When Taxi Drivers Meet Dynamic Pricing: A Lesson from Singapore's JustGrab Program*

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Abstract

This paper studies how dynamic pricing influences taxi drivers' behaviors using a unique event, the inception of the JustGrab program in Singapore in 2017, which introduces dynamic pricing to some, but not all, taxi drivers. This is the first time in history that traditional taxi drivers have access to dynamic pricing. Using data covering the universe of taxi trips before and after the inception of JustGrab, we find that there is spatial reallocation that directs more taxi drivers to the previously less-served areas, that there is also a temporal reallocation that directs more taxi drivers to rush hours, as well as lunch hours, and that there is an overall increase in labor supply. Our results suggest that taxi drivers benefit from access to dynamic pricing. As the proliferation of app-based ride-hailing technology has encountered various degrees of opposition from the taxi industry in cities across the globe, such a lesson from JustGrab is worth attention.

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1 Introduction

For a long time, most taxi operations in cities around the globe have been subject to metered fares based on distance and time traveled, with some minor adjustments according to the specific locations or the time of the day. The underlying rationale behind such a scheme is clear – to mitigate issues of pirate taxis that stem from the asymmetric information between drivers and consumers.[1] However, taxi markets are highly localized, as drivers and customers search for each other in their nearby vicinity. Taxi demand and supply are time- and location-specific, and they vary substantially across locations and the time of day. Thus, the traditional metered fares can be quite rigid in the sense that the fares do not reflect real-time equilibrium prices at each location of the city. The extent of (latent) excess demand/supply can be substantial as seen by various anecdotal evidence on idling taxis or frustrated consumers who struggle to get a taxi when they need one.

App-based ride-hailing (ride-hailing for short) services started by Uber in 2009 have changed the broadly defined taxi market radically. While it brings considerable convenience to consumers, it also clashes with traditional taxi operators and drivers as they are close substitutes. One important feature of such ride-hailing services is the dynamic/surge pricing which adjusts prices in real time according to the excess demand/supply at each location.[2] This offers a potential answer to the problem of uncleared markets. Whether and how does dynamic pricing help clear the markets? What are the implications if dynamic pricing is applied to traditional taxi operators and drivers? This paper attempts to answer these questions empirically using a unique quasi-natural experiment in Singapore.

In effect from March 29, 2017, Grab, a ride-hailing service company in Singapore and much of Southeast Asia, introduces a JustGrab program that allows taxi drivers to have access to dynamic pricing. Singapore's traditional taxi market is an oligopoly environment, comprising a dominant taxi company, ComfortDelgro (henceforth CDG), accounting for about 60% market share, and five other smaller companies (henceforth non-CDG). Grab used to serve non-CDG

[1] Taxi fare schemes do not completely avoid the issue of asymmetric information, as a tourist unfamiliar with the city can still be cheated by drivers who take long detours. However, such an issue is lessened in the era of online GPS-augmented maps.

[2] One important benefit of dynamic pricing is that in contrast to traditional taxi fare schemes under which prices are only finalized when the trips are over, the prices mediated by the app are mutually agreed upon between the drivers and consumers before the rides begin, largely eliminating issues of asymmetric information. Besides dynamic pricing, two other crucial merits of app-based ride-hailing services are (1) **breaking entry barriers** that have existed in the traditional taxi markets by circumventing the taxi license/medallion system, (2) **improved matching efficiency** through a combination of an easy-to-operate mobile phone app and a platform that collect and analyze real-time big data to facilitate matching between drivers and customers.

taxi drivers as a matching platform through GrabTaxi, under which drivers are still subject to metered fares. JustGrab merges non-CDG taxi drivers with Grab's pool of private-hire drivers under dynamic pricing so that (1) any customer requesting a ride through JustGrab is subject to dynamic pricing, and (2) for non-CDG taxi drivers, dynamic pricing applies when picking up requests through JustGrab. This is the first time in history that traditional taxi drivers have access to dynamic pricing. Note that JustGrab is not available to CDG drivers, which serve as convenient counterfacturals for our analysis. More background information is provided in Section 2.

With a unique data set containing the universe of taxi trips in March and April 2017 in Singapore and the fact that JustGrab allows access to dynamic pricing to some, but not all, taxi drivers, we have a rare opportunity to obtain clean identification of the impact of dynamic pricing (or, more broadly, the price mechanism) on taxi market outcomes by contrasting the changes in behaviors of non-CDG drivers induced by the introduction of JustGrab to that of CDG drivers. Specifically, the market outcomes that we examine are the spatial and temporal allocation of taxi resources, as well as taxi drivers' overall labor supply and their responses to random weather shocks.

Our hypotheses are framed as follows. First, as in many cities, taxis in Singapore are less available to customers in suburban or peripheral locations because taxi drivers are less willing to be in those locations due to longer time and distance to reach a street-hail or a booking customer than in central areas. In particular, Singapore's city structure is heavily monocentric with a bustling downtown, and the city-area surcharge in the traditional taxi fare scheme encourages drivers to be around downtown. As a result, we hypothesize that there might be a spatial reallocation effect so that the price adjustment would cause drivers to shift from serving downtown or other "hot spots" (such as the airport, casinos, and other tourist attractions) to serving suburban and periphery locations. In other words, there may have existed a (latent) excess demand in suburban and peripheral locations under the rigid taxi fare scheme, but under dynamic pricing, this demand might have surfaced, and the price increases to clear the market.[3]

Second, there might be a similar reallocation effect along the time dimension. On the one hand, demand surges at rush hours due to commuting needs; on the other hand, under a rigid

[3]Note that observing empirically a spatial reallocation as described above would not be a tautology because the effects might be small or it might be that the hot spots actually suffer from excess demand under the traditional fare scheme. Based on our personal experiences, we conjecture that it is more likely that periphery locations suffer from excess demand.

taxi fare scheme, supply could be limited as drivers may find it undesirable to work during rush hours if easier matching, "peak-hour surcharges" (which exist in Singapore), and time charges (due to slower speed in traffic jams) are insufficient to cover various congestion-related costs. Thus, an excess demand is more likely to occur during rush hours than non-rush hours. With dynamic pricing, price increases at rush hours reduce demand but promote supply, inducing the reallocation of taxi labor supply from non-rush hours to rush hours.[4]

Third, we also study whether there is an overall increase in taxi drivers' labor supply. As dynamic pricing was a new option to non-CDG taxi drivers and all previous options were intact, we expect that there should be an increase in daily revenue per driver, and thus an upward-sloping supply curve would imply an increase in overall labor supply by taxi drivers.[5]

Fourth, we explore the role of rainfall – "random" shocks that often occur in Singapore's daily life – as exogenous demand and supply shocks that potentially amplify the spatial and intertemporal misallocation of taxis under rigid taxi fares. Given Singapore's tropical/rainforest climate, thunderstorms are frequent, and heavy rains could in general occur at any time of the day. The coverage of such weather events is rather local as there could be heavy rainfall at one location but no rainfall several kilometers away from that location. In the event of heavy rainfall, taxi demand surges but drivers usually find it too risky to drive in heavy rain and thus supply shrinks. Under the rigid taxi fare scheme which does not account for these weather events, markets are unlikely to clear. We expect that, relative to CDG drivers, non-CDG drivers would work more during rainfall by reacting to dynamic pricing.

Our empirical evidence indicates that the above hypotheses are all affirmative. We find significant effects of dynamic pricing on spatial reallocation and overall labor supply. The effect on drivers' reaction to rainfall is also rather strong. The temporal reallocation effect is evident once lunchtime is pooled with morning and evening rush hours. The above conceptual formulation focuses on price increases that eliminate excess demand, but we should also note that the base fare under dynamic pricing is generally lower than the traditional taxi fare. Thus, during non-rush hours or in suburban and periphery locations when the base fare is likely to apply, demand may increase, and non-CDG drivers may find it better to take up JustGrab booking requests than roam on the streets or wait for a booking via other methods. This also helps explain the

[4]Again, it may also be possible that there is excess supply at rush hours and excess demand at non-rush hours. For example, the demand may be low at rush hours due to peak-hour surcharges and heavy traffic, and the supply may be high at rush hours due to easier matching and peak-hour surcharges.

[5]As we do not observe drivers' income, we could not speak to the debate over reference-dependent preference in taxi drivers' labor supply behavior (Camerer et al., 1997; Farber, 2015; Thakral and Tô, 2021).

above-mentioned spatial and temporal reallocation effects.

Although the quantitative magnitude of welfare changes due to the introduction of JustGrab is beyond the scope of the current paper, two standard arguments suggest that JustGrab is welfare-improving. First, as a non-CDG taxi driver, one can choose to accept a booking from JustGrab under dynamic pricing, or to accept a booking from GrabTaxi under metered fares, or to accept a booking from its own company's dispatch system (the old phone-radio dispatch system), or to roam for a street hail. Because JustGrab was a new option for non-CDG drivers with all of the other options intact, our empirical findings that non-CDG drivers changed their behaviors in response to the introduction of JustGrab suggest that non-CDG drivers' revenue and welfare must have increased by a standard revealed-preference argument.[6] Second, as the directions of resource reallocation are all in accord with our hypotheses that dynamic pricing helps clear a market in which there was previously excess demand or excess supply, this suggests that dead-weight losses were reduced/eliminated and thus welfare improves. In other words, consumers also benefit from JustGrab.

Our study contributes to the understanding of the price mechanism in general. Government regulations of market operations that mute or dampen the price mechanisms are not uncommon. For instance, in the housing market, local governments in several cities in the United States have implemented regulations that limit the increase in rents charged by landlords. It has been shown that removing rent control improves market efficiency (Autor et al., 2014; Diamond et al., 2019). Related, we seek to examine the role of the price mechanism in the taxi market.

This paper also adds to the policy debate on resolving the tension between taxi drivers and ride-sharing companies. Since the inception of Uber in 2009 and various other versions (e.g., Lyft in the US, Didi in China, Ola in India, and Grab in Southeast Asia) that followed and flourished in different parts of the world, consumers in those regions experienced improved travel convenience empowered by the new ride-sharing technology. However, the apparent more efficient technology (Cramer and Krueger, 2016) "disrupted" the traditional taxi markets and encountered strong opposition from the market incumbents, including taxi companies, taxi drivers, and medallion/license holders.[7] Studying taxi drivers' response to dynamic pricing is important in knowing how effective this approach of sharing the benefits of new technology with traditional

[6] Part of the increase in revenue (and hence earnings) may be extracted as fees by the taxi companies, but again the same revealed-preference argument suggests that such extraction was not too excessive.

[7] Using data from the US, Berger et al. (2018) have documented about a 10% reduction in taxi drivers' earnings due to the entry of Uber.

taxi drivers may be. If so, other city governments around the globe may want to consider adopting this approach to ease the tension between incumbents and this "disruptive" new technology without compromising the opportunity for the price mechanism to improve welfare.

Our work is closely related to Brodeur and Nield (2018), Lu et al. (2018), and Shapiro (2018). Brodeur and Nield (2018) study the effects of weather shocks (rainfall) on taxi, Lyft, and Uber rides in New York City, and find that the number of Uber (Lyft) rides rose much more than the number of taxi rides. Lu et al. (2018) investigate how information on dynamic pricing influences the location choices of Uber drivers using a natural experiment arising from an outage of the system that generates the dynamic pricing heat map. Shapiro (2018) shows that the benefit of Uber relative to taxicabs is tied to population/employment density and that the source of this benefit is mainly from Uber's superior matching technology than taxicabs which exerts more in low-density places. Our work differs from Brodeur and Nield (2018) and Lu et al. (2018) because we focus on the above-described spatial and temporal reallocation of resources. Moreover, our study singles out the effect of dynamic pricing, whereas what Brodeur and Nield (2018) identifies is the mixed effects of dynamic pricing and matching technology. Relative to Lu et al. (2018), our study renders policy implications on the traditional taxi markets. Our result of spatial reallocation also points toward benefits for the low-density areas as in Shapiro (2018), but the source here is dynamic pricing rather than matching technology.

Also related is the work by Buchholz (2020) and Castillo (2019) who investigate the benefits of dynamic pricing or a more flexible pricing scheme than taxi fares through the lens of structural models. Our work complements these studies in documenting empirically the effects of dynamic pricing on resource allocations. Castillo et al. (2017) theoretically demonstrate one benefit of dynamic pricing – it helps avoid the problem of "wild goose chase". Our study is also related to the broader literature on the taxi/ride-hailing industry, e.g., Angrist et al. (2017), Chen et al. (2019), Cohen et al. (2016), Frechette et al. (2019), Gorback (2020), Lam et al. (2020), Ming et al. (2019), among others.

The rest of the paper is organized as follows. Section 2 details the background of JustGrab and Singapore's taxi market, the taxi data, and the empirical strategy. Section 3 presents the empirical results. Section 4 concludes.

2 Background: The Taxi Market in Singapore and the Introduction of JustGrab

The traditional taxi market in Singapore comprises six operators, CDG, Premier, Prime, Trans-Cab, HDT, and SMRT. CDG was formed in a merger in 2003 that combined two taxi fleets "Comfort" and "CityCab" and is currently the largest taxi operator. The number of CDG taxis accounts for about 58% the total number of taxis in our data set.

Traditionally, the main taxi dispatch service involved each individual taxi company taking telephone calls from customers and maintaining radio communications between the dispatcher and drivers. As dispatch services exhibit network economies, the CDG taxi drivers enjoyed the highest rate of customer calls compared to those working for the other taxi companies. The dispatch technology has improved drastically since app-based ride-hailing was developed for urban transportation with the inception of Uber in 2009 in San Francisco.

For clarity, we describe the standard steps of booking an app-based ride-hailing trip with dynamic pricing as follows. First, a customer sets up the destination and pick-up point through the app. Then, the app informs the customer of a fare that is calculated by an algorithm using the local demand and supply information at the time. As long as the customer agrees, the app/platform informs nearby drivers of the fare and trip information. Once a driver picks up the request, a deal is made, and the fare is then fixed. Such a process eliminates the fare uncertainty that typically exists in the traditional taxi market. It also eliminates the incentives for drivers to exploit asymmetric information by detouring or prolonging a trip for a higher fare.

Uber entered Singapore in 2013, and in the same year, GrabTaxi, a company that was founded in Malaysia as MyTeksi in 2012, also entered Singapore. In 2013 and 2014, the landscape of the taxi/ride-hailing market consisted of CDG taxis with two of its own dispatch services (a traditional radio dispatch and an app-based dispatch), Uber serving as a platform for private-hire cars, and GrabTaxi connecting all non-CDG taxi drivers using a mobile app under the same name. Recall that non-CDG drivers did not benefit much from the traditional radio dispatch as the sizes of fleets they belonged to were small; thus, the fact that GrabTaxi linked drivers from smaller operators besides CDG exerted network economies that these drivers did not enjoy before.

In May 2014, the company GrabTaxi introduced GrabCar, which connected private-hire cars in essentially the same way as Uber and became Uber's direct competitor in Singapore. In the same year, the company also moved its headquarter to Singapore. In January 2016, GrabTaxi was re-branded as Grab, which encompasses GrabTaxi (the app), GrabCar, and other services such as carpooling. Note the key difference between GrabTaxi and GrabCar: by calling GrabTaxi, a customer gets a taxi (could be from any non-CDG taxi operator) and pays the standard metered fares, whereas a private-hire service from GrabCar, like Uber, is subject to dynamic pricing.

The major event concerning this paper occurred on March 29, 2017, when Grab introduced the service of JustGrab, which combined its fleet of private-hire drivers (GrabCar drivers) with taxi drivers from its taxi operating partners (non-CDG taxi drivers) for a new dynamic pricing service after the transport authority approved the introduction of dynamic pricing for taxis. A customer who books a trip through JustGrab will be picked up by either a GrabCar driver or a non-CDG taxi driver. As GrabCar and GrabTaxi continued operating as separate functions, a non-CDG taxi driver now had JustGrab as a new channel with dynamic pricing, and the existing options with fixed metered rates (street hail, GrabTaxi, and traditional radio dispatch) were all intact. As a visual summary, Figure 1 illustrates the different types of taxis in Singapore and their corresponding matching platform.

Letting dynamic pricing be accessible to taxi drivers is an innovation that has not been seen elsewhere in the world when JustGrab was introduced. The event is unique in that some but not all taxi drivers are suddenly exposed to dynamic pricing with the matching technology being unaffected during the process. This feature allows for a clear identification of the impact of dynamic pricing as it partials out the change in the matching technology as a potential confounder. As demand and supply vary across locations and time, fares under dynamic pricing vary to a larger extent than the rigid metered taxi fares. By comparing non-CDG drivers to CDG drivers, we expect to gain knowledge of how taxi drivers' behaviors respond to price signals. In other words, this unique event of JustGrab provides an ideal context for understanding whether and how the price mechanism works.[8]

[8]In January 2018, Uber and CDG later partnered to introduce UberFlash, of which the function is essentially the same as JustGrab. However, this event "erased the control group" by giving all taxi drivers in Singapore access to dynamic pricing. Thus, our study focuses on JustGrab rather than UberFlash. In March 2018, Grab acquired Uber's business in the entire Southeast Asia. After the merger, the Singapore government mandated JustGrab to be accessible to all taxi drivers in Singapore.

3 Data and Empirical Strategy

3.1 Data and Variables

Our empirical analysis relies on three data sources. The most important dataset contains taxi trips from the Land Transport Authority (LTA) in Singapore. The raw dataset contains the universe of trips made by 25,208 taxis across all fleet operators between 1 March 2017 and 30 April 2017. Among the total, 16,024 taxis belong to CDG and 9,184 taxis belong to non-CDG operators. We define non-CDG taxis as our treatment group and CDG taxis as our control group. There are 26,974,759 trips recorded for both groups combined during the sample period. For each trip, we observe its origin and destination coordinates, the starting and ending time of the trip, and the specific route recorded at a 30-second interval.

Figure 2 presents the kernel density of four key trip attributes summarized separately for the treatment group and the control group using information prior to the introduction of JustGrab. The four attributes are taxi-specific average number of trips per day, average number of trips per day during rush hours, average service time per trip, and average service time per trip during rush hours.[9] As shown in the figure, there exist systematic differences between the treatment group and the control group along those four dimensions. Specifically, the first two panels show that CDG taxis take on more trips on average than non-CDG taxis, measured either for the full day or for rush hours only. The bottom two panels suggest that the control group generally exhibits shorter service time than the treatment group.

The large differences in trip attributes between the treatment and control groups could undermine the underlying parallel trend assumptions when we implement a set of differencing strategies to identify the impact of dynamic pricing on various market outcomes. To mitigate this concern, we adopt the propensity score matching technique to match the taxi drivers along the four attributes before conducting our main regression analysis. We adopt the neighbor matching without replacement based on Becker and Ichino (2002) and Leuven and Sianesi (2003). We impose the common support condition in the estimation of the propensity score and perform matching within each 20 equally spaced internals of the propensity score. The propensity score matching with common support restrictions reduces the number of taxis to 11,048, which is equally split between the treatment and the control groups.

After the propensity score matching, the taxi-specific trip attributes before the shock present

[9]Rush hours are defined as between 7:00 am and 9:00 am and between 5:00 pm and 8:00 pm.

a high degree of homogeneity as shown in Figure 3. Compared to the kernel densities prior to the matching, those after matching present common supports for both the treatment and the control groups. The treatment and control groups also have similar means, despite slight variation in the dispersion of the distributions. The homogeneity in the distributions of trip attributes between the treatment and control groups ensures that the two groups are comparable along various dimensions and mitigates concerns on potential unobserved factors that may invalidate our identification.

Table 1 reports the summary statistics of the taxi-type-specific trip attributes based on the raw sample and the matched sample, as well as the differences between the treatment and control groups in both samples. Specifically, Columns (1) and (2) show the means and standard errors of the trip attributes in the raw sample for the treatment and control groups separately. Large and significant differences between these two groups are seen and reported in Column (3) which echoes the kernel density estimates in Figure 2. Columns (4) and (5) report the means and standard errors of the trip attributes for the treatment and control groups based on the matched sample. As shown in Column (6), the differences in the service time-related attributes between the treatment and control samples are small and statistically insignificant at the 5 percent significance level. The treatment-control differences of the attributes related to the average number of trips are still statistically significant at the 5 percent significance level, but the magnitude has been dramatically reduced and has become intrinsically small.

Besides information on taxi trips, we also obtain data on dynamic pricing and location-specific rainfall measures to supplement our analysis. First, we capture the fares under dynamic pricing by simulating JustGrab calls using the Grab App from 1 April to 30 April, 2017, after JustGrab was launched. Specifically, we chose 80 distinct origin-destination pairs that produced the most frequent taxi trips before the introduction of JustGrab. We run queries at each origin-destination pair at fixed intervals (30 to 60 minutes, depending on the specific pair) between 7:00 am and 11:00 pm and record the fare of the ride returned by the App. This procedure produces a data set that captures the dynamic taxi fares between 7:00 am and 11:00 pm for both weekdays and weekends in April 2017. Second, we obtain rainfall information from the National Environmental Agency of Singapore that is collected from 57 weather stations scattered throughout Singapore. Rainfall in Singapore can be very localized, as is typical under a tropical/rainforest climate. To identify the amount of rainfall in a specific hour and at a specific area, we identify the weather station within the area and assign the average amount of rainfall recorded by the station in the hour to that area. If the area does not contain any weather station, we use the rainfall data recorded by the nearest weather station.

3.2 Empirical Strategy

We implement a set of differencing strategies to identify the impact of dynamic pricing on the spatial and temporal reallocation of taxi trips. To frame the spatial and temporal dimensions, we use the area-specific and hour-specific taxi trip intensity prior to the introduction of JustGrab as the treatment variables in the difference-in-differences specifications. We exploit this cross-sectional and inter-temporal variation in trip intensity to identify the spatial and temporal responses separately for the CDG and non-CDG taxis. We also compare the magnitude of the responses between the CDG and non-CDG taxis in a triple-differencing framework in which we control for high-dimensional interacting fixed effects to ensure unbiased estimates.

The spatial units in our setting comprise 309 subzones (areas) defined by the Urban Redevelopment Authority (URA) in Singapore.[10] We capture area-specific trip intensity using data prior to the implementation of JustGrab. The areas are delineated in Figure 4. The upper panel demonstrates the spatial variation in the area-adjusted number of trips initiated in the area. The lower panel presents a heat map of the starting locations of taxi trips. We specify 500 meters as the radius and use the Epanechnikov function to determine the kernel shape for the heat map. Both figures present a high degree of spatial variation in area-specific trip intensity prior to the shock. We rely on this spatial variation to capture how the change in the number of taxi trips varies cross-sectionally after dynamic pricing becomes accessible to a subset of taxi drivers.

We start by estimating the following equation,

$$TripCounts_{(t,d,a)} = \alpha_a Treat(Type)_{(t,a)} \times After_{(d,a)} + \boldsymbol{X}_{(t,d,a)}\boldsymbol{\beta}_a + \varepsilon_{(t,d,a)}, \quad (1)$$

where a indexes an area; d indexes a date (there are 61 dates in our sample); t indexes the taxi type (CDG versus non-CDG); $TripCounts_{(t,d,a)}$ captures the number of trips per day in area a, date d, and by taxi type t; $Treat(Type)_{(t,a)}$ is a discrete treatment variable that indicates non-CDG taxis; $After_{(d,a)}$ takes value 1 if the date is after JustGrab and takes value 0 otherwise; $\boldsymbol{X}_{(t,d,a)}$ captures a set of fixed effects, i.e., taxi type fixed effects and area-day fixed effects.[11] In

[10] There are 55 planning areas in Singapore as delineated by the URA, and each planning area is sub-divided into subzones.

[11] Note that by date we mean a specific calendar date, and by day we mean day of the month. Thus, the date fixed

this specification, we allow all coefficients to vary by area (or groups of areas) with different trip intensities. An examination of the difference in the estimated coefficient α_a informs the varying degrees of trip responses in areas with different trip intensities prior to the shock in a triple-differencing framework.

The identification assumption is that CDG and non-CDG taxi drivers exhibit similar counter-factual changes in their labor supply behaviors (where and when to roam and work) before and after the shock in the absence of JustGrab (in a difference-in-differences setup) and, even in the event that the before-after changes are not the same across taxi types, such differences are not systematically different across areas with different extent of trip intensity (in a triple-differencing setup).

To speak directly to the spatial reallocation effects, we then estimate an alternative specification:

$$TripCounts_{(a,d,t)} = \alpha_t Treat(AreaIntensity)_{(a,t)} \times After_{(d,t)} + \boldsymbol{X}_{(a,d,t)}\boldsymbol{\beta}_t + \varepsilon_{(a,d,t)}, \quad (2)$$

where $TripCounts_{(a,d,t)}$ and $After_{(d,t)}$ are defined as in Equation (1); $Treat(AreaIntensity)_{(a,t)}$ is a continuous treatment variable that represents the average area-specific daily taxi trips fulfilled by both CDG and non-CDG taxis before JustGrab (i.e., cross-sectional variation in area-specific trip intensity prior to the introduction of JustGrab); $\boldsymbol{X}_{(a,d,t)}$ captures a set of fixed effects, i.e., date fixed effects and area-day fixed effects. We allow all coefficients to vary by taxi type. The key coefficient of interest is α_t which captures the extent to which different areas receive different responses in taxi trips. The difference in the differences of the estimated coefficient α for CDG and non-CDG taxis informs the spatial reallocation responses of the treatment and control groups in a triple-differencing framework.

The identification strategy relies on the assumption that areas with different trip intensity prior to the shock exhibit similar counter-factual trends in the number of trips before and after the shock (in a difference-in-differences setup) and, even in the event that the trends are not parallel, the differences in the pre-trends across different areas are not systematically different between the CDG and non-CDG taxi trips (in a triple-differencing setup).

Similarly, to test whether there is an inter-temporal reallocation of taxi trips, we use the following two specifications to capture how different types of taxis respond to hour-specific trip

effects capture date-specific unobserved characteristics that are homogeneous across areas, and the area-day fixed effects capture all area-specific unobserved traits and allow these traits to vary across days of the month.

intensity.

$$TripCounts_{(t,d,h)} = \alpha_h Treat(Type)_{(t,h)} \times After_{(d,h)} + \boldsymbol{X}_{(t,d,h)}\boldsymbol{\beta}_h + \varepsilon_{(t,d,h)}. \tag{3}$$

$$TripCounts_{(h,d,t)} = \alpha_t Treat(HourIntensity)_{(h,t)} \times After_{(d,t)} + \boldsymbol{X}_{(h,d,t)}\boldsymbol{\beta}_t + \varepsilon_{(a,d,t)}, \tag{4}$$

In the above two specifications, h indexes the hour and $(HourIntensity)_{(h,t)}$ is a continuous treatment variable that represents the average hour-specific daily taxi trips fulfilled by both CDG and non-CDG taxis before JustGrab (i.e., intertemporal variation in hour-specific trip intensity prior to the introduction of JustGrab). The rest of the variables and indexes are the same as before. We allow all coefficients to vary by taxi type in Equation (3) and all coefficients to vary by the hour of the day (or groups of hours) in Equation (4). A further comparison of the estimated α_t between different types of taxis or the estimated α_h across different hours of the day identifies the intertemporal reallocation effect in the triple-differencing framework.

4 Empirical Results

4.1 Graphical Evidence

We first present graphical evidence to illustrate the spatial variation in the responses of taxi trips following the introduction of JustGrab. Figure 5 shows the average area-specific daily trips before and after the introduction of JustGrab stratified by the ventiles of such trips before JustGrab. Specifically, the horizontal axis describes the ventiles of the average daily trips before and ranked in order. The vertical axis describes the average daily trips in each ventile relative to the mean of daily trips averaged across all ventiles. A comparison of the spatial distribution of taxi trips before and after JustGrab reveals a large fall in the areas with the highest trip intensity but mild increases across all ventiles other than the top five.

Whereas Figure 5 captures the changes in levels (relative to each month's mean), Figure 6 shows the percentage changes in each ventile. First note that large falls in levels for the top few ventiles in Figure 5 amount to relatively small percentage decreases in Figure 6 because of the large volume of taxi trips to start with. The remaining ventiles see larger percentage increases when taxi trips are reallocated to these non-top ventiles; such effects are especially strong for the lowest three ventiles. Taken together, Figures 5 and 6 indicate a spatial reallocation in which a large volume of taxi trips from a few intensively-serviced areas are dispersed to a large number of less-serviced areas.

Figure 7 further summarizes the percentage change in average daily trips before and after JustGrab separately for CDG and non-CDG taxis. Since non-CDG taxis are affected by dynamic pricing due to the introduction of JustGrab, we expect to see larger shifts of non-CDG taxi trips across the ventiles than those of CDG taxi trips. Figure 7 demonstrates that non-CDG trips indeed experience larger shifts across ventiles in average daily trips compared to that of CDG trips. We observe lesser but similar responses to CDG trips compared to non-CDG trips. This could be driven by potential demand externalities triggered by JustGrab so that the overall demand for app-based dispatch in previously-less-serviced areas increases. As CDG also has its own app, such demand externalities could be a result of comparison shopping across Grab, Uber, and CDG. Nevertheless, Figure 7 suggests that the spatial reallocation of taxi trips observed in Figures 5 and 6 is mainly driven by the changes in the behavior of non-CDG taxis.

Next, from an intertemporal perspective, we show how taxi fares adjust throughout the day under the dynamic pricing scheme, in comparison to the fixed taxi fare scheme. We utilize the taxi fares retrieved for 80 fixed origin-destination pairs via the Grab App at different times of the day in April 2017 to plot the taxi fares under dynamic pricing in Figure 8. We also impute the standard taxi fares based on the shortest-distance route of the travel of the same set of origin-destination pairs and present the average metered taxi fares on the same figure.[12] The horizontal axis presents the hour of the day (between 7:00 am and 11:00 pm) and the vertical axis presents the mean of taxi fares averaged across all origin-destination pairs for each hour. We present the fluctuations in taxi fares for weekdays and weekends separately. As expected, the dynamic taxi fares fluctuate much more throughout the day on weekdays, in comparison to that on weekends or to metered taxi fares. Dramatic increases in dynamic taxi fares during weekday rush hours reveal a potential mismatch in supply and demand under the metered fares.

The potential mismatch in supply and demand along the temporal dimension could induce an intertemporal reallocation of taxi trips. As shown in Figure 9, there is a clear trip reallocation in the morning from non-rush hours (such as between 9:00 am and 10:00 am) to rush hours (such as between 7:00 am and 9:00 am) when we compare the hour-specific trip intensity before and after JustGrab. There is also a slight increase in trip intensity in the afternoon rush hours, but it is not as striking as that observed in the morning, perhaps due to the fact that people may schedule their post-work trip more flexibly. Such intertemporal reallocation of taxi trips is more clearly

[12]We discuss the details of the imputation process in the Appendix.

observed in terms of percentages as shown in Figure 10 and is mainly driven by the change in behaviors of non-CDG taxi drivers.

4.2 Baseline Estimates

Motivated by the graphical evidence, we set out to identify the spatial and intertemporal reallocation of taxi trips in a rigorous regression framework.

In Table 2, we specify the treatment variable as the dummy indicating non-CDG taxis. We estimate a difference-in-differences specification separately for areas with different levels of trip intensity, consistent with the regression specification in Equation (1). The estimated coefficient associated with the interaction term is large and significant for lowest-trip-intensity areas as shown in Columns (1). This coefficient decreases in magnitude and eventually turns negative when we move to the highest-trip-intensity areas in Column (4). As the estimated coefficients are likely to be underestimated because of potential demand externalities, the real effect of the dynamic pricing could be larger.[13] The evidence is consistent with our hypothesis that, compared to CDG drivers, non-CDG drivers have stronger incentives to move out of previously popular locations and take on trips in previously less-served locations after the introduction of JustGrab.

Table 3 reports the estimation results of Equation (2). We estimate the regression specification both by pooling all taxis together (Columns (1)) and for non-CDG and CDG taxis separately (Columns (2) and (3)). The estimated coefficients associated with the interaction terms in these three settings are -0.0962, -0.1580, and -0.0822 and they are all statistically significant at the 1% significance level. Consistent with evidence illustrated in Figures 5-7, the estimates suggest a significant spatial reallocation of taxi trips following the implementation of JustGrab. Specifically, low-intensity areas experience an increase in trip counts and high-intensity areas experience a drop in trip counts. This shift is mainly driven by the shifts of non-CDG trips although CDG drivers also respond to a smaller extent. We perform the Chi-Squared test to test the significance of the difference between the responses of the non-CDG taxis and CDG taxis in a seemingly unrelated regression setup, we find a statistically significant difference between the two, consistent with predictions in the triple-differencing framework.

In Table 4, we report the estimated coefficients based on Equation (3). We capture the hour-

[13]The changes in CDG taxi drivers' behaviors could be due to the potential demand externalities as mentioned in Section 4.1.

specific trip intensity based on whether the hour belongs to rush hours or non-rush hours. We use the type of taxi as the treatment dummy and estimate the effects separately for rush hours and non-rush hours. We find that compared to CDG taxi drivers, non-CDG taxi drivers are more likely to increase their supply during rush hours and decrease their supply during non-rush hours. The evidence is clearly in line with the temporal reallocation effect that we conjecture.

In Table 5, we report the estimated coefficients based on Equation (4) to identify the intertemporal reallocation of taxi trips. We observe a significant increase in taxi trips during rush hours when both types of taxis are pooled together, as shown in Column (1). However, the evidence on the temporal reallocation of non-CDG taxis is not significant despite the large magnitude. CDG taxi trips decrease during rush hours likely due to the crowd-out effect of increased non-CDG taxi supplies induced by the price surge. As we believe lunchtime may introduce special dynamism into the intertemporal reallocation of taxi trips, we define extended rush hours by adding lunchtime and interact it with the after dummy as direct controls in Columns (4)-(6). We find that once lunchtime is incorporated, there is a significant and large intertemporal reallocation effect from non-CDG taxis.

4.3 Heterogeneity, Rainfall, and Learning Effects

Next, we examine interactive spatial and temporal responses, the effects of rainfall, as well as the learning effect. Table 6 reports heterogeneous spatial reallocation effects separately for rush hours and non-rush hours. Specifically, Columns (1), (3), and (5) report the estimates for all taxis, non-CDG taxis, and CDG taxis based on the rush-hour sample, whereas Columns (2), (4), and (6) report the corresponding estimates based on the non-rush-hour sample. The evidence suggests that the spatial reallocation response is more pronounced during rush hours, especially so for non-CDG drivers. While trips fulfilled by CDG drivers are also reallocated toward the low-trip-intensity areas, there are no significant differences in the responses between rush hours and non-rush hours.

Next, we exploit an exogenous source of variation created by rainfall to supplement the previous analyses, and the results are shown in Table 7. The demand for taxis surges during rainfall, and the taxi supply may shrink because of the hazards associated with driving under heavy rains. Therefore, there would be an excess demand for taxis during heavy rainfall under the metered fare scheme, whereas the prices may surge under dynamic pricing in reaction to the excess demand. As a result, rainfall should trigger stronger supply responses for non-CDG drivers relative to the CDG drivers. In addition, because areas with higher trip intensity have higher potential excess demand during rainfall, the induced supply responses could potentially dominate the spatial reallocation effect and reverse the spatial reallocation pattern that we observed previously. Both conjectures are verified in Table 7. We observe higher supply responses of non-CDG taxis than CDG taxis and such difference is especially pronounced during rainfall and in areas with high-trip intensity.

We further explore potential learning effects. If it takes time for non-CDG drivers to learn the functions of JustGrab and their best responses in terms of locations and timing to roam/work to utilize the benefits of dynamic pricing, and/or if it takes time for Grab users to realize the existence and convenience of JustGrab, one may suspect that the spatial responses of non-CDG trips are not immediate. This conjecture is evidenced by the patterns observed in Table 8 where we report the spatial reallocation of taxi trips separately for the first half of the month and the second half of the month. We observe a stronger response in the second half of the month and this is especially so for non-CDG drivers. The responses of CDG drivers are not significantly different for the first and the second half of the month.

4.4 Taxi Labor Supply

Next, we explore taxi drivers' labor supply responses. We capture the taxi labor supply using the daily number of trips, daily service time, and daily working time computed for each individual taxi. The service time counts the total number of minutes when the driver is en route with a passenger. The working time includes the service time and the time when the driver is roaming or in response to a call. We compare the outcomes of CDG drivers and non-CDG drivers before and after the introduction of JustGrab in a similar difference-in-differences framework. For each outcome, we also explore how the responses vary in a full-day setting versus during rush hours only. All regression estimates are obtained after controlling for date fixed effects and taxi fixed effects.

As shown in Columns (1) and (2) of Table 9, non-CDG taxis perform 2.4% more trips daily on average and 3.14% more trips daily during rush hours. Column (3) shows that the total service time increases by 3.5% on an average day. This could be due to longer trips originating from previously-less-serviced areas or increases in incentives to work due to price surges. The rush-hour service time increases by about 4%, as shown in Column (4). We find larger responses when focusing on the total working time, as shown in Columns (5) and (6). Evidence suggests that dynamic pricing increases both taxi trips and service time supplied by non-CDG drivers, whereas the effects are especially pronounced during rush hours because of the price surges at those times.

4.5 Taxi Revenue

How much does the JustGrab program benefit the non-CDG drivers? To answer this question, we examine the extent to which the non-CDG taxi drivers' total revenue has increased in response to JustGrab. As we lack the direct data on revenue per taxi, we impute the revenue based on detailed route recordings of the trips. In particular, we impute an upper bound and a lower bound for the changes in revenue per taxi.

Lower bound: Our evidence clearly points to the fact that dynamic pricing was adopted by non-CDG drivers when it became available. A non-CDG driver can keep using the metered fare and continue his/her routine as in March 2017 before JustGrab was launched. Think about the revenue per taxi per day as the product of labor supply per day (total working hours in a day for a taxi) and the revenue per hour. A standard revealed-preference argument implies that revenue per hour is unlikely to decrease because taxi drivers can keep their routine as before. However, we show that the labor supply has increased by 5.09% in Table 9. Thus, we can obtain a lower bound of 5.09% for the increase in revenue per taxi per day.

Upper bound: When evaluating the options between using dynamic pricing and metered taxi fares, it is unlikely that one dominates the other. During peak hours, dynamic pricing may be used more frequently because price surges motivate drivers to take up this option. During non-peak hours, it is unclear whether non-CDG drivers prefer metered fares to dynamic pricing. On the one hand, the metered fares are higher than the base fare of dynamic pricing, which is likely to apply during non-peak hours; on the other hand, the fact that this base fare is lower incentivizes customers to request taxi rides more through JustGrab, and hence drivers may find it easier to match with a customer via JustGrab. Since we do not observe which trip is under dynamic pricing or not, we impute an upper bound as follows. The full details of the imputation process are relegated to the Appendix.

First, we compute a *surge ratio* for each of the 80 origin-destination pairs (as those mentioned in Section 3.1) for each day and hour by dividing the fare under dynamic pricing by the metered fare. Second, we assign all of the non-CDG trips in our data to each of the location-day-hour bins, each of which has a specific surge ratio. Third, we impute the fare of each trip as the dynamic pricing fare if the surge ratio is greater or equal to 1 and as the metered fare if the surge ratio is less than 1. Fourth, we impute the taxi fares by the metered fare scheme for the period before JustGrab for non-CDG taxis and for the whole sample period for CDG taxis. Last, contrasting the before-after differences between non-CDG taxis and CDG taxis, we arrive at an increased revenue of 25.7%. This number likely provides an upper bound because, by construction, we always assign the higher fare during the imputation process.

5 Conclusion

This paper exploits the launch of the JustGrab program in Singapore as a unique quasi-experiment in which some, but not all, taxi drivers, who used to operate under traditional metered fares, suddenly gained access to dynamic pricing via a previously available matching platform. Such an exogenous event, combined with a comprehensive dataset that covers the universe of taxi trips before and after the event, allows us to explore the impact of dynamic pricing on spatial and intertemporal reallocations of taxis and taxi drivers' labor supply responses, by employing a set of differencing strategies. We find that areas less served before the introduction of JustGrab experienced an increase in the number of taxi trips initiated in those areas, whereas the previous "hotspots" for taxi pickups experienced a decline. Such spatial reallocations are mainly driven by the type of taxis that are exposed to dynamic pricing due to the introduction of JustGrab. We also find intertemporal reallocation from non-rush hours to rush hours among the treated taxis. In terms of labor supply, we find that taxi drivers increase their total amount of working hours by 5.1% in response to the event.

As explained in Section 4.5, the imputed lower- and upper-bound of percentage changes in taxi revenues are 5.1% and 25.7%, respectively. From both viewpoints of the customers and taxi drivers, this added option (with all previous options intact) is welfare improving by a standard revealed-preference argument. The clear evidence of taxi drivers' behavioral changes indicates that the JustGrab Program (and the price mechanism!) is effective. Furthermore, the fact that there is a significant increase in taxi revenue suggests that allowing taxi drivers access to dynamic pricing can be an effective tool to ease the tension between traditional taxi drivers and app-based ride-hailing.

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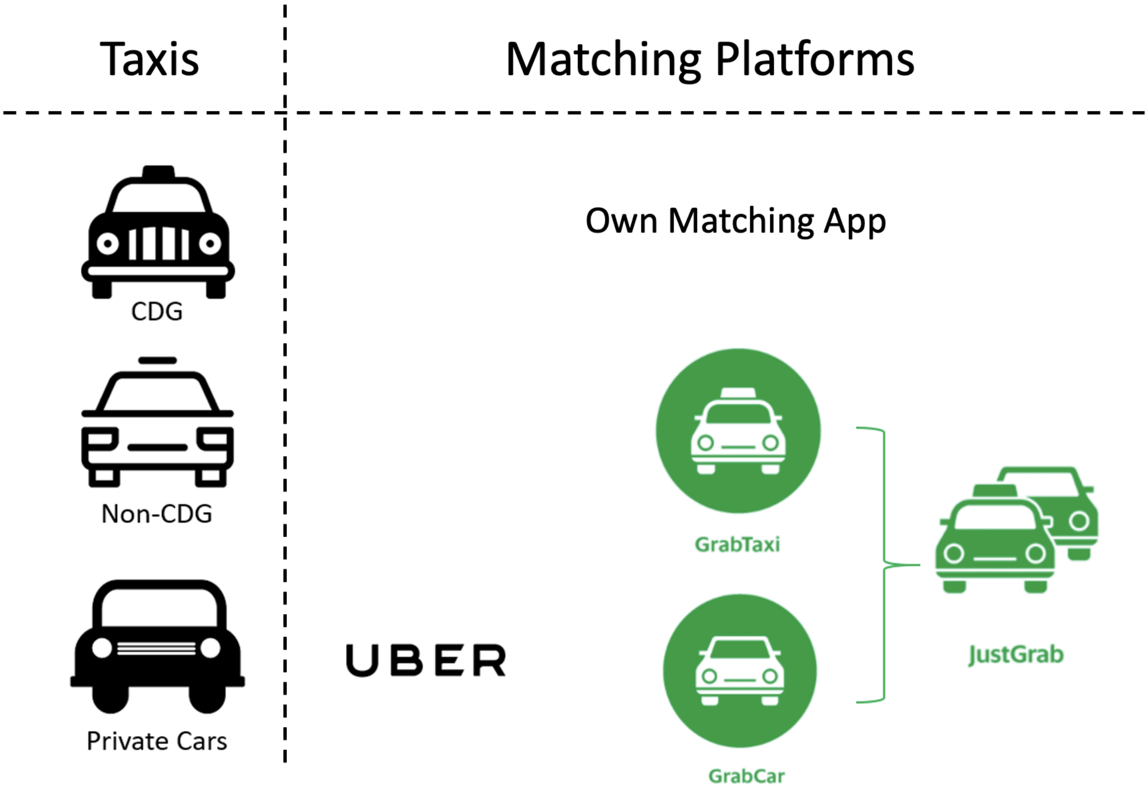

Figure 1: JustGrab Program

Notes: This figure illustrates the different types of taxis on the market and their corresponding matching platforms.

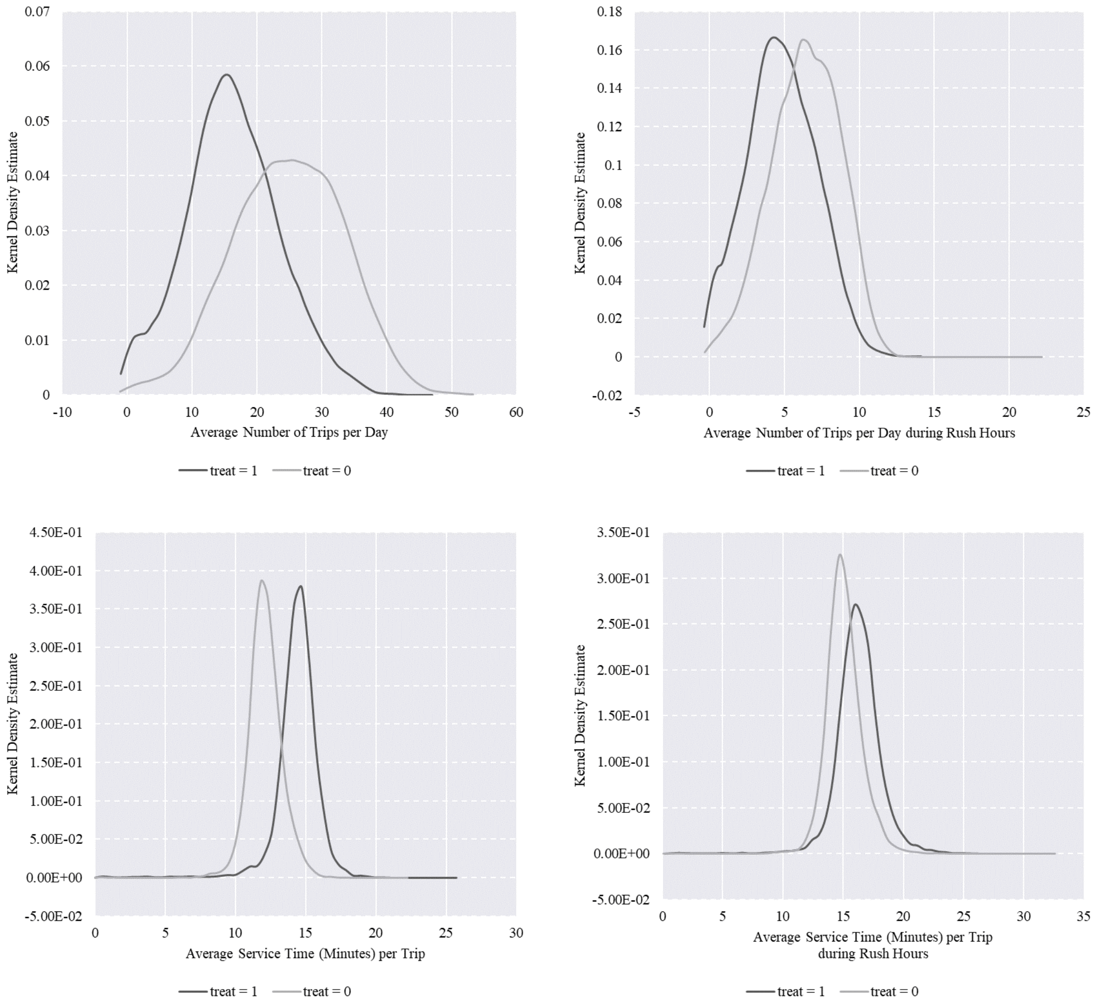

Figure 2: Kernel Density of Trip Attributes before Matching

Notes: This figure plots the kernel densities of four trip attributes separately for the treatment and control groups based on the *raw* data. The four trip attributes are average number of trips per day (upper left panel), average number of trips per day during rush hours (upper right panel), average service time per trip (lower left panel), and average service time per trip during rush hours (lower right panel). The kernel density estimates are based on the Epanechnikov kernel.

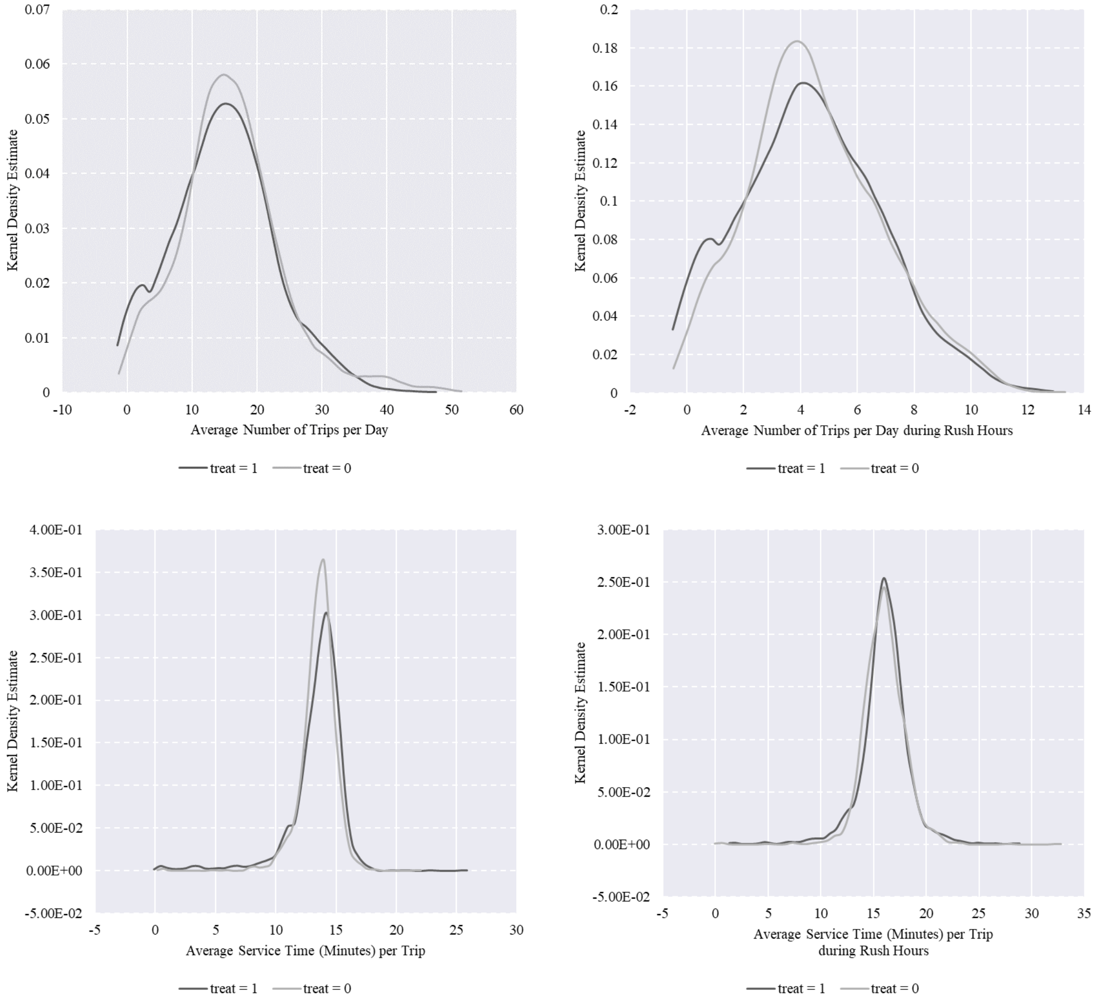

Figure 3: Kernel Density of Trip Attributes after Matching

Notes: This figure plots the kernel densities of four trip attributes separately for the treatment and control groups based on the *matched* data. Sample matching relies on propensity score matching of nearest-neighbor without replacement (Becker and Ichino 2002 and Leuven and Sianesi 2003). We impose the common support condition in the estimation of the propensity score and perform matching within each 20 equally spaced internals of the propensity score. The four trip attributes are average number of trips per day (upper left panel), average number of trips per day during rush hours (upper right panel), average service time per trip (lower left panel), and average service time per trip during rush hours (lower right panel). The kernel density estimates are based on the Epanechnikov kernel.

Figure 4: Average Daily Taxi Trips before JustGrab

Notes: This figure plots the spatial variation in area-specific trip intensity. The upper panel plots the thematic map based on the average number of trips per square meter of the area. The lower panel plots the heat map based on the trips and their exact locations. We specify 500 meters as the radius and use the Epanechnikov function to determine the Kernel shape for the heat map.

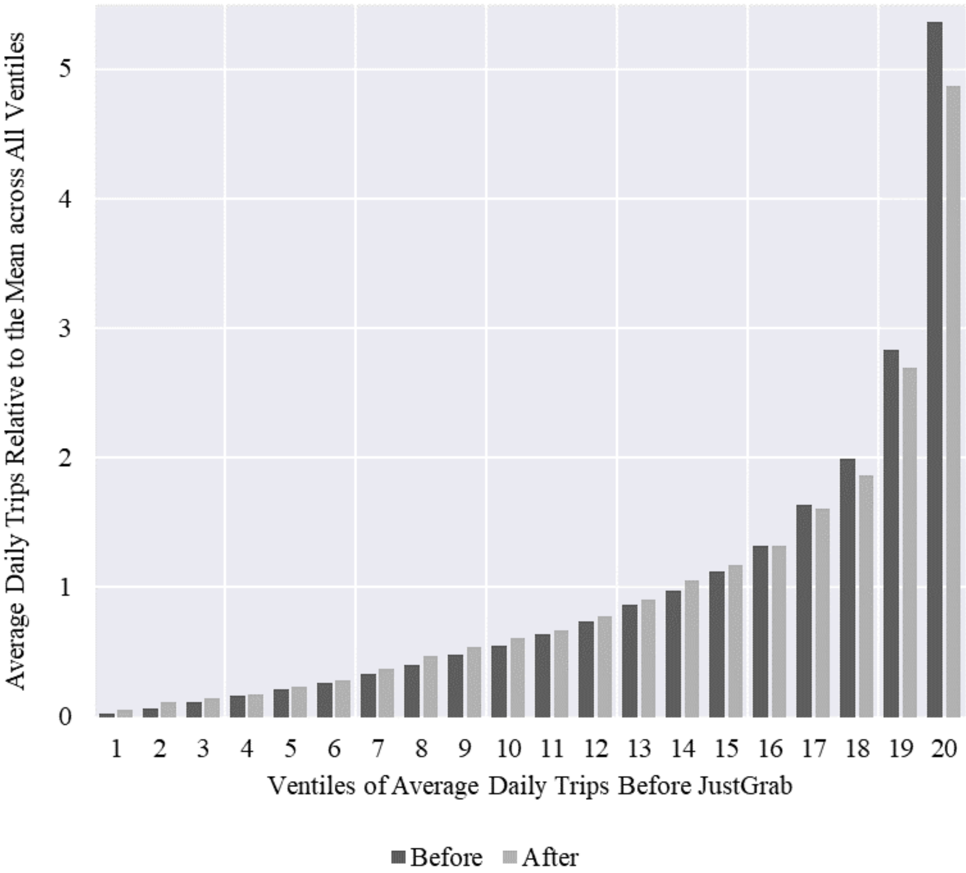

Figure 5: Average Area-level Daily Trips Before and After JustGrab

Notes: The horizontal axis describes the ventiles of the average daily trips before JustGrab. The vertical axis describes the average daily trips in each ventile relative to the mean of daily trips averaged across all ventiles. We report the numbers for both before and after the introduction of JustGrab.

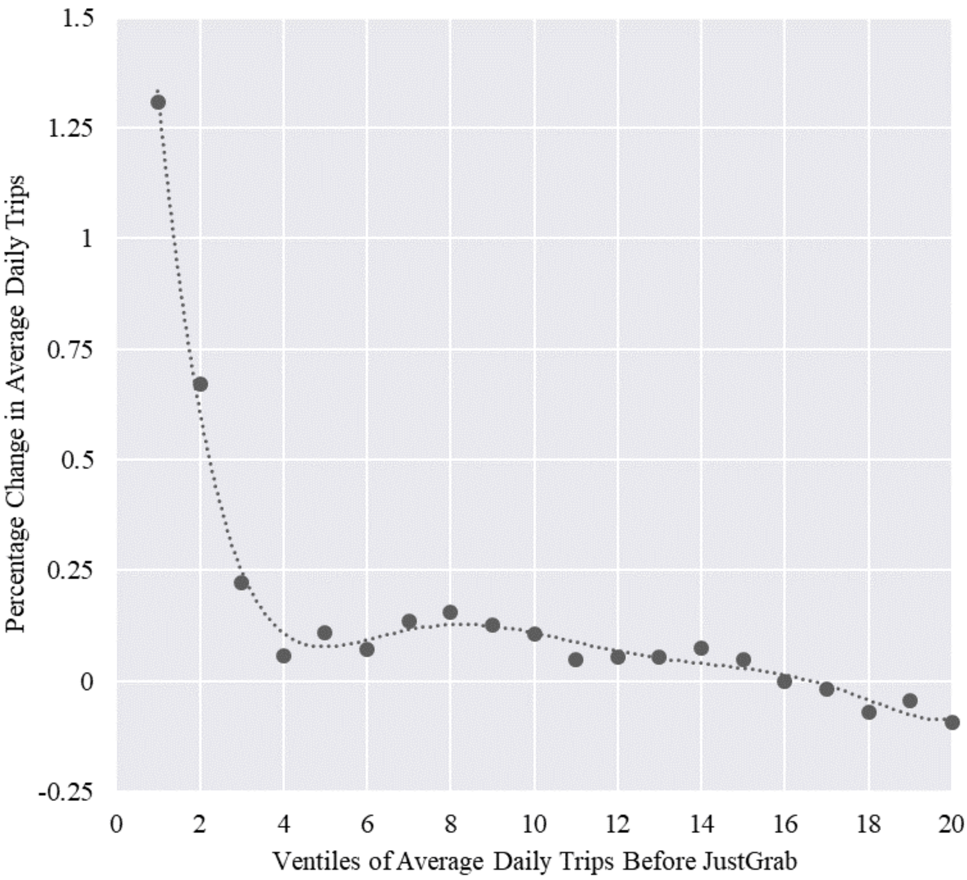

Figure 6: Percentage Change in Average Area-level Daily Trips Before and After JustGrab

Notes: The horizontal axis describes the ventiles of the average daily trips before JustGrab. The vertical axis describes the percentage change in the mean-adjusted average daily trips before and after JustGrab.

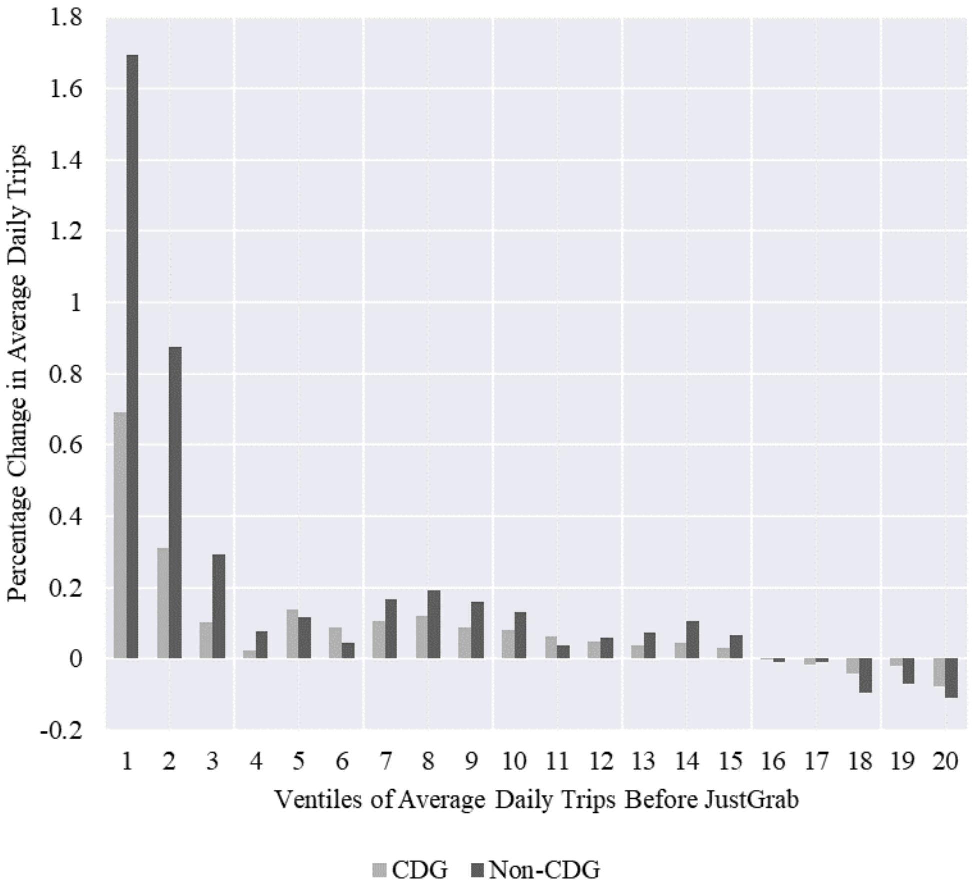

Figure 7: Percentage Change in Average Daily Trips Stratified by Taxi Type

Notes: The horizontal axis describes the ventiles of the average daily trips before JustGrab. The vertical axis describes the percentage change in the mean-adjusted average daily trips before and after JustGrab separately for CDG and non-CDG taxis.

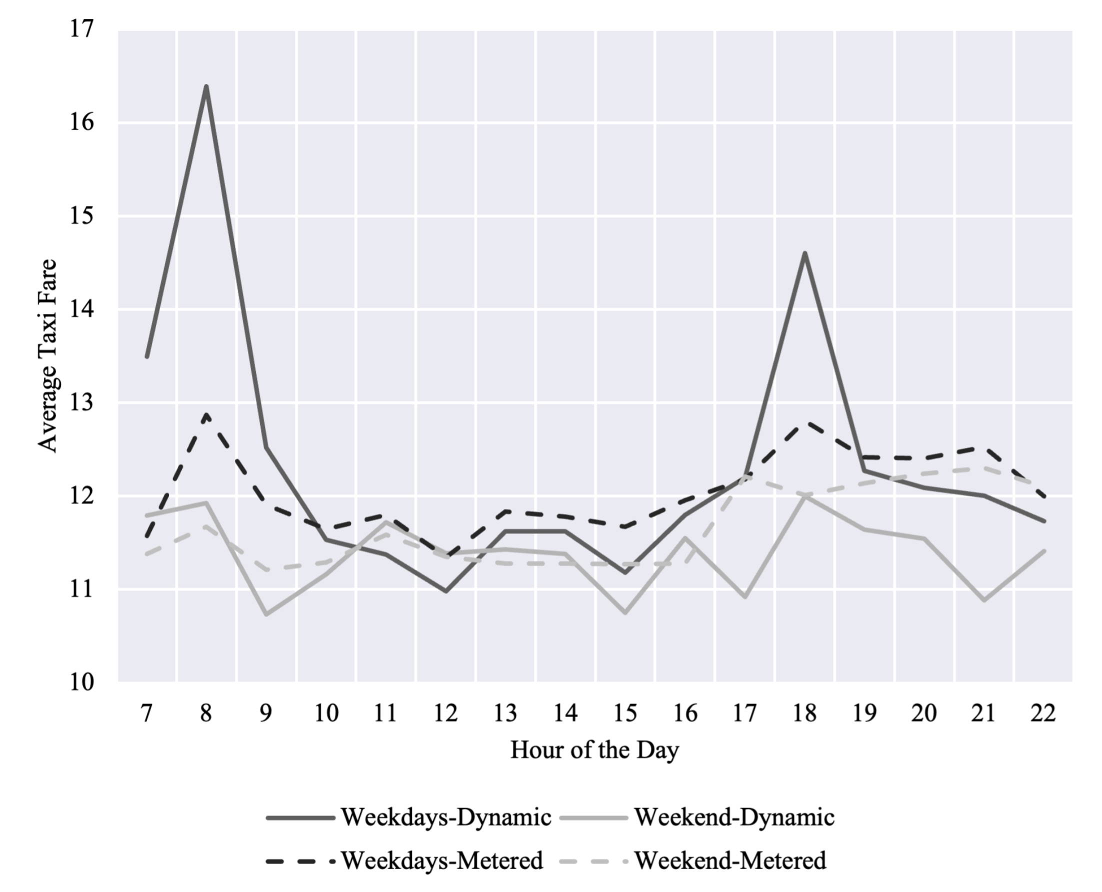

Figure 8: Taxi Fares within a Day

Notes: The horizontal axis represents the specific hour of the day. The vertical axis describes the average taxi fares under dynamic pricing and under metered fares for 80 fixed origin-destination pairs.

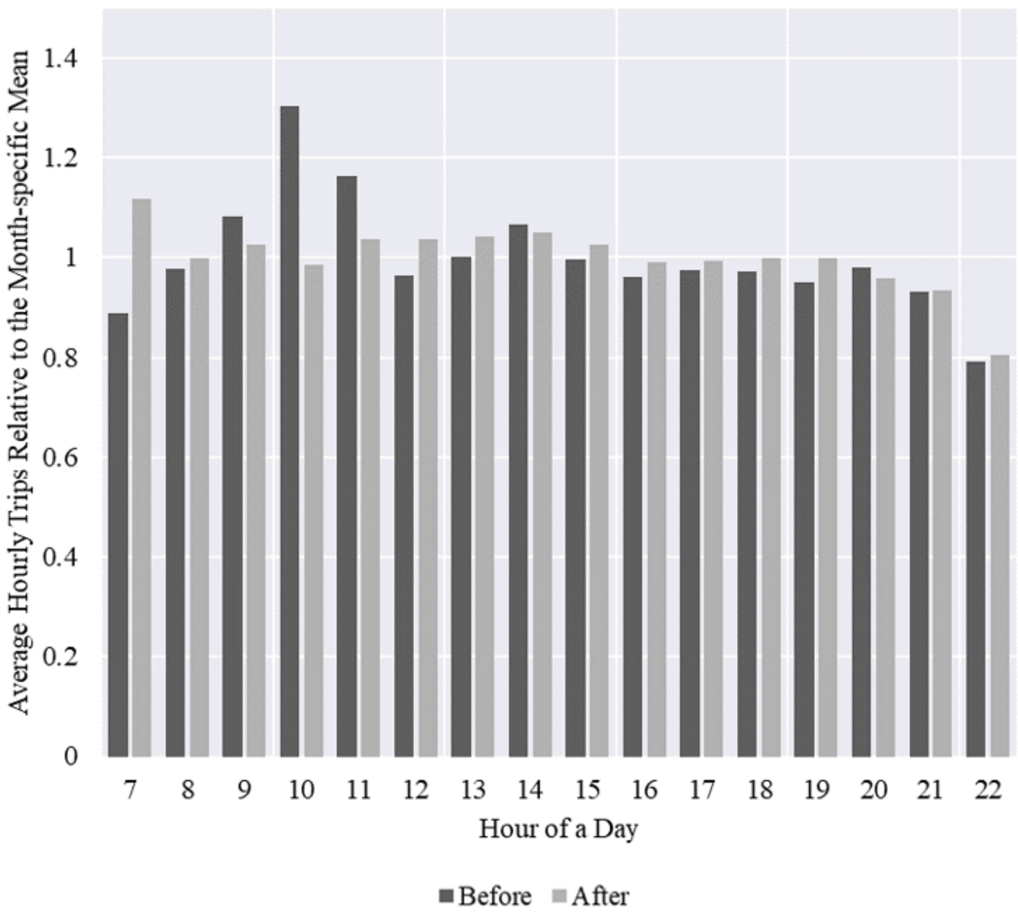

Figure 9: Average Hourly Trips Before and After JustGrab

Notes: The horizontal axis represents the hour of a day. The vertical axis represents the average hourly trips relative to the period-specific mean. We report the numbers for both before and after JustGrab.

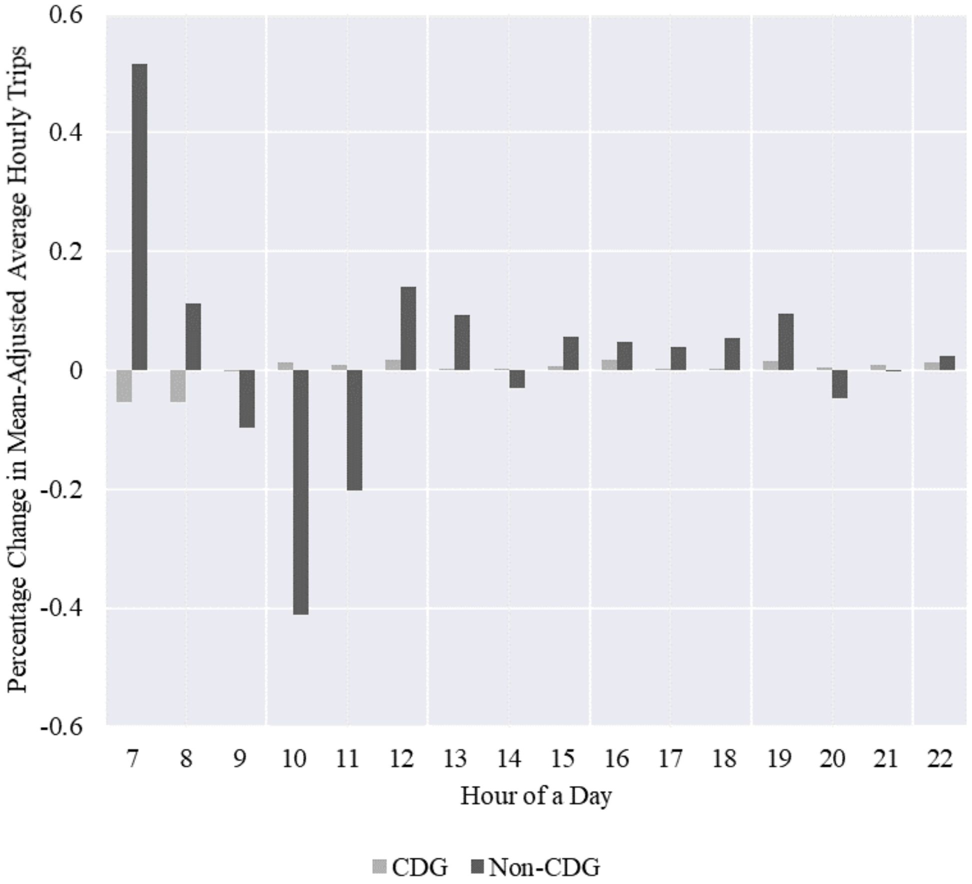

Figure 10: Percentage Change in Average Hourly Trips Stratified by Taxi Type

Notes: The horizontal axis specifies the specific hour of the day. The vertical axis describes the percentage change in the mean-adjusted average hourly trips from before to after JustGrab separately for CDG and non-CDG taxis.

Table 1: Summary Statistics of Taxi-Specific Trip Attributes

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample			Matched Sample		
	Control	Treat	Difference	Control	Treat	Difference
Average Number of Trips per Day	24.8178	16.1958	8.6220	15.8966	14.7716	1.1250
	(0.0668)	(0.0755)	(0.1008)	(0.1932)	(0.1893)	(0.2705)
Average Number of Trips per Day during Rush Hours	6.3934	4.8067	1.5867	4.5118	4.3362	0.1756
	(0.0181)	(0.0240)	(0.0300)	(0.0562)	(0.0594)	(0.0818)
Average Service Time per Trip	12.1263	14.3655	-2.2392	13.5353	13.4191	0.1162
	(0.0098)	(0.0172)	(0.0198)	(0.0351)	(0.0561)	(0.0661)
Average Service Time per Trip during Rush Hours	15.0680	16.2466	-1.1786	15.9657	16.0515	-0.0858
	(0.0119)	(0.0203)	(0.0236)	(0.0489)	(0.0542)	(0.0730)

Notes: The full sample contains 16,024 CDG taxis (control group) and 9,184 non-CDG taxis (treatment group). The matched sample contains 5,524 CDG taxis (control group) and 5,524 non-CDG Taxis (treatment group). Sample matching relies on propensity score matching of nearest-neighbor without replacement (Becker and Ichino 2002 and Leuven and Sianesi 2003). We impose the common support condition in the estimation of the propensity score and perform matching within each 20 equally spaced internals of the propensity score. Taxi-specific trip attributes are produced based on trips fulfilled in March 2017 (prior to the introduction of JustGrab). The trip attributes based on the full sample exhibit large and statistically significant differences between the treatment and control groups. The attributes documented using the matched sample are more homogeneous between the treatment and control groups compared to the unmatched sample. Standard errors are reported in parentheses.

Table 2: The Impact of Dynamic Pricing on the *Spatial* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day in Each Area

(Treatment by Taxi Type)

	(1)	(2)	(3)	(4)
	1-15 percentiles	15-50 percentiles	50-85 percentiles	85-100 percentiles
Treat(Type) $\times$ After	13.8248***	3.8624**	0.4278	-65.7832***
	(2.0756)	(1.8506)	(3.4120)	(18.0939)
Type Fixed Effects	YES	YES	YES	YES
Area $\times$ Day Fixed Effects	YES	YES	YES	YES
Date Fixed Effects	YES	YES	YES	YES
Adjusted R-Squared	0.602	0.668	0.731	0.903
Observations	5,170	10,182	13,596	5,044

Notes: Treat(Type) is a discrete treatment variable that indicates non-CDG taxis. We stratify the sample based on the percentiles of area-specific trip intensity and estimate separate difference-in-differences specifications for each group of areas. Standard errors clustered at the area level are reported in parentheses.

Table 3: The Impact of Dynamic Pricing on the *Spatial* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day in Each Area

(Treatment by Area-Specific Trip Intensity)

	(1)	(2)	(3)
	All	Non-CDG	CDG
Treat (Area Intensity) × After	-0.0962***	-0.1580***	-0.0822***
	(0.0200)	(0.0377)	(0.0125)
Chi Squared	NA	9.49	
Empirical P Value	NA	0.0021	
Area × Day Fixed Effects	YES	YES	YES
Date Fixed Effects	YES	YES	YES
Adjusted R-Squared	0.980	0.962	0.988
Observations	16,968	16,968	16,968

Notes: Treat (Area Intensity) is a continuous treatment variable that describes cross-sectional variation in the area-specific trip intensity prior to the introduction of JustGrab. We estimate difference-in-differences specifications separately for all taxis, non-CDG taxis, and CDG taxis. Standard errors clustered at the area level are reported in parentheses. We report Chi-squared statistic to test for the difference of the estimated coefficients in Column (2) and Column (3).

Table 4: The Impact of Dynamic Pricing on the *Temporal* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day-Hour Block in Each Area

(Treatment by Taxi Type)

	(1)	(2)
	Rush-hour	Non-Rush-hour
Treat(Type) $\times$ After	2.5582***	-0.8228***
	(0.1670)	(0.1146)
Type Fixed Effects	YES	YES
Hour $\times$ Day Fixed Effects	YES	YES
Month Fixed Effects	YES	YES
Area Fixed Effects	YES	YES
Adjusted R-Squared	0.667	0.594
Observations	209,254	354,080

Notes: Treat(Type) is a discrete treatment variable that indicates non-CDG taxis. We stratify the sample based on whether the hour in which the trip starts falls in the rush-hour period or non-rush-hour period and estimate separate difference-in-differences specifications. We only consider the range of hours between 7:00 am and 11:00 pm. We define the rush hours as between 7:00 am and 9:00 am and non-rush hours as between 5:00 pm and 8:00 pm. Standard errors clustered at the area level are reported in parentheses.

Table 5: The Impact of Dynamic Pricing on the *Temporal* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day-Hour Block in Each Area

(Treatment by Hour-specific Trip Intensity)

	(1)	(2)	(3)	(4)	(5)	(6)
	All	Non-CDG	CDG	All	Non-CDG	CDG
Rush-hour × After	2.7585***	3.0495	-0.2910*	-	-	-
	(0.1708)	(1.8686)	(0.1611)	-	-	-
Extended Rush-hour × After	-	-	-	3.8975***	3.8925**	0.0050
	-	-	-	(0.2372)	(1.4932)	(0.1172)
Chi Squared	NA	3.23		NA	4.24	
Empirical P Value	NA	0.0723		NA	0.0396	
Hour × Day Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Area Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.736	0.555	0.821	0.737	0.555	0.821
Observations	283,160	283,160	283,160	283,160	283,160	283,160

Notes: Rush-hour Dummy is a dummy variable that takes value 1 if the hour is defined as in the rush hours and 0 if otherwise. The extended rush-hour dummy is a dummy variable that takes the value 1 if the hour is defined as either in the rush hours or lunchtime (between 12:00 pm and 2:00 pm) and 0 if neither. We only consider the range of hours between 7:00 am and 11:00 pm. We define the rush hours as between 7:00 am and 9:00 am and non-rush hours as between 5:00 pm and 8:00 pm. We estimate difference-in-differences specifications separately for all taxis, non-CDG taxis, and CDG taxis. Standard errors clustered at the area level are reported in parentheses. We report Chi-squared statistic to test for the difference of the estimated coefficients in Column (2) and Column (3).

Table 6: The Impact of Dynamic Pricing on the *Spatial and Temporal* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day-Hour Block in Each Area

(Rush-Hour versus Non-Rush-Hour)

	(1)	(2)	(3)	(4)	(5)	(6)
	All		Non-CDG		CDG	
	Rush-hour	Non-rush-hour	Rush-hour	Non-rush-hour	Rush-hour	Non-rush-hour
Treat(Area Intensity) × After	-0.4903***	-0.2177***	-0.7890***	-0.4093***	-0.1513***	-0.1631***
	(0.0592)	(0.0421)	(0.0472)	(0.0754)	(0.0182)	(0.0245)
Chi Squared	152.88		174.05		1.34	
Empirical P Value	0.0000		0.0000		0.2472	
Area × Day × Hour Fixed Effects	YES	YES	YES	YES	YES	YES
Date Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.918	0.927	0.930	0.867	0.962	0.955
Observations	101,702	279,316	101,702	279,316	101,702	279,316

Notes: Treat (Area Intensity) is a continuous treatment variable that describes cross-sectional variation in the area-specific trip intensity prior to the introduction of JustGrab. We stratify the sample based on the type of taxi as well as rush-hour versus non-rush-hour. Standard errors clustered at the area level are reported in parentheses. We report the Chi-squared statistic to test for the difference of the estimated coefficients associated with rush hours and non-rush hours of the same type of taxis.

Table 7: The Impact of Dynamic Pricing on the *Spatial and Temporal* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day-Hour Block in Each Area

(Rainfall versus No Rainfall)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-15 percentiles		15-50 percentiles		50-85 percentiles		85-100 percentiles	
	Rainfall	No Rainfall	Rainfall	No Rainfall	Rainfall	No Rainfall	Rainfall	No Rainfall
Treat(Type) $\times$ After	1.7542***	0.7076***	1.3774***	0.0207	2.8402***	-0.1057	6.5926***	-2.8498***
	(0.2665)	(0.1179)	(0.1820)	(0.0777)	(0.2251)	(0.1374)	(0.6064)	(0.7585)
Area $\times$ Day $\times$ Hour Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Date Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.517	0.401	0.646	0.483	0.772	0.585	0.871	0.677
Observations	8,172	77,294	22,780	222,234	31,910	318,410	11,286	120,910

Notes: Treat(Type) is a discrete treatment variable that indicates non-CDG taxis. We stratify the sample based on the percentiles of area-specific trip intensity as well as with rainfall versus without rainfall. Standard errors clustered at the area level are reported in parentheses.

Table 8: The Impact of Dynamic Pricing on the *Spatial and Temporal* Reallocation of Taxi Trips
Dependent Variable: Number of Trips per Day-Hour Block in Each Area

(Learning Effect)

	(1)	(2)	(3)	(4)	(5)	(6)
	All		non-CDG		CDG	
	First Half	Second Half	First Half	Second Half	First Half	Second Half
Treat(Area Intensity) × After	-0.1331***	-0.4562***	-0.1444***	-0.7486***	-0.1563***	-0.1648***
	(0.0257)	(0.0644)	(0.0373)	(0.0589)	(0.0223)	(0.0232)
Chi Squared	52.86		375.61		3.68	
Empirical P Value	0.0000		0.0000		0.0551	
Area × Day × Hour Fixed Effects	YES	YES	YES	YES	YES	YES
Date Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.940	0.912	0.883	0.911	0.955	0.959
Observations	190,240	190,778	190,240	190,778	190,240	190,778

Notes: Treat (Area Intensity) is a continuous treatment variable that describes cross-sectional variation in the area-specific trip intensity prior to the introduction of JustGrab. We stratify the sample based on the type of taxi as well as the first half of the month versus the second half of the month. Standard errors clustered at the area level are reported in parentheses. We report the Chi-squared statistic to test for the difference of the coefficients associated with the first half and the second half of the same type of taxi.

Table 9: The Impact of Dynamic Pricing on Taxi Labor Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	log(Daily Trips)		log(Daily Service Time)		log(Daily Working Time)	
	All	Rush Hours	All	Rush Hours	All	Rush Hours
Treat(Type) × After	0.0240***	0.0314***	0.0350***	0.0401***	0.0509***	0.0511***
	(0.0037)	(0.0057)	(0.0013)	(0.0041)	(0.0014)	(0.0046)
Date Fixed Effects	YES	YES	YES	YES	YES	YES
Taxi Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R-Squared	0.419	0.300	0.230	0.228	0.247	0.226
Observations	613,426	613,426	613,426	613,426	613,426	613,426

Notes: Treat(Type) is a discrete treatment variable that indicates non-CDG taxis. Standard errors clustered at the taxi level are reported in parentheses.

Appendix: Imputation of the Upper Bound of Taxi Revenue

In order to impute the taxi fare based on the specific travel route and timing, we first compile the rules applied to taxi fares as follows.[14]

First, the basic taxi charges are shown in the following table.

Table A1: Basic Charges

CDG (Hyundai i-40)	non-CDG (Trans-Cab Toyota Prius)
The first 1 km or less (Flag Down)	
$3.70	$3.60
Every 400m thereafter or less up to 10km	
Every 350 thereafter or less after 10km	
Every 4 seconds of waiting or less	
$0.22	$0.22

Notes: We choose to use the taxi fare applied to Trans-Cab Toyota Prius as the standard taxi fare for non-CDG taxis because Trans-Cab maintains the largest number of taxi fleets among all non-CDG companies and Toyota Prius is its standard model.

In addition to the basic charges, the following rules are also applied to both types of taxis:

1. Midnight surcharge
   - 12:00 am to 6:00 am: 50% additional on top of metered fare
2. Peak-hour surcharge
   - 6:00 am to 9:30 am on Monday to Friday: 25% additional on top of metered fare
   - 6.00 pm to 12:00 am on Monday to Sunday and Public Holiday: 25% additional on top of metered fare

[14]We obtained the rules from the LTA website in Singapore in January 2018 (https://www.lta.gov.sg/content/ltagov/en/getting_around/taxis_private_hire_cars/taxi_fares_payment_methods.html). The distance rate, the waiting-time rate, and the maximum distance for the flag-down are all the same as the guideline numbers in the Public Transport Council (Taxi Fare Pricing Policy) Order 2016, which was published on 22 January 2016 (https://sso.agc.gov.sg/SL-Supp/S30-2016/Published/20160122180000?DocDate=20160122180000&WholeDoc=1). Therefore, it should be safe to assume that the same scheme was also applied during our sample period (March and April of 2017).

3. Central Business District (CBD) surcharge

   - 5.00 pm to 12:00 am on Monday to Sunday and Public Holiday (at the time of boarding): $3.00 (Not applicable when the midnight surcharge is payable)

4. Location surcharge

   - Every trip starting from Changi Airport, Changi Air Freight Centre, Airport Police, and Airport Logistic Park of Singapore
     - 5.00 pm to 12:00 am on Friday to Sunday: $5.00
     - All other times: $3.00
   - Every trip starting from Resorts World Sentosa & Garden By the Bay
     - All times: $3.00
   - Every trip starting from Seletar Airport
     - All times: $3.00
   - Every trip starting from Singapore Expo Centre
     - All times: $2.00
   - Every trip starting from Marina Bay Cruise Centre Singapore
     - 5.00 pm to 10:59 pm on Monday to Sunday and Public Holiday: $5.00
     - All times: $3.00

Second, we define the surge ratio as the ratio of the dynamic-pricing fare to the metered taxi fare. We impute the surge ratio for trips connecting the 80 origin-destination pairs. The dynamic pricing fares were obtained directly by simulating trips using the Grab App for different times of the day and for all the days throughout April 2017, as detailed in Section 3.1. For metered taxi fares, we impute the route of travel based on the shortest-distance travel for each trip connecting the 80 origin and destination pairs and then apply the above non-CDG taxi pricing rules to those trips to infer the corresponding metered taxi fares. Specifically, we impose the basic charge, the peak-hour surcharge, the CBD surcharge, and other location surcharges on the imputed trips whenever the rules apply.[15] Note that as the dynamic pricing fares for the 80 pairs are only

[15] For scenarios in which the trip spans across a period in which peak-hour surcharge is partially applied, we impose the peak-hour surcharge only to the portion of the trip that falls into the peak-hour period, assuming a constant speed of travel for the entire trip.

collected between 7:00 am and 10:59 pm, the calculation of the metered fares is also within this time range. We then obtain average location-day-hour-specific metered fares and compute the surge ratio for each location-day-hour cell correspondingly.[16]

Third, we apply the taxi fare rules above to impute metered taxi fares for actual CDG and non-CDG taxi trips that are recorded in our taxi travel dataset. For each trip, the metered fare is calculated based on the shortest-distance travel, applying type-specific (CDG vs. non-CDG) fare rules and various surcharges whenever they apply. The imputation includes only the trips conducted by matched taxis in our baseline analysis after propensity score matching and only those started between 7:00 am and 10:59 pm.

Fourth, to impute the dynamic pricing fare for each non-CDG trip after JustGrab, we multiply each trip's imputed metered fares (the third step) by the imputed location-day-hour-specific surge ratio (the second step) if the trip belongs to that location-day-hour cell. For the non-CDG trips after JustGrab, we then compare the dynamic pricing fare with the metered fare and assign the larger amount of the two as the final imputed fare of the trip.

[16] Averaging the imputed taxi fares across all locations in an hour separately for weekdays and weekends allows us to obtain the hour-specific dynamic pricing fares and metered taxi fares as plotted in Figure 8.