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The market impacts of sharing economy entrants: evidence from USA and China

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Abstract
This paper studies the link between the diffusion of the sharing economy and traditional mature industries by empirically examining the economic impacts of sharing economy entrants. This study adds to the ongoing debate over whether and how ride-hailing platforms influence new car sales in USA and China. Our results suggest that the short-term impact of Didi Chuxing's entry on new car sales is positive. Unlike the effect of Didi Chuxing on new car sales in China, Uber's entry negatively influences new car sales in USA. The entry of Didi Chuxing is related to a 9.24% increase in new car sales in China and the entry of Uber is related to an 8.1% decrease in new car sales in USA. We further empirically confirm that the impact of ride-hailing companies is trivial in small cities.

Keywords Collaborative consumption models · Uber · Didi · Ride-hailing services · Sharing economy · Two-sided platforms

1 Introduction

Over the last few years, the rapid proliferation of smartphones and the associated applications have fueled rapid growth of the online sharing economy, such as those of Uber, Airbnb, Lyft, Turo, and Peerby. These emerging online peer-to-peer platforms, collectively known as 'collaborative consumption', have made a great deal

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of money by enabling individuals to share their under-utilized resources and earn meaningful income. Anecdotal evidence shows that incumbent firms in the taxi, hotel and other industries are facing fierce competition from these sharing economy companies (e.g., [1]). For instance, eMarketer [2] forecasts that nearly 15 million adults will use the ride-hailing services of Uber, Lyft or other companies at least once in 2016, an increase of 20.5% from 2015. Many studies have explored the impact of introducing ride-hailing apps on local regulations (e.g., [3], the market of ride-hailing (e.g., [4]), and the algorithm optimization of ride-hailing apps (e.g., [5]). However, the impact of ride-hailing on new car demand has not been formally examined and understood. On the one hand, passengers now have convenient and cost-efficient access to redundant car resources, thereby avoiding the financial, emotional, or social burdens of ownership [6]. As the use of ride-hailing apps becomes more prevalent, an individual who plans to purchase a car in the coming few months (e.g., a fresh college graduate) may change his or her purchase decision, thinking that buying and owning a new car is not immediately necessary. Recent reports show that many Uber users are holding off new car purchases because of the availability of ride-hailing services [7]. Thus, improving the utilization of the existing cars and delaying some individuals' purchase plans could contribute to the decrease of new car sales in developed countries.

On the other hand, using ride-hailing apps could lead to a positive impact on new car sales in a developing country in which the number of cars per household is still comparatively low (e.g., China and India). Uber is creating 50,000 new 'driver jobs' globally each month and tens of thousands of people have joined various ride-hailing platforms as full-time or part-time drivers [8]. In China and other developing countries, due to the low percentage of car ownership and lower household income levels, such flexible job opportunities can attract people to join ride-hailing platforms as full-time drivers. For example, Didi launch a driver-to-own program that provides a new car to a new registered driver as long as the driver puts down a deposit of 20,000 RMB (roughly equivalent to 3034 U.S dollars) [9]. Consequently, Didi's effort to recruit more driver in ride-hailing may positively impact new car sales. As reported by [10], "*The plan is for Didi to purchase a million second-hand and new cars through us in the coming 3 years*… adding that some of the vehicles will be allocated to Didi drivers through rental and financial leasing arrangements." As discussed below, ride-hailing platforms cooperate with car dealers to expand diver pool by offering flexible new car payment opinions and discounts. It is also worth noting that the negative effect of rail-hailing apps on new car sales may also exist in these developing countries because some passengers give up or delay their new car purchase plans. Their decisions are driven by the advantages of using ride-hailing platforms to facilitate convenient, point-to-point urban travel [11]. Consequently, the overall impacts of ride-hailing apps on new car sales in developed and developing countries remain as empirical questions.

The purpose of this paper is to quantify the economic impact of ride-hailing companies on new car sales using a unique dataset of vehicle registrations from the U.S.—the biggest developed country and China—the biggest developing country. We propose that ride-hailing platforms will significantly decrease new car sales in those affected U.S states, but the negative effect of using ride-hailing apps on new car sales will be slightly weakened because a few Uber drivers have to purchase new cars to meet the vehicle requirements of Uber. For instance, all Uber cars' vehicle models must be from 2001 or later (2006 in some cities). As discussed above, we further suggest that ride-hailing platforms will significantly increase new car sales in those affected Chinese provinces if the number of individuals who tend to purchase a new car and become a full-time ride-hailing driver is larger than the number of individuals who enjoy the benefits of rail-hailing apps and give up car ownership. Figure 1a demonstrates the preliminary evidence on this topic and illustrates

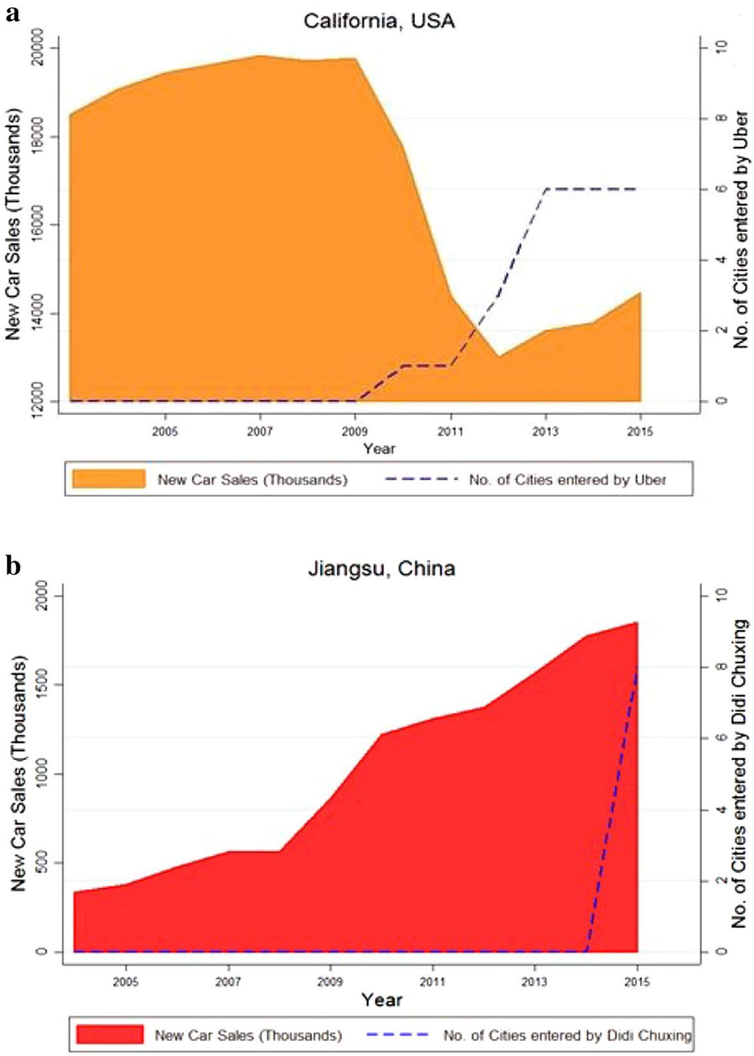

Fig. 1 **a** The Relationship between New Car Sales and Uber's entry into California. **b** The Relationship between new car sales and Didi Chuxing's entry into Jiangsu Province

the relationship between new car sales and Uber's entry into California. Figure 1b demonstrates the trend of new car sales as a result of Didi Chuxing's entry into the Jiangsu province of China.

Our paper aims to make a few contributions to the literature. We are among the first to investigate the link between the diffusion of the sharing economy and traditional mature industries by empirically examining the economic impacts of sharing economy entrants. The results of our study can inform academics, policy makers, environmental health practitioners, and other relevant stakeholders regarding the impacts of online collaborative consumption on traditional industries. The rich nature of our dataset allows us to examine the effect of the entry of ride-hailing platforms on new car sales in both developed and developing countries.

Our work contributes to the small, but growing, literature in information systems about the social and economic impacts of online two-sided platforms. Our study also adds to the ongoing debate over whether and how ride-hailing platforms influence new car sales. Our empirical analysis provides additional evidence suggesting that the effect of ride-hailing platforms on new car sales could vary with the percentage of car ownership per household and income levels. It may be the case that Didi Chuxing is simultaneously increasing the total number of cars on the road by creating new job opportunities and the demand for private car services because of its convenience and low price. Alternatively, Uber may be increasing the utilization of existing cars and delaying households' new car purchase plans. Moreover, this research serves as an open call to extend similar research into other aspects of the sharing economy, such as the effect of Airbnb on the dry-cleaning industry, the effect of TaskRabbit on the unemployment rate, and the effect of Wework.com on the survival ability of start-up firms.

2 Relation to existing literature

Our paper is connected to several strands of literature. First, our paper is related to the literature that examines the societal impacts of Internet-enabled platforms. Since the advent of Internet-enabled platforms (e.g., Craigslist, Uber, Lyft, TaskRabbit, Airbnb), online technology has permeated many aspects of our lives, and it has substantial impacts on business practices, social and economic activities by serving as digital intermediaries between suppliers and consumers [10]. This literature begins with [12], who show the expansion of a classified advertisements website, Craigslist significantly increases the spread of sexual transmitted diseases. Following this study, a stream of literature has examined various consequences of the expansion of Internet-enabled platforms that occurred in the U.S. recently (e.g., [13–16]). These studies find that an increase in the supply of Airbnb listings is associated with a significant decrease in hotel revenue [13], an increase in the popularity of Uber is associated with a decline in the number of complaints about taxi services [11], drunk driving [14, 17], traffic congestion [18] and sexual assault [17, 19]. Following [12], Greenwood and Agarwal [14] further examine how the impact of Craigslist on HIV incidence varies within subpopulations, based on race, gender, and socioeconomic status (SES). Their research shows that the absolute and relative increases in the

HIV incidence rate with the entry of Craigslist are significantly larger among one historically at-risk population, African Americans. They also found that men and women do not experience significantly differences in terms of the HIV incidence rate although men are more likely to use the Internet. Cohen et al. [20] show that Uber leads a higher consumer surplus and generates about $2.9 billion in consumer surplus in the four U.S. cities: Chicago, Los Angeles, New York, and San Francisco. Cramer and Krueger [1] find that Uber drivers may achieve significantly higher capacity utilization rates than taxi drivers due to four factors including a more efficient Internet-based driver-passenger matching technology, huge network efficiencies, inefficient taxi licensing regulations, and flexible labor supply model and surge pricing. Their research findings show that the productivity of Uber is 30% higher in terms of time and 50% higher than taxi in terms of miles. Chan et al. [21] find that the entry of Craigslist to a county leads to a 17.58% increase in prostitution cases. They further suggest that the entry of Craigslist has a stronger impact in counties with a past history of prostitution and produces spillover effects in neighboring locations that are not directly served by Craigslist. Burtch and Chan [22] find that one of the largest medical crowdfunding websites in the United State, GiveForward has a significant and negative impact on the incidence of personal bankruptcy filing. We separately examine the effects of the entry of ride-hailing platforms on new car sales in U.S. and China and show that Uber's entry has a negative impact on new car sale in U.S. whereas Didi Chuxing's entry has a positive impact on new car sale in China.

Second, our paper also contributes to the literature on car-sharing. A significant amount of research has investigated the effects of car-sharing adoption from economic, environmental and social perspectives. The main objective of car sharing is to encourage an individual to share cars with other members through joining a car-sharing organization. Vehicles are usually deployed in a community or a transit station such as a bus station, airport, or railway station. Findings from this stream of research have important managerial implications for the question of whether car sharing can effectively solve the environmental and transportation problems typically faced by metropolitan areas, such as New York, London and Paris [23]. Cervero et al. [24] show that car sharing can contribute to a significant decrease in net vehicle miles traveled (VMT) and fuel consumption from 2001 to 2005. Fellows and Pitfield [23] rely on cost–benefit analysis techniques to examine the potential of car-sharing to alleviate traffic congestion and environmental pollution through reducing vehicle kilometers, increasing average speeds and saving in fuel. Jacobson and King [25] find that car sharing can alleviate air and noise pollution, improve traffic congestion, and reduce the costs of vehicle travel. Their research findings show that a saving of 5.4% in annual fuel consumption can be achieved if one in every ten cars were to share with passengers. Martin et al. [26] find that carsharing platforms considerably reduce the number of on-road vehicles and they have taken between 90,000 and 130,000 vehicles off the road in North America during the past decade. Bardhi and Eckhardt [27] examine access-based consumption in the context of car sharing via an interpretive study of Zipcar consumers. They find that four of six dimensions distinguishing among the range of access-based consumption are identified in the car sharing context including lack of identification, varying significance of use and sign value, negative reciprocity resulting in a big-brother model of governance, and a deterrence of brand community. Katzev [28] find that individuals' occasional need for a vehicle and the financial savings are two major factors that encourage people to join car sharing platforms. They further find that although an individual does not drive fewer vehicle miles after he or she join car sharing platforms, 26% of car owners sell their personal vehicles and 53% are able to avoid an intended purchase. Organization-based car sharing is rather different from ride-sharing based on the Internet and smartphone in that the initial car sharing policy is designed to transport a group of individuals to a common destination at the same time. In contrast, ride- sharing apps act as peer-to-peer, two-sided platforms that connect demand and supply via the mobile Internet. On the one hand, individuals can utilize a ride-sharing platform to find riders and earn money; on the other hand, passengers can also use the platform to find drivers and vehicles at any time of day and any day of the year. While previous studies have investigated various benefits accrued by introducing car-sharing policies, it is imperative to understand the market impacts of emerging car-sharing mobile applications on new car sales in both developed and developing countries.

Third, our paper is also related to those studies that investigate the substitution and complementarity effects of goods sharing on incumbent firms offering similar goods or services [29]. Hennig-Thurau et al. [30] examine whether sharing of motion pictures is a major threat to the movie industry and they find that DVD rentals and purchases are responsible for theaters' annual revenue losses of $300 million in Germany. Seamans and Zhu [31] examine the impact of Craigslist on the subscription number and price of traditional newspapers. They find that on the subscriber side, newspapers have experienced an increase in subscription prices, a decrease in circulation while on the display-ad side, affected newspapers have faced a decrease in display-ad rates. Our study complements these studies by examining whether the entry of online car sharing platforms is a major threat to the automotive industry. A recent survey published by the Shared-Use Mobility Center also suggest that individuals are less likely to own a car and spend less on transportation if they prefer to use more shared transportation modes, including bike sharing, car sharing and ride-hailing platforms [32].

Moreover, some recent reports claim that the purpose of ride-hailing platforms is to improve the efficiency of car utilization so that more and more people will no longer need to own a car. For example, Travis Kalanick, CEO of Uber said, "Our intention is to make Uber so efficient, cars so highly utilized that for most people it is cheaper than owning a car" [33]. Jean Liu, President of Didi Chuxing, put for ward a similar opinion and she said, "I hope you give up buying a car, driving in traffic through a busy city can be boring" [34]. However, ride-haling platforms also actively cooperate with car dealers to offer flexible financial repayment options to attract more people to own a new car and become drivers. For example, "Lyft is partnering with the National Independent Automobile Dealers Association to work around that. Dealers can sign up to become Lyft referral partners and earn money by referring new drivers to the ride-sharing company. The scheme will also allow drivers to apply money they earn driving for Lyft to the purchase of a car. That bonus and any future Lyft earnings can be applied directly to the down payment and monthly car payments. In theory, drivers can literally pay off their cars by working for Lyft." [35]. Uber or Didi also offer similar financial solutions and cooperate with car dealers to expand their driver pool. For example, Uber's new drivers will obtain as much as $7500 new car discounts from a Toyota or General Motors dealership [36]. Didi is in the process of raising $1.6 billion to help the car-leasing companies on its platform procure new vehicles [37]. Thus, it seems that a growing number of reports have documented positive and negative empirical links between ride-hailing platforms and car ownership. However, few empirical studies have examined the link between the diffusion of ride-hailing and new car sales. We contribute to this nascent literature by examining the effects of ride-hailing platforms on new car sales. Our study is closely related to two contemporaneous papers [38, 39] that contribute to this stream of research by empirically examining the impacts of Didi Chuxing's and Uber's entries on new car sales in dozens of cities across China. Their analysis provides evidence of a positive impact of Didi's or Uber's entry on new car sales. Gong et al. [38] find that Uber entry is associated with a considerable increase (8%) in new vehicle ownership in China and that the number of local employed persons and the number of registered public buses also positively influence new car sales. Guo et al. [39] find that Didi's entry can also lead to an increase (5%) in the number of car sales. However, whether ride-hailing platforms can offer many people attractive job opportunities depends on the average household income and the rate of private car ownership. To resolve this tension, we exploit a natural experiment, the variation in the timing of Uber's entry into different cities in U.S between 2010 and 2013 and the variation in the timing of Didi's entry into different cities in China between 2014 and 2015.

3 Data

Our study explores the relationship between the entries of ride-hailing platforms and new car sales in the US and China by estimating new car sales as a function of ride-hailing entry into the market. First, to identify the entry impacts of Uber, we rely on a natural experiment associated with Uber's expansion in the US. During its expansion, the ride-hailing service offered by Uber was available in certain locations at each time period, thereby providing variation in ride-hailing entry across states and years. We consolidated the annual number of new car registration and licensing records for each state from the US Department of Transportation. To examine the entry timing of ride-hailing platforms into a location, we collected data on the year in which Uber was launched. With this data, we constructed a binary entry indicator for a state for a given year. There may be a time lag between Uber entry and its impact on new car sales. In order to alleviate this concern, we only chose 22 US states where Uber entered between 2010 and 2013 as our treated groups and constitute a national panel data set across a period of 9 years (2006–2014). The 3-year pre-treatment period and the 1-year post-treatment period allowed us to examine the lagged effect of Uber on new car sales and the parallel trends assumption, as discussed below. Second, another natural experiment operating in parallel to examine the relationship between Didi

Chuxing's entry and new car sales in China was also conducted. We constructed a national panel data set for 16 Chinese provinces across a period from 2008 to 2016 (i.e., 9 years). Didi Chuxing entered into 16 Chinese provinces between 2014 and 2015, and thus we can examine the lagged effect of Didi Chuxing and parallel new car sales trends between treated and untreated groups. We construct a unique longitudinal data set that contains new car registrations in China from 2014 to 2015.

We ran panel regressions of new car sales on Uber and Didi Chuxing's entry with state (or province) and year fixed effects, and include multiple controls to account for demographic features, socioeconomic factors, and traffic intensity, which may affect new car sales. These control variables for the US and China are collected from the Chinese annual statistical books and U.S. Census Bureau and Bureau of Economic Analysis respectively. GDP Per capita, income, registered unemployed and population size are included as four covariates to account for the level of urbanization of each location. GDP Per capita refers to the final products at market prices produced by all resident units in a region during a certain period of time. Income refers to the average wage per person in a region. Population size is the average number of the population at every time point in a region. Registered unemployed refers to the number of registrations at certain working ages (16 years old to retirement age), who are capable of working, unemployed and willing to work, and have been registered at local employment service agencies to apply for a job. We also collect the geographic coverage of public transportation (i.e., the total number of registered public buses) to serve as the control variable, which can influence the use of ride-hailing apps. The total number of registered public buses refers to the total number of vehicles under operation by public transport enterprises (units) at the end of year, on the basis of the records of operational vehicles by the enterprises (units). A series of checks are performed to examine the robustness of the main results. In particular, we include time-varying city covariates to control for effects not captured by the state and year fixed effects, rely on propensity score matching techniques to address potential confounding effects from unobservable factors, and perform falsification checks to ascertain that the estimated effect was not spurious. In establishing the validity of our analyses, a set of systematic checks is performed to examine whether Uber's and Didi Chuxing's entry is exogenous with respect to new car sales.

We also note that the possible effect of license limitation on our base results. Until 2017, seven cities have implemented license lotteries or auctions to control the number of passenger cars that can be registered each year. The seven cities include Beijing, Shanghai, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen. To remove the influence of license lotteries or auctions on the main result, we first exclude three Municipality cities (i.e., Beijing, Shanghai and Tianjin) from our analysis. Moreover, we ran panel regressions of new car sales on Uber and Didi Chuxing's entry at the state (or province) level, thus these annual quotas in other four cities may have a relatively small influence on the number of vehicles purchased annually in a state or province. Thus, we do not think the strict restriction for buying new cars is a major issue that can change the sign (i.e., positive or negative) of our base analysis.

4 Empirical methodology

4.1 Main analysis

The main goal of our empirical analysis is to identify the impact of a ride-hailing platform's entry on new car sales using a difference in differences (DID) identification strategy. To implement the DID strategy, we define treated regions to be those states/provinces in the US/China with an Uber/Didi Chuxing presence, and non-treated regions to be those states/provinces in the US/China with no Uber/Didi Chuxing presence. Specifically, the expansions of Uber and Didi Chuxing into different locations over various time periods create a natural experiment that allows the comparison of the difference in new car sales after and before a ride-hailing platform's entry for regions to the same difference for other regions that have yet to introduce the ride-hailing platform. We exploit the exogenous variation in Uber's and Didi Chuxing's entry across states/provinces and years in this experiment as the basis for identifying the entry impacts on new car sales in the US and China. This identification strategy has been implemented in several extant studies (e.g., [13, 40, 41]).

The key identification assumption we have to make to support a causal interpretation of this DID estimate is that there are no unobserved, time-varying, region-specific factors that are correlated with both Uber's (Didi Chuxing's) entry and new car sales in the US and China, which may result in endogeneity. Stated differently, we assume that unobserved factors that could potentially jointly affect both Uber/Didi Chuxing adoption and new car sales do not systematically vary both between different states/provinces and over time. For example, the following unobserved factors will be accounted for in our estimate and do not bias our estimates: (1) state (province)-specific time-invariant differences in adoption rates (e.g., consumers in California overall being more likely to use Uber than consumers in Alaska); (2) factors that vary arbitrarily over time but do not vary across cities (e.g., a general increasing awareness of Uber is shared across all consumers in California over time); and, (3) state (province)-specific trends, which allow for unobserved confounders that vary both between regions and over time according to a pre-specified functional form (linear or quadratic). To test for site entry effects, we estimate the following regression equation

$$Y_{ct} = \boldsymbol{A}_c + \boldsymbol{B}_t + g \cdot \boldsymbol{Z}_{ct} + p \cdot \boldsymbol{R}_{ct} + e_{ct} \tag{1}$$

where c indexes states/provinces and t indexes time (t = 2006–2015); Y_{ct} is the growth rate of new car registration plates for state/province c in year t; Ac is a vector of 22 states' (and 16 provinces') fixed effects; and $\boldsymbol{B}_t$ is a vector of time fixed effects. Further, $\boldsymbol{Z}_{ct}$ is a vector of state/province demographics features and socio-economic indicators, which includes a logarithm of population size, GDP growth rate, per capita income, per capita bus transportation, and per capita road kilometers. Moreover, $\boldsymbol{R}_{ct}$ is the binary indicator for ride-hailing app entry, that is, $\boldsymbol{R}_{ct} = 1$ if the state/province has Uber/Didi Chuxing in a particular year, zero otherwise, and ect is an error term. The coefficient p is the difference-in-difference estimate of the effect of Uber's and Didi Chuxing's entry on the number of new car sales. If $p > 0$, then a ride-hailing app's entry has caused an increase in new car sales.

In the above specification, the region-level fixed effects control for time-invariant differences across states/provinces and the year fixed effects control for common macroeconomic shocks across time. The inclusion of these fixed effects makes each state/province in a given year comparable to any other province at other time periods. In addition to the region and year fixed effects, certain demographic and socioeconomic trends may also drive the number of new car registrations. To account for such effects, several control variables, $\boldsymbol{Z}_{ct}$, are included in the model specification to account for factors that vary within each region over time. For all model specifications, the error terms are clustered at the state/province level to account for autocorrelation in the data [42]. We weight our regressions by the relevant regional populations [43]. The fixed effects framework together with covariates may not be able to account for potential time-varying effects that influence new car sales. To assess the robustness of our results, following several prior studies (e.g., [44]), we further run regression models with time-varying controls. We execute this check by including interaction terms of the state/province covariates with the linear time trend as follows:

$$Y_{ct} = \boldsymbol{A}_c + \boldsymbol{B}_t + g \cdot \boldsymbol{Z}_{ct} + p \cdot \boldsymbol{R}_{ct} + v \cdot \boldsymbol{Z}_{ct} \cdot \boldsymbol{T}_t + e_{ct} \tag{2}$$

We further assess the robustness of the results with respect to confounding effects from unobservable variables by using a matched sample of observations derived from propensity score matching. We use population size, per capita income, GDP growth rate, and public transportation as attributes for matching. Samples are matched based on the nearest neighbor algorithm within a caliper size of 0.05, with replacement. To account for differences in entry times over the year, we run separate regressions using an alternative measure of site entry which labels locations experiencing entry in the late part of the year as having entry in the subsequent year.

4.2 Falsification checks

It is plausible that the previous set of regressions may pick up spurious entry effects as a result of coincidence. The relationship between the entry variables and new car sales may also be driven by unobserved confounding factors. To check the above-mentioned DID parallel trend assumption and to understand how long it takes for significant effects to manifest, we assess whether the increase in new car sales due to pre-entry events overlaps with the period of Uber (Didi Chuxing) entry at various locations. Following [12], [45], and [18], we conduct a falsification test through the use of placebo dummy variables in our regressions. We include 2 years of pre-entry dummies as placebos along with 2 years of post-entry dummies to capture potential inter-temporal entry effects as follows

$$Y_{ct} = \boldsymbol{A}_c + \boldsymbol{B}_t + g \cdot \boldsymbol{Z}_{ct} + \sum_j p_j \cdot R^j_{ct} + e_{ct} \tag{3}$$

where j ∈ [30 2], indicating whether year t is the jth year since Uber's (Didi Chuxing's) entry in states. In these regressions, the omitted category is the year of Uber

(Didi Chuxing) entry (R^0_{ct}). In the presence of an overlapping trend of increasing new car sales prior to site entry, the placebo indicators would produce positive and significant coefficients. In addition, the coefficients of the post-entry indicators would reflect the immediacy of entry impacts on new car sales.

5 Empirical extensions

While our baseline model can estimate the entry effects of Uber and Didi Chuxing on new car sales in the US and China, the aggregate nature of the data prevents us from examining how the overall effect varies under different boundary conditions. In this study, we consider one potential moderator: the population size of affected regions, which should correlate with the car service demand in the local market. We examine how the effect of ride-hailing apps on new car sales varies across different cities. We note that Uber and DiDi Chuxing entered into large urban states and provinces first (e.g. California, Boston in the US; and Zhejiang, and Jiangsu in China), followed by smaller cities. An important question we want to know is whether Uber and Didi Chuxing have a more significant impact on new car sales in large metropolitan or rural areas. It seems reasonable to assume that Uber and Didi Chuxing may be well received in large urban regions due to a large population so that their entry effects on new car sales are likely to be larger in big metropolitan areas than in small cities. Alternatively, it is also possible that the effect would be smaller in large cities because many densely-populated metropolises around the world get bogged down in severe traffic congestion and thus have an extensive and developed public transport network, such as metros/underground and buses. To avoid traffic congestion, people may choose to use public transit or non-driving modes like walking and cycling, which diverts the adoption of Uber and Didi Chuxing. We divide the cities into two groups according to city population and estimate the extended model for each city group separately.

6 Results

6.1 Base model

Table 1 presents the main results for our Didi Chuxing empirical analysis. Under an unweighted regression in Model 1, we can see that the binary entry variable yields a positive and significant coefficient. This estimate represents a 63.1% increase in new car sales growth rate attributed to the entry of Didi Chuxing. Under a weighted regression in Model 2, we observe that the coefficients for the entry of Didi Chuxing are similar to Model 1 in sign and statistical significance. To assess the robustness of the main results with respect to time-varying state factors, we estimate the baseline model with the inclusion of interaction terms of covariates with a linear time trend. As shown in Model 3, the inclusion of time-varying state covariates did not change the main results qualitatively.

Table 1 Impact of Didi Chuxing entry on new car sales, with Robustness checks

	Model 1	Model 2	Model 3	Model 4
DiDi entry	0.631*	0.617*	0.661*	0.924*
	(1.80)	(1.76)	(1.80)	(1.74)
ln(population)	− 14.69	− 14.09	− 11.29	− 22.27
	(− 1.42)	(− 1.40)	(− 1.09)	(− 0.85)
GDP per capita	0.028	0.026	0.047	0.081*
	(1.04)	(1.03)	(0.86)	(2.00)
ln(income)	− 2.445	− 2.293	− 2.479	− 2.014
	(− 1.16)	(− 1.16)	(− 0.75)	(− 1.21)
Age 15–64 proportion	4.005	4.061	17.47	22.64**
	(0.55)	(0.57)	(1.58)	(2.14)
Public transportation	0.322*	0.309*	0.259	0.234
	(1.71)	(1.71)	(1.29)	(1.05)
Registered unemployed	0.572	0.567	0.819	0.700
	(0.82)	(0.81)	(0.91)	(0.69)
No. of cities entered	− 0.152	− 0.143	− 2.217	− 0.149
	(− 1.38)	(− 1.36)	(− 0.65)	(-1.41)
Constant	282.9	270.5	209.8	390.8
	(1.41)	(1.40)	(1.02)	(0.84)
Observations	270	270	270	160
Adjusted R^2	0.098	0.093	0.087	0.123
Weighted by population	No	Yes	Yes	Yes
Controls × trend	No	No	Yes	No
P-score matched sample	No	No	No	Yes

The dependent variables for models 1–4 are the growth rate for new car registration plates in China. Robust t values are reported in parentheses below coefficient values, clustered by province level. Models 1 is un-weighted regressions, while Models 2–3 are weighted regressions All regressions employ an ordinary least square specification. All models have binary entry regressors and include state and year fixed effects

$^*p<0.1$, $^{**}p<0.05$

To account further for potential unobservable factors that may affect the estimates by making entry decisions endogenous, we re-estimate the baseline model using cities that are matched by demographic factors and socioeconomic characteristics under a propensity score matching scheme. As shown in Model 4, the entry estimate remains positive and statistically significant.

Table 2 presents the main results for our Uber empirical analysis. Unlike the effect of Didi Chuxing's entry on new car sales in China, Uber's entry negatively influences new car sales in the United States. Under a weighted regression in Model 2, the binary entry variable has a negative and significant coefficient. To assess the robustness of the main results with respect to time-varying state factors and potential unobservable factors, we re-estimate the baseline model with the

Table 2 Impact of Uber entry on new car sales, with robustness checks

	Model 1	Model 2	Model 3	Model 4
Uber entry	− 0.026	− 0.061**	− 0.069**	− 0.081**
	(− 1.27)	(− 2.23)	(− 2.38)	(− 2.41)
ln(population)	0.269	0.620***	0.396**	0.660*
	(1.53)	(2.84)	(2.04)	(2.00)
GDP per capita	− 0.001	0.001	− 0.002	0.001
	(− 1.05)	(0.63)	(− 0.70)	(0.22)
Age 15–64 proportion	− 0.204	3.249	− 6.319	7.578
	(− 0.10)	(0.52)	(− 0.83)	(0.44)
Public transportation	0.006	0.005	0.001	0.001
	(1.01)	(0.67)	(0.06)	(0.01)
Registered unemployed	0.013	− 0.398	− 3.295	1.126
	(0.01)	(− 0.21)	(− 1.10)	(0.49)
Constant	-4.090	− 9.373**	− 3.817	− 10.98*
	(− 1.30)	(− 2.39)	(− 0.92)	(− 1.87)
Observations	528	528	528	304
Adjusted R^2	0.058	0.092	0.090	0.062
Weighted by population	No	Yes	Yes	Yes
Controls × trend	No	No	Yes	No
P-score matched sample	No	No	No	Yes

The dependent variables for models 1–4 are the growth rate for new car registration plates in U.S. Robust *t* values are reported in parentheses below coefficient values, clustered by state level. Models 1 is un-weighted regressions, while Models 2–3 are weighted regressions All regressions employ an ordinary least square specification. All models have binary entry regressors and include state and year fixed effects

$^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

inclusion of interaction terms of covariates and with the propensity score matching scheme. The entry estimates in Models 3 and 4 remain negative and statistically significant.

In sum, while the growing popularity of ride-hailing will make private car ownership less desirable in the long run, intense competition among ride-hailing platforms may boost new car sales in the short run. Rival platforms may offer strong incentives to motivate potential drivers to sign up for their platforms. Indeed, competing ride-hailing companies in China offered potential drivers significant discounts to purchase new cars that will be used to provide ride-hailing service. In the short run, these incentives can boost new car sales, especially in the time window that immediately follows the entry of a major ride-hailing platform like Didi. In the US, most people have already owned private cars, and they can register their cars for ride-hailing if they want to. Thus, motivating them to sign up as drivers by offering new car discounts will be a less effective strategy. In addition, the average compensation from working as a ride-hailing driver is much more attractive in China than in US. Therefore, it is much easier for platforms to attract new drivers by offering new car discounts in China.

6.2 Falsification checks

In our falsification test, we examine whether the increase in new car sales propagated from earlier time periods. Results of this falsification test are reported in Tables 3 and 4. Across all models, we observe that the 3 year pre-entry placebo variables did not pick up any pre-entry effect. This suggests that the positive relationship between new car sales and Uber (DiDi Chuxing) entry observed in previous analyses is unlikely to be an artifact effect that propagated from periods prior to Uber (Didi Chuxing) entry.

Table 3 Falsification test using pre- and post-entry indicators (DiDi Chuxing)

	Model 1	Model 2
DiDi entry_{-3}	0.720	0.692
	(1.28)	(1.24)
DiDi entry_{-2}	0.976	0.945
	(1.58)	(1.53)
DiDi entry_{-1}	0.783	0.759
	(1.61)	(1.56)
DiDi entry_{1}	0.428*	0.434*
	(1.82)	(1.92)
ln(population)	− 12.15	− 11.63
	(− 1.44)	(− 1.42)
GDP per capita	0.009	0.009
	(0.48)	(0.49)
ln(income)	− 1.315	− 1.244
	(− 0.98)	(− 0.99)
Age 15–64 proportion	4.597	4.799
	(0.62)	(0.67)
Public transportation	0.305*	0.290*
	(1.73)	(1.73)
Registered unemployed	0.521	0.521
	(0.72)	(0.73)
Constant	225.7	215.5
	(1.43)	(1.41)
Observations	270	270
Adjusted R^2	0.084	0.080
Weighted by population	No	Yes

The dependent variables for models 1–2 are the growth rate for new car registration plates in China. Robust t values are reported in parentheses below coefficient values. All regressions employ an ordinary least square specification. All models include province and year fixed effects

$*p < 0.1$

Table 4 Falsification test using pre- and post-entry indicators (Uber)

	Model (1)	Model (2)
Uber entry$_{-3}$	0.010	0.021
	(0.68)	(1.30)
Uber entry$_{-2}$	0.025	0.034
	(1.05)	(1.53)
Uber entry$_{-1}$	0.008	0.032*
	(0.36)	(1.72)
Uber entry$_{1}$	−0.008	−0.037*
	(−0.58)	(−1.69)
ln(population)	0.226**	0.444***
	(1.97)	(3.19)
GDP per capita	−0.001	0.001
	(−1.15)	(0.33)
Age 15–64 proportion	−0.201	−1.444
	(−0.22)	(−1.26)
Public transportation	−0.674	−0.246
	(−0.48)	(−0.08)
Registered unemployed	0.000	0.002
	(0.02)	(0.41)
Constant	−3.263*	−5.900***
	(−1.75)	(−2.80)
Observations	528	528
Adjusted R^2	0.222	0.295
Weighted by population	No	Yes

The dependent variables for models 1–2 are the growth rate for new car registration plates in U.S. Robust *t* values are reported in parentheses below coefficient values. All regressions employ an ordinary least square specification. All models include state and year fixed effects

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

6.3 Effect by population

We re-estimate the relative time model on two city groups: small and large cities. We have divided cities into two groups based on the median population size. Then we rerun the regression in the two groups of large and small cities and report the results respectively. Results suggest that under an unweighted regression, we see that Didi entry variable has a negative and significant coefficient while the presence of Uber has a higher negative impact on large city when population is weighted. Compared to small cities, large cities have excellent public transit and increasing levels of car traffic make streetcars painfully slow and thus residents who live in large cities often prefer the use of public transit (Tables 5, 6).

Our empirical results suggest that, while improving the utilization of the existing cars can contribute to the decrease of new car sales in both China and US, ride-hailing apps can have a positive impact on new car sales in a developing country like China where number of cars per household is still comparatively low. One plausible explanation is that, due to the low percentage of car ownership and lower household income levels, working as a registered platform driver is much more attractive to residents in developing countries. Therefore, it is much easier and cost effective for ride-hailing platforms to recruit drivers by incentivizing them to purchase new cars. Furthermore, because of platform competition (e.g., [46]), competing ride-hailing platforms often have strong incentives to expand their networks of registered drivers to preempt their rivals. In China where number of cars per household is still comparatively low and platform drivers are viewed by many as decent job opportunities,

Table 5 Small city versus large city: Didi Chuxing in China

	Small city (1)	Large city (2)	Small city (3)	Large city (4)
DiDi entry	0.396	− 0.444*	0.389	− 0.409
	(0.95)	(− 1.77)	(0.95)	(− 1.52)
ln(population)	− 21.96	7.301	− 21.45	7.168
	(− 1.48)	(1.60)	(− 1.47)	(1.55)
GDP per capita	0.0422	0.030	0.040	0.031
	(0.92)	(1.47)	(0.90)	(1.40)
ln(Income)	− 3.862	0.723	− 3.747	0.719
	(− 1.15)	(1.43)	(− 1.15)	(1.41)
Age 15–64 proportion	22.42	4.079	22.75	4.052
	(1.21)	(0.52)	(1.22)	(0.52)
Public transportation	0.548	− 0.002	0.536	0.001
	(1.59)	(− 0.02)	(1.58)	(0.01)
Registered unemployed	0.949	− 0.266	0.977	− 0.249
	(0.98)	(− 0.59)	(0.99)	(− 0.54)
No. of cities entered	–	–	–	− 0.012
				(− 0.49)
Constant	384.4	− 140.3	374.6	− 137.9
	(1.46)	(− 1.69)	(1.46)	(− 1.64)
Observations	126	144	126	144
Adjusted R^2	0.140	0.052	0.135	0.044
Weighted by population	No	No	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

The dependent variables are the growth rate of the number of sales for small automobiles with maximum passengers less than 9 persons registered in China. Cluster-robust t-statistics (at the province level) are reported in parentheses below coefficient values. Model (1) and (2) is unweighted regression, while Model (3) and (4) is weighted regression

*$p < 0.1$

Table 6 Small city versus large city: Uber in US

	Small city (1)	Large city (2)	Small city (3)	Large city (4)
Uber Entry	0.007	−0.033	0.051	−0.073**
	(0.15)	(−1.51)	(0.95)	(−2.47)
ln(Population)	−0.045	0.484*	−0.299	0.865**
	(−0.16)	(1.71)	(−0.74)	(2.53)
GDP per capita	−0.002	0.001	−0.001	0.002
	(−1.13)	(0.22)	(−0.55)	(0.82)
Age 15–64 proportion	0.817	−4.055	−1.255	−1.433
	(0.43)	(−1.04)	(−0.86)	(−0.47)
Public transportation	−2.209	3.720	−5.051*	18.58
	(−0.97)	(0.23)	(−2.05)	(0.90)
Registered unemployed	0.011	0.007	0.014	0.007
	(1.54)	(1.03)	(1.43)	(0.79)
Constant	0.126	−5.028	4.920	−12.86**
	(0.03)	(−0.86)	(0.83)	(−2.15)
Observations	253	275	253	275
Adjusted R^2	0.192	0.019	0.184	0.072
Weighted by population	No	No	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

The dependent variables are the sales growth for private automobiles registered in the current year in US. Cluster-robust t-statistics (at the US state level) are reported in parentheses below coefficient values. Model (1) and (2) is unweighted regression, while Model (3) and (4) is weighted regression

$^{*}p<0.1$, $^{**}p<0.05$

competing platforms can quickly expand their driver networks by aggressively offering new car discounts and other types of promotions. Thus, aggressive network expansion driven by platform competition may significantly boost new car sales in the short run. From this perspective, our empirical results are consistent previous studies suggesting network externalities can significantly influence business strategies and the trajectories of market competition (e.g., [47–49]).

7 Discussion and implications

Online collaborative consumption platforms have emerged as a major trend in recent years, partly driven by the continued strong penetration of smartphones and tablets, and the prevalence of the mobile Internet. In this study, we assess and quantify the impacts of the entries of two leading peer-to-peer car service in China and U.S. (i.e., Didi and Uber) on new car sales. Our empirical results suggest that new platform entries have negative overall impacts on new car sales in the U.S. and positive overall impacts on new car sales in China. To our best knowledge, our study represents the first empirical effort that compares the impacts of ride-hailing platforms' entries on new car sales between U.S. and China. Our work provides empirical evidence demonstrating that online collaborative consumption platforms are significantly changing consumption patterns, as opposed to generating purely incremental economic activities, as has been argued in prior work.

This study provides several important managerial insights that can help to inform car manufacturers, policy makers and ride-hailing platform practitioners. First, because the entry-induced increase in new car sales is evident in China, many Chinese car manufacturers can benefit rather than losing-out from partnering directly with ride-hailing platforms. Thus, partnering through appropriate business arrangement such as auto leasing options, Chinese car companies can motivate more drivers to use the ride-hailing service. Therefore, Chinese car manufacturers are unlikely to suffer from ride-hailing platforms in the short run; on the contrary, ride-hailing platforms have an immediate and negative impact on new car sales in U.S. because most households own private cars and most people don't need to purchase new cars to register as Uber drivers. Our results regarding the heterogeneous effects across small and large cities further suggest that new car sales in large cities are more likely to decrease due to the entry of Didi or Uber. It seems that, as most small city residents own private cars, the popularity of ride-haling platforms is lower in rural areas than in densely-populated metropolises.

Our paper has a few limitations. Addressing them can pave the way for future research in this area. First, one must recognize that our findings are representative of U.S. and China. Thus, directly generalizing them to other small countries may not be appropriate given the varying of dynamics of supply and demand for transportation across different regions. Additional studies that model the impacts of ride-hailing apps across other middle or small size markets (e.g., Uber in the UK) could be a useful contribution. A second limitation of our work is that we analyze the effect of Didi Chuxing and Uber China on state (province)-level new car sales because we do not have complete car sale data at the city level for the U.S. market. Uber and Didi were introduced into city areas within states (provinces) and it will be ideal to examine its impact on car sale at the city level. A consolidated and standardized data set on U.S. car sale at the metropolitan areas over the study period is not readily available. So obtaining city level car sale data in U.S. would be very helpful in advancing this stream of research. It is also worth noting that, while many factors may influence new car sales, we can only incorporate some of them into our model because of data availability constraints. We also acknowledge that the majority of car buyers should be 21 or above. However, Chinese annual statistical books and U.S. Census Bureau only offer population data for the three age groups including 0–14, 15–64, and 65 or over. Thus, we can't use the 21 and above group as a control variable. Finally, it is important to note that this research addresses only a part of the overall effect of the entries of ridesharing services. Our study focuses on the Didi Express service in China and its US counterpart, the discount Uber X service, as opposed to the premium services (e.g., Didi premium and Uber Black). It would be inappropriate, therefore, to draw any conclusions from this study about the aggregate impacts of ride-hailing on new car sales. Future work may examine the market impacts of different ride-hailing services to ensure the robustness of the results. Notwithstanding these limitations, this work represents the first empirical attempt in comparing the effect of ride-hailing platform entry in two major countries (the biggest developed country and the biggest developing country) via with a set of robust empirical tests performed under a natural experiment setting.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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