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Opportunities or Threats: The Rise of Online Collaborative Consumption (OCC) and its Impact on New Car Sales

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Abstract

Online collaborative consumption models, such as Uber and Airbnb, have emerged as popular peer-to-peer platforms in the sharing economy. The recent introduction of ride-hailing apps for smartphones has generated a powerful medium for passengers to call cars effortlessly and flexible job opportunities for drivers. A central question surrounding the introduction of online collaborative consumption regards its impact on incumbent firms. For example, ride-hailing services could discourage private car ownership, potentially leading to a subsequent decline of new car sales. Our study investigates whether the adoption of a leading ride-hailing platform, Didi Chuxing, increases or decreases new car sales shortly after the platform's entries across 51 cities in China. Our empirical results suggest that the initial entry of a dominant ride-hailing company like Didi Chuxing positively impacts new car sales in the short run. However, we suspect that this positive effect will be transitory. Whether the auto industry can leverage the ride-hailing platforms to achieve sustainable benefits remains to be seen in the long run.

Keywords: collaborative consumption models, propensity-score matching, network effects**,** ride-hailing services, sharing economy, two-sided platforms.

"*Our intention is to make Uber so efficient, cars so highly utilized that for most people it is cheaper than owning a car…*" Travis Kalanick, former CEO of Uber.

"*I hope you give up buying a car, driving in traffic through a busy city can be boring…*" Jean Liu, President of Didi Chuxing.

1. Introduction

Over the last few years, the rapid proliferation of smartphones and the associated widespread use of mobile phone applications has fueled the rapid growth of Internet-enabled sharing platforms around the world, such as those of Uber, Airbnb, Lyft, Turo, and Peerby. These emerging online peer-to-peer platforms, collectively known as the 'sharing economy', have made a great deal of money by enabling individuals to share their under-utilized resources. Anecdotal evidence has shown that incumbent firms in the private car hire, hotel and other industries are facing fierce competition from these sharing economy companies (e.g., Barro, 2014; Fischer-Baum and Bialik, 2015; Guttentag, 2015; Cramer and Krueger, 2016). For instance, eMarketer (2016) estimated that nearly 15 million adults used the ride-hailing services from Uber, Lyft or other companies at least once in 2016, an increase of 20.5% from 2015. According to Knight (2016), every week in London, 30,000 consumers order a car service through Uber, which has successfully launched its ride-hailing platform in over 66 countries and 507 cities around the world (Uber, 2016). These ride-hailing services operate as mobile platforms that connect individuals who want to use cars with drivers – people who would like to share their cars. Uber now has a $66 billion valuation: higher than those of several well-known U.S. public companies such as Ford, GM, Fox, Time-Warner Cable, and eBay (Rosoff, 2015).

Our study investigates the impact of ride-hailing companies on the new car market by using a unique dataset of vehicle registrations from China — the biggest emerging auto market in the world. We focus on China's homegrown ride-hailing platform Didi Chuxing[1]. There are several plausible reasons that suggest the adoption of ride-hailing apps could negatively impact new car sales. From the perspective of passengers, using ride-hailing apps benefits from ease of booking, lower prices, quick response, and plenty of driver options. Compared to taxi services, using a ride-hailing service is extremely convenient and often much cheaper. As the use of ride-hailing apps becomes more prevalent, more and more people may find car ownership unnecessary. Unlike catching a taxi, which requires passengers to stand on the street until an available vehicle drives by, and where payment is sometimes inconveniently cash only, the adoption of ride-hailing apps allows passengers to summon a car via a smartphone, making payment electronically. Recent reports show that many Uber users are holding off on car purchase because of the availability of ride-hailing services (Diamicis, 2015). Taxi firms facing higher fixed costs have started to view competition from these ride-hailing companies as a serious threat. Many of them consequently have become more reluctant to acquire new cars.

On the other hand, it is plausible that the adoption of ride-hailing apps may positively impact new car sales by generating new suppliers (i.e., drivers). For example, according to Fiegerman (2014), Uber creates around 50,000 new job opportunities globally each month. Because ride-hailing apps provide a great deal of flexibility to drivers as they can choose to work at any time, tens of thousands of people have joined ride-hailing platforms as full-time or part-time drivers. In order to become a ride-hailing driver, an individual must have a car (or purchase one) and the car must meet the vehicle requirements of the ride-hailing firm. Thus, automotive manufacturing industry may benefit from the incremental demand created by the ride-hailing firms like Uber. Moreover, some auto dealers such as Toyota's dealers provide

[1] As the result of a merger between two major ride-hailing firms, Didi Dache and Kuaidi, Didi Chuxing has become the most dominant ride-hailing company in China, accumulating more than 400 million users in 400 Chinese cities.

flexible leasing options to cooperative ride-hailing drivers (e.g., those of Uber) who are not eligible in applying for loans from banks or other financial institutions because of poor credit scores (Lutz, 2015).

The overall impact of ride-hailing apps on new car sales remains as an empirical question. Previous research has examined the impact of introducing ride-hailing apps on local regulations (e.g., Rauch and Schleicher, 2015; Ranchordás, 2015; Cohen and Sundararajan, 2015), the market of ride-hailing (e.g., Zha et al., 2016), and the algorithm optimization of ride-hailing apps (e.g., Agatz et al., 2011). However, the impact of ride-hailing on new car demand has not been formally examined and understood. In this paper, we aim to bridge this gap by investigating how the adoption of ride-hailing apps affects new car sales.

Our paper contributes to the extant literature from several aspects. By providing empirical evidence of the economic impact associated with the sharing economy, our study is among the first few studies that focus on the interplay between the sharing economy and traditional mature industries. Our research provides compelling empirical evidence demonstrating that the entry of Didi Chuxing can meaningfully increase new car sales in the short run. In addition, the granular characteristics of our dataset allows us to examine the impacts of Didi Chuxing's entry on new car sales from different categories, such as economy, business and luxury. Identifying the types of cars significantly affected by Didi Chuxing's entry can help policy makers and regulators better understand the policy implications for the emerging ride-hailing platforms.

The remainder of this paper is organized as follows. We first review the related extant literature in Section 2. Subsequently, in Section 3, we explain the data and research design used in the study. We then delineate the base model and its extensions in Section 4. Section 5 summarizes the results of our statistical analyses. Finally, we discuss the implications and the limitations of our study in the last section.

2. Prior Literature

In this section, we review various streams of relevant literature, including previous research on digital two-sided platforms and car sharing.

2.1 Digital Two-Sided Platforms

Internet-enabled two-sided platforms have profoundly changed business practices, social activities and economic activities by working as Internet intermediaries between suppliers and consumers (Adner and Kapoor, 2010; Bailey and Bakos, 1997; Brynjolfsson et al., 2003; Constantinides and Barrett, 2014; Tilson et al., 2010). One major stream of research on two-sided platforms examines their impacts on social and public issues (Chan and Ghose, 2013; Greenwood and Agarwal, 2015; Alexander and Gonzalez, 2015; Greenwood and Wattal, 2015; Chasin and Scholta, 2015). Investigating the antecedents and consequences related to individuals' participation in different online two-sided platforms is another topic that has received extensive attention in the research (e.g., Kim, et al., 2015; Abramova et al., 2015; Weber, 2016; Gerber and Hui, 2013; Burtch et al., 2013). Other recent studies on individuals' participation and decision mechanisms in crowdfunding platforms include Agarwal et al. (2011), Lin and Viswanathan (2014) and Wei and Lin (2015). Finally, some research on online two-sided platforms examines their substitution and complementarity effects on incumbent firms offering similar goods or services (Cusumano 2015; Malhotra and Van Alstyne, 2014).

While these studies have uncovered a multitude of issues regarding digital two-sided platforms across a variety of aspects, the relationship between the presence of Internet-enabled two-sided platforms and the overall demand for purchasing sharing goods is far from clear (Horton and Zeckhauser, 2016; Jiang and Tian, 2016). Our paper aims to ameliorate this research gap by examining the impact of ride-hailing platforms on new car sales in China. Because we examine the impact on new car sales shortly after the entry of a dominant two-sided platform, we can investigate whether the cross-side network effects are sufficiently strong to incentivize large-scale new driver participation. By providing empirical evidence of a positive effect of platform entries on new car sales, our study demonstrates that the positive cross-side network effects generated by a dominant platform can quickly overwhelm the same-side negative network effects (note that on the driver side the competition for riders intensifies as more drivers sign up for the same platform).

2.2 Car Sharing

Focusing specifically on the car-sharing business model, a stream of research has investigated the effects of car-sharing adoption, including studies from economic, environmental and social perspectives, such as examining the alleviation of air and noise pollution, improving traffic congestion, and reducing the costs of vehicle travel (e.g., Cervero et al., 2007; Martin et al., 2010; Jacobson and King, 2009). A key goal of the car sharing business model is to incentivize individuals to join the platform and share their cars with other members. Vehicles are usually deployed in a community or a transit station such as a bus station, airport, or railway station. The outcomes of this stream of studies have significant managerial implications regarding the question of whether the car sharing model can effectively address the environmental and transportation issues typically faced by metropolitan areas like New York, London and Paris. Jacobson and King (2009) investigate how a ride-hailing policy can reduce fuel consumption. They find that a reduction of 5.4% in annual fuel consumption can be achieved if one in every ten cars were routinely shared by passengers. Using cost-benefit analysis techniques, Fellows and Pitfield (2000) examine the prospect of car-sharing to ameliorate traffic congestion and environmental pollution through reducing vehicle kilometers, increasing average speeds and saving in fuel. While digital ride-hailing platforms (e.g., Uber) share similarities with traditional car sharing models, they are distinctively technology-driven two-sided platforms that connect demand and supply on a real time basis.

While this stream of work has investigated various benefits accrued by introducing car-sharing policies, no previous studies have investigated whether the entry of a car-sharing platform with a dominant market share can meaningfully impact new car sales. On the one hand, because many people use ride hailing services on a non-regular basis, their car purchasing decisions may not be strongly influenced by the availability of ride hailing services. On the other hand, there are many potential car buyers who would have purchased new cars without ride hailing services (therefore conveniently available ride hailing services may depress the new car demand from this population). From the potential Didi drivers' perspective, their new car purchasing decisions need to be justified by the expected economic returns from joining the ride hailing platform. It is worth noting that drivers who have already owned cars enjoy advantages over those potential drivers who need to purchase new cars to sign up for Didi. Thus, potential Didi drivers may not have enough incentives to purchase new cars if they face uncertain demand and significant initial costs. However, Didi Chuxing is a leading two-sided platform that enjoys increasing returns to scale.[2] Many studies have demonstrated that network effects (i.e., network externalities) have important strategic implications for competitive dynamics in the digital economy (e.g., Kauffman and Li, 2005; Li, 2005). In a market with strong network externalities, a large network that has reached critical mass could generate significant new demand in a very short time period (Li, 2004; Kauffman and Li, 2005). This insight is directly applicable to two-sided markets with strong cross-side network effects (assuming that the same-side network effects are not extremely negative). In addition, this type of new demand drive by positive network feedback is often amplified by the herding mentality of many market players (Kauffman and Li, 2003; Li, 2004; Li et al., 2014). Therefore, Didi's entries into various cities across China allow us to empirically examine whether the strong

[2] According to cnbc.com and Wall Street Journal, Didi Chuxing's market valuation could reach $80 billion in a potential IPO (Browne, 2018). Its gigantic market shares in the online ride-hailing business can generate powerful cross-side network effects that strongly incentivize new driver participation.

network feedback generated by a dominant network can meaningfully increase market demand in the short run.

3. Research Design

To accomplish the objective of investigating the effect of ride-hailing app entry on new car sales, we created a national monthly panel dataset for 102 prefecture-level cities. Among them, 51 cities which Didi Chuxing entered in 2015 are used as the treat group while the other 51 cities which Didi Chuxing did not enter by 2015 are used as the control group. This can be further justified as follows. First, according to the Diffusion of Innovations Theory (Rogers, 2003), only a few groups of innovators are likely to adopt and use new products, while later the benefits of innovations are recognized by many other people. Ride-hailing apps were first introduced as a new service into China in 2012. Subsequently, large sums of money were spent aggressively on promotion, and a brutal subsidy war ensued in which competitors aimed to attract riders and private drivers, particularly in 2014[3]. Thus, in 2014, the prospect of benefits (e.g., flexible work schedule, low travel costs, or earning a decent income) were more likely to crystallize in the minds of riders and drivers. More importantly, by 2015 Didi Chuxing has emerged as the dominant ride-hailing platform in China (Uber decided to sell its Chinese business to Didi Chuxing and quit the Chinese market in 2016). Consequently, when Didi Chuxing announced its entry into a particular new city during 2015, local residents of the city who wished to become full-time Didi Chuxing drivers – who did not already own a suitable car – were likely to purchase new cars with little hesitation. Similarly, some passengers may give up or delay their new car purchase plans by virtue of the established cognition that Didi Chuxing can effectively fulfil an unserved demand for convenient, point-to-point urban travel. Second,

[3] In June 2012, Orange Technology was established and Didi Dache, the initial incarnation of Didi Chuxing's ride-hailing service, was launched as a mobile app for ordering taxis for immediate pick-up. In 2014, Didi Dache opened its platform to the private car hire market. The major investor is the Chinese Internet giant Tencent Holdings Limited. In the same year, Uber launched its operations in China on February 13. In 2015, Didi Dache decided to merge with its major local competitor, Kuai Di Dache, backed by the Alibaba Group, and created a new $6 billion net worth company, Didi Kuaidi. In September 2015, Didi Kuaidi registered its brand name as Didi Chuxing. In 2016, Uber decided to sell its Chinese business to Didi Chuxing and quit the Chinese market (Weinberger, 2016).

in February 2015, Didi Dache merged with Kuai Di Dache and the unification of these two companies into Didi Chuxing subsequently dominated more than 80 percent of the Chinese ride-hailing market as of June 2015 (TECHINASIA, 2015). As a result, a possible interaction effect when two or more ride-hailing apps enter into the same city at the same time can be significantly eliminated. Didi Chuxing, as the dominant platform provider, can significantly benefit from positive network externalities and herding. Third, it takes only one or two weeks to buy and register a car in China. To observe the entry influence of Didi Chuxing into a city, we obtained new private car registration license data in the months following Didi Chuxing's entry. Because Didi Chuxing gradually expanded its platform into many cities, we can capture the enough variation in the timing of Didi Chuxing entry across different cities and months. Descriptive statistics for the dataset are summarized in Table 1. We consolidated the monthly number of new car registration and licensing records for each city from various Chinese Vehicle Management Offices under the administration of the Ministry of Public Security. Appendix A lists Didi Chuxing's launch time for the cities in the research treatment group sample. Using these official records, we developed a binary entry variable for a city during a specified month.

To justify the latent unobservable effects influencing new car sales for each city, we incorporated several control variables into our base model, including demographic characteristics, social and economic factors, traffic intensity and the number of mobile phone subscriptions. These control variables for each city are mainly downloaded from the China City Statistical Yearbook, which is an annual official statistical report that summarizes key indicators related to the economic and social development of China. All key statistical data are available at the national level and at local levels for province, autonomous region, and municipality directly under the control of Central Government. Specifically, we identify per capita income, GDP growth rate and population size as three covariates to explain the level of urbanization of each location. We also computed the number of mobile phone subscriptions, the geographic coverage of public transportation (i.e., the total number of registered public buses), and the intensity of paved roads to serve as three control variables, each of which can influence the use of ride-hailing apps.

Table 1. A Summary of Descriptive Statistics

Key Variable	Observation.	Mean	Std. Dev.	Min	Max
Ln (Car Sales)	6192	7.847	0.983	5.147	10.971
Didi Chuxing Entry	6192	0.007	0.083	0.000	1.000
Ln (Population Size)	6192	5.840	0.688	2.986	7.080
GDP Growth	6192	0.057	0.024	0.017	0.170
Per Capita (Thousands)	6192	16.708	17.135	3.114	166.749
Ln (Mobile)	6192	14.901	0.747	12.853	17.274
Bus	6192	8.090	7.534	0.500	103.770
Road	6192	13.249	20.751	0.590	442.950
Taxi	6192	7.363	1.002	4.828	9.973

Note: Per Capita (Thousands) denotes per capita income in thousands of RMB.

4. Empirical Methodology

4.1 The Base Model

Didi Chuxing's expansion into different cities over various months generates a natural experiment that allows us to discern the difference in new car sales after and before ride-hailing app entry for certain cities to the same difference for other cities that have yet to introduce the Didi Chuxing's service. We capture the exogenous discrepancy in Didi Chuxing's entry into various cities and months in the natural experiment as the foundation for recognizing the impact of its entry on new car sales. The identification approach has been employed by several prior studies (e.g., Dranove et al., 2003; Jin and Leslie, 2003; Zervas et al., 2017). We rely on the following base log regression model to capture the entry of Didi Chuxing:

$$\mathrm{Ln}(Y_{ct}) = \boldsymbol{A}_c + \boldsymbol{B}_t + g\cdot\boldsymbol{Z}_{ct} + p\cdot\boldsymbol{R}_{ct} + e_{ct} \quad (1)$$

where c represents cities and t refers to time (t = January 2015 to December 2015); Y_{ct} is the number of new car registration plates for city c at time t; $\boldsymbol{A_c}$ represents a vector capturing city fixed effects; and $\boldsymbol{B}_t$ represents a vector capturing time fixed effects. Further, $\boldsymbol{Z}_{ct}$ represents a vector reflecting city demographical features and socioeconomic indicators, such as, population size, GDP growth rate, per capita income, the number of mobile phones possessed, per capita bus transportation, and per capita road kilometers. Moreover, $\boldsymbol{R}_{ct}$ is a binary variable to indicate the entry of the ride-hailing app. In this case, $\boldsymbol{R}_{ct} = 1$ if Didi Chuxing becomes available in city *c* at time *t*, else $\boldsymbol{R}_{ct} = 0$ if not, and e_{ct} represents an error term. The coefficient *p* represents the estimation of the effect of Didi Chuxing's entry on the number of new car sales. If $p > 0$, then the ride-hailing app expansion has contributed to an increase in new car sales. The null hypothesis is that the effect of Didi Chuxing's entry on new car sales is not statistically significant (i.e., the p value of coefficient of a variable >0.1). In other words, Didi's entry has no significantly positive or negative influence on new car sales.

In the above model, we use city-level and time fixed effects to control for time-independent variances across cities and time. By incorporating these fixed effects into the base model, we can compare the differences of new car sales between different cities at different times. Moreover, we assume that demographic and socioeconomic factors possibly contribute to the increase of new car registrations. To justify such effects, several demographic and socioeconomic factors are included in the base model. We clustered the error terms at the city-level to discern the autocorrelation in the data (Bertrand et al., 2004). In addition, our regressions were weighted by city population size (Carpenter, 2005).

We realize that fixed effects model with these above covariates cannot capture latent time-varying effects related to new car sales. To evaluate the robustness of the main results, following prior studies (e.g., Athey and Stern 2002), we further include time-varying control variables into the base model and repeat the regression. We implement this examination by adding interaction terms that consider the variation of cities at different time periods as follows:

$$\mathrm{Ln}(Y_{ct}) = \boldsymbol{A}_c + \boldsymbol{B}_t + g\cdot\boldsymbol{Z}_{ct} + p\cdot\boldsymbol{R}_{ct} + \mathrm{v}\cdot\boldsymbol{Z}_{ct}\cdot\boldsymbol{T}_t + e_{ct} \quad (2)$$

We also judge the robustness of the main outcomes related to confounding effects derived from unobservable variables by means of a matched sample of observations (i.e., propensity score matching). We use population size, per capita income, GDP growth rate, and public transportation as matching characteristics and employ the nearest neighbor matching algorithm with replacement and caliper (0.05). Our DID analysis constructs a counterfactual outcome using a set of untreated cities, i.e., no Didi entry during the observation window period. The intuition behind matching is that the more similar treated and untreated cities are in their observed characteristics, the less likely they are to differ in unobserved ways, including bias-inducing factors. Matching methods aim to reduce endogeneity concerns by ensuring comparability between treated and untreated units (Heckman and Navarro-Lozano, 2004). In this study, we identify another 51 prefecture-level cities as the untreated (i.e., control) group based on the propensity score matching scheme (Didi did not enter the 51 cities during the study period).

In sum, the key identification assumption we have to make to support a causal interpretation of this Difference in Difference estimate is that there are no unobserved, time-varying, city-specific factors that are correlated with both Didi's entry and new car sales, resulting in endogeneity. In other words, we assume that unobserved factors that could potentially jointly affect both Didi's entry and new car sales do not systematically vary both between different cities and over time. For instance, the following unobserved factors are accounted for in our estimate and do not bias our estimates: (1) city-specific time-invariant differences in new car sales (e.g., the number of new car sales in Shanghai overall being more likely to be higher than those of small cities in China). This is the city fixed effect captured by $\boldsymbol{A_c}$ in Equation 1; (2) factors that vary arbitrarily over time but do not vary across cities (e.g., a generally increasing awareness of using Didi platform across all consumers in China over time). This is the month-fixed effect captured by $\boldsymbol{B}_t$ in Equation 2; (3) city-specific trends, which allow for unobserved confounders that vary both between cities and over time (i.e., $\boldsymbol{Z_{ct}} \cdot \boldsymbol{T_t}$ in Equation 2).

The first difference is taken using the city fixed effects, which allow for time-invariant differences in city new car sales between treated cites (i.e., Didi's entry) and non-treated cities (i.e. no Didi entry). The second difference in our DID specification is taken over time using month fixed effects Bt which allow for unobserved time-varying car sale differences that are common across different cities. The coefficient of interest is Rct, which has the usual DID interpretation: it is an estimate of the percentage change in new car sales in treated cities subsequent to Didi's entry compared against a baseline of changes in new car sales over the same time period in untreated (non-Didi entry) cities.

We interpret a statistically significant negative coefficient on new car sales as indicating that Didi's entry reduces the number of car sales. We interpret a coefficient that is not statistically different from zero as indicating that Didi's entry has no effect on new car sales. (i.e., the null hypothesis). We interpret a positive coefficient as indicating that Didi's entry stimulates new car sales.

4.2 Falsification Examination

It is possible that the main regressions will observe unauthentic concurrence entry effects. Some unobserved confounding factors may contribute to the relationship between Didi Chuxing and new car sales. To check the abovementioned DID parallel trend assumption and to understand how long it takes for significant effects to manifest, we evaluate whether any pre-entry events happening in the same period as Didi Chuxing's expansion into various cities led to the variation of new car sales. Following Chan and Ghose (2013) and Greenwood and Wattal (2015), we carry out a falsification examination by including a placebo dummy variable in our regressions. A one month pre-entry dummy along with two months of post-entry dummies are used as placebos to examine possible inter-temporal entry effects as follows:

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

where j belongs to {-1, 1, 2}, representing whether month t is the j_{th} month since Didi Chuxing's entry. We ignore the month of Didi Chuxing entry (Rct 0) in our regressions. The coefficients of pre-entry placebo variables should be positive and significant if the main results are more likely to be caused by any pre-entry events happened in the same time period as that of Didi's entry. The coefficients of the post-entry placebo variables would be positive and significant if Didi Chuxing's entry increases new car sales.

4.3 Exogeneity Concerns

We were concerned that Didi Chuxing's decision for entering into a city is endogenous and may be determined by unobserved passenger preferences predominant in a region. For example, a growth in the percentage of persons who prefer to hail a taxi would concurrently contribute to more new car sales and a higher likelihood of Didi Chuxing's entry. To ensure the validity of the causal relationship identified by the major findings, we must assure that the entry of Didi Chuxing is exogenous in its relationship to new car sales. To assess systematically if unobservable factors related to new car sales influence Didi Chuxing entry choices, we developed a hierarchical duration model (HDM) to forecast the entry of Didi Chuxing. The HDM includes demographic variables, socioeconomic factors, traffic intensity, the number of mobile phone subscriptions, and the number of new car sales as the predicative variables.

In the duration models, the dependent variables are a series of zeros or ones, which indicates Didi Chuxing's entry month in a city. By measuring the effect of Didi Chuxing's entry on new car sales, we can effectively inspect whether the number of mobile phone subscriptions and other related demographic and socioeconomic factors correlated with the increase of new car sales determine the entry patterns. The coefficients for the number of new car sales of this examination can potentially identify absent variables bias and reverse causality harming our main regression results.

5. Results

5.1 Base Model Regression

Our base model regression results are provided in Table 2. Model 1 runs an unweighted regression and we find that the coefficient of the binary entry variable is positive and significant. The estimation implies that Didi Chuxing's entry into a city can lead to a 6.5 percent increase (i.e., 277 new cars using the mean number of new car sales in the research sample as a reference point) in new car sales of the focal city per month[4]. Moreover, in Model 2, the regression is weighted by city population size and its results are very similar to those of Model 1 (i.e., the coefficients for the entry of Didi Chuxing are still positive and statistically significant). To examine the robustness of our base model regression results related to time-varying city factors, we include interaction terms of city covariates with various time periods in Model 3; the results remain basically unchanged.

To examine further potential unobservable factors that may disturb the base model estimation, we re-estimate the base model using cities that have matched demographic factors and socioeconomic indicators. This is achieved by using a propensity score matching scheme (as shown in Model 4). We find that the regression coefficients are still positive and statistically significant and that a 21.4 percent increase in new car sales occurs following Didi's entry.

In addition, there are 13 cities in which Uber and Didi both entered in 2015, we do attempt to control for the potential effect of the introduction of Uber on car purchase by using search volume data to proxy for the popularity of Uber. ln(Uber) is the natural log of the Baidu index of search terms related to Uber including Uber and Youbu (Uber Chinese name and the search term is in Chinese). The Baidu Index data were collected for the search terms for each month. We re-estimate the Model 4 by including the control variable Ln(Uber) and we find that the regression coefficients are still positive and statistically significant, but the positive effect is

[4] This estimation is reasonable given that the latest statistics report that the sales of new cars in China in May is over 840,000. Please refer to http://www.qichexl.com/a/xiaoliangpaixing/2017/0610/2944.html.

slightly weakened (as shown in Model 5). We further re-estimate the Model 4 using cities that only Didi entry in 2015. In other words, 13 cities that Didi and Uber entered at the same time and 13 matched cities (i.e. no Didi and Uber entry) are removed from our sample. The re-estimation result is added into Table 2 as shown in Model 6. We also find that the regression coefficient of Model 6 is still positive and statistically significant (with the positive effect slightly weaker than that of Model 4).

Table 2. The Impact of Didi's Entry on New Car Sales (with Robustness Checks)

Key Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Binary Entry (Didi Chuxing)	0.065***	0.062***	0.055*	0.214***	0.041***	0.048***
	(2.98)	(4.08)	(1.71)	(5.50)	(2.96)	(2.81)
Ln (Population Size)	0.250	0.749	0.170	29.610***	0.768	0.755
	(0.35)	(1.32)	(0.41)	(6.27)	(1.39)	(1.35)
GDP Growth	-0.412	-0.242	0.043	-7252.100***	-0.211	-0.226
	(-1.13)	(-0.81)	(0.18)	(-6.04)	(-0.73)	(-0.76)
Per Capita (Thousands)	0.040	0.060*	0.057	11.910***	0.063*	0.064*
	(1.32)	(1.89)	(1.65)	(6.07)	(1.93)	(1.91)
Ln (Mobile)	0.556***	0.613***	0.152	70.190***	0.437**	0.424**
	(2.90)	(3.45)	(1.40)	(6.14)	(2.41)	(2.18)
Bus	0.002	0.000	0.002	15.540***	-0.001	-0.001
	(0.70)	(0.02)	(0.55)	(6.07)	(-0.44)	(-0.75)
Road	-0.002	-0.003	-0.002	-24.190***	-0.003	-0.003
	(-0.81)	(-0.74)	(-0.71)	(-6.07)	(-0.88)	(-0.87)
Taxi	0.168**	0.143**	0.083*	-207.300***	0.118**	0.118**
	(2.29)	(2.34)	(1.74)	(-6.09)	(2.33)	(2.41)
Ln (Uber)					0.020**	0.022**
					(2.33)	(2.39)
Constant	0.065***	0.062***	0.055*	0.214***	-4.206	-3.945
	(2.98)	(4.08)	(1.71)	(5.50)	(-0.88)	(-0.78)
Weighted by population		Yes	Yes	Yes	Yes	Yes
Control × Time Trend			Yes	Yes	Yes	Yes
P-Score Matched Samples				Yes	Yes	Yes
Only Didi Entry						Yes
Observations	6192	6192	6192	6192	6192	5919
Adjusted R^2	0.961	0.962	0.965	0.911	0.962	0.958

Note: The log number of new car sales is the dependent variable. Robust t-values are stated in parentheses below coefficients and clustered by city level. Model 1 is the unweighted regression, while Models 2–3 are weighted regressions All regressions employ an ordinary least squares specification. All models include city-level and month fixed effects. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

5.2 Falsification Examination

We examine if the increase in new car sales already proliferated before Didi entry. We find that the number of new cars sold significantly increases after Didi Chuxing's entry (see Figure 1).

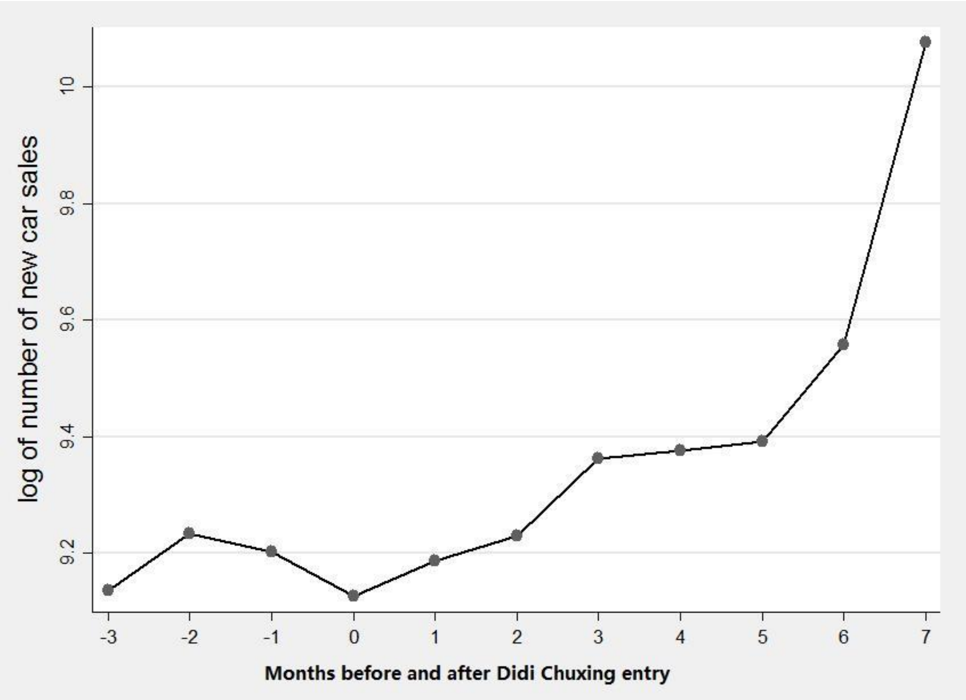

Figure 1. New Car Sales Before and After Didi Chuxing's Entry

As shown in Table 3, in models 1 (unweighted) and 2 (weighted), the one-month pre-entry placebo dummy variable failed to capture any pre-entry Didi Chuxing influence. Thus, it is unlikely that the positive relationship between new car sales and Didi Chuxing's entry found in prior regression results is a deceitful effect. It is also worth noting that the coefficient of the first entry month (i.e., Didi Chuxing Entry1) is not significant, suggesting that Didi Chuxing's entry has a delayed effect on increasing new car sales. The effect on new car sales only occurs in the second month after Didi Chuxing's entry, demonstrating a one-month delay between Didi Chuxing's entry and its impact on new car sales. It is reasonable for the local new car sales to increase several weeks after Didi Chuxing's entry as potential drivers need one or two weeks to purchase and register cars with Didi Chuxing. We argue that the presence of non-first-month entry effects, as shown in Table 3 further confirms the validity of the effect captured by the entry variables.

Table 3. Falsification Examination

	Model 1	**Model 2**
DiDi $Entry_{-1}$	-0.005	0.023
	(-0.21)	(0.85)
DiDi $Entry_{1}$	0.025	0.046
	(0.46)	(0.96)
DiDi $Entry_{2}$	0.101^{***}	0.110^{***}
	(3.57)	(4.87)
Log Population Size	0.251	0.746
	(0.36)	(1.35)
GDP Growth	-0.399	-0.230
	(-1.14)	(-0.80)
Per Capita (Thousands)	0.039	0.058^{*}
	(1.31)	(1.85)
Log Mobile	0.565^{***}	0.625^{***}
	(2.90)	(3.50)
Bus	0.002	0.000
	(0.68)	(0.04)
Road	-0.002	-0.003
	(-0.79)	(-0.72)
Taxi	0.174^{**}	0.144^{**}
	(2.37)	(2.36)
Constant	-2.669	-7.115
	(-0.51)	(-1.50)
Observations	6192	6192
Weighted by population	No	Yes
Adjusted R^2	0.960	0.962

Note: The log number of new car sales is the dependent variable. Robust t-values are shown in parentheses below coefficients All regressions employ an ordinary least squares specification. All models include city-level and month fixed effects. * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01.

5.3 Didi Chuxing's Entry Exogeneity

We were concerned whether potential unobservable variables related to new car sales influence Didi Chuxing's entry decisions. Consequently, we developed HDM including demographic variables, socioeconomic factors, and new car sales, to forecast Didi Chuxing's entry.

The results of the exogeneity examination offer insights into the estimation bias due to absence of unobservable variables and reverse causality. As shown by models 1 & 2 in Table 4, a number of demographic factors and the number of mobile subscriptions significantly influence Didi Chuxing's entry. As the number of mobile phone users increases, the propensity to download and use Didi Chuxing is enhanced.

As a new car sales variable is added in Model 3, we expect to observe effects driven from unobserved factors that determine the increase in new car sales and the entry of Didi Chuxing simultaneously. We find that the estimated coefficients on new car sales are not significant, suggesting that entry decisions have little relationship with the increase in new car sales over time and that it is unlikely there exist unobserved effects influencing new car sales and the entry of Didi Chuxing simultaneously. These empirical results confirm that Didi Chuxing's entry is exogenous in its relationship with the new car sales. We therefore reject the supposition that unobserved factors lead to the relationship between Didi Chuxing's expansion and new car sales.

Table 4. Hierarchical Duration Models Predicting Entry into Cities

	Logistic Regression		
Key Variables	**Model 1**	**Model 2**	**Model 3**
Log Population Size	1.711***	-0.346	-0.191
	(5.00)	(-0.70)	(-0.35)
GDP Growth	29.99***	25.920***	29.660***
	(6.13)	(5.32)	(4.97)
Per Capita (Thousands)	0.021***	0.000	0.003
	(3.57)	(0.05)	(0.24)
Log Mobile		2.054***	2.638***
		(6.02)	(5.17)

Bus		-0.016*	-0.017*
		(-1.76)	(-1.72)
Road		0.002	0.001
		(0.50)	(0.43)
Log New Car Sales			-0.579
			(-1.57)
Constant	-17.89***	-36.20***	-41.510***
	(-7.95)	(-11.43)	(-8.22)
Observations	6251	6193	6192
Log likelihood	-223.34	-203.73	-202.65
Note: The dependent variable is a series of 0s or 1s in the month that Didi Chuxing enters into a city. Robust t-values are shown in parentheses below coefficients and clustered by city level. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.			

5.5. The Impact on Specific Car Categories

We have provided evidence that ride-hailing apps have a positive impact on the overall new car sales across China. In this section, we explore the heterogeneous impacts of ride-hailing apps across different car categories, and deliver detailed empirical evidence. While ride-hailing apps can positively impact new car sales, it is unlikely that the overall growth of new car sales is consistent across all types of cars. We ran the regression models on five subsamples of different car models. Table 5 shows that the coefficients of Didi Chuxing's entry are positive and significant for Toyota Corolla and two comparable models of Geely, suggesting that the entry of Didi Chuxing has the strongest impact on the sales of economy vehicle models. These economy models are the most preferred models for ride-hailing drivers not only because they are designed for low-cost purchase and fuel savings, but also because these car manufacturers offer special policies for Didi Chuxing drivers. For example, Geely offers a "ready-to-register" Didi Chuxing service for all customers so that all new car owners can immediately join the Didi Chuxing platform as its drivers. As we expected, for business or luxury vehicle models (e.g., Toyota Camry and Mercedes Benz-C series), consumers' purchasing decisions are not strongly motivated by the entry of Didi Chuxing.

Table 5. Estimates of Heterogeneity for Didi Chuxing's Impact on New Car Sales

Variables	COROLLA	GEELY_Dihao	GEELY_Yuanjing	CAMRY	BENZ-C
Binary Entry (Didi Chuxing)	0.247***	0.233***	1.146***	0.097	0.140
	(5.03)	(4.43)	(5.84)	(1.62)	(1.49)
Log Population Size	-0.003	1.576	0.627	-0.544	0.167
	(-0.00)	(0.73)	(0.13)	(-0.43)	(0.12)
GDP Growth	-0.338	-1.113	1.609	0.213	-0.404
	(-0.53)	(-0.89)	(0.70)	(0.37)	(-0.63)
Per Capita (Thousands)	-0.013	0.167***	-0.149	0.043	-0.00479
	(-0.21)	(3.40)	(-1.35)	(1.06)	(-0.20)
Log Mobile	1.964***	1.364***	5.599***	-1.049***	1.041**
	(4.47)	(3.76)	(6.07)	(-4.83)	(2.64)
Bus	0.032***	0.011	0.016	-0.005	0.00243
	(2.97)	(1.36)	(1.13)	(-0.88)	(0.20)
Road	-0.006	-0.003	0.024	-0.010*	0.00941
	(-0.87)	(-0.58)	(1.07)	(-2.01)	(1.04)
Taxi	0.236	0.339**	0.622**	-0.120	0.149
	(1.37)	(2.21)	(2.34)	(-0.94)	(0.55)
Constant	-30.710**	-45.470***	-97.350**	27.25**	-17.33
	(-2.69)	(-2.92)	(-2.15)	(2.61)	(-1.41)
Weighted by population	Yes	Yes	Yes	Yes	Yes
Observations	6539	4159	2911	6518	11528
Adjusted R^2	0.864	0.885	0.664	0.897	0.357

Note: The dependent variable is the log number of new car sales. Robust t-values are shown in parentheses below coefficients and clustered by city level. All regressions employ an ordinary least squares specification. All models include city-level and month fixed effects. * denotes p < 0.1, ** denotes p < 0.05, *** denotes p < 0.01..

6. 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 research, we empirically examine the impact of the entry of Didi Chuxing, the leading peer-to-peer car service in China, on new car sales in 51 cities across the country. Our study provides compelling evidence that shows the positive impact of Didi Chuxing's entry on new car sales. Based on Didi Chuxing's different entry times into various cities, we can assess the overall effect of this new platform's entry on new car sales. Our empirical results suggest that, while the long term impacts of these emerging platforms remain to be seen, sharing economy platforms with dominant market shares can meaningfully change consumption behavior and market dynamics in the short run. Our results are consistent with previous studies demonstrating that Internet-enabled two-sided platforms, once reach critical mass, can rapidly change market dynamics, especially in those markets subject to strong network effects and herding (Brynjolfsson et al., 2003; Kauffman and Li, 2003; 2005; Constantinides and Barrett, 2014; Li et al., 2014). It is worth noting that, like the impacts of many other technological breakthroughs, the positive impact on new car sales documented in our study is likely to be transitory (Li, et al., 2006). We believe that, in order to leverage the ride-hailing platforms to achieve sustainable benefits in the long run, market players need to design appropriate incentive mechanisms and to build relational contracts that promote reciprocity and mutual trust (Kauffman, et al., 2010, Li, 2014).

Our study has several important managerial implications. The entry-induced increase in new car sales can benefit economy car manufacturers, especially those that directly partner with ride-hailing platforms. As economy model cars are well suited for ride-hailing drivers, certain business and marketing strategies, such as launching economy vehicle models or offering special ride-hailing driver-partner discounts, can effectively target potential ride-hailing drivers. On the contrary, as the entry of Didi Chuxing has little effect on the sales of business and luxury vehicle models, manufacturers of these models will not meaningfully benefit from ride-hailing platforms, at least in the short run.

By identifying those car models and manufacturers that experience nontrivial increases in new car sales due to the prevalence of ride-hailing platforms like Didi Chuxing, our results provide policy makers with a number of insights into how they can better design policies/regulations for different market segments. Moreover, environmental protection policy makers can more effectively reduce fuel consumption and alleviate pollutions by incentivizing car manufacturers to develop new car models and fuel technologies that can better leverage the emerging platforms.

Our paper has a few limitations, some of which represent future research opportunities in this area. First, our findings are obtained based on the entry timing of China's leading ride-hailing platform, Didi Chuxing, and local new car sales in various Chinese cities. Thus, generalizing our results to other countries may not be appropriate because of many country-specific market characteristics and industry policies. Therefore, future studies may be needed to investigate the impacts of ride-hailing apps in other major auto markets (e.g., Uber in the USA). The second limitation of our study is that it only examines the impact of Didi Chuxing's entry (it is possible that auto market dynamics may be influenced by the entry of a second-tier ride-hailing platform like Yidao). Nevertheless, as these second-tier players have trivial market shares and negligible growth in China, it is unlikely that our major findings are significantly biased because of their presence. Lastly, Didi Chuxing does not disclose the private information of its platform drivers, and consequently we cannot investigate how demographic factors (e.g., race, gender, age, or socio-economic status) influence new car sales driven by Didi Chuxing's market entry.

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APPENDIX

Table A1: Didi Chuxing Entry Timing

No.	Province	Enter City	Didi Chuxing	Density of population (person/per square kilometer)
1	Anhui	Hefei	Jun-2015	825
2	Beijing	Beijing	May-2015	1525
3	Chongqing	Chongqin	May-2015	1872
4	Fujian	Fuzhou	Jun-2015	593
5	Fujian	Quanzhou	Jun-2015	635
6	Fujian	Xiamen	Jun-2015	1220
7	Guangdong	Dongguan	Jun-2015	3349
8	Guangdong	Foshan	Jun-2015	2717
9	Guangdong	Guangzhou	May-2015	1859
10	Guangdong	Huizhou	Jun-2015	447
11	Guangdong	Shenzhen	May-2015	5551
12	Guangdong	Zhongshan	Jun-2015	1784
13	Guangdong	Zhuhai	Jun-2015	989
14	Guangxi	Nanning	Jun-2015	301
15	Hainan	Sanya	Jun-2015	357
16	Hebei	Shijiazhuang	Jun-2015	646
17	Hebei	Tangshan	Jun-2015	574
18	Heilongjiang	Harbin	Jun-2015	200
19	Henan	Luoyang	Jun-2015	423
20	Henan	Zhengzhou	Jun-2015	1149
21	Hubei	Wuhan	May-2015	1152
22	Hunan	Changsha	Jun-2015	596
23	Jiangsu	Changzhou	Jun-2015	1050
24	Jiangsu	Huai'an	Jun-2015	536
25	Jiangsu	Nanjing	Jun-2015	1213
26	Jiangsu	Nantong	Jun-2015	852
27	Jiangsu	Suzhou	Jun-2015	1233
28	Jiangsu	Wuxi	Jun-2015	1331
29	Jiangsu	Xuzhou	Jun-2015	762
30	Jiangsu	Yanghzou	Jun-2015	672
31	Jilin	Changchun	Jun-2015	373
32	Liaoning	Dalian	Jun-2015	505
33	Shandong	Dongying	Jun-2015	626
34	Liaoning	Shengyang	Jun-2015	838
35	Shaanxi	Xi'an	Jun-2015	229
36	Shandong	Jinan	Jun-2015	743
37	Shandong	Linyi	Jun-2015	630
38	Shandong	Qingdao	Jun-2015	694
39	Shandong	Weihai	Jun-2015	444
40	Shandong	Yantai	Jun-2015	473
41	Shanxi	Taiyuan	Jun-2015	604
42	Sichuan	Chengdu	May-2015	1158
43	Tianjin	Tianjin	May-2015	1270
44	Yunnan	Kunming	Jun-2015	299
45	Zhejiang	Hangzhou	May-2015	543
46	Zhejiang	Jiaxing	Jun-2015	1150
47	Zhejiang	Jinhua	Jun-2015	491
48	Zhejiang	Ningbo	Jun-2015	786
49	Zhejiang	Shaoxing	Jun-2015	595
50	Zhejiang	Taizhou	Jun-2015	634
51	Zhejiang	Wenzhou	Jun-2015	774