. Like the previous one, this model has two kinds of fixed effects, namely, time fixed effect and MSA fixed effect.

Table 8 presents the results of the relative time analysis. The three columns are for labor force participation, unemployment rate, and the unemployment rate of people below the poverty level, respectively. None of the models exhibit a statistically significant pretreatment trend. In labor force participation, as shown in column 1, the Uber effect became significant since Uber's entry and even increased over time. The second column presents the unemployment rate results. The effect became significant two years after Uber's entry. This occurrence could be the reason why the effect is unobserved under the basic DID model. We only included three time periods before and after Uber entry because the time span of UR_BP is short (2011-2016), as shown in column 3. Uber's negative impact on the unemployment rate of people below poverty level became stable and significant

Table 7. Main results of the macro analysis with alternative measure.

DVs	ln (CivilianLabor Force)	Unemployment Rate	Unemployment Rate of people below poverty level
Uber_usage	0.002***(0.001)	-0.010(0.016)	-0.049(0.085)
ln(Population)	0.868***(0.046)	4.832***(1.224)	18.696(14.059)
ln(Income per capita)	0.048(0.031)	-3.061*(1.578)	-6.499(9.962)
ln(GDP)	0.094***(0.022)	-4.881***(0.823)	-13.335**(5.324)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	3,324	3,324	1,960
Time period	2005-2016	2005-2016	2011-2016
Number of MSAs	277	277	281
R-squared	0.620	0.825	0.384

Note: MSA = Metropolitan Statistical Areas.

Table 8. Relative time model for macro analysis.

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

Note: MSA = Metropolitan Statistical Areas.

approximately one year after its entry. We also plotted the coefficients of the relative time dummies in Online Supplemental Figure A2 (in Appendix D). In these estimates, the entry of the ride-sharing platform is positively associated with labor participation and negatively associated with the unemployment rate of people below the poverty level in the MSAs. We concluded with confidence that Uber empowers people by improving their employment status. Specifically, Uber increases labor force participation and reduces the unemployment rate of people below the poverty level.

We further conducted a systematic placebo test of our results. We used the permutation approach from Abadie et al. [1] to address the potential for false significance in our estimates as a result of spurious relationships. Specifically, we deleted the observations belonging to the post-treatment period and kept those from pretreatment. We obtained 2,802 observations in 277 urban areas. We created a pseudo (placebo) Uber entry time variable for the subsample dataset consisting only of pretreatment observations. The value of the pseudo Uber entry time for each urban area in the subsample was obtained using a random number generator between 2005 (the beginning year of our sample) and the actual entry year for that urban area. A standard DID model that is an Uber presence dummy was then estimated with time and location fixed effects. We replicated the procedure 1,000 times and saved the coefficient of the pseudo-treatment each time. Thereafter, we compared the actual treatment with the pseudo-treatments in terms of mean and standard deviation, as shown in Table 9. The probability of observing the Uber effect purely by chance is statistically impossible ($p < 0.001$). The placebo

Table 9. Results of the placebo tests.

	Placebo Coefficient Mean	Placebo Coefficient Std. Dev.	Uber Dummy Coefficient	Z score	P value
ln(Civilian Labor Force)	0.0011	0.0025	0.009***	3.16	p < 0.001
Unemployment Rate of people below poverty	0.0249	0.0641	-0.990*	-15.8	p < 0.00001

coefficients for the two models are near zero, thereby suggesting that the correlation within the MSA-year was considered and the models are robust.

Supply-Side Empowering Effect: Household Perspective

Main Results

Table 10 presents the results for overall households. We checked the effects of Uber entry on the percentage of households receiving food stamps (column 1), the percentage of households the below the poverty level (column 2), household median income (column 3), and the percentage of households with no working adult (column 4). No significant effect was observed except for a downward effect on the percentage of households with no working adults. However, as shown in Table 11, the effects for the same measures are significant on households with low income, which are identified as households receiving food stamps. Uber's entry significantly reduces the percentage of households below the poverty level (column 1) and increases the household median income (column 2), suggesting that Uber empowers people by improving their financial status. Uber's entry also significantly reduces the percentage of households with no working adults (as shown in column 3), suggesting that it empowers people by improving their employment status. With regard to the number of households with no working adults, the absolute value of the coefficient is larger for low

Table 10. Household perspective analysis for overall households.

DVs	Households receiving food stamps	Households below poverty level	ln(Median income)	Percent of households with no workers
Uber_dummy	0.003(0.002)	-0.120(0.112)	0.002(0.004)	-0.237**(0.116)
lnHouseholds_60	0.013(0.014)	-1.192(1.014)	-0.030(0.033)	5.349***(1.049)
lnHouseholds_18	0.023***(0.01)	0.609(0.660)	0.127***(0.022)	-3.914***(0.80)
lnHouseholds_Disable	0.061***(0.01)	3.000***(0.52)	-0.089***(0.02)	1.935***(0.469)
lnHouseholds_White	-0.042*(0.025)	-6.52***(1.94)	0.199***(0.059)	0.330(1.931)
MSA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observations	3,300	3,300	3,298	3,226
Number of MSAs	275	275	275	275
R-squared	0.639	0.285	0.675	0.438

Note: MSA = Metropolitan Statistical Areas.

Table 11. Household perspective analysis for households with low income.

DVs	Percent below poverty level _FS	ln (Median income _FS)	Percent of households with no workers_FS
Uber_dummy	-1.038**(0.433)	0.026**(0.011)	-1.598***(0.434)
lnHouseholds_60	-1.098(4.415)	0.017(0.107)	5.498(3.437)
lnHouseholds_18	0.257(2.950)	0.136*(0.082)	-4.947*(2.979)
lnHouseholds_Disable	0.015(2.066)	0.047(0.049)	-1.502(1.768)
lnHouseholds_White	4.437(5.301)	-0.015(0.140)	6.508*(3.922)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of MSAs	275	275	275
Observations	3,300	3,298	3,226
R-squared	0.238	0.449	0.045

income households than for all households (Table 10, column 4 vs. Table 11, column 3), thereby suggesting a much greater empowering effect from Uber on households with low income. Overall, these results from the household perspective provide additional evidence that Uber has an empowering effect, especially on low-income households.

Additional Analyses and Robustness Checks

We conducted the same set of additional analyses following the macro perspective analysis (using the alternative measures of Uber's entry, relative time model, IV analysis, permutation test, and additional analysis considering the effect of Lyft). Table 12 shows the results of the models using an alternative measure. As seen, the effects are significant and consistent with the models using the Uber entry dummy. Table 13 shows the results of the relative time model and Online Supplemental Figure A3 (in Appendix D) presents the coefficients plot. No pretreatment trend is seen in the three dependent variables. Uber's effects become significant in the entry year or one year after entry. Therefore, the results suggest there is no pre-treatment trend, and the main model is robust and consistent. Table 14 shows the results of the random implementation (shuffle) tests. Like the macro perspective analysis, we ran the model with the pseudo-treatment dummy 1,000 times and compared the coefficient of the

Table 12. Household perspective analysis (alternative measure).

DVs	Percent below poverty level _FS	ln(Median income _FS)	Percent of households with no workers_FS
Uber_usage	-0.173*(0.094)	0.002*(0.002)	-0.062***(0.008)
lnHouseholds_60	7.228(6.230)	-0.024(0.143)	1.474***(0.469)
lnHouseholds_18	3.565(3.825)	0.164*(0.096)	0.990**(0.382)
lnHouseholds_Disable	-2.500(2.246)	0.086(0.057)	-0.388*(0.210)
lnHouseholds_White	-5.023(7.469)	0.224(0.203)	-0.825(0.654)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of MSAs	170	170	170
Observations	2,040	2,039	2,005
R-squared	0.260	0.507	0.983

Note: MSA = Metropolitan Statistical Areas.

Table 13. Relative time model of the household perspective analysis.

DVs	Percent below poverty level _FS	ln(Median income _FS)	Percent of households with no workers_FS
Four years before	-0.213(0.429)	0.005(0.011)	-0.131(0.400)
Three years before	0.263(0.436)	-0.001(0.010)	0.171(0.397)
Two years before	-0.463(0.427)	0.008(0.011)	0.040(0.381)
One year before		Omitted	
Entry Year	-0.555(0.495)	0.004(0.011)	-1.024**(0.446)
One year after	-1.214**(0.536)	0.044***(0.013)	-1.270***(0.481)
Two years after	-1.498**(0.673)	0.053***(0.017)	-2.002***(0.579)
Three years after	-1.333*(0.776)	0.045**(0.019)	-3.330***(0.630)
Four years after	-1.883**(0.803)	0.069***(0.024)	-4.229***(0.750)
lnHouseholds_60	-0.270(3.966)	0.011(0.092)	5.820*(3.092)
lnHouseholds_18	-0.462(2.592)	0.179***(0.068)	-5.820**(2.634)
lnHouseholds_Disable	-0.793(1.790)	0.060(0.043)	-2.410(1.675)
lnHouseholds_White	6.409(4.904)	-0.049(0.119)	7.142**(3.469)
MSA fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of MSAs	332	332	332
Observations	3,984	3,981	3,881
R-squared	0.237	0.447	0.046

Note: MSA = Metropolitan Statistical Areas.

Table 14. Results of the placebo tests for the household perspective analysis.

	Placebo Coefficient Mean	Placebo Coefficient Std. Dev.	Uber Dummy Coefficient	Z score	P value
Percent below poverty level _FS	0.044	0.434	-1.038**	-2.493	p<0.01
ln(Median income _FS)	0.0005	0.0103	0.026**	2.476	P<0.01
Percent of households with no workers_FS	-0.068	0.376	-1.598***	-4.069	p<0.01

actual treatment with the coefficient of the pseudo-treatments. As shown in the results, the probabilities of observing the significant coefficient purely by chance were exceptionally low for all three dependent variables. The estimated placebo coefficients were insignificantly different from zero in all models according to T tests. This finding suggests that the correlation within the MSA year was accounted for. We also conducted analysis controlling for Lyft effect; the discussions and results are presented in Online Supplemental Appendix E.

Demand-Side Competition Effect

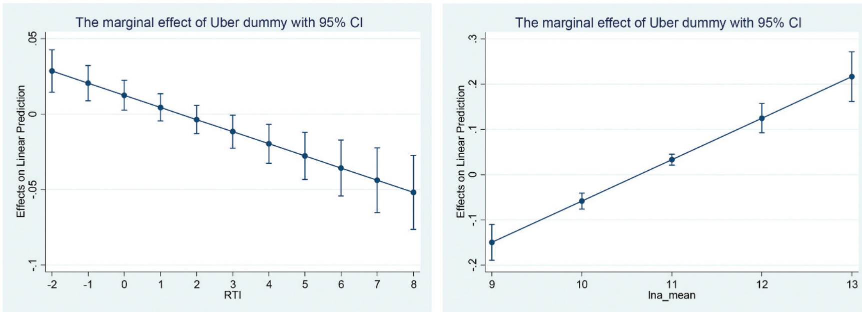
Main Results

Table 15 presents the results of Models 2 and 3. In this section, we used robust standard errors clustered at the MSA level. Specifically, we used RTI to identify low-skill positions in Model 2 (column 1) and annual wage to determine low-wage positions in Model 3 (column 2). Our dataset has three hierarchies: job, MSA, and year. Specifically, we controlled for job fixed effect, MSA fixed effect, year fixed effect, and area-specific trends. Robust standard errors were also used. Employment and wage variables have missing values for distinct positions in different years and in various areas. Therefore, the data completeness for different variables is different, and the panel is unbalanced. We also observed different numbers of total observations in two columns. In column 1, the coefficient estimate for the Uber entry dummy is statistically significant and positive but insignificant for RTI. The interaction term (Uber * RTI) for total employment is significantly negative. This result highlights that Uber's entry significantly reduces the employment number for low-skill jobs. Figure 2a shows the marginal effect of the Uber entry dummy at different RTI values. The Uber effect is significantly negative for the positions with RTI around and

Table 15. Main results for competition effect analysis.

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

Note: MSA = Metropolitan Statistical Areas.



(a) X-axis: RTI (b) X-axis: Annual Wage

Figure 2. Marginal effect of Uber entry on total employment.

greater than 4. In jobs with the RTI at approximately 4, 5, 6, 7, and 8, Uber's entry reduces the employment number by 2 percent, 2.8 percent, 3.6 percent, 4.4 percent, and 5.2 percent, respectively. Column 2 of Table 15 and Figure 2b show the results for low-wage jobs. Uber's entry significantly reduces the employment for these jobs. For jobs with ln(Annual Wage) of 10 and 9, Uber's entry reduces the employment number by 5.8 percent and 15 percent, respectively.

Additional Analyses and Robustness Checks

As previously discussed, we used Uber_usage as an alternative measure for Uber entry and conducted the same analysis (Model 2 and Model 3). The results are shown in Table 16. As RTI increases (Uber_usage * RTI is significantly negative) and as the annual wage decreases (Uber_usage * ln(AnnualWage) is significantly positive), Uber_usage has an increasingly negative effect on employment number. We see that both the size and direction of the coefficients are consistent with the main analysis (Table 15). The conclusion that Uber's entry significantly reduces the employment number of low-skill and low-wage jobs is valid.

We conducted the relative time model to validate the results. Table 17 illustrates the results from *Three Years Pre, Two Years Pre, Entry Year, One Year Post, Two Years Post*, and

Table 16. Competition effect analysis with alternative measure.

DVs	ln(TotalEmployment)	ln(TotalEmployment)
Uber_usage	0.002***(0.001)	-0.225***(0.030)
RTI	-0.003*(0.002)	
ln(AnnualWage)		-0.053*(0.031)
Uber_usage * RTI	-0.001***(0.000)	
Uber_usage * ln(AnnualWage)		0.021***(0.003)
MSA fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Job fixed effect	No	Yes
Area specific trend	Yes	Yes
Number of MSAs	288	288
Observations	273,525	279,037
R-squared	0.4869	0.8887

Note: MSA = Metropolitan Statistical Areas.

Table 17. Relative time model for competition effect.

DV	ln(TotalEmployment)	DV	ln(TotalEmployment) _Emp)
Three Years Pre	0.011***(0.004)	Three Years Pre	0.001(0.118)
Two Years Pre	0.000(0.004)	Two Years Pre	-0.119(0.114)
One Year Pre	Omitted	One Year Pre	Omitted
Uber Entry Year	0.001(0.005)	Uber Entry Year	-0.412***(0.096)
One Year Post	0.015**(0.007)	One Year Post	-0.609***(0.121)
Two Years Post	0.036***(0.008)	Two Years Post	-0.850***(0.135)
Three Years Post	0.050***(0.010)	Three Years Post	-1.247***(0.170)
RTI	-0.001(0.002)	ln(AnnualWage)	-0.042(0.033)
Three Years Pre * RTI	-0.003(0.002)	Three Years Pre * ln(AnnualWage)	0.001(0.011)
Two Years Pre * RTI	-0.001(0.002)	Two Years Pre * ln(AnnualWage)	0.012(0.011)
One Year Pre * RTI	Omitted	One Year Pre * ln(AnnualWage)	Omitted
Uber Entry Year * RTI	-0.003*(0.002)	Uber Entry Year * ln(AnnualWage)	0.039***(0.009)
One Year Post * RTI	-0.002(0.002)	One Year Post * ln(AnnualWage)	0.058***(0.011)
Two Years Post * RTI	-0.010***(0.002)	Two Years Post * ln(AnnualWage)	0.080***(0.013)
Three Years Post * RTI	-0.018***(0.003)	Three Years Post * ln(AnnualWage)	0.116***(0.016)
MSA fixed effect	Yes	MSA fixed effect	Yes
Year fixed effect	Yes	Year fixed effect	Yes
Job fixed effect	No	Job fixed effect	Yes
Area specific trend	Yes	Area specific trend	Yes
Number of MSAs	288	Number of MSAs	288
Observations	277,931	Observations	283,527
R-squared	0.4851	R-squared	0.8877

Note: MSA = Metropolitan Statistical Areas.

Three Years Post dummies and their interactions with *RTI* and *ln(Annual Wage)*. We also plot the coefficients in Online Supplemental Figure A4 (in Appendix D). The estimates suggest the employment numbers have no systematic change over the years leading up to Uber's entry. In all periods after Uber's entry, relative to the omitted group, the employment number of low-skill and low-wage jobs is significantly reduced even though the percentage of change varies from year to year. The results are robust and consistent, and we can conclude that Uber has a competition effect on conventional low-skill and low-wage jobs by attracting workers away from those positions.

Furthermore, we also found additional evidence that Uber's entry significantly increases the wage of those jobs, which captures companies' response to the decreasing labor supply. We describe the analysis and results in Online Supplemental Appendix F.

Discussion

The sharing economy represents a type of digital business model based on the efficient matching of underutilized resources, such as personal time or property, with demand from entities willing to pay a price for temporary access instead of ownership. In the last few years, sharing economy platforms have been developed in many business domains to facilitate this matching process. To the best of our knowledge, the current study is one of the first to systematically analyze sharing economy's effect on both the supply side and the demand side of the U.S. labor market. We examined whether ridesharing platforms have an empowering effect on workers and a competition effect on low-skill and low-wage jobs. We leveraged a quasi-experimental setting wherein Uber enters different MSAs at varying points in time. The differences in several measures of the labor market before and after Uber enters an MSA can be compared with that of MSAs without Uber service.

Our results revealed that ridesharing platforms have an empowering effect on the supply side of the labor market and a competition effect on the demand side of the labor market. More importantly, we provided evidence for heterogeneity effects. On the supply side, the empowering effect is most evident for workers with lower skills or at lower income levels. On the demand side, the competition effect is the strongest for low-skill or low-wage jobs. As previously discussed, the prominent characteristics of sharing economy jobs are flexibility and low entry barriers. These characteristics empower several groups of people: first, those who do not have time to work nine-to-five jobs; second, those who have low skills and cannot find a job in the competitive labor market; and third, those who want to supplement their existing income. From both the macro and household perspectives, we found that Uber's entry improves the employment and financial status of individuals, especially those with lower income. Traditional firms lose employees because of the competition effect. This mechanism is validated by evidence that Uber's entry reduces employment and increases the wages of low-skill and low-wage positions. One thing that needs to be noted here is that taxi drivers may suffer as ridesharing services compete with traditional taxi services. However, researchers have also found that employment of payroll taxi services did not decrease but increased after the introduction of the Uber platform [13]. Our paper does not focus on ridesharing's impact on the taxi industry and its drivers specifically but its impact on the overall labor market.

This study makes several important contributions to the related literature. First, the study comprehensively examines both the supply side and demand side of the sharing economy platforms on the labor market. Although the sharing economy's effect on the demand side has been discussed [24, 29], research regarding the supply side of these markets remains nascent. In one of the few papers on this subject, Burtch et al. [15] found that Uber's entry reduces the number of unsuccessful crowdfunding campaigns and provides necessity-based entrepreneurs with a preferable, alternative source of employment. Our study contributes to this area and explores a critical yet less considered question around how these platforms influence the labor market by creating flexible employment options for individuals with a potentially limited set of alternatives. An interesting opportunity for future work lies in examining if the sharing economy platforms affect income inequality. There are two competing hypotheses regarding this question. While the sharing economy may reduce income inequality due to the two effects revealed in this work and, in essence benefit impoverished segment of the population, it may also increase inequality by transferring tremendous value to the platform operator and investors. Platform owners and their investors are appropriating large amounts of value from users on both sides of the market. The effect of sharing platforms on social inequalities has attracted considerable attention. This research serves as a call for future scholars to delve deeper into the social or worker welfare of sharing economy platforms.

Another contribution of this work applies to economic literature related to the effects of new technologies on the labor market. From technological unemployment to the recent findings on the negative effects of robots on wages [2], technological progress has always been considered a potential nightmare by people with low skills and low income. Many negative aspects, including the labor market polarization [21], income inequality [3], and job destruction [37] are related to technological progress. However, the technological innovation (the Uber platform) studied in this work has a significant empowering effect, especially on low-skill/low-income individuals. This empowering effect lies in the sharing economy's unique features. Our work reveals that these aspects of this working arrangement are bringing people who were displaced during the recession back into the workforce. Such individuals now have another chance to take initiatives and overcome difficult circumstances instead of remaining impoverished. The freedom and flexibility provided by sharing economy platforms are enjoyed by a growing number of people. Again, this conclusion is not drawn without restriction. The empowering effect is derived based on the impact on the overall labor market. The ridesharing platform attracts customers and workers from the traditional taxi industry that may hurt some workers financially [13]. However, this paper reveals that the ridesharing platform has an empowering effect on workers by providing flexible working opportunities with low entry barriers.

Finally, we provide insights for policymakers who have been debating on the sharing economy's effects on workers. The debate around labor issues has largely concerned standard economic variables, such as wages, benefits, and protection, and the classification of "employees" versus "independent contractors." Although the temporary working relationship has certain disadvantages, its advantages, including flexibility and low entry barriers, largely benefit workers. Several studies have shown the benefits of such features. For example, Chen et al. [16] estimated that Uber drivers earn more than twice the surplus of those in conventional sectors due to real-time flexibility. Angrist et al. [8] found that ridesharing drivers benefit considerably from the chance to drive without leasing a taxi medallion. The current research takes this a step further by providing evidence that the sharing economy empowers certain segments of workers.

This study is subject to certain limitations. First, this work shed light on a specific scenario and its generalizability to other settings is unclear. As previously mentioned, this study focused on one sharing economy platform: Uber. Uber is unique and special compared with other sharing economy platforms. The effects on the labor market are based on the nature and characteristics of the job. Our findings may not directly apply to other sharing platforms. Future studies investigating other sharing economy platforms, such as online labor markets, are certainly warranted. Second, we lacked Uber driver-level data, which could allow us to analyze their financial statuses and employment histories directly. This limited us to use macro-level and household-level public data to estimate the effects indirectly. Future researchers with access to such detailed data from companies like Uber could make a further contribution because they would be able to study the effect of sharing economy jobs on workers at the individual level. Third, as discussed, our analysis depended on the key assumption that the entry of sharing economy platforms is exogenous with respect to labor participation and other dependent variables in our analysis, depending on the controls. While we took numerous steps to ensure the robustness of the findings, such as examining pretreatment trends using several robustness checks to evaluate the validity of key assumptions, the entries of Uber into different areas are likely not random. However, we argue that field experiments around Uber entry are not feasible. Bearing the aforementioned in mind, we hope that this work is a first step toward a broad and deep examination of the sharing economy's effect on the labor market, an examination that will provide insights for policymakers, managers, and potential participants in the sharing economy.

Further related to this study and should be noted is that, the COVID-19 pandemic has caused significant economic and social disruptions, and may have lasting effects on employment, income, and working conditions. Millions of Americans lost their jobs and the overall unemployment rate in the US nearly quadrupled between February and June of 2020, producing some of the most extreme unemployment levels ever recorded. In this pandemic, the debate surrounding the sharing economy's labor issue becomes more controversial. Sharing economy workers are generally classified as independent contractors and do not receive sick pay or health benefits. Pressure from different stakeholders has led some sharing economy companies to implement emergency policies to protect workers' income and provide paid leave and benefits, such as health insurance.[8] While ridesharing services are seeing a dramatic drop in ridership during the pandemic, the novel coronavirus positively impacted other sharing economy jobs. For example, UberEats, Postmates, DoorDash, and Instacart saw a surge in demand because more people order groceries and food delivery to avoid leaving their homes. Pure play ridesharing companies, such as Lyft, are shifting gears by collaborating with local organizations for delivery services.[9] Ridesharing drivers deliver medical supplies to health centers, bring meals to kids and seniors, and provide rides to medical appointments for those in low-income communities. Further, there is a surge in activities of online sharing economy platforms for labor contracting, as more people move to the work mode of work from home. In summary, investigating the societal impact of the sharing economy under the COVID-19 pandemic, while out of the scope of this study, will be an important question for future research.

Conclusion

This paper investigates the impact of the leading ridesharing platform on both the supply and the demand sides of the U.S. labor market. We theoretically proposed and empirically evaluated two effects of the introduction of a ridesharing platform: the empowering effect on workers and the competition effect on traditional jobs. We analyzed labor market data during Uber's staggered rollout across different MSAs in the United States. Our findings show that the introduction of a ridesharing platform empowers workers with respect to their employment status and financial status. In these MSAs, the platform attracts low-paid workers from conventional low-skill positions, causing a decrease in employment and increase in wages for low-skill jobs. Our research contributes to the literature on the sharing economy and labor markets by providing empirical evidence on the impacts of an IT innovation and the growth of the sharing economy. The findings also suggest that policymakers and platform operators should account for this broader impact when they devise policies and make strategic decisions.

Notes

1. "Alternative work arrangements" refer to temp agency workers, on-call workers, contract workers, and independent contractors or freelancers.
2. Metropolitan Statistical Areas (MSAs) are defined by the U.S. Office of Management and Budget for statistical purposes (https://www.census.gov/programs-surveys/metro-micro/about.html).
3. According to World Bank's World Development Report, "empowerment" refers to "the enhancement of an individual or group's capacity to make choices and transform those choices into desired actions and outcomes." We use the World Bank definition of this term. It is important to point out that it is somewhat different than the dictionary definition of empowerment.

4 A survey conducted by the Benenson Strategy Group was released on December 7, 2015. The survey found that flexibility is a top motivating factor for people to work as Uber drivers (https://www.uber.com/newsroom/driver-partner-survey/).
5 https://www.uber.com/newsroom/driver-partner-survey/.
6 We acquired this information from one Uber operations manager during a company visit and verified its accuracy using multiple online news sources.
7 "Employees" are all part-time and full-time workers who are paid a wage or salary. The survey does not cover self-employed individuals, such as owners and partners in unincorporated firms, household workers, or unpaid family workers.
8 https://www.cnbc.com/2020/03/09/uber-lyft-doordash-react-to-coronavirus-workers-say-its-not-enough.html.
9 https://www.lyft.com/blog/posts/supporting-our-community.

ORCID

Yili Hong http://orcid.org/0000-0002-0577-7877

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About the Authors

Ziru Li (ziruli@asu.edu) is a Ph.D. candidate in the department of Information Systems at the W. P. Carey School of Business, Arizona State University. Her research focuses on business analytics in online platforms, such as sharing economy platforms, mobile software platforms. She is also interested in big data analysis, machine learning, stochastic modelling and network analysis. She received Outstanding Research Award in the Department of Information Systems for Academic Year 2018-2019.

Yili Hong (yilihong@uh.edu; corresponding author) is a Professor and Bauer Senior Fellow in the Department of Decision & Information Sciences in the C. T. Bauer College of Business at University of Houston, where he also manages the Bauer College Ph.D. programs. His research areas are future of work, digital platforms, and human-AI interaction. Dr. Hong's research has been published in such journals as *Management Science, Information Systems Research, Journal of Management Information Systems, MIS Quarterly, Journal of AIS*, and others. He is a Senior Editor of *Production and Operations Management* and an associate editor of other journals.

Zhongju Zhang (Zhongju.Zhang@asu.edu) is Professor of Information Systems and Data Analytics at the W. P. Carey School of Business, Arizona State University. His research focuses on how information systems/technology and data analytics impact consumer behavior, create business value, and transform business models. He has specific interests in online collaborative platforms and social media, fraud and fake news detection as well as its business and social impacts, platform economy and business models, economic aspects of digital transformation, machine learning and data science. Dr. Zhang's work has appeared in such journals as *Information Systems Research, Journal of Management Information Systems, MIS Quarterly, Production* and *Operations Management*, and many others. He serves on the editorial boards of several journals and has won numerous research and teaching awards.