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Labor market outcomes under digital platform business models in the sharing economy: the case of the taxi services industry

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Abstract
This research investigates the effects of ride-sharing online platforms on the taxi and limousine industry. It also compares and contrasts labor market outcomes between conventional taxi drivers and Uber drivers during the Covid-19 pandemic. The empirical study finds that Uber's online platform has an inconsequential impact on labor supply and earnings among conventional taxi drivers. It suggests that taxi drivers under the traditional employment system behave differently from Uber drivers under an online business platform in the sharing economy, which is further construed by a standard theory that illustrates the operations of the sharing economy.

Keywords Labor market · Employment structure · Sharing economy · Digital infrastructure platforms · Digital technology

1 Introduction

A current popular phrase in the business community is the 'sharing economy' (Sundararajan 2014; Avital et al. 2015), involving the peer-to-peer sharing of goods or services (Cohen and Sundararajan 2015), and offering some positive connotations as opposed to owning specific assets (Kim et al. 2015). The sharing economy is based on online peer-to-peer business transactions, which seek or provide goods and services in hopes of bringing economic benefits to all participants. It is rapidly becoming a new business model for many industries, such as taxi, limousine, travel, lodging, car loaning, finance, staffing, music and video streaming, and shared facilities. The core concept of the sharing economy is that, while a good or service is not in use, someone else may use it for a reasonable fee. The economic benefits go to both users and providers, since the user pays less than what is required to purchase, while the provider earns money when his/her good or service is not being utilized.

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Many electronic commerce (e-commerce) vendors, such as Amazon.com and others, commonly use a traditional business model of supplier and consumer (Zervas et al. 2017) or "one vendor for all consumers." The sharing economy brings suppliers and consumers together where a supplier can find a matching consumer or "many vendors for many consumers." In recent years, the sharing economy has brought dramatic changes in how firms, workers and consumers interact in a market. This is rapidly becoming a significant business sector, projected to reach $40 billion in revenues by the year 2022 and $335 billion by the year 2025 (Tabcum 2020). There is also a surge of interest among American consumers, and a recent report revealed that 72% of American adults have used at least one of eleven different shared or on-demand online services (Jiang 2019).

There are tangible benefits to the sharing economy—resource conservation, environmental friendliness, cost reduction, high utility, and enjoyment (Hamari et al. 2016; Kim et al. 2015; Schor and Fitzmaurice 2015). Some argue that a sharing economy offers environmental friendliness to the extent that sharing goods and services reduces manufacturing and consumption, preserving natural resources and energy. The key enablers of the sharing economy are the growing use of social media and mobile devices. Social media-equipped mobile technologies provide a number of tantalizing technical features (Choi and Im 2015) and allow people to purse their sharing economy opportunities.

A substantial literature has drawn attention to the role of the sharing economy. Part of it focuses on labor market outcomes. Studies of Uber document that its online platform increases capacity utilization, working hours and the number of rides per hour through improved driver-passenger matching (Cramer and Krueger 2016). One study finds that Uber's online platform also has encouraged people in other lines of work to become self-employed Uber drivers, and has increased the labor supply of both self-employed taxi drivers and conventional taxi drivers (Berger et al. 2018). Additionally, Uber drivers have higher earnings than conventional taxi drivers (Berger et al. 2018; Hall and Krueger 2018). Another recent study, however, challenges these positive findings, citing issues associated with methodology, sample selection, data samples, and other factors (Berg and Johnston 2019). Yet another study, which uses nationally representative data, finds that hourly earnings among conventional drivers declined in cities where Uber became available, but there is, so far, no evidence of an adverse employment effect from Uber (Berger et al. 2018). The Covid-19 pandemic and the accompanying economic crisis also may affect the relevance of some of these results.

This study uses an interdisciplinary approach to examine the impact of Uber's online platform on labor market outcomes in the taxi and limousine services industry. We first empirically investigate whether conventional drivers in the taxi and limousine services industry under the traditional employment system are influenced by online platforms used by Uber, Lyft and other ride-hailing companies. We pay particular attention to examining their labor supply and earnings using the 2009–2019 American Time Use Survey data. We also demonstrate how the digital platform business model in the sharing economy creates "social and economic transactions," using the Social Exchange Theory that illustrates the operations of the sharing economy, and discuss how the digital platform business model affects conventional taxi drivers as well as ride-sharing application drivers and their employment, from a Management Information Systems perspective. Lastly, we discuss the current challenges and the potential issues associated with the employment system and the labor market outcomes of Uber drivers amid the Covid-19 pandemic and the accompanying economic crisis.

This study finds that labor supply and earnings among conventional taxi drivers and chauffeurs are *not* impacted by Uber. This empirical finding is also supported by a prediction based on the employer and employee relationship using the Social Exchange Theory. Additionally, the finding of this research signals that there are significant differences in how the two types of drivers are treated by employers with respect to employment conditions, protections, labor unions, fringe benefits, performance evaluation and promotion. Lastly, the empirical exercise using national data adds external validity to the results, but it faces data limitation and sample size issues.

The remainder of this paper proceeds as follows. Section II presents the empirical strategy, data, descriptive statistics, and empirical results for the effect of online platforms on conventional taxi drivers. Section III offers the predominant theory of the sharing economy in Management Information Systems that supports our empirical findings. Section IV discusses employment outcomes in the taxi and limousine services industry during the Covid-19 pandemic. Section V presents major findings of this study. Lastly, we summarize and conclude in Section VI.

2 Labor market impacts of Uber platform in the taxi and limousine services industry

Ride service passengers have a choice of using either conventional taxi drivers or ride-sharing participating drivers. As a result of the diffusion of ride-sharing apps in recent years, are the time allocation decisions and earnings among conventional drivers in the taxi and limousine services industry affected by digital platforms, such as Uber?

2.1 American time use survey data

We use American Time Use Survey (ATUS) data[1] for the years 2009–2019. This data allows us to measure conventional taxi drivers' actual time spent on driving before and after Uber's online platform was implemented in the US,[2] yet excludes a potential structural break in the data caused by the Covid-19 pandemic.

The ATUS respondents are randomly selected from individuals that have completed their eighth and final month of interviews for the Current Population Survey (CPS), and are interviewed only once about how they spent their time. The multi-year micro data that are used in this paper have six data sources: (1) the *respondent* file; (2) the *roster* file; (3) the *activity* file; (4) the *activity summary* file; (5) the *who* file; and (6) the *ATUS-CPS* file.

The *respondent* file contains one record per individual with information, including their demographic status (such as age, sex, race, ethnicity, educational attainment, marital status, metropolitan living status, wage, weeks worked, occupation, industry, and employment status). The *roster*

[1] The American Time Use Survey data for 2009–2019 is sponsored by the United States Bureau of Labor Statistics (BLS), conducted by the U.S. Census Bureau, and is available at https://www.bls.gov/tus/#data (BLS, 2020a). The American Time Use Survey User's Guide is available at https://www.bls.gov/tus/atususersguide.pdf (BLS, 2020b).

[2] The app-based ride-hailing service was first introduced by Uber in May 2010.

file contains information about the age, sex, and relationship to the ATUS respondent of every household member. The *activity* file includes activity-level information collected in the ATUS. The *activity summary* file has information collected in the ATUS diary, with over 400 categories of time use, and contains ATUS respondents' detailed accounts of the total number of minutes spent on each activity during the diary date for a 24-h window, starting at 4 AM on the day before the interview and ending at 4 AM on the day of the interview.[3] The *who* file contains codes that indicate who was present during each activity. The *ATUS-CPS* file gathers one record per household member for all households in which an individual participates in the ATUS and contains each household member's demographic status.

The 2009–2019 ATUS data, gathered from six linked ATUS files using information on the ATUS-CPS file, initially contains 519,536 respondents and includes household members aged 18 and older. In this study, we are interested in respondents who: (i) report an ATUS person line number, which identifies each individual in the household; (ii) are in the labor force and report occupation (either main job or second job);[4] (iii) are eligible to work and drive, which leads to those aged 18–85 at the survey date.[5] After restrictions, the sample size falls to 342,101, and only 1214 respondents (or 0.35%) report occupation as taxi drivers and chauffeurs, including employee-drivers and owner-drivers, and report earnings.[6] Categories of interest in this paper are actual time spent on work and the socio-demographic status of respondents. Furthermore, we focus on the primary and the secondary activities of respondents.

2.2 Empirical strategy

A substantial portion of respondents did not report time spent per day on working because some respondents were in the labor force but (i) absent from work (due to unpaid leave of absence or other reasons); or (ii) did not allocate time to work (due to a day off or other reasons) on the date of the diary interview. To gain both external and internal validity in the empirical results, this study uses a selected sample that consists of only those who report time spent per day on working, record valid earnings, and claim to be in the taxi and limousine services industry on the date of the diary interview.

In this study, the dependent variable is the total number of minutes spent per day on working; hence, our selected sample is censored and consists of no observations (reported by respondents who were absent from work or reported invalid response), zero value observations (reported by respondents who did not allocate time to work) and non-zero value observations (reported by those who worked) on the survey date.

To account for the qualitative differences among records with no observation, zero observations and continuous observations, while also taking into account sample selection bias, we estimate the following equation using a Tobit model (Tobin 1958).

$$T^{*}_{\mathrm{it}} = \delta \mathrm{Uber}_{\mathrm{it}} + X_{\mathrm{it}}\beta + \varepsilon_{\mathrm{it}}, \tag{1}$$

where $T_{\mathrm{it}}{}^{*}$ denotes the respondent's amount of time spent per day on working, $\mathrm{Uber}_{\mathrm{it}}$ represents a dummy variable that takes a value of one in year t when Uber arrives in a metropolitan area in a specific state, and $\varepsilon_{\mathrm{it}}$ is a mean zero individual error term. Furthermore, X_i in Eq. (1) is a vector of exogenous variables of respondent characteristics, which include: (i) age; (ii) gender; (iii) race; (iv) ethnicity; (v) education; (vi) marital status; (vii) number of household members; (viii) employment status; (iv) metropolitan living status; and (v) region. We also control for the respondent's hourly earnings, the unemployment rate (a macro indicator), and the season (of the year) when the diary was completed.

Post-estimation analysis is recommended when working with a Tobit model. We thus also present marginal effects of all explanatory variables in the estimated specifications using the decomposition procedure developed by McDonald and Moffit (1980). Marginal effect is the conditional mean of the dependent variable (time spent per day on working), when the explanatory variable (i.e., hourly wage) changes by one unit.

2.3 Descriptive statistics

Table 1 shows selected socio-economic characteristics of respondents with a particular focus on those in the taxi and limousine services industry. In the 2009–2019 ATUS data, only 0.35% (or 1,214 out of 342,101 workers) claim to be conventional taxi drivers and chauffeurs in the U.S. The hourly earnings of conventional taxi drivers and chauffeurs are lower than *non*-taxi drivers and chauffeurs ($1,368.21

[3] Time use categories include working and work-related activities (05). A detailed description is available in the American Time Use Survey Multi-Year Activity Coding Lexicons 2003–2019 (BLS, 2020c).

[4] In the 2009–2019 dataset, 65.85% of respondents (or 342,101 out of 519,536 respondents) are in the labor force at the survey date.

[5] In the 2009–2019 dataset, the age of the respondents, who report occupation, claim to be in the taxi drivers and chauffeurs occupation (9140 occupation code) and are eligible to work, is ranged from 18 and 85.

[6] In the data survey, the respondents who report their occupation as Taxi Drivers and Chauffeurs (9140 occupation code based on the Census Occupation Classification System) include *all* drivers and chauffeurs since the survey does not ask further details (i.e., employee-drivers and owner-drivers are *not* clearly defined).

Table 1 Selected socio-economic characteristics of taxi drivers by employment status, 2009–2019

Socio-economic variables	(1) Taxi driver and chauffeurs $n = 1214$			(2) Non-taxi driver and chauffeurs $n = 340,887$			(3) All workers $n = 342,101$		
	Total	Mean	SD	Total	Mean	SD	Total	Mean	SD
Time spent on working per day (in min)	148	490.770	214.452	44,971	434.41	201.92	45,119	434.60	201.99
Hourly earnings									
Age	564	1368.21	851.51	200,484	1796.27	1425.74	201,048	1795.07	1424.63
18–34	245	0.202	0.402	112,279	0.329	0.470	112,524	0.329	0.470
34–44	269	0.222	0.415	88,371	0.259	0.438	88,640	0.259	0.438
45–54	322	0.265	0.442	79,365	0.233	0.423	79,687	0.233	0.423
55–64	252	0.208	0.406	46,563	0.137	0.343	46,815	0.137	0.344
65–85	126	0.104	0.305	14,309	0.042	0.201	14,435	0.042	0.201
Gender									
Male	1020	0.840	0.367	176,911	0.519	0.500	177,931	0.520	0.500
Female	194	0.160	0.367	163,976	0.481	0.500	164,170	0.480	0.500
Education									
Less than HS Diploma	108	0.089	0.285	26,368	0.077	0.267	26,476	0.077	0.267
HS Grad-Diploma or Equiv	388	0.320	0.467	75,887	0.223	0.416	76,275	0.223	0.416
Some College/ Assoc Degree	330	0.272	0.445	80,546	0.236	0.425	80,876	0.236	0.425
At least Bachelor's Degree	194	0.160	0.367	89,204	0.262	0.440	89,398	0.261	0.439
Race									
White only	539	0.444	0.497	210,517	0.618	0.486	211,056	0.617	0.486
Black only	343	0.283	0.450	41,640	0.122	0.327	41,983	0.123	0.328
Asian only	104	0.086	0.280	12,695	0.037	0.189	12,799	0.037	0.190
Other	34	0.028	0.165	7153	0.021	0.143	7187	0.021	0.143
Ethnicity									
Hispanic	190	0.157	0.363	54,218	0.159	0.366	54,408	0.159	0.366
Non-Hispanic	830	0.684	0.465	217,787	0.639	0.480	218,617	0.639	0.480
Marital status									
Married	702	0.578	0.494	198,615	0.583	0.493	199,317	0.583	0.493
Unmarried	512	0.422	0.494	142,272	0.417	0.493	142,784	0.417	0.493
Metropolitan living status									
Metropolitan living	957	0.788	0.409	232,500	0.682	0.466	233,457	0.682	0.466
Non-metropolitan living	61	0.050	0.219	37,432	0.110	0.313	37,493	0.110	0.312
Region									
Northeast	371	0.306	0.461	58,987	0.173	0.378	59,358	0.174	0.379
Midwest	168	0.138	0.345	75,604	0.222	0.415	75,772	0.221	0.415
South	377	0.311	0.463	125,742	0.369	0.482	126,119	0.369	0.482
West	298	0.245	0.431	80,554	0.236	0.425	80,852	0.236	0.425

Time spent on working per day: (a) 258,046 out of 342,101 (or 75%) of all workers did not report at the survey date; (b) the presented figure is measured by those who reported positive minutes (45,119 out of 84,055 respondents)

Hourly earnings: 141,053 out of 342,101 (or 41%) of all workers did not report at the survey date

Education, Race, and Ethnicity: 69,076 out of 342,101 (or 20%) respondents had invalid responses

Metropolitan living status: 71,151 out of 342,101 (or 21%) respondents had invalid responses

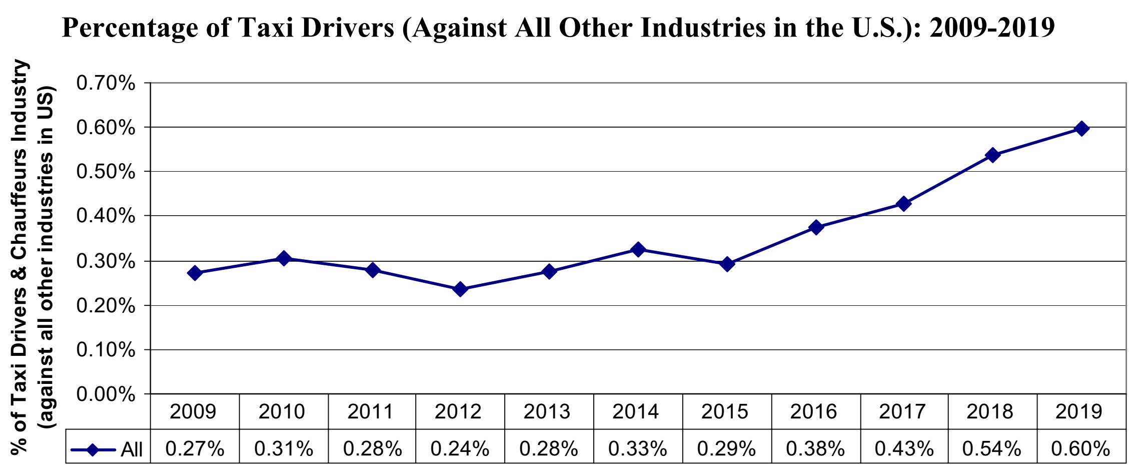


Fig. 1 Percentage of taxi drivers (against all other industries in the USA): 2009–2019

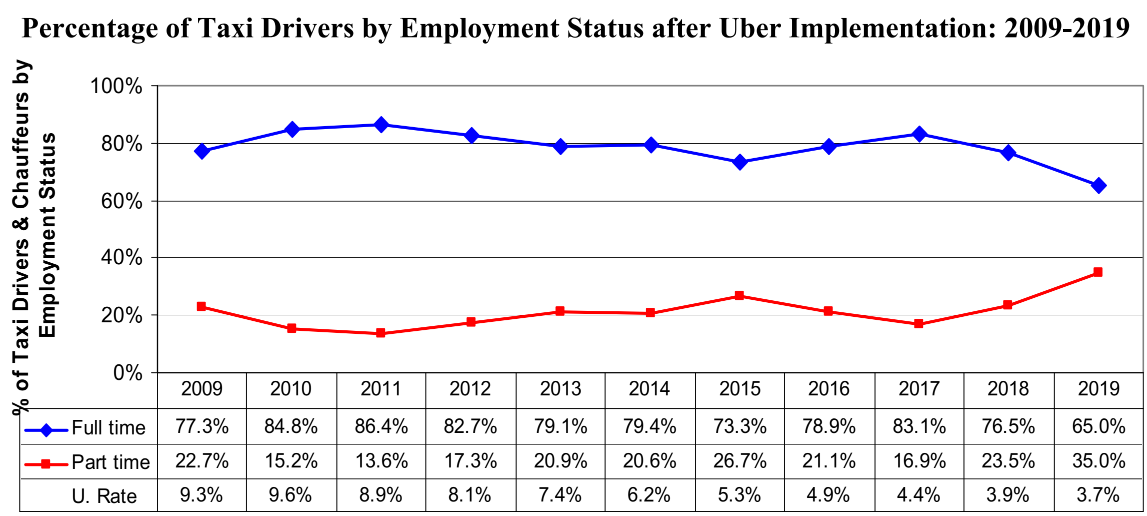


Fig. 2 Percentage of taxi drivers by employment status after Uber implementation: 2009–2019

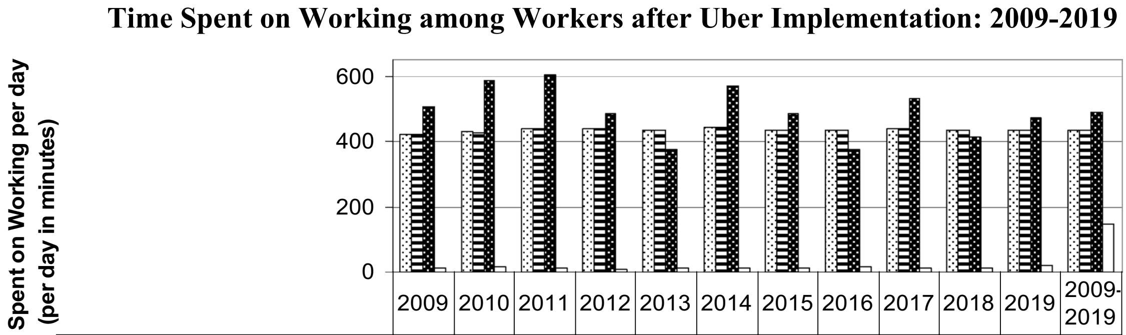
vs. $1,796.27).[7] The table also shows that taxi drivers and chauffeurs are likely to be older (10% of them are older than 65 years old), male (only 16% are female), less educated, and more apt to be living in metropolitan areas, compared to workers in all other industries.

Figure 1 shows that the percentage reached a low of 0.24% in 2012, which possibly resulted from the U.S. Great Recession and/or Uber competition, and it reached a high of 0.60% in 2019 when the overall national unemployment rate reached a low of 3.7%. These results suggest that the taxi and limousine services industry represents a very small workforce and that the industry is sensitive to changes in economic and market conditions.

Figure 2 shows the employment status of conventional taxi drivers after Uber implementation. On average, 79% of conventional taxi drivers were *full*-time workers for the years 2009–2019. In addition, the percentage of *full*-time conventional taxi drivers during the 2009–2017 period was rather stable at around 80% (except in 2015 when it was at a low of 69%), then it started to decline in 2017 and reached 65% in 2019.

Figure 3 shows time spent on working per day in minutes among conventional taxi drivers. On average, conventional taxi drivers work longer hours than *non*-taxi drivers (8.19 vs. 7.25 h per day). Although there are some

[7] In the data sample, the minimum hourly earnings for both taxi drivers & chauffeurs and *non*-taxi drivers & chauffeurs is reported as $0, while the maximum hourly wage for taxi drivers & chauffeurs and *non*-taxi drivers & chauffeurs are reported as $12,121.42 and $192,307, respectively.



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2009-2019
All Workers	421	429	437	440	435	444	434	436	440	433	434	435
Non-Taxi Drivers & Chauffeurs	421	428	437	440	435	444	433	436	440	433	434	435
Taxi Drivers & Chauffeurs	505	587	604	485	377	571	485	378	530	415	472	492
Taxi Drivers & Chauffeurs: n=	14	15	13	10	11	12	13	16	11	12	21	148

* Workers who reported zero minutes for time spent working per day are not included in calculation.

Fig. 3 Time spent on working among workers after Uber implementation: 2009–2019. *Workers who reported zero minutes for time spent working per day are not included in calculation

fluctuations on time spent on working per day among conventional taxi drivers during the years 2009–2019, it appears that conventional taxi drivers' working time is less sensitive to changes in economic and market conditions, because their working time is fairly consistent regardless of varied unemployment rates during the 2009–2019 period (e.g., 485 minutes, or 8.08 hours per day when the unemployment rate was 8.1% in 2012 vs. 472 minutes, or 7.87 hours per day when the unemployment rate was 3.7% in 2019).

2.4 Empirical results

Table 2 shows the results of the Tobit estimates, including the marginal effects of estimated explanatory variables on one's amount of time spent per day on working for taxi drivers and chauffeurs and for *non*-taxi drivers and chauffeurs. We focus on the analyses of taxi drivers and chauffeurs only.

The coefficient of $Uber_{it}$ in the table is positive, indicating that conventional taxi drivers' actual time spent per day on driving increases with the implementation of Uber's online platform; however, the coefficient of the estimate and the marginal effect of $Uber_{it}$ are both statistically insignificant. It implies that Uber's online platform had an inconsequential impact on conventional taxi drivers' actual time spent on working per day. This result is consistent with the existing finding that there is no evidence of an adverse employment effect from Uber (Berger et al. 2018).

Column (2) in Table 2 further shows that the coefficient of the *hourly wage* is negative, suggesting that conventional taxi drivers' actual time spent per day on driving decreases with the hourly wage; however, the magnitude of the coefficient is near zero and the coefficient of the estimate and the marginal effect of *hourly wage* are both statistically insignificant. It suggests that hourly wage also had an inconsequential effect on conventional taxi drivers' actual time spent on working per day. This result may be driven by the fact that two types of taxi drivers (employee-drivers and owner-drivers) behave differently with respect to hourly wage.

The coefficient of *metropolitan living* in Column (2) in Table 2 is also negative, suggesting that conventional taxi drivers' actual time spent per day on driving is lower when drivers are in metropolitan areas; however, the coefficient of the estimate and the marginal effect of *metropolitan living* are both statistically insignificant. A similar result emerges from education, race and ethnicity, marital status and the number of persons in their household, confirming that each of these factors also had an insignificant effect on time spent on working per day among conventional taxi drivers.

On the other hand, Column (2) in Table 2 shows that the marginal effect of being male on time spent per day on working for conventional taxi drivers is 53 min. This result is weakly supported empirically and suggests that male conventional taxi drivers work longer than female counterparts. In addition, the coefficient of *full*-time employment status is positive and statistically significant. It confirms that *full*-time employment status increases actual time spent on work per day by 3.17 hours (or 189.91 minutes) and the marginal effect is 1.03 hours (or 61.98 minutes).

These results suggest that the actual time spent on driving among conventional taxi drivers is not dependent on the ride-sharing apps (such as Uber), hourly wage, location, or drivers' socio-economic factors, given the nature of their work. It is rather influenced by their employment status, suggesting that compliance with employment laws and regulations appears

Table 2 Tobit estimate and marginal effect of time spent on working: 2009–2019

All Workers: n = n = 342,101 Y = time spent on working (in minutes)	Taxi driver and chauffeurs n = 1214		Non-taxi driver and chauffeurs n = 340,887	
	(1)	(2)	(3)	(4)
	Estimated coefficient	Marginal effect	Estimated coefficient	Marginal effect
Uber	31.451	10.590	− 5.486	− 2.251
	(138.066)	(46.316)	(5.850)	(2.401)
Hourly wage	− 0.004	− 0.001	− 0.002**	− 0.001
	(0.030)	(0.010)	(0.001)	(0.000)
Age: 18–85	37.101	12.661	46.885***	19.451***
	(152.275)	(52.468)	(8.888)	(3.731)
Age: 34–44	200.237	70.683	50.452***	20.982***
	(134.353)	(49.192)	(9.030)	(3.809)
Age: 45–54	157.564	54.865	54.402***	22.708***
	(134.041)	(48.022)	(8.975)	(3.813)
Age: 55–64	89.315	30.620	57.762***	24.248***
	(122.498)	(42.601)	(9.131)	(3.923)
Gender: male	164.049	53.175*	45.840***	18.808***
	(101.517)	(31.602)	(3.567)	(1.465)
Education: high school with diploma	33.056	11.211	7.753	3.187
	(154.316)	(52.519)	(8.183)	(3.372)
Education: some college/associate degree	20.300	6.870	23.646***	9.754***
	(156.111)	(52.901)	(8.096)	(3.360)
Education: at least bachelor's degree	110.884	38.405	35.076***	14.4266***
	(165.016)	(58.428)	(8.199)	(3.383)
Race: White only	224.795	74.746	− 9.624	− 3.959
	(209.793)	(68.671)	(12.050)	(4.978)
Race: Black only	302.481	105.808	− 13.113	− 5.344
	(208.827)	(75.330)	(12.925)	(5.239)
Race: Asian only	160.113	56.793	1.484	0.609
	(256.863)	(95.111)	(14.496)	(5.953)
Ethnicity: Hispanic	97.955	33.911	− 0.931	− 0.382
	(116.095)	(41.189)	(5.403)	(2.213)
Marital status: married	− 56.758	− 19.152	− 10.230**	− 4.197**
	(96.271)	(32.488)	(4.149)	(1.703)
Number of person in household	10.711	3.619	− 1.571	− 0.644
	(31.106)	(10.511)	(1.442)	(0.591)
Employment: full time	189.913**	61.976**	124.908***	48.607***
	(95.671)	(30.166)	(5.052)	(1.864)
Metropolitan living (yes = big city)	− 164.139	− 58.216	3.411	1.396
	(176.440)	(65.206)	(6.321)	(2.584)
Constant	5952.494	–	− 1381.062	–
	(131,250.900)	–	(6299.420)	–
/sigma	435.855	–	423.448	–
	(34.891)	–	(1.704)	–
Other variables	Yes	Yes	Yes	Yes
Pseudo R^2	0.016	–	0.002	–

*Standard errors are shown in parentheses. ***, **, * indicate significant at the 1%, 5% and 10% levels, respectively

Table 3 Social exchange theory transaction types

Type of relationship	Type of Transaction	
	Social exchange	Economic exchange
Social exchange	#1. Social transaction in a social relationship	#2. Economic transaction in a social relationship
Economic exchange	#3. Social transaction in an economic relationship	#4. Economic transaction in an economic relationship

to be an important factor for conventional taxi drivers' time allocation decision regarding actual time spent per day.

3 Applying the social exchange theory to the labor market

3.1 Employment relationships

To frame the empirical work of this study and interpret its findings, the Social Exchange Theory (SET) (Cropanzano and Mitchell 2005) is useful.

The SET evaluates the social and economic transactions between individuals or groups of individuals to explain how a transaction affects relationships and outcomes among the participants. Given the connections between social and economic exchanges and obligations, a relationship may be initiated by either party or both may reciprocally influence each other. For example, an employee has certain job responsibilities and obligations. Table 3 illustrates the theory. The SET identifies a transaction using one of the four cells or categories. Within the scope of this paper, we focus on the employer and employee relationship applying the SET lens to ride-sharing applications, such as Uber or Lyft.

The empirical findings of this study indicate that economic exchange did not appear to play a significant role in the outcomes among conventional taxi drivers. Instead, the social factor, which refers to the employment status and relationship with the taxi company, appears to be the decisive factor for them. Molm (1994) discusses the interdependent exchanges through a reciprocal form. This involves mutual and complimentary arrangements that benefit both parties; the employee (i.e., taxi driver) gives his/her availability and full-time work to the employer (i.e., the taxi company) and, in return, the employer pays a salary.

It is important to note that our discussion based on the SET apply to conventional taxi drivers who are under a formal employment contract with a taxi company. Since our empirical analyses are likely to include both employee-drivers and owner-drivers (due to data limitations) our discussion faces some shortcomings.

3.2 Ride-sharing application drivers versus conventional taxi drivers

Based on the Social Exchange Theory (SET) presentation, we compare and contrast ride-sharing application drivers and conventional taxi drivers.

Given the ongoing surge in the use of social media and popular mobile apps, more people are becoming accustomed to smartphone-driven transactions and activities. According to a report (Jiang 2019), the ride-sharing population doubled in size from 2015 to 2018 and is growing across demographic groups. Cramer and Krueger (2016) indeed find that Uber's application increases capacity utilization and the number of rides per hour through improved driver-passenger matching for its drivers. With this rapid growth, more work opportunities are likely being provided to ride-sharing application drivers than to conventional taxi drivers. Based on the 'economic transaction in an economic relationship' in Cell #4 in Table 3, the driver and the ride-sharing application are viewed as an employer and employee relationship because the driver can *only* participate through the application. In this case, the ride-sharing apps, such as Uber or Lyft, significantly increase work opportunities *only* to those app participating drivers, from the employee's perspective.

As it is also well recognized, ride-sharing application drivers, such as Uber drivers, are not legally employed by the app providers, and ride-sharing application drivers are often not *full*-time. The driver can be "on or off" as a participating Uber driver whenever s/he wants to be. In reality, many Uber drivers have other jobs and their driving is part time work. Based on the 'social transaction in an economic relationship' as the employee and employer relationship in Cell #3 in Table 3, the employee is legally contracted only to his employer under a traditional employer and employee relationship. In this circumstance, conventional taxi drivers are under a formal employment contract with a taxi company, while Uber drivers are not. This explains why ride-sharing application drivers differ from conventional taxi drivers.

In a crisis similar to the current Covid-19 pandemic, there may be a massive workforce reduction among *all* drivers; however, the magnitude might differ between ride-sharing application drivers and conventional taxi drivers. Uber drivers may have more flexibility and get more opportunities to earn, but they also be easily denied work if either the application is not available or the passengers do not respond to the application (e.g., by exercising social distancing in the wake of Covid-19). Thus, ride-sharing application drivers, who can *only* participate through the application without a formal employment contract, are more likely to experience a workforce reduction relative to conventional taxi drivers, in the event of a sharp decline in the demand for a ride-sharing service.

4 Employment system and labor market outcomes during the Covid-19 pandemic

After the World Health Organization declared a Covid-19 pandemic on March 11, 2020, and the U.S. declared a national emergency on March 13, 2020, the demand for ride services for both conventional taxi drivers and Uber (and other app-based ride-hailing) drivers suddenly and sharply declined. When the first U.S. lockdowns and social distancing protocols were enacted, leading to a drop in ridership, some application participating drivers had to shift to food delivery, and some stopped working, for fear of contracting the virus or other reasons (UCSC 2020). Many app-based ride-hailing drivers lost significant income (Katta et al. 2020; UCSC 2020). This phenomenon is consistent with the fact that application participating drivers are easily denied work if either the application is not available or potential passengers do not use the application.

At the beginning of the pandemic, when conventional taxi drivers became unemployed, they were able to apply for standard unemployment insurance (UI) benefits as employees of taxi and limousine companies, while Uber (and other app-based ride-hailing) drivers were not. Uber and other ride-hailing companies treat drivers as “independent contractors” who choose when and how much to work (Katta et al. 2020; NPR 2020), and self-employed individuals, including “independent contractors,” usually are not eligible for UI benefits.

In response to massive unemployment at the beginning of the pandemic, the federal Coronavirus Aid, Relief and Economic Security (known as CARES) Act became law on March 27, 2020. The Pandemic Unemployment Assistance (PUA) Program was offered to workers who were previously uncovered by UI programs, including self-employed workers, *gig workers*, and independent contractors. Uber (and other app-based ride-hailing) drivers thus became temporarily eligible for UI benefits (Kovalski and Sheiner 2020; and NPR 2020). The PUA Program was extended to March 14, 2021 under the Continued Assistance for Unemployed Workers (known as CAUW) Act of 2020 (Department of Labor 2021).[8]

The Covid-19 pandemic has highlighted how the labor market outcomes of Uber (and other app-based ride-hailing) drivers and conventional taxi drivers vary significantly as a result of differences in hiring conditions, the employment system, and labor union privileges.[9] The Covid-19 pandemic also has raised a question about the role of the ride-sharing apps, such as Uber’s online platform, for app participating drivers in the labor market.

5 Discussion

5.1 Current workforce in the sharing economy

In light of the empirical results indicating that Uber’s online platform has had an insignificant effect on labor supply and earnings among conventional taxi drivers, there are a few important points. First, it could be that, in practice, app-driven ride-hailing services and conventional taxi services are imperfect substitutes for each other. This limits the application of the Social Exchange Theory. Second, the impact of an online platform in the sharing economy appears to be inconsequential for conventional taxi drivers, who are under the traditional employment system, although it is vital for Uber drivers.

Third, as suggest by the first point, conventional taxi drivers and Uber drivers are behaving differently in the market. To support this argument, we consider that conventional taxi drivers’ labor supply is likely to follow reference-dependent preferences,[10] while that of Uber drivers does not. In this case, conventional taxi drivers have a target for daily earnings and/or hours worked, and work until the target is reached, following the reference-dependent preference model, while Uber drivers, who have a high earnings and/or a strong income-smoothing preference, will work longer without setting a target, following the standard neoclassical model of labor supply.

[8] The Continued Assistance for Unemployed Workers (CAUW) Act moved the Pandemic Unemployment Assistance (PUA) Program expiration date from December 31, 2020 to March 14, 2021. The maximum PUA eligibility has been extended from 39 to 50 weeks (minus the weeks the individual received regular unemployment benefits and Extended Benefits) (DOL, 2021).

[9] National Taxi Workers’ Alliance (NTWA) is a U.S. labor union, which was initially founded by the New York Taxi Workers’ Alliance in 1998, and it became an affiliate of the AFL-CIO in 2011. See Henry-Offor (2012) for detail about how taxi workers have attempted and reached labor union privileges.

[10] The theory of the reference-dependent preference has its root in a *target earnings behavior*, and it argues that an employee who is a *target earner* sets a daily income target, works until earnings reach the target level, and then quits. (Koszegi and Rabin 2006, 2007; Tversky and Kahneman 1991; and others). Existing studies on labor supply among taxi drivers find that income reference-dependent preference plays a substantial role in their labor supply decisions (Crawford and Meng 2011; Farber 2008, 2005; Camerer et al. 1997; and others); taxi drivers indeed do have reference-dependent preferences (e.g., Agarwal et al. 2015; Chou 2002).

Fourth, there are significant differences in how the two types of drivers are treated in the labor market. Conventional taxi drivers, for example, are more likely to be (i) reliant on an employer and/or a labor union for employment, capital (mainly a vehicle), benefits and protection, (ii) exempt from a customer rating system, and thus, (iii) are less concerned about their reputations, while Uber drivers are not. The experience of the Covid-19 pandemic further confirms these notions in which conventional taxi drivers are a protected workforce, while Uber drivers are a highly vulnerable workforce.

Fifth, conventional drivers are less likely to be more geographic and population dependent than Uber drivers. It is evident that location and population density affect the demand for ride services for both types of taxi drivers, but the Uber platform is more effective in highly populated metropolitan areas than in less populated suburban areas.

Lastly, empirical exercises using nationally represented datasets, such as ATUS and CPS often face data limitations. Indeed, the small number of respondents in the taxi drivers and chauffeurs occupation in the ATUS and CPS data poses a question on robustness in our empirical findings. The lack of details on respondents' information in the data sample also includes *all* self-identified taxi drivers and chauffeurs (employee-drivers and owner-drivers); hence, our dataset limits the scope of our results. Additional empirical tests using publicly available private datasets could offer reliable results, but weaker external validity. All these are debatable points left for future research and discussion concerning the role of online platforms in the sharing economy and labor market outcomes in the taxi and limousine services industry and other relevant industries.

5.2 Future workforce in the sharing economy

As the sharing economy further expands with the diffusion of digital platform business models, the number of so-called *gig workers*, including Uber (and other app-based ride-hailing) drivers, is expected to increase. It is important for *gig workers* to obtain employment protections, fringe benefits, opportunities for promotion, and labor union privileges. We offer the following proposals.

First, the reclassification of *gig workers* in the occupational classification systems would be beneficial. The classification of *gig workers* is currently inconsistent (Maurer 2019), and *gig workers* are spread among diverse occupation groups and are not easily identified in surveys of employment and earnings (Torpey and Hogan 2016). A clear scheme of classifying *gig workers* will assist career exploration and planning. For example, job seekers, employment counselors, and employers need job classifications to understand the requirements and descriptions of jobs and occupations. It also would allow collection of occupational statistics for *gig workers* and analysis of changes or patterns of occupation in the labor force.

Second, another beneficial development would be the establishment of a temporary labor agency (or a contract firm) that hires *gig workers* as regular employees. Currently, *gig workers* are likely to be in non-regular employment (Torpey and Hogan 2016), such as contingent or alternative employment arrangements, or both.[11] *Gig workers* can be employed and dispatched by a temporary labor agency (or a contract firm) to work in the sharing economy using a specific digital platform for a fixed term. For example, Uber drivers might be employees of a temporary labor agency (or a contract firm). In this case, *gig workers* can be on the payroll of a temporary labor agency (or a contract firm), eligible for employment benefits, including UI benefits, and could possibly attain labor union privileges.

Third, it may be useful to expand the digital platform business model to other occupations. Currently, *gig workers* are found in a number of occupations, not just in the ride-sharing sector. Given that the sharing economy market may continue to grow exponentially, and that the Covid-19 pandemic may linger for years (Zhang 2020), it is likely that the market for *gig workers* will grow.

Fourth, the usefulness of digital platforms has been growing as their features have been enhanced. Initially, such platform simply connected a customer and a *gig worker*, as when the Uber app simply allowed a customer to find a nearby driver. Now, the app also offers a rating system that indicates the trust level. Trust has been a prominent issue in the sharing economy (Hawlitschek et al. 2016). It must be addressed to give confidence and provide a safe environment for both customers and *gig workers*. Recently, there are growing issues with safety (Salam 2019), vandalism (Lim 2018), and privacy (Mettler 2019). Additionally, a report reveals that 72% of consumers who have used the sharing economy feel that the experience is not consistent, and 69% of them agree that they will not trust a sharing economy vendor unless someone they trust recommends them (PricewaterhouseCoopers 2019). The act of rating both customer and *gig worker* through the digital platform mechanisms or protocols will give participants more confidence in entering sharing economy transactions.

[11] Contingent workers are those who don't have an implicit or explicit contract for long-term employment, while alternative employment arrangements include independent contractors (also called freelancers or independent consultants), on-call workers, and workers provided by temporary help agencies or contract firms. Tashiro (2017) discusses non-regular employment in detail.

6 Concluding remarks

The primary interest of this study is to examine the role of online platform business models in the sharing economy. To do so, this study uses an interdisciplinary approach to examine the effect of Uber's online platform on labor market outcomes in the taxi and limousine services industry. We first examine whether Uber's online platform affects labor supply and earnings among conventional drivers in the taxi and limousine services industry in the USA. We further evaluate how "social and economic transactions" affect ride-for-hire services offered by ride-hailing companies, such as Uber, via online platforms, and then support our empirical findings using the Social Exchange Theory.

The empirical analyses find that the Uber online platform had insignificant effects on both labor supply and earnings among conventional taxi drivers and chauffeurs. It suggests that conventional taxi drivers, who are under the traditional employment system, behave differently than Uber drivers, who are under an online business platform in a sharing economy, due to their differences in the response to reference-dependent preferences, employment conditions, protections, labor union privileges, fringe benefits, performance evaluation and promotion. The Covid-19 pandemic also confirms that labor market outcomes vary between conventional taxi drivers and Uber drivers due to employment status. The analyses further suggest that an empirical exercise using a nationally represented dataset data gains external validity in its results but faces data limitations, sample size issues, and possibly time lags.

From the perspective of Management Information Systems, the unique application of the Social Exchange Theory (SET) to the digital platform business model demonstrates that the ride-sharing application, such as Uber, creates "social and economic transactions" among users, and it impacts ride-sharing application drivers, traditional drivers and their employment. The SET presentation, in conjunction with our empirical findings, also suggests that economic exchange did not appear to play a significant role in the outcomes among conventional taxi drivers. Instead, the social factor, such as the employment status and relationship with the taxi company, appears to be the decisive factor for them. Additionally, it confirms that traditional drivers differ from ride-sharing application drivers in the market, and that online platform business models in a sharing economy are expected to influence traditional business models of suppliers and consumers in various industries, including the taxi and limousine services industry.

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