The Economic Impacts of Private Ridesharing - Quality of Urban Mobility and Labor Market Effects

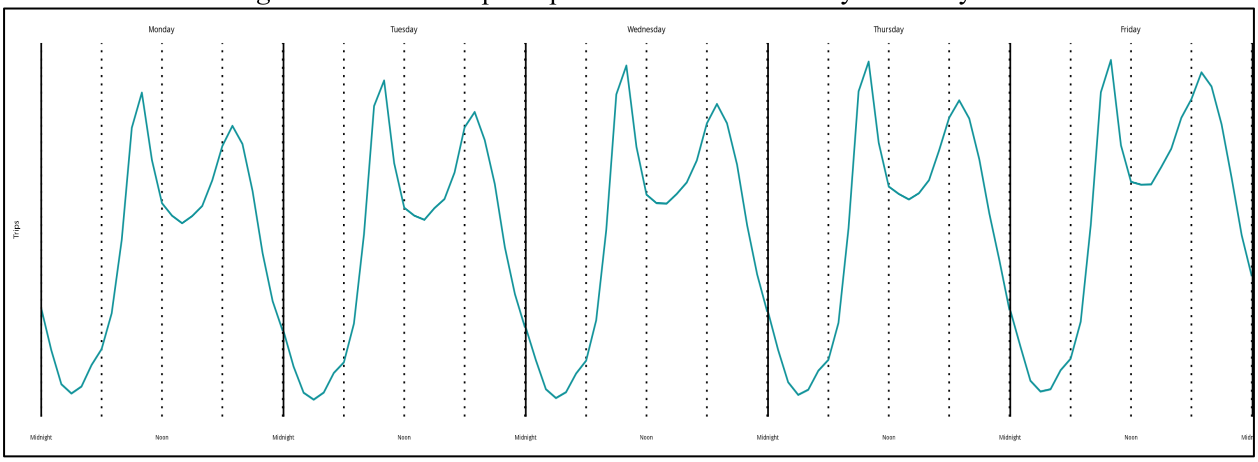
1. An Empirical Analysis of the Impact of Ridesharing on Congestion

1.1 Motivation

Cities around the world, especially in developing countries, are grappling with the problem of traffic congestion. A recent study by the Centre for Science and Environment (CSE)[1] reports that Delhi experiences almost twelve hours of 'peak hour traffic'. Congestion adversely impacts economic activity and worker productivity, air pollution, and fuel costs, rendering it a major scourge of cities worldwide.

Emergent research suggests that a modal shift in cities from motorised low occupancy transport solutions (e.g. car, motorcycle, and hail taxi services) to ridesharing platforms has the potential to significantly reduce congestion. For example, Cramer and Krueger (2016) demonstrate significant advantages of the ridesharing platform, Uber, over traditional hail taxis. They find that the capacity utilization rates for UberX drivers in the U.S. are 30 percent higher when measured by time and 50 percent higher when measured by miles. These benefits of ridesharing platforms and ensuing utilization rates are unsurprising given the typical distribution of demand for rides or taxi services. Figure 1, which presents the average number of UberX dropoffs per hour in Delhi NCR by weekday, emphasizes the bimodal distribution of demand for rides during this period. That is, weekday demand for taxi rides peaks for portions of the morning and evening and for the interim period, it is low. This demand distribution is reversed on weekends but is robust to all other days of the week.

Figure 1: UberX Dropoffs per hour in Delhi NCR by Weekday

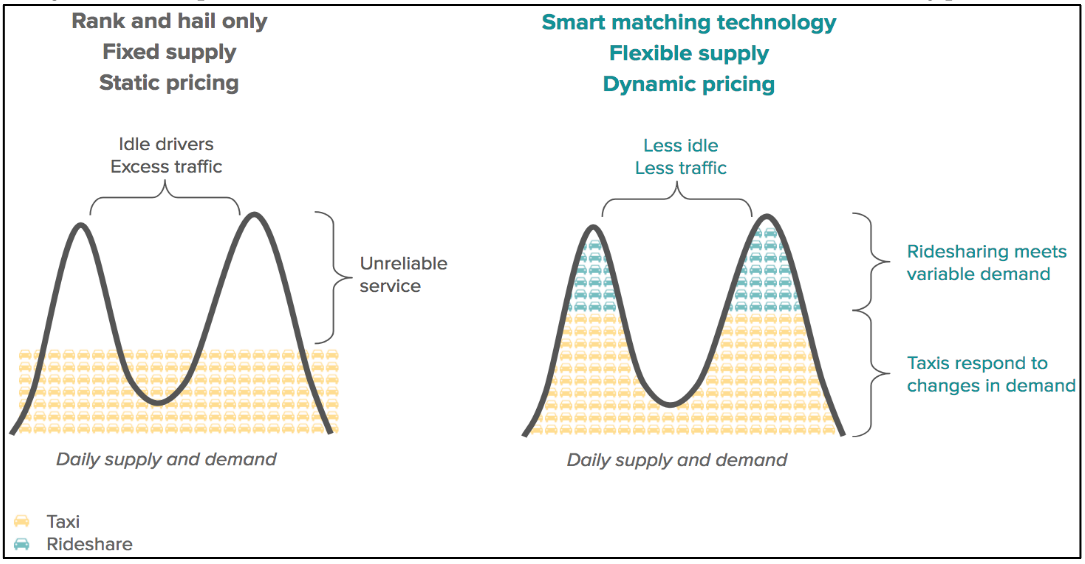


Source: Uber Data

[1] https://www.cseindia.org/userfiles/Google-analysis-by-CSE-graphs-and-charts.pdf

As shown in Figure 2, such bimodal demand is best addressed through a flexible labor supply model as the one that characterizes ridesharing platforms. In the case of traditional mobility services such as taxis, a demand-agnostic, constant supply of drivers results in economic inefficiencies - unfulfilled demand or unreliable service during peak hours and idle drivers and congestion during non-peak hours. In contrast, in the case of ridesharing services, a flexible labor supply model allows for variable peak demand to be addressed, and yields less idle time and traffic during non-peak hours.

Figure 2: Comparison of business model of hail taxi services with ridesharing platforms



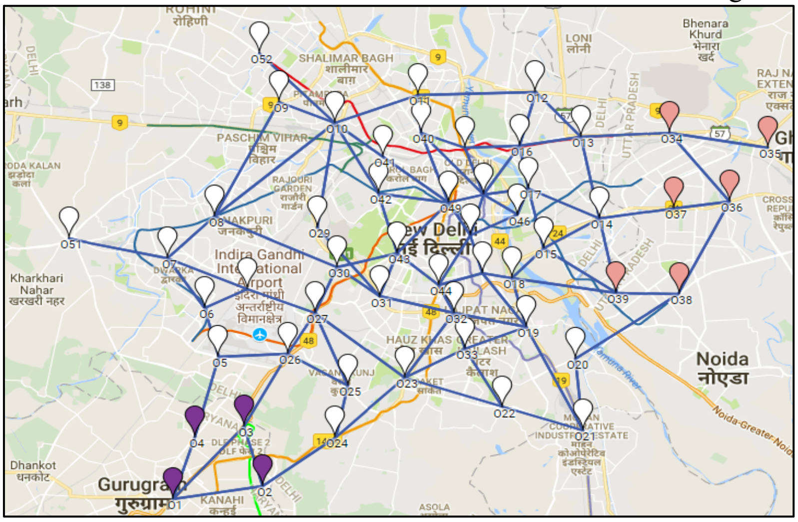
Source: Uber Data

That ridesharing platforms reduce congestion and improve quality of urban mobility assumes that these platforms substitute private car ownership to reduce each individual's vehicle miles travelled (VMT) and congestion. However, an emergent body of research (Clewlow and Mishra, 2017; Schaller, 2017) also suggests that ridesharing platforms might draw commuters from public transport and other high occupancy shared mobility services, thereby, increasing VMT and congestion. This mixed empirical evidence on the impacts of ridesharing platforms is largely an outcome of lack of quality data and an appropriate empirical setting. In this study, we use an exogenous disruption of ridesharing services in Delhi to causally estimate the impact of ridesharing platforms on congestion. Our analyses of impact are informed by granular route-level traffic data collected from Google Maps and complementary ridership data from the Delhi Metro Rail Corporation (DMRC) and other transport services.

1.2 Data, Methodology and Results

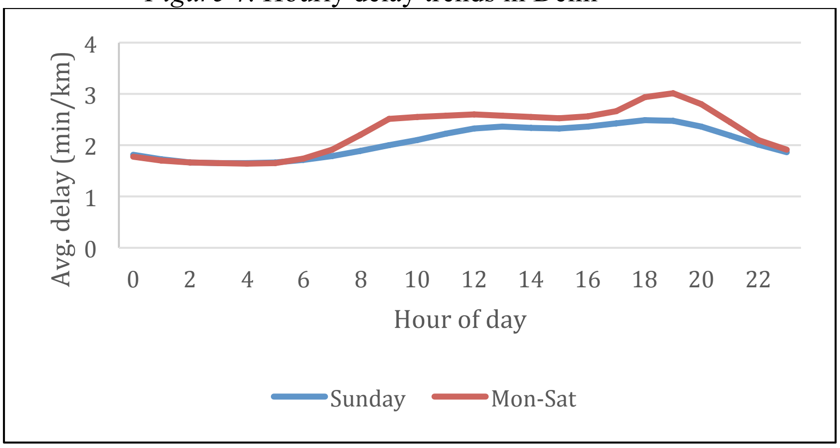
Drivers of Uber and Ola, dominant ridesharing platforms in India, went on a strike in New Delhi from February 11 - 23, 2017, demanding better pay. During this period, ridesharing services were completely disrupted, providing the setting for a natural experiment to measure the effect of ridesharing on congestion. We obtained granular traffic data for a set of 186 routes for the period January 1, 2016 – February 16, 2017[2], giving us six days' overlap with the strike. Specifically, for the routes shown in Fig. 3, we obtained crowdsourced data on estimated trip time according to live traffic conditions per Google Maps queries every 20 minutes, 24 hours per day. The routes were chosen to cover major traffic corridors in the city.

Figure 3: The set of routes for which we collected data from Google Maps



Our measure of congestion is travel delay (delay*,* henceforth), which is the estimated time in minutes to cover a kilometer, under live traffic conditions. By definition, more congested roads will see higher travel delays and vice versa. Figure 4 below presents the average delay in Delhi for the entire time period of the data. As expected, Sundays see significantly improved traffic conditions relative to weekdays.

Figure 4: Hourly delay trends in Delhi



[2] We gratefully acknowledge Gabriel Kreindler, who shared these data with us.

We restrict our analyses to six days during the strike (Feb 11 – 16, 2017), and six days before the strike (Feb 4 – 9, 2017). As shown in Figure 5, there is an immediate drop in mean delay at the start of the strike, indicating lower congestion in the absence of ridesharing.

Figure 5: Delay comparison during the first week of the strike, with the week before

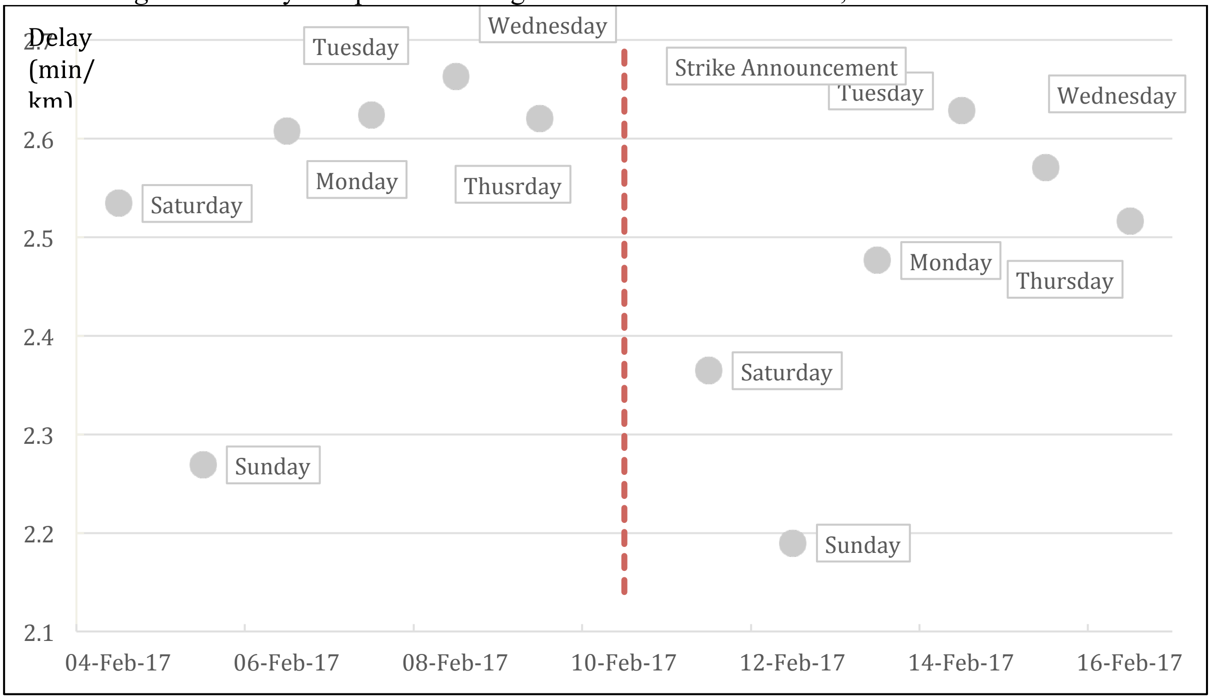


Table 1 presents estimates of the impact of ridesharing services on travel delay. On average, traffic was faster by around 0.10 minutes / km during the strike, between 8am and 9pm. To put this in perspective, average delay on Sundays is lesser compared to the other six days in our data by 0.25 minutes/km. This implies that the strike had about 39% of the effect that a typical Sunday has in reducing congestion[3].

Table 1: Comparison of delay reduction during the strike and a typical Sunday

OLS	(1) Delay (min/km)	(2) Delay (min/km)
Strike dummy	**-0.10***** **(0.003)**	
Sunday dummy		**-0.25***** **(0.001)**
Constant	1.28*** (0.021)	1.71*** (0.004)

[3] Diverse news articles about traffic conditions during the strike corroborate this result- http://www.hindustantimes.com/delhi-news/driving-is-a-breeze-as-cabs-stay-off-roads-in-delhi/story-0Y7HvGhPF9BxAD1tPWSGgJ.html
https://timesofindia.indiatimes.com/city/noida/cab-strike-leads-to-sharp-drop-in-citys-traffic-jams/articleshow/57213939.cms

Route fixed effects	Y	Y
Hour fixed effects	Y	Y
Day of week fixed effects	Y	Y
Observations	93,744	3,036,836
R-squared	0.71	0.63

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In order to assess the robustness of our result, we estimate a difference-in-differences (DiD) specification that compares the documented impact with similar dates for the previous year. We use February 4 – 16, 2017 (excluding Feb 10) as the treated period ("Treated"), and February 6 – 18, 2016 as the untreated period. For both periods, the last 6 days are taken as the post period ("Post"), and their interaction gives the DiD estimate ("Strike DiD"). Table 2 shows that the results are qualitative similar, although slightly lesser in magnitude. Traffic was faster during the strike by 0.08 minutes/ km, which points to 33% of the effect of a typical Sunday in reducing congestion.

Table 2: Difference in differences estimate

OLS	Delay (min/km)
Treated	-0.01*** (0.003)
Post	-0.01*** (0.003)
Strike DiD	**-0.08***** **(0.004)**
Constant	1.32*** (0.016)
Route fixed effects	Y
Hour fixed effects	Y
Day of week fixed effects	Y
Observations	178,746
R-squared	0.70

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These results suggest that people do not substitute ridesharing with low occupancy, privately owned vehicles that increase congestion. A question that assumes importance in this light is what people substituted toward during the strike - less congestion-prone shared mobility services, including public transport, or reduced labor supply (or both). In order to answer this question, we use ridership data from two shared mobility services – the Delhi Metro Rail Corporation that operates the Delhi Metro and Shuttl, a bus aggregator that offers shuttle bus services to its commuters. For both services, we use daily ridership data for each station from the Delhi Metro for two weeks of the strike, and the corresponding period during the previous year. Delhi Metro allows users to either pay per trip by buying tokens, or use pre-paid smart cards. We use data on total ridership, along with the split between tokens and smart cards. Our assumption is that pre-paid smart card usage is representative of frequent metro commuters. Conversely, we assume token users are non-regular metro users.

Our analyses of the metro ridership data find a significant increase in total ridership during the week of the strike (Table 3). We further assess the robustness of our results to a DiD estimation articulated earlier, and find similar results (Table 4). We repeat these analyses for use of tokens as well as smart cards. A simple OLS specification shows that ridership using tokens increased during the period of the strike, but there was no significant effect on ridership using smart cards. The DiD specification, however, yields a positive and significant coefficient for both token and smart card ridership.

Table 3: Comparison of metro ridership during and before the strike

OLS	(1) Total ridership (ln)	(2) Token ridership (ln)	(3) Smart card ridership (ln)
Strike dummy	**0.022***** **(0.006)**	**0.047***** **(0.005)**	**0.010** **(0.007)**
Constant	10.246*** (0.036)	9.547*** (0.030)	9.628*** (0.042)
Station fixed effects	Y	Y	Y
Day of week fixed effects	Y	Y	Y
Observations	1,812	1,812	1,812
R-squared	0.979	0.991	0.973

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Differences in differences estimate for metro ridership

OLS	(1) Total ridership (ln)	(2) Token ridership (ln)	(3) Smart card ridership (ln)
treated	0.068***	-0.018***	0.100***
	(0.006)	(0.005)	(0.008)
post	-0.020***	0.026***	-0.050***
	(0.006)	(0.005)	(0.008)
strike did	**0.042*** **	**0.021*** **	**0.060*** **
	(0.009)	**(0.007)**	**(0.011)**
Constant	10.177***	9.538***	9.512***
	(0.028)	(0.023)	(0.034)
Station fixed effects	Y	Y	Y
Day of week fixed effects	Y	Y	Y
Observations	3,624	3,624	3,624
R-squared	0.974	0.990	0.965

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, we use ridership data from Shuttl, an app-based bus sharing service that is operational in cities like Gurgaon, Delhi and Bangalore. Shuttl operates in two business segments: B2B and B2C. We obtain route-day-hour level data for each day between February 3 and 16, 2017 for both segments. Specifically, we assess whether total number of bookings, bookings per trip, and number of new users of the service increased during the period of the strike. We run an OLS specification as in Table 1, for each segment, after controlling for route, day-of-week and hour-of-day fixed effects. Regression results are reported in Table 5 for the B2B category, and in Table 6 for the B2C category.

Table 5: Shuttle ridership (B2B)

VARIABLES	**(1) Bookings (ln)**	**(3) Bookings per trip (ln)**	**(4) New users (ln)**
Strike dummy	**-0.021**	**-0.017**	**0.074** **
	(0.042)	**(0.037)**	**(0.035)**
Constant	1.276***	1.697***	-1.137***
	(0.241)	-0.166	(0.196)
Hour fixed effects	Y	Y	Y
Route fixed effects	Y	Y	Y
Day of week fixed effects	Y	Y	Y
Observations	480	480	480
R-squared	0.793	0.867	0.557

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Shuttle ridership (B2C)

VARIABLES	**(1)** **Bookings (ln)**	**(3)** **Bookings per trip (ln)**	**(4)** **New users (ln)**
Strike dummy	**0.143*** **	**0.118*** **	**0.636*** **
	(0.047)	**(0.039)**	**(0.036)**
Constant	3.298***	3.109***	-0.094
	(0.208)	(0.185)	(0.172)
Hour fixed effects	Y	Y	Y
Route fixed effects	Y	Y	Y
Day of week fixed effects	Y	Y	Y
Observations	1,198	1,198	1,198
R-squared	0.356	0.270	0.418

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We find that in the B2B category, there was no significant difference in the number of bookings or bookings per trip, but there was a significant increase in the number of new users. The B2C category, however, saw a significant increase in the total number of bookings, bookings per trip as well as the number of new users, suggesting that the absence of ridesharing services led people to substitute with Shuttl, at least during the strike.

1.3 Conclusion – Implications for Policy

Greater thrust on high-occupancy and demand-responsive mobility platforms

Our results emphasize the need to incentivize efficient modes of shared mobility that service more than one trip at a time (buses, carpooling, etc.). Traditional scheduled public transport is invaluable in servicing high capacity and high frequency of service but needs to be complemented with newer taxi-buses. Indeed, ridesharing bus services like Shuttl have the potential to redefine the concept of urban public transport by leveraging vast amounts of data on city routes and commuters to be a demand-responsive service that changes routes dynamically to respond to real-time demand. Citymapper's innovative bus-taxi is an example of such a service.

Enable effective business models in shared mobility

A flexible labor supply model is critical to realizing the benefits of ridesharing including improvements in economic productivity and urban mobility. If the barriers to entry and exit for ridesharing platforms are high, then it becomes difficult for drivers to self select into the supply pool to respond to dynamic demand conditions. Additionally, drivers who select into these platforms are incentivised to drive longer durations to cover the investments associated with high barriers to entry, leading to greater congestion. It is likely that the current licensing regime in India, which imposes strict barriers to entry, does not allow for private ridesharing and precludes creation of a demand-responsive mobility service, is contributing to the congestion effects documented in our study. Less onerous licensing requirements that provide private vehicle owners the option to flexibly select into these platforms may yield an optimal match between supply and demand for mobility services, as shown in Figure 2, leading to lower congestion. This can be best demonstrated by repeating our analysis for a city, which does not impose strict licensing requirements. In the absence of this evidence, however, this argument is inconclusive.

Anticipate impacts and plan for modal shifts

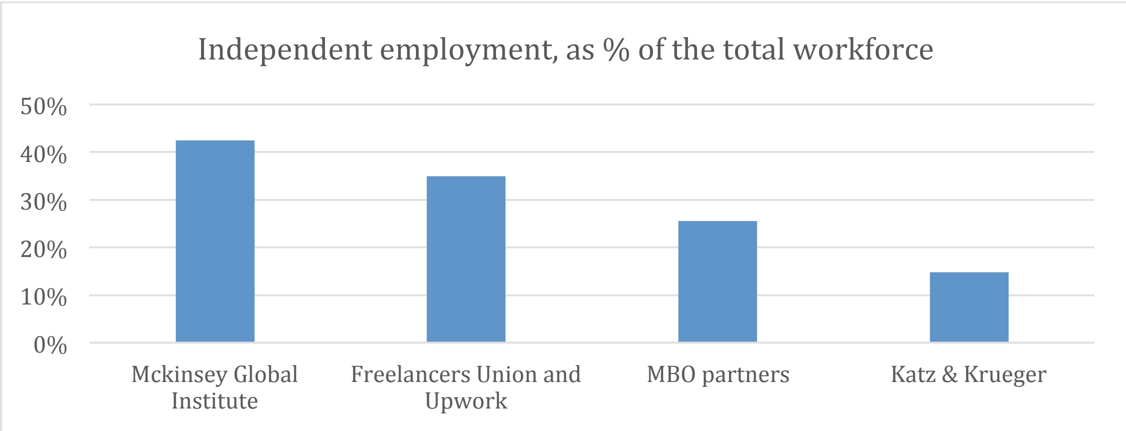
A limitation of our work is that we only evaluate short-term effects. We find for decreased congestion through greater use of the metro and shared bus services when the ridesharing taxi services were disrupted. However, it is possible that commuters perceived the disruption to be temporary and hence, engaged in such substitution, but would select private car ownership as a mobility solution if there were no ridesharing services altogether. Notwithstanding, is shared models of vehicle ownership will provide a bulk of mobility services, it is important for public authorities to plan for and guide the deployment of these models including management and allocation of public space for parking and released from parking.

2. An Empirical Analysis of the Labour Market Effects of Ridesharing Platforms

2.1 Motivation

Diverse studies document a significant increase over the past two years in the number of “freelancers” worldwide - independent workers, who pursue non-employed work. As shown in Figure 6 below, the estimates of this non-employment workforce varies from 15% to 43% (Katz and Krueger 2016; MBO Partners 2016; Freelancers Union and Upwork 2016; Mckinsey Global Institute 2016) depending on the underlying data and methods. Notwithstanding the variation in these estimates, the studies collectively demonstrate that independent employment represent a significant proportion of the worldwide labor force.

Figure 6: Independent employment, as a percent of the total workforce



Ridesharing platforms that are a dominant component of the sharing economy have the potential to accelerate this shift towards independent employment. Indeed, a rich body of emergent work (Cohen et al. 2016) documents the potential value of ridesharing platforms to drivers. For example, Hall and Krueger (2015) demonstrate valuable flexibility accorded by the Uber platform – driver-partners can self-select their work hours as well as respond to dynamic, almost hourly, changes in demand. In turn, driver-partners benefit from higher capacity utilization and higher hourly earnings than traditional taxi drivers (Cramer and Krueger 2016; Hall and Krueger 2015) and alternate work arrangements that do not offer this flexibility (Chen et al 2017). Not surprisingly, in the United States, Uber has seen an exponential growth in its population of active driver-partners from a base of near zero in mid-2012 to more than 160,000 at the end of 2014 with the rate of growth rising throughout this period. In India too, the company has over 450,000 registered drivers while its competitor, Ola, has over 650,000 drivers on its platform spread across cabs, bikes, autos and buses.

Despite ongoing and extensive debate and discussion about the effects of ridesharing on the quantum and nature of self-employment, there is little systematic empirical evidence of these impacts. Berger et al. (2015) find an insignificant impact of ridesharing on self-employment and wages thereof in taxi services; however, the data that informs their study, notably, the American Community Survey, is not representative of driver partners of ridesharing platforms (Hathaway and Muro 2016; Koustas 2018). Burtch et al. (2016) find that that the gig-economy platforms offer viable employment for the un- and under-employed; however, while they estimate self-employment at the level of an economic area using data from the Current Population Survey, prior research (Perry et al.; 2016) and BLS data notes[4] emphasize that these survey data cannot provide reliable estimates even at the state level. We seek to address these gaps in prior research to estimate the quantum of self-employment and income engendered by ridesharing platforms such as Uber[5].

We additionally examine whether certain classes of the workforce are more likely to self-select into ridesharing platforms and benefit from it more than others. Specifically, classes of workers such as women or veterans, who are relatively more constrained in undertaking wage employment and hence, excluded by traditional employment, may value more the flexibility of ridesharing platforms. As a result, these platforms can spur new employment patterns, which could lead to greater economic activity and wealth.

Finally, emergent research (e.g. Berger et al. 2015; Cramer and Krueger 2016) find that earnings and employment in traditional taxi services are negatively impacted by the entry and growth of private ridesharing platforms such as Uber. However, the net effect of ridesharing not only depends on the direct implications on self-employment and wage-employment in taxi services but also on the extent to which the flexible and efficient supply of mobility solutions fuels other economic activity. Indeed, labor market effects in other sectors may be amplified as ridesharing platforms evolve beyond enabling pure mobility solutions to allowing their partners access to other jobs such as delivery of food and other services. Yet, with the exception of Burtch et al. (2016), who find that gig-economy platforms reduce lower quality entrepreneurial activity, there is limited research on the second order effects of ridesharing. Given this omission, the net benefit or detriment of ridesharing on employment or economic development itself remains an open question. Answering the above questions is the precise goal of this report. We use the staggered entry of Uber across different

[4] https://www.bls.gov/ore/pdf/st990280.pdf; https://www.bls.gov/lau/laufaq.htm
[5] Data limitations prevent us from studying labor market effects of ridesharing platforms in India. For this reason, our analyses are situated in the context of the United States.

Metropolitan Service Areas (MSAs) in the US between 2009 and 2015 to explore in greater detail the above mentioned labor market effects of ridesharing platforms.

The flexibility and control accorded by the sharing economy and the resultant labor market effects are especially salient to developing countries like India. In India, the informal sector accounts for over 84% of the non-agricultural employment in the country but yet, constitutes only 21% of the GDP in the country and provides weekly wages that are approximately 40% of those in the formal sector (Srija and Shirke 2014; NSSO 68th Round 2014). In these contexts, the potential of the sharing economy to create large-scale microentrepreneurial opportunities at relatively lower capital outlay in addition to facilitating the reduction of income inequality assumes critical importance, and is aligned with the stated objectives of the Ministry of Small and Medium Enterprises. Therefore, it is important to assess and document the magnitude and nature of labor market impacts of ridesharing platforms like Uber in these markets.

2.2 Data

As noted earlier in this report, data limitations prevent us from studying labor market effects of ridesharing platforms in India. Therefore, we situate our analyses in the United States and extrapolate findings thereof to the Indian context. In order to assess the impact of ridesharing platforms, we use Uber as a canonical example of ridesharing platforms and acquire data from multiple sources to assess labor market shifts engendered by the platform.

First, we use data on Non-Employer Statistics (NES) from the United States Census Bureau to examine independent employment engendered by Uber. The NES data, derived from tax records at the Internal Revenue Service, tracks the activity of businesses that earn gross revenues of at least USD 1,000 per year but employ no workers. Nearly 93 percent of these "businesses" are self-employed, unincorporated sole proprietors in the rides and rooms industries, and are increasingly used in emergent research[6] (Hathaway and Muro, 2016) to construct proxies for labour participation in the gig economy. Specifically, we use the number of drivers in the taxi and limousine service category (NAICS 4853) and the total dollar receipts in the category to estimate the impact of Uber on independent employment in taxi services. We complement these data with statistics on Uber's driver partners in 169 cities worldwide, which are all in the top 50th percentile of cities in terms of weekly trips and launched the Uber platform no later than January 1, 2017. These statistics provided by Uber

[6] https://www.heinz.cmu.edu/ced/file/the-uber-effect-businesses-and-receipts-in-pa.pdf

offer insights into the nature of independent employment engendered by the platform, notably, the distribution of driver partners by gender and hours worked per week.

We subsequently use the American Community Survey (ACS) to examine the impact of Uber on employment and wages in traditional taxi services for each MSA-year.

We use Babar and Burtch (2017) to discern the entry year of Uber for every MSA by manually mapping each city to a MSA. In regressions, our main independent variable of interest is the dummy variable that indicates whether Uber is present in a city in a given year (*Uber* = 1). Table 7 presents the descriptive statistics for the sample used in this study.

Our unit of observation is an MSA-year pair. We estimate the labor market effects of Ubery entry relative to a matched sample constructed using Coarsened Exact matching (CEM, henceforth; Iacus *et. al* 2009). Specifically, we match MSAs using observable attributes of an MSA such as its total population, population between age 20 and 60, total labor force, total unemployed population, unemployed women and median earnings as of the year prior to the entry of Uber. In brief, if the year of first entry of Uber in an MSA was 2011, we use data from 2008 to 2010 to identify its matched MSAs.

The use of CEM enables us to potentially overcome an important limitation of our data – our dependent variables, wages and number of workers in an occupation, are perhaps determined at equilibrium, at the intersection of labor supply and demand for the respective occupation. Our attempt to match MSAs in which Uber is present (treated) versus not (control) is an attempt to recreate an experiment like setting in which the treatment is randomly assigned in the absence of an instrument that exogenously shifts supply or demand for each of the occupations. Moreover, since it is plausible that the entry of Uber in an MSA is also related to employment and wages in the MSA, ideally, we would also require an instrument that is correlated with entry but not with employment or wages to overcome issues of self-selection. Given that we do not have an instrument that exogenously varies the likelihood of Uber's entry that is also uncorrelated with the demand for Uber or the supply of labourers, our use of CEM enables us to overcome this issue of endogeneity.

Table 7: Descriptive statistics

		Full Sample			Matched sample		
Variable	**Source**	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Total Population	ACS	1,305	947,640	1,899,218	686	556,891	740,995
Population, aged between 20 and 60	ACS	1,305	530,188	1,086,464	686	306,421	426,658
Total labour force	ACS	1,305	486,564	993,696	686	282,549	410,452
Total unemployed population	ACS	1,305	40,519	87,565	686	22,264	28,925
Unemployed women	ACS	1,305	18,800	41,062	686	10,231	13,574
Median earnings ($)	ACS	1,305	28,341	4,600	686	27,632	4,348
Uber	Babar and Burtch (2017)	1,305	0.24	0.43	686	0.21	0.41
Median driver hourly wage ($)	ACS	1,046	11	9	549	11	9
Num drivers	ACS	1,305	1,303	5,696	686	582	1,556
Num self employed drivers	ACS	1,305	397	2,295	686	162	686
Num wage employed drivers	ACS	1,305	907	3,459	686	419	935
Num driver nonemployers	NES	1,235	1,081	5,845	661	398	1,912
Total receipts from driver non-employers ('$000)	NES	1,235	34,886	250,393	661	10,136	48,715

Table 8, shows that the treated and the control MSAs are statistically similar on most observed attributes except for median earnings, which although is statistically different even after matching, exhibits an economically small magnitude of difference of USD 1,698. After matching, we obtain 686 MSA-year pairs that we use for the purposes of our analysis.

Table 8: Covariates before and after matching

	Full sample			Matched sample		
Variable	**Uber=0**	**Uber=1**	**Diff.**	**Uber=0**	**Uber=1**	**Diff.**
Population	623098	1971910	1348812*** (117229)	546945	594656	47711 (69675)
Population aged 20-60	345112	1114296	769184*** (67083)	300667	328271	27604 (40118)
Labour force	316424	1023535	7071111*** (61323)	277037	303481	26445 (38594)
Unemployed population	28348	78933	50585*** (5497)	22698	20618	2080 (2720)
Unemployed women	13045	36963	23918*** (2576)	10407	9560	847 (1276)
Median earnings	27595	30692	3097*** (285)	27278	28976	1698** (404)
N	991	314		543	143	

2.3 Results

Impact of ridesharing on self-employment

We first examine the effect of Uber's presence on the extent of independent employment and revenue thereof. Table 9 presents results of OLS regressions in the matched sample of Uber's presence on the number of independently employed drivers and their dollar receipts (both in natural log). Given that we include a fixed effect for every matched stratum in the sample, our regressions compare the wages and number of drivers between MSAs in which Uber operated (treated) with those in which it did not. In our regressions, we also include a variety of controls, such as population, proportion of population in the labour force, unemployment rate, proportion of unemployed women and median earnings. Column 1 of Table 9 suggests that the presence of Uber increases independent employment of drivers by about 51 percent. Further, the results in column 2 suggest that the revenues of independently employed drivers too increase with the entry of Uber by about 29 percent.

Table 9: Self employed drivers

VARIABLES	**Num. drivers (log)**	**Total receipts from drivers (Log)**
Uber dummy	0.507^{***}	0.288^{***}
	(0.065)	(0.068)
Log population	1.608^{***}	1.664^{***}
	(0.120)	(0.126)
Proportion of population between age 20 to 60	-4.122^{***}	-4.742^{***}
	(1.224)	(1.285)
Proportion of labour force	3.662^{***}	3.813^{***}
	(1.066)	(1.119)
Proportion unemployed	-0.272	9.862^{*}
	(5.093)	(5.345)
Proportion unemployed women	-11.652	-22.732^{**}
	(9.874)	(10.362)
Median earnings (log)	0.000^{***}	0.000^{***}
	(0.000)	(0.000)
Constant	-16.470^{***}	-13.885^{***}
	(1.558)	(1.635)
Strata fixed effects	Y	Y
Observations	661	661
R-squared	0.793	0.786

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Taken together, these results suggest that the presence of Uber significantly increases independent employment and income in taxi services. Stated otherwise, our results suggest a shift in demand post the entry of Uber. A mere increase in labour supply without any shifts in demand would decrease wages. The observed increase in the equilibrium quantity of both supply of independently employed drivers as well as their income when Uber enters an MSA is indicative of the fact that the independently employed drivers dynamically respond to demand surges unmet by traditional taxi services. The results emphasize the potential welfare increases that may result with the introduction of ridesharing.

Impact of ridesharing on the nature of self-employment

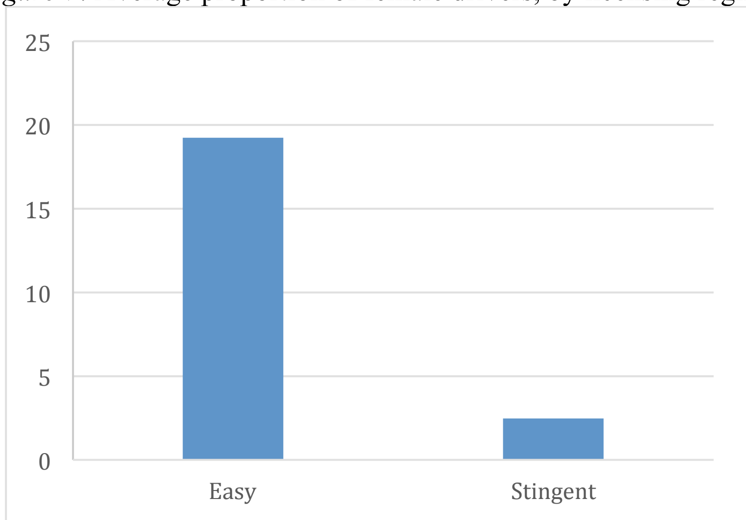
As noted earlier in this report, the benefits of ridesharing platforms are best realized through a flexible labour supply model that allows drivers to easily select in and out of a supply pool to respond to dynamic demand conditions. Such a flexible labour supply model has the potential to shift not only the quantum of self-employment as demonstrated above but also the nature of self-employment. Hall and Kreuger (2015), in their survey of Uber's driver partners, find that the latter highly value the flexibility that the platform accords to drivers to choose their hours and days of work. They also find that hourly earnings for Uber's driver-partners are invariant to hours worked during the week. Together, these results suggest that the entry of Uber might influence greater participation of individuals who want to work part-time or intermittently, as such work typically incurs a wage penalty in labor markets.

The NES data on employment and wages are not separated by gender and other categories. Therefore, in order to understand how Uber shifts the nature of employment, we acquired data from Uber by city for 169 cities worldwide, which are all in the top 50th percentile of cities in terms of weekly trips and launched the Uber platform no later than January 1, 2017. Hall and Krueger (2015) show that the flexibility that ridesharing platforms provide makes it particularly attractive to women drivers, who make up 14% of Uber's driver population, vis-à-vis 8% in the traditional taxi category.

We also examine the extent to which a city regulates ridesharing on participation of women and part-time drivers. The more stringent the licensing requirements, the lower is the flexibility accorded by the ridesharing platform, the greater is its consonance with traditional labour markets, and the lower is the participation of groups that are typically excluded by traditional markets. Unlike the other data sources used to examine the labour market effects of Uber, the unit of observation in these analyses is a city. We classified each of the 169 cities "stringent" or "easy" based on Uber's assessment of the costs and effort required to obtain a license in the city. We examine the extent of participation of women who completed at least one trip for UberX in a city, between September 1st 2016 and August 31st, 2017 and that of part-time drivers or (drivers who completed at least one UberX trip, but whose total number of hours worked was less than 10 hours per week for August 2017.

We present the results of this analysis in figures 7-10 below. Figure 7 shows that cities with stringent licensing requirements are likely to have a significantly lower share of female drivers (difference of 16.78%, $p<0.001$).

Figure 7: Average proportion of female drivers, by licensing regime

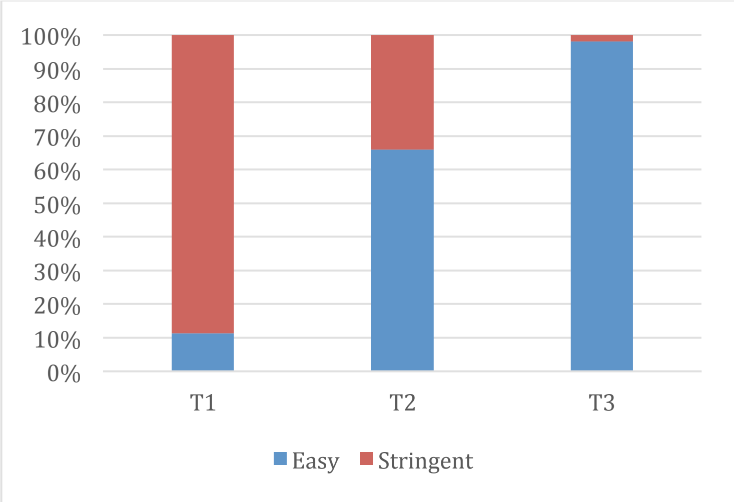


Source: Uber data

In Figure 8, we split the sample of cities into terciles, T1, T2 and T3, in increasing order of presence of female drivers. We find that cities with stringent licensing requirements make up the bulk of T1 and T2. 54 out of 55 cities which fall in T3 have easy licensing requirements, with Seattle being the only city in this category having stringent licensing.

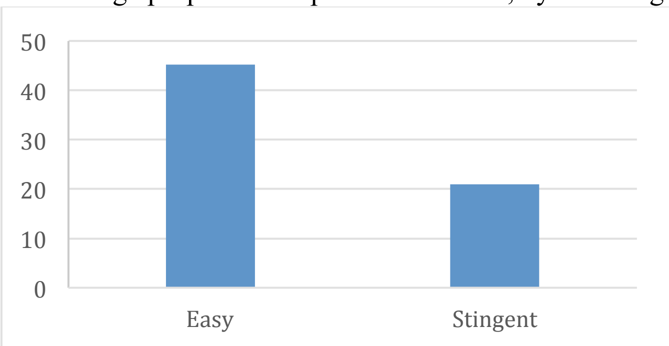
In Figures 9 and 10 we examine the influence of the stringency of licensing on the proportion of part-time drivers. Figure 9 shows that cities with more stringent licensing requirements are likely to have signficiantly lower share of part-time drivers (difference of 24.24%, $p<0.001$).

Figure 8: Terciles by presence of women drivers: We split the sample of cities into terciles based on the proportion of women drivers (i.e. T1 represents the cities with the lowest proportion of women drivers, and so on). Each column represents the proportion of cities in the respective tercile in the pertinent licensing regime.



Source: Uber data

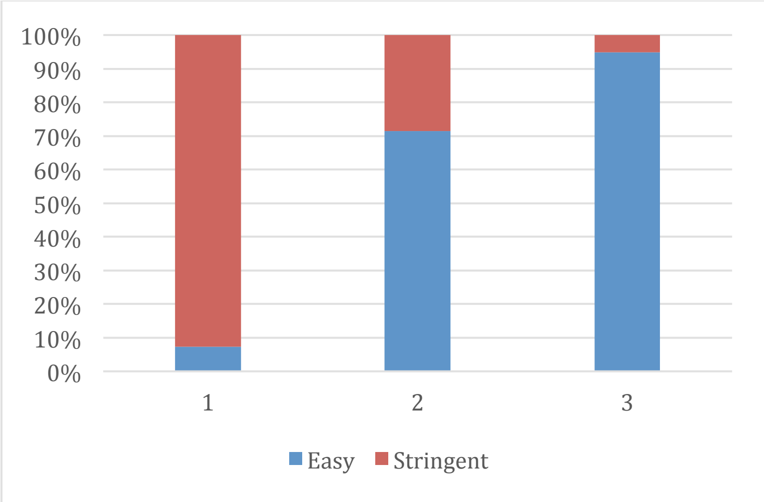
*Figure 9***:** Average proportion of part-time drivers, by licensing regime



Source: Uber data

As with Figure 8, in Figure 10, we split the sample of cities acquired from Uber, into terciles, T1, T2 and T3, in increasing order of presence of part-time drivers. Figure 10 shows that cities with stringent licensing requirements make up the bulk of T1 and T2. Figure 10 thus suggests that cities with minimum barriers to entry are also likely to witness a greater participation of part-time drivers. Thus, to the extent that less stringent licensing is correlated with a greater presence of Uber, greater Uber activity appears to be correlated with both a higher presence of women and part-time drivers both of whom who might desire more flexible work.

Figure 10: Terciles by presence of part-time drivers: We split the sample of cities into terciles based on the proportion of part-time drivers (i.e. T1 represents the cities with lowest proportion of part-time drivers, and T3, the highest). Each column represents the proportion of cities in the focal tercile in the pertinent licensing regime.



Source: Uber data

Influence of ridesharing on wage employment

(a) Influence of ridesharing on wage employed drivers

Next in Table 10, we examine the effect of Uber on employment and wages in traditional taxi services using OLS specifications. Note Columns 1 and 2 of Table 10 shows that while the entry of Uber did not significantly influence the earnings of waged-employed taxi drivers, it decreased the total number of drivers in the sector by about 0.03 standard deviations. Using the sample standard deviation, we find that the decrease in the total number of drivers is about 11.8 percent per MSA-year relative to the sample mean. These results suggest that the entry of Uber decreases the demand (inward shift) for services offered by traditional taxi drivers and attracts them into ridesharing platforms.

Table 10: Wage employment in traditional taxi services

VARIABLES	**Driver hourly wage (log)**	**Num drivers (std)**
Uber dummy	-0.150	-0.027***
	(0.096)	(0.009)
Log population	-0.014	0.090***
	(0.170)	(0.017)
Proportion of population between age 20 to 60	-2.422	-0.041
	(1.768)	(0.169)
Proportion of labour force	-3.420**	-0.029
	(1.572)	(0.146)
Proportion unemployed	-7.320	0.327

	(7.537)	(0.702)
Proportion unemployed women	1.084	-0.724
	(14.470)	(1.352)
Median earnings (log)	0.000	0.000***
	(0.000)	(0.000)
strata fixed effects	Y	Y
	Y	Y
Constant	5.296**	-1.360***
	(2.201)	(0.221)
Observations	549	686
R-squared	0.064	0.895

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) *Influence of ridesharing on other occupations*

Next, we explore the second order effects of Uber's entry on other types of economic activity. To this end we examine the impact of Uber's entry on distinct categories of occupation other than drivers, using BLS data described earlier. To this end, for each broad occupational category, we examine the effect of Uber's presence in an MSA on the median hourly wage. Give that the median hourly wage is been top coded at $90/hr, we estimate a Tobit specification on the matched sample constructed using CEM, with the same set of covariates as in table 10. Tables 11A-11B classifies these estimated effects as follows: In column 1 of Table 11A, we list occupations for which the presence of Uber decreases the quantum of employment but increases wages which signals a reduction in the supply. This reduction in supply might be an outcome of one of two shifts triggered by Uber: movement of workers to other potentially more lucrative occupations such as the ones listed in column 2 of Table 11A, or movement of workers to the sharing economy. Column 2 of Table 11A, lists occupations that show an increase in the quantum of employment but a decrease in wages. In Table 11B, we list occupations that encounter potential demand shifts because of the presence of Uber. In column 1 of Table 11B, we list occupations that show decreases in both median wages as well as employment, signalling an inward shift in demand for such occupations. Column 2 of Table 11B lists occupations that show increases in both median wages as well as employment, signalling an inward shift in demand for such occupations.

In brief, our results suggest that the second order effects of the presence of Uber are likely to have differential effects that are conditioned by the nature of the occupation itself. While some might encounter inward or outward shifts in supply, other may witness similar shifts in demand. An important limitation of these analyses is that the matched sample does not consider employment and wage distribution across the sectors for the focal MSA. A more careful analysis, including exploring impacts on the specific sub-occupations within these categories, is required to further examine the differential effects of ridesharing.

Table 11A: Occupations with potential supply shifts

Potential supply decreases	*Potential supply increases*
Food Preparation and Serving Related Occupations	Farming, Fishing, and Forestry Occupations
Business and Financial Operations Occupations	Education, Training, and Library Occupations
Computer and Mathematical Occupations	
Healthcare Practitioners and Technical Occupations	
Protective Service Occupations	
Sales and Related Occupations	
Building and Grounds Cleaning and Maintenance Occupations	
Healthcare Support Occupations	
Office and Administrative Support Occupations	
Installation, Maintenance, and Repair Occupations	
Personal Care and Service Occupations	
Legal Occupations	
Construction and Extraction Occupations	
Architecture and Engineering Occupations	

Table 11B: Occupations with potential supply shifts

Potential demand decreases	*Potential demand increases*
Production Occupations	Life, Physical, and Social Science Occupations Community and Social Service Occupations Management Occupations Arts, Design, Entertainment, Sports, and Media Occupations

2.4 Conclusion – Policy Implications

Or study finds evidence of positive impacts of ridesharing on labour market outcomes in point-to point transportation services. We find that independent employment and income thereof expanded in cities that adopted the Uber platform. Further, inward shifts in demand in traditional taxi services resulted in contraction in employment with no corresponding decrease in wages. While our results are suggestive of spillovers to other sectors, further research is required to understand these second-order effects of ridesharing platforms. While our findings cannot be generalized across countries, our estimates do caution policy efforts to ban or restrict the proliferation of ridesharing platforms.

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