Transportation Research Part A 150 (2021) 349–366

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Plunge and rebound of a taxi market through COVID-19 lockdown: Lessons learned from Shenzhen, China

Hongyu Zheng, Kenan Zhang, Yu (Marco) Nie *

Department of Civil and Environmental Engineering, Northwestern University, 2145 Sheridan Road, Evanston, IL 60208, USA

ARTICLE INFO

Keywords:
COVID-19
Lockdown
Taxi market
GPS trajectory
Clustering

ABSTRACT

This paper traces the plunge and rebound of the taxi market in Shenzhen, China through the COVID-19 lockdown. A four-week taxi GPS trajectory data set is collected in the first quarter of 2020, which covers the period of lockdown and phased reopening in the city. We conduct a spatiotemporal analysis of taxi demand using the data, and then select taxis that continued to operate through the analysis period to examine whether and how they adjusted operational strategies. We find, among other things: (i) the taxi demand in Shenzhen shrank more than 85% in the lockdown phase and barely recovered from that bottom even after the city began to reopen; (ii) the recovery of taxi travel fell far behind that of the overall vehicle travel in the city; (iii) most taxis significantly cut back work hours in response to the lockdown, and many adjusted work schedule to focus on serving peak-time demand after it was lifted; (iv) taxi drivers demonstrate distinct behavioral adaptations to the pandemic that can be identified by a clustering analysis; and (v) while the level of taxi service dropped precipitately at the beginning, it quickly rebounded to exceed the pre-pandemic level, thanks to the government's incentive policy. These empirical findings suggest (i) incentives aiming at boosting supply should more precisely target where the boost is most needed; (ii) the taxi market conditions should be closely monitored to support and adjust policies; and (iii) when the demand is severely depressed by lockdown orders or when the market is oversupplied, taxi drivers should be encouraged and aided to use more centralized dispatching modes.

1. Introduction

The COVID-19 pandemic began to sweep through the globe at the beginning of 2020 (Sohrabi et al., 2020). Within but a few months, it had pushed economies of many countries to the brink of collapse and disrupted the normal lives of billions beyond recognition (Baldwin and di Mauro, 2020). At the time of writing (August of 2020), COVID-19 is still rapidly spreading in many parts of the world, notably North and South America, albeit several regions, East Asia and Europe in particular, had managed to largely contain it after suffering devastating losses.

Few industries have been hit as hard as public transportation by COVID-19. The lockdown orders implemented in many countries had eliminated all but essential travel. As a result, transit ridership dropped precipitately. In many European countries, transit lost more than 80% of its ridership in the initial phase of the pandemic (Chapuis et al., 2020). In the US, the worst loss amounts to about 75% of the pre-pandemic ridership, according to transitapp.com. When reopening slowly kicked in, transit operators struggled to win

* Corresponding author.
E-mail address: y-nie@northwestern.edu (Y.(M. Nie).

https://doi.org/10.1016/j.tra.2021.06.012
Received 14 August 2020; Received in revised form 18 April 2021; Accepted 14 June 2021
Available online 28 June 2021
0965-8564/

back passengers. In Paris, transit ridership was still 40% below normal more than a month after its official reopening (early June of 2020). In most US cities, this number hovered around 50% (transitapp.com). Even in China, where the economy was fully opened after March of 2020, transit ridership was still far below the pre-pandemic level (Liu et al., 2020). This slow recovery may be due to several reasons. First, pandemic-induced tele-activities temporarily lower the overall travel demand. Second, the capacity of transit systems is severely restricted by the safety requirements, especially social distancing. Last but not least, travelers are avoiding transit, especially trains and buses, for safety concerns. A survey conducted by IBM shows that nearly half Americans would either avoid using mass transit all together (20%) or use it less frequently (28%) (IBM, 2020).

Transit services remain indispensable to the functioning of big cities, even when most people are told to stay at home. Among the passengers who ride transit through the pandemic in the US, 92% are commuters whose jobs are considered essential (transitapp.com). However, a major shift to private modes, especially solo driving, is likely to take place, which would hinder the recovery of transit ridership. In fact, the signs of worsened traffic congestion have already emerged on the streets of some Chinese megacities (UBS, 2020). Ultimately, our returning to the semblance of normalcy depends on restoring the confidence in operating and using transit systems. This, in turn, requires a concerted effort ranging from mitigating the infection risks involved in transit use to redesigning the existing systems to address the safety concern of wary travelers. To these ends, we need to first understand when, where and how a pandemic like COVID-19—and human societies' response to it—inflicts damages on both the supply of and the demand for various transit services. It is also important to draw useful lessons from such experience: what can be done to mitigate the adverse impacts on passengers and operators, both when the pandemic-induced restrictions are still in place and after they are lifted. This paper attempts to make a modest contribution to laying this foundation, through a case study focusing on taxi services.

We analyze the taxi market in the city of Shenzhen, China using a set of panel data collected in the first three months of 2020. Shenzhen is selected for the case study for several reasons, the most obvious of which is the availability of data. Shenzhen has been continuously tracking its entire taxi fleet through GPS devices since early 2010s, and the data accumulated in the process have been used in numerous studies (e.g., Yuan et al., 2012; Tu et al., 2016; Nie, 2017; Xie et al., 2017; Ma et al., 2017; Zhang et al., 2019a; Zhang et al., 2019b). Another reason to choose Shenzhen is timing. COVID-19 broke out in China in January of 2020. While sustained community spreading was largely confined within the original epicenter (i.e., Wuhan, Hubei province), the entire country, Shenzhen included, was strictly locked down for several weeks. In retrospect, the drastic measures, which were not without controversy at the time, might have contributed to the speedy containment of the pandemic in the country. By mid-February of 2020, Shenzhen had begun phased reopening, and by the end of March, its economy had mostly reopened and workers were allowed to return to work. Thus, Shenzhen had experienced, within a span of two months, a cycle of full lockdown, phased reopening and recovery, which makes it an ideal choice for observing the shot-term impact of COVID-19.

To the best of our knowledge, this is one of the first studies that examine COVID-19's short-term impact on a taxi market. We not only conduct a spatiotemporal analysis of taxi demand throughout the crisis, but also investigate whether and how taxis adjusted their operational strategies in response. Our findings will reveal the demand and supply for taxi travel in Shenzhen first plunged and then rebounded, and link this big swing to the implementation and lift of various lockdown measures. They will also lead to a number of policy recommendations aiming to maintain adequate and efficient taxi services through the shock and recovery phases of a major global pandemic.

The remaining of the paper is organized as follows. Section 2 reviews the related studies. The taxi trajectory data, lockdown policies and information about Shenzhen's taxi market are described in detail in Section 3. Sections 4 and 5 examine the taxi demand and supply patterns under COVID-19, respectively. Section 6 investigates taxis' behavioral adaptation and level of service, as well as the effectiveness of the city government's stimulus policy aiming to boost taxi supply. Section 6 also discusses broader policy implications of our empirical findings. Section 7 concludes the paper with a summary of main findings.

2. Literature review

Taxi GPS trajectories offer a gold mine to researchers who are interested in human mobility. The breadth of the work enabled by this source of data is remarkable, ranging from analyzing urban functions (e.g., Yuan et al., 2012) and inferring urban traffic emissions (e.g., Liu et al., 2019) to making short-term traffic predictions (e.g., Cachon et al., 2017) and understanding travel behaviors (e.g., Xie et al., 2017). Like most work in this category, this research aims to uncover interesting mobility patterns through in-depth data-driven analyses. It is built upon two previous studies using trajectory data from the same city. In the first, Nie (2017) analyzes the impact of the emerging transportation network industry on the taxi market in Shenzhen, China and how taxi drivers responded to the competition from ride-sourcing services. The other (Zhang et al., 2019b) proposes a novel, image-based clustering method to identify different taxi drivers' strategies when searching for passengers.

COVID-19 has attracted a staggering amount of attention from the academic community[1]. In transportation, however, the enthusiasm has yet to turn to published works, due in part to its relatively long publication cycles. Tahlyan and Mahmassani (2020) investigate traffic and collision data in Chicago during the COVID-19 crisis. They find, although the number of crashes decreases, the severity of resulting injuries actually increases. Using taxi data collected in Chicago, Ale-Ahmad and Mahmassani (2020) show the stay-at-home order enacted in March reduced taxi ridership by 95% and the number of operating taxis by 85%. Using a modified compartment model (Sattenspiel et al., 1995), Qian and Ukkusuri (2021) attempt to quantify the spread of infectious disease in urban

[1] https://www.insidehighered.com/news/2020/06/08/fast-pace-scientific-publishing-covid-comes-problems

areas through transportation systems. Oum and Wang (2020) investigate the effect of lockdown and travel restriction measures on mitigating the impact of a pandemic. They show socially optimal measures may be different from those preferred by individuals. Using a simulation-based approach, Ivanov (2020) analyzes COVID-19's influence on global supply chains. He finds that closing and reopening facilities at different stages play an important role. Using a simple BPR function and data from the American Community Survey of the US Census Bureau, Hu et al. (2020) argue that big US cities with large transit ridership could experience extreme traffic congestion in the post-COVID era, due to travelers' potential exodus from transit.

3. Data description

3.1. Overview

The "City Of Shenzhen Taxi" (COST) data used in this study include GPS trajectories of all registered taxis in Shenzhen, China. Each data entry contains a time stamp, a taxi plate number, the coordinates, and the instantaneous velocity, heading and occupancy status. In this study, all taxi trajectories during four weeks in the first quarter of 2020 are extracted from the COST raw data and processed to generate occupied (with passenger) and search (without passenger) trips using the method described in Nie (2017). The trip origins and destinations are then matched to the 3,561 traffic analysis zones (TAZ) in the city (see Fig. 1).

Fig. 2 illustrates the four weeks selected for this study, against the numbers of daily confirmed COVID-19 cases in Shenzhen and China. Table 1 summarizes the basic information of the GPS data in each of the four weeks. There are only 9,542 taxis that kept operating (i.e., making at least one occupied trip per week) in all four weeks. These active taxis made 10,198,255 trips in the four weeks, including 4,612,380 occupied trips (about 483.38 per taxi) and 5,585,875 search trips.

3.2. Restriction measures through the study period

Since the first COVID-19 case was confirmed in China on January 10, 2020, Week 1 (January 1 to 7) is used as a benchmark to represent the normal pre-pandemic state. On January 23, the Chinese government imposed a strict lockdown in Wuhan and its surrounding areas (the first COVID-19 epicenter), closing public transit services, inter-city railway and air travel, and major highways[2]. This lockdown order expired on April 8, 2020. Shenzhen reported its first COVID-19 case on January 19, 2020. Five days later, its government closed all tourist attractions and entertainment establishments, banned large gatherings, and mandated mask-wearing in all public spaces.

The spread of COVID-19 in Shenzhen was not well synchronized with the whole country. It peaked in late January (Week 2) and had been largely contained—with daily caseload dropped below 5—by mid-February (Week 3); see Fig. 2. Thus, we choose Week 2 to mark the peak of the COVID-19 crisis in the city. It is a coincidence that this week happens to overlap with the Chinese New Year[3], the longest and most important holiday that usually shuts much of the country down from work. Apparently, restaurants in Shenzhen were not asked to close indoor dining during this period[4], although many (if not most) did voluntarily close door or opt for take-out only operation.

Following the end of the Chinese New Year Holiday, the Shenzhen government kept all but essential workers from returning to work until February 10, when phased reopening began. At the same time, the government mandated body-temperature checks at the gate of any residential complex for entry or exit. Week 3 is meant to be a snapshot of the city's early reopening stage. According to an estimation published by Baidu Inc.[5], the so-called *work resumption rate*—i.e., the percentage of "active workers" who had returned to their regular work routine—had reached 30% by the end of Week 3[6]. It is also in this week that the government ordered half of the restaurants in the city be closed for indoor-dining.

Week 4 is about one month after the pandemic was contained in Shenzhen. By this time, the city had been largely reopened for work and business, though most schools and movie theaters remained closed. In this week, Baidu's work resumption rate reached 73% in Shenzhen. In late March, the government reported that 96% of migrant workers had returned to the city[7] and 94.8% of businesses had resumed regular operation[8].

Finally, on February 3, 2020 (right after Week 2), Shenzhen closed some subway stations, suspended 31% of bus lines, and adjusted operating frequencies for others. On February 24 (a few days after the end of Week 3), subway and bus systems began to resume regular operations, and by March 1 all services had returned to the pre-COVID level. However, according to Zhang et al. (2020), Shenzhen's transit ridership in Weeks 2 and 3 were only at 10%, and 12% of the pre-pandemic level, respectively.

---

2 https://www.reuters.com/article/us-china-health-who-idUSKBN1ZM1G9

3 The 2020 Chinese New Year Holiday was supposed to run from January 24 to 30, 2020, but extended to February 2 to help control COVID-19.

4 Our search failed to locate any specific policy or ordinance.

5 https://huiyan.baidu.com/news, in Chinese.

6 It is unclear how an active worker is defined. We assume those working from home would not be counted as active workers.

7 A majority of Shenzhen workers are not permanent residents. Most went home for Chinese New Year before the lockdown.

8 http://www.sz.gov.cn/szzt2010/yqfk2020/szzxd/content/post_7148117.html, in Chinese.

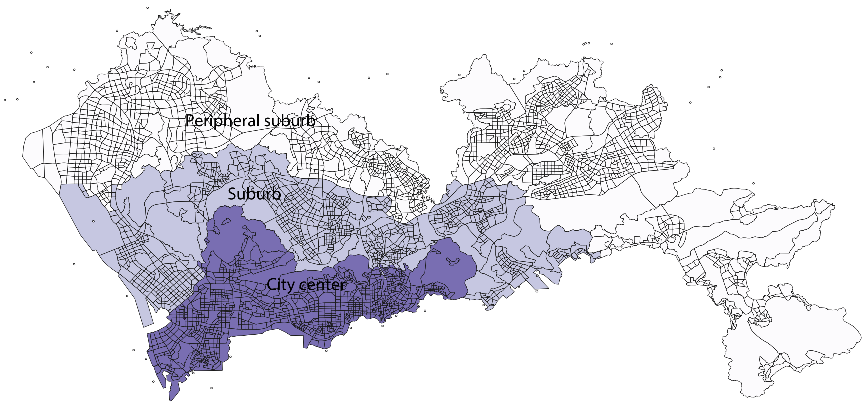


Fig. 1. Traffic analysis zones in Shenzhen's urban travel planning model.

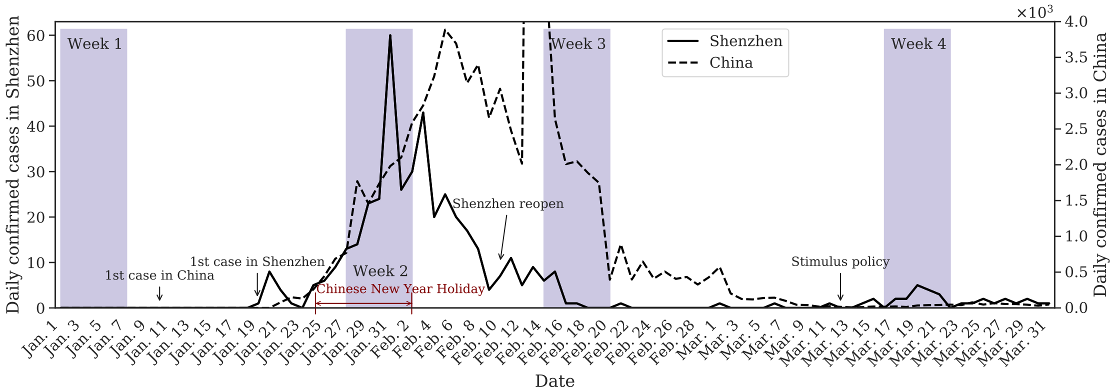


Fig. 2. Illustration of the study period against the numbers of daily confirmed COVID-19 cases in Shenzhen and China. Taxi data are collected in the four weeks highlighted in the timeline. (The abnormal peak in the number of national cases after February 12 is due to the inclusion of clinically diagnosed cases in confirmed cases.).

Table 1
Overview of the COST data used in this study.

Week	Period	#Taxis	GPS points (million)	GPS points with passenger (million)
1	01/01/2020–01/07/2020	20,427	262.18	119.14
2	01/27/2020–02/02/2020	12,300	194.91	52.03
3	02/14/2020–02/20/2020	12,006	172.09	39.00
4	03/16/2020–03/22/2020	19,044	282.68	78.70

3.3. *Taxi subsidy policies*

During the COVID-19 pandemic, taxi drivers' income dropped sharply because of the decline in demand. At the same time, however, they still had to bear regular operating expenses including fuel cost, business license fee, vehicle rent and maintenance, and insurance. It is reported that the total operation cost, *excluding* fuel cost, is about ¥9,000 per month per taxi in Shenzhen[9]. This means a taxi must serve at least 450 trips per month to break even[10]. To help taxi drivers survive the crisis, the Shenzhen government and taxi companies offered, starting from late January, a subsidy of ¥1,000 and ¥3,000, respectively, per taxi per month, whether they choose to work or not. While this aid no doubt brought about huge relief, it would not be enough to cover even half of the operating expenses. In other words, taxi drivers would still lose money if they cannot generate more than half of their regular businesses. Meanwhile, on March 12, 2020, the city government introduced another subsidy specifically designed to stimulate taxi supply. From February 7 to

[9] https://www.sohu.com/a/370655307_355788, in Chinese.

[10] The revenue per trip is estimated as the average fare (obtained using the trip data in Week 1 and the standard taxi metered fare in Shenzhen) less the fuel cost.

April 6 (two months in total), each taxi driver would be rewarded ¥50 a day if s/he operates up to 100 km or 5 h[11]. In total, the government distributed ¥23.3 million in the first month (from February 7 to March 6)[12][13] and ¥45.2 million in the second month (from March 7 to April 7) for this incentive program[14].

4. Demand analysis

In this section, we follow the taxi demand pattern in the four weeks described in the previous section. It should be noted that the dramatic changes manifested in trajectory data about taxi travel are closely related to and should be understood in the context of the restrictions imposed by the government on travel, work and recreational activities (as detailed in Section 3). However, while restrictions play a major role, at least some of the taxi trips were no doubt voluntarily forgone or diverted to other modes (e.g., private automobile) due to the concern about the infection risk. On the other hand, some transit passengers may consider taxi a safer mode than train or bus. Thus, the demand pattern revealed herein is the outcome of these complex forces that sometimes pull in opposite directions.

4.1. Temporal distribution

Fig. 3 reports the number and average speed of occupied trips in Shenzhen in each of the four weeks relative to Week 1. As expected, occupied taxi trips in Week 2 plummeted to less than 15% of the level in Week 1, due primarily to the combined effect of the COVID-19 and Chinese New Year. Surprisingly, the trip production continued to decline in Week 3, even though the city had begun to reopen by then (recall that Baidu recorded a work resumption rate of 30% for this week). What seems more unexpected is the sluggish performance in Week 4. Despite the work resumption rate had reportedly reached 70% in this week, the taxi market's output was still more than 50% below the level right before the shock.

Fig. 3 also shows taxis enjoyed the highest average speed in Week 2, likely because the holiday and the lockdown removed much of the vehicular traffic off streets. In Week 3, the average speed was still significantly higher than the normal level, but began to dip. Finally, in Week 4, it went all the way back to the pre-COVID level.

The above results suggest taxi travel fell far behind the recovery of work and the overall vehicle trips in the city. When traffic began to cause congestion on road (Week 3), taxi travel was at its lowest level. When a majority of people return to work and the city fully regained its traffic congestion (Week 4), taxi recovered barely half of its ridership. Non-work related activities—dining, entertainment and school—might have slowed the recovery of taxi ridership. Yet, given the observed level of congestion, it seems likely that travelers were also substituting taxi trips with driving or other transportation modes, possibly to avoid being infected.

To analyze the temporal patterns of taxi trips on weekdays and weekends, we plot the number of hourly occupied trips on Tuesday and Saturday in each week (see Fig. 4). It should be mentioned that most people were working as usual in Weeks 1 and 4. Hence, the overall temporal patterns are quite similar in these two weeks, except that the Tuesday morning peak in Week 4 is much stronger. This result implies that taxi demand recovered the fastest in the period when most commuters rushed to work. Because Week 2 completely overlaps with the Chinese New Year holiday, the demand on Tuesday and Saturday in Week 2, as well as that on Saturday in Week 3, displayed a similar "weekend pattern", with only a weak peak in the afternoon. In contrast, the demand on Tuesday in Week 3 had a clear "weekday pattern", with two peaks around 8 AM and 6 PM, respectively. This is consistent with the fact that the government had begun to lift stay-home orders right before Week 3 (on February 10, 2020). Yet, the total number of occupied taxi trips in Week 3 was lower than that in Week 2. This suggests that the increase in commute trips was not enough to offset the deficit in other market segments (e.g., off-peak trips driven by recreational activities). In Week 4, the number of trips recorded in the morning rush hour had reached more than 70% of normal level, which strongly correlates with the work resumption rate reported by Baidu Inc. (about 70%). While we believe the rebound of taxi travel in Week 4, especially during the morning rush hour, is primarily driven by reopening, it is possible the stronger supply brought about by the city government's stimulus policy also played a role.

4.2. Spatiotemporal analysis

In this section, we continue to analyze the spatiotemporal pattern of taxi trips. To this end, we divide the city into three regions, i.e., city center, suburb, and peripheral suburb (see Fig. 1), and each day into three time periods, i.e., peak period (6 AM - 10 AM and 5 PM - 8 PM), mid-of-day period (10 AM - 5 PM), and off-peak period (8 PM - 6 AM). Fig. 5 reports the cumulative distribution function (CDF) of the *relative* change in the number of occupied trips originated from each TAZ (Week 1 is used as the benchmark), weighted by the population in that TAZ. The calculation procedure is reported in Nie (2017) and also included in Appendix A for the convenience of the reader.

In Fig. 5, a CDF closer to the upper-left corner (see, e.g., those shown in Fig. 5(a)) indicates a greater reduction in trip production compared to Week 1. Since the CDF is weighted by the population in each TAZ, it also indicates, on average, how many travelers experienced a given level of a reduction. For example, from Fig. 5(a), we can read in Week 4, 80% of the people in city center still

[11] http://www.sz.gov.cn/szzt2010/yqfk2020/szzxd/content/post_6908656.html, in Chinese.
[12] http://jtys.sz.gov.cn/zwgk/jtzx/tzgg/content/post_7269864.html, in Chinese.
[13] http://jtys.sz.gov.cn/ydmh/jtzx/tzgg_1508/content/post_7270108.html, in Chinese.
[14] http://jtys.sz.gov.cn/zwgk/ztzl/kjfy/jtjzxd/content/post_7843248.html, in Chinese.

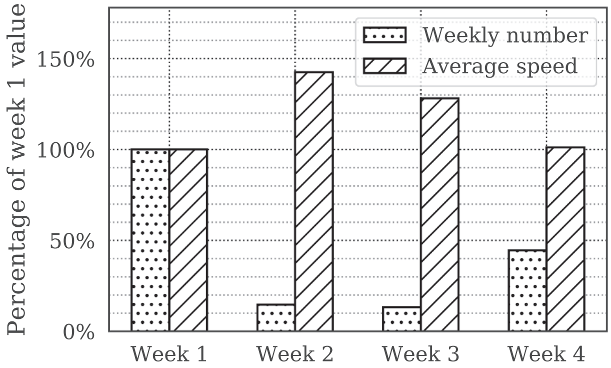
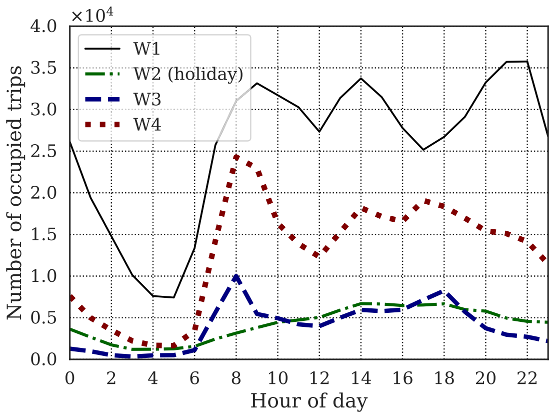
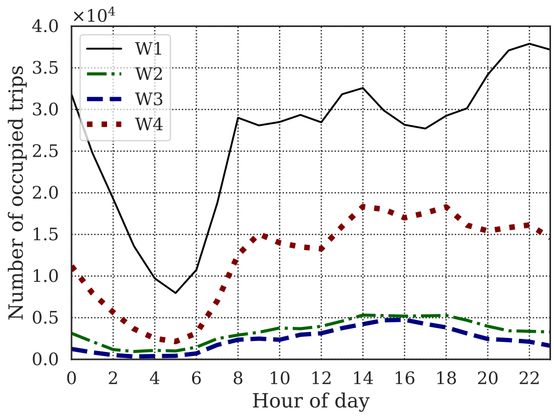


Fig. 3. Weekly number and average speed of occupied taxi trips relative to Week 1. (The number and average speed in Week 1 are 4.39 million and 19.53 mph, respectively.).



(a) Weekday (Tuesday)



(b) Weekend (Saturday)

Fig. 4. Number of hourly occupied taxi trips in the four weeks (Wi, $i = 1, 2, 3, 4$ refers to Week i).

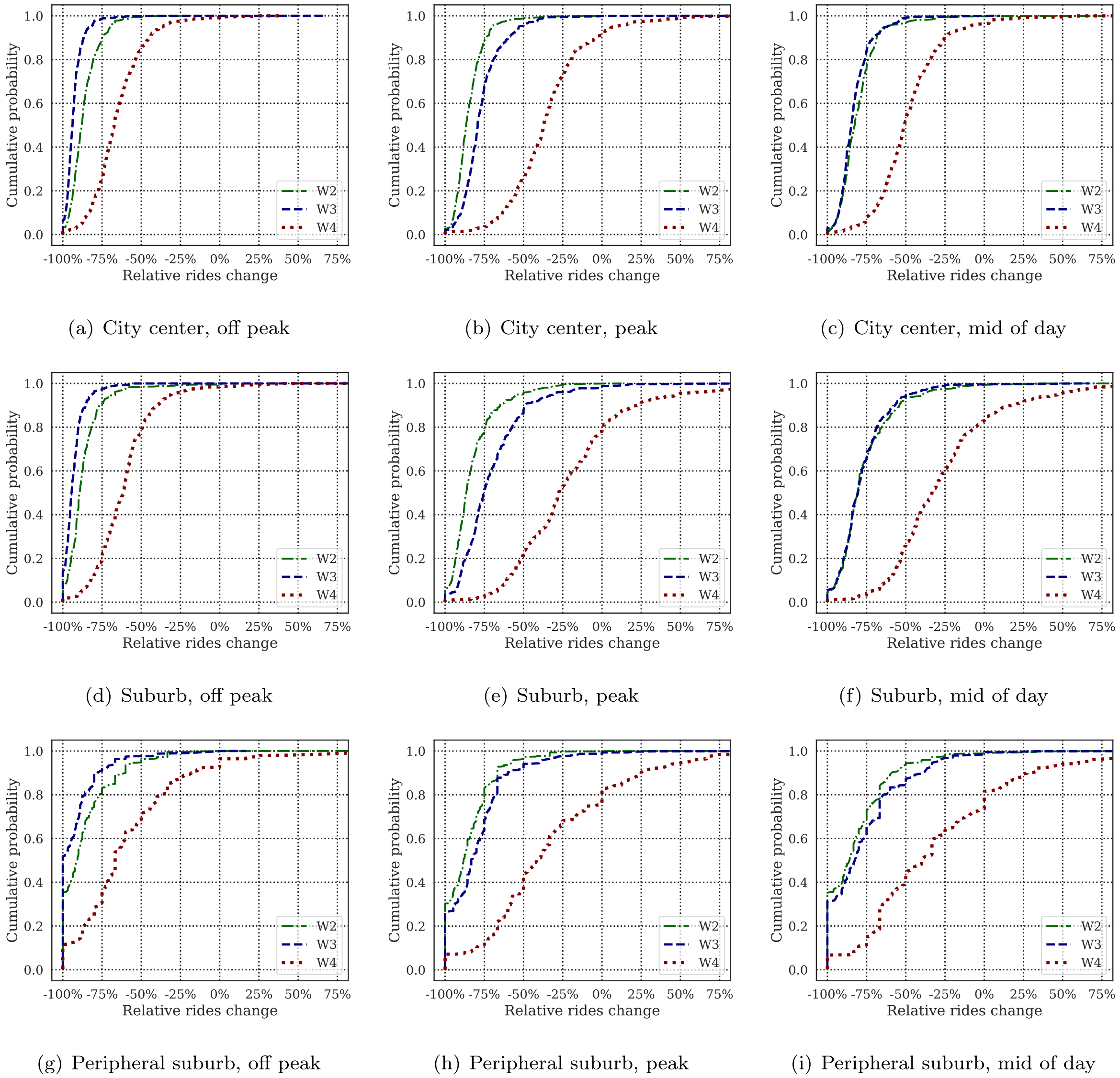
experienced a 50% or more reduction in the taxi trips originating from their TAZs, compared to Week 1.

Comparing the subplots of Fig. 5 by columns, one can find that the off-peak period suffered the greatest loss and recovered the slowest (note that CDFs in the left column consistently lie closer to the top left corner than the plots in other columns). The peak period, on the other hand, recovered the fastest. Take city center as an example. The losses during off-peak and peak periods were almost the same in Week 2 (specifically, about 90% of travelers experienced a decrease of 75% or more). In Week 3, the loss in the off-peak period was even worse, with 95% of travelers experiencing a decrease of 75% or more of taxi travel. In the peak period, however, the same percentage of travelers dropped to about 70%, likely because the city's reopening brought some commuters back on road. For mid-of-day period, the reopening in Week 3 barely made any differences. Once again, we can see that the initial reopening mostly stimulated taxi travel in the peak period, with a negligible, if not slightly negative, impact on the other periods.

Furthermore, the relative changes in taxi travel demonstrate noticeable spatial heterogeneity in the peak and mid-of-day periods, particularly in Week 4. City center clearly endured the most severe demand reduction. Take the peak period as an example. In Weeks 2 and 3, there were respectively 98% and 95% of travelers in city center experiencing a decrease of taxi travel by 50% or more. By Week 4, the taxi travel for over 90% of the population in city center was still below the level in Week 1, and more than 70% of them still had a 25% or more reduction. On the other hand, the recovery of taxi demand in suburb and peripheral suburb was much faster: about 20% of travelers actually increased their taxi travel during peak and mid-of-day periods in Week 4. A possible explanation for this spatial heterogeneity is that the residents in city center have better access to other modes (e.g., bike-sharing, bus, and subway), and hence they may be less dependent on taxi trips than people living in suburbs.

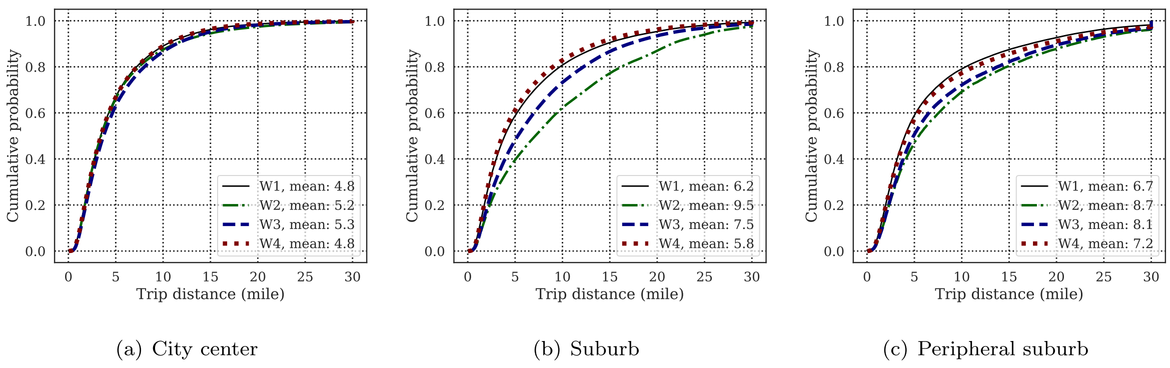
4.3. Trip distance distribution

Fig. 6 plots the CDF of the occupied trip distance by areas. One can see that the trips originated in city center tend to be shorter than those in the other two areas. Nearly 90% of the trips in city center are shorter than 10 miles, whereas the same fraction reduces to 80% in suburb and peripheral suburb. While the distance distribution varies very little in city center over the four weeks, it changes



(a) City center, off peak
(b) City center, peak
(c) City center, mid of day
(d) Suburb, off peak
(e) Suburb, peak
(f) Suburb, mid of day
(g) Peripheral suburb, off peak
(h) Peripheral suburb, peak
(i) Peripheral suburb, mid of day

Fig. 5. Cumulative probability of relative rides change (i.e., the population-weighted change in the number of occupied trips, relative to Week 1). Rows 1, 2, and 3 report the results for city center, suburb and peripheral suburb. Columns 1, 2, and 3 report the results for off-peak, peak and mid-of-day periods.



(a) City center
(b) Suburb
(c) Peripheral suburb

Fig. 6. CDF of the distance of occupied taxi trips by areas. (The mean trip distance for each week is reported in the plot.).

significantly in suburb. Specifically, the proportion of long-distance trips increased sharply in Week 2, so much so that the average trip distance jumped from 6.2 miles in Week 1 to 9.5 miles in Week 2 (a more than 50% increase). The fraction of long-distance trips in suburb, however, dropped in Week 3 and almost returned to the pre-COVID level in Week 4.

The above phenomenon can be better illustrated by Fig. 7, which reports the number of occupied trips (normalized by Week 1) by distance and area. As shown in Fig. 7(a), in both city center and peripheral suburb, the decline in taxi trips evenly distributes over trip distance. In contrast, the pattern is quite different in suburb. In Week 2, the loss significantly decreases with the trip distance. In other words, a larger portion of long-distance trips (especially those over 7.5 miles) were not affected by the pandemic. Although these trips sharply dropped in Week 3, the "preference" for long-distance trips still exist, as also evident in Fig. 6.

To explain this peculiar preference for long distance trips in Weeks 2 and 3, we examined taxi trips originating from the two zones that each contains the airport and the main railway station of the city, and compared the trends of these trips against those originating from other suburban zones. The results plotted in Fig. 8 are normalized by the trip numbers in Week 1. As shown in Fig. 8, in Weeks 2 and 3, taxi trips originating from the airport and the train station are much less affected compared to those from other areas. In Week 2, for example, airport and train station trips were down by less than 50% whereas those from the other areas lost well over 80%. Importantly, the average distance of the trips associated with the airport and the train station is 17.8 miles and 10.5 miles respectively, much longer than that of the trips from the other areas (5.4 miles). It is thus reasonable to attribute the preference for long trips in Weeks 2 and 3 to the higher percentage of trips associated with the main transportation hubs that tend to be much longer. Similarly, we can observe from Fig. 7 that the short-distance trips recovered faster than the long-distance trips from Week 3 to Week 4, which might have resulted from the slower recovery of taxi demand in transportation hubs than in other areas (see W4 in Fig. 8). Interestingly, this sharp contrast seems to suggest that the pandemic shock reaches the inter-city travel market much later than the intra-city market.

As a side note, even though the average trip distance increased markedly in suburb and peripheral suburb, travelers actually spent slightly less time per trip on average in Weeks 2 and 3, thanks to the dramatically improved traffic conditions. For example, in suburb, the average trip duration decreased from 17.5 min in Week 1 to 17.4 min in Week 2 and 16.2 min in Week 3.

5. Supply analysis

We expect that COVID-19 would impact the taxi supply in at least two ways. First, the significant drop in demand may prolong the search for passengers, and thus lower the overall productivity (measured by the ratio of occupied time). Second, taxi drivers may reduce work hours and adjust work schedules, either as a response to demand depression or in order to mitigate personal infection risks. Of course, some drivers may choose to work even more if they anticipate less competition in a smaller yet robust market.

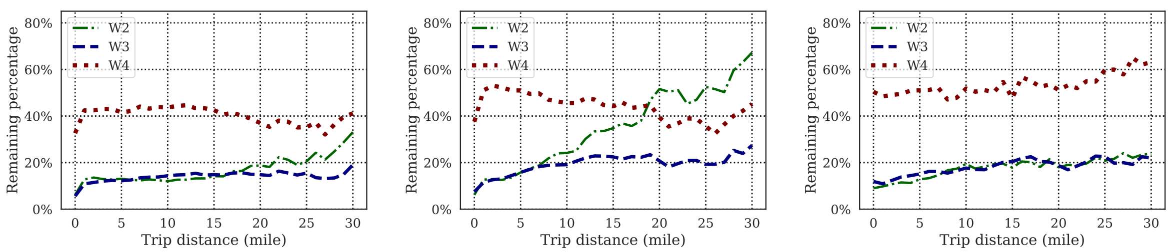
Table 1 indicates that roughly 60% taxis remain in active service in Weeks 2 and 3 (based on the number of taxis spot in the data). In Week 4, thanks to both reopening and the stimulus policy, more than 90% of the taxis were back to work. In fact, it seems that taxi activities had fully returned to the normal level in Week 4, based on the number of GPS points recorded. To better understand the changes in taxi supply, we extract 5,021 taxis that made at least ten occupied trips in each of the four weeks, and analyze their work schedules (Section 5.1), productivity (Section 5.2), and search behaviors (Section 5.3).

5.1. Work schedule

In this study, work schedule refers to how long a taxi works in a day, and how these work hours distribute within the day. A taxi's work schedule may reflect the perceived profitability in the market and the risk of infection due to continuous operation.

Fig. 9 compares the work schedules of the selected taxis over the four weeks. Fig. 9(a) shows the *maximum* weekly work hours (WWH) in all four weeks were roughly the same, i.e., about 140 h. Thus, there were always taxis working almost all the time, even at the peak of the COVID-19 crisis. However, Fig. 9(a) also reveals very large variations in WWH among the taxis. While 90% taxis worked more than 75 h in Week 1, only about 12% maintained this level of workload in Weeks 2 and 3. Even in Week 4, this percentage only returned to 59%, still one third below normal. Most taxis significantly reduced WWH in Weeks 2 and 3, with averages of 45.6 and 47.4 h, respectively.

Fig. 9(b) reports the fraction of taxis by the number of working days in a week. In both Weeks 1 and 4, the vast majority of taxi drivers worked every day in the week, even though the average WWH in Week 4 is far below that in Week 1. In contrast, only half of the



(a) City center (b) Suburb (c) Peripheral suburb

Fig. 7. Percentage of occupied trips by distance and area (Week 1 = 100%).

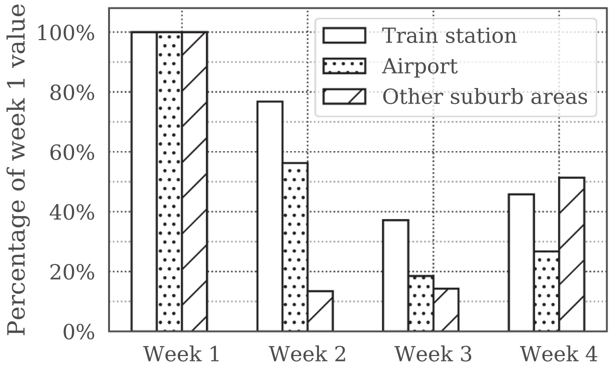
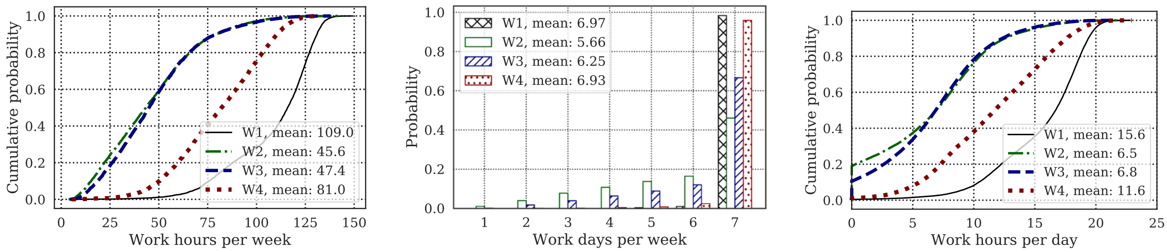


Fig. 8. Weekly number of occupied taxi trips in train station, airport, and other suburb areas.



(a) Weekly work hours (WWH) (b) Weekly work days (WWD) (c) Daily work hours (DWH)

Fig. 9. Work schedules of the selected 5,021 taxis in the four weeks. (The mean value for each week is reported in each plot.).

taxis in Week 2 and 60% in Week 3 worked in the entire week. The daily work hours (DWH) has a similar pattern as WWH (see Fig. 9 (c)). In Week 1, more than 60% the taxis worked 15 h or more per day, whereas there were barely any taxis working this hard in Weeks 2 and 3. Even though DWH recovered much ground in Week 4, only 25% taxis worked more than 15 h a day.

We proceed to analyze the taxi operation patterns on weekdays to see if drivers strategically adjusted work schedules in response to the crisis. Fig. 10 compares the CDF of DWH in different periods of day. After a dramatic drop in Week 2, DWH in the peak period partially recovered in Week 3 and returned to the same level of Week 1 in Week 4. However, this is not the case in off-peak and mid-of-day periods. In fact, the pattern is exactly the opposite in Week 3, when taxis worked even less during off peak compared to Week 2 (the CDF curve of Week 3 lies to the left of that of Week 2 in Fig. 10(a)). And taxis worked for almost the same time in Weeks 2 and 3 during the mid-of-day period. *These results demonstrate convincingly that a large portion of taxis adjusted their work schedules to focus on serving peak-time demand*.

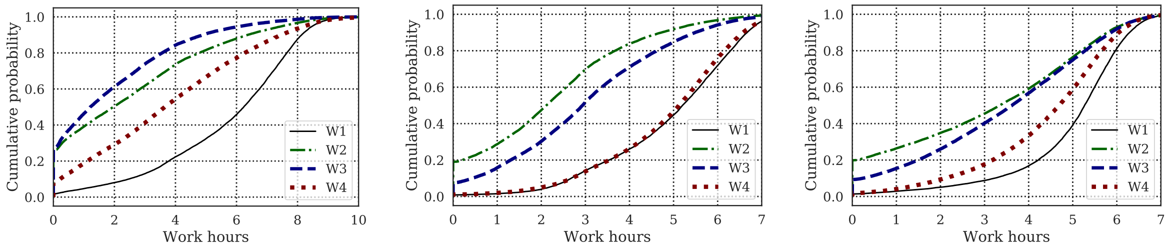
Fig. 11 further explores the correlation of WWH between paired weeks. Note that the four diagonal subplots are the probability density functions (PDFs) of WWH in each week, while the off-diagonal subplots show the joint distribution of WWHs in two weeks.

As shown in the subplots on the leftmost column, taxis working very hard (more than 100 h per week) in Week 1 also worked very hard in Week 4. This can be read from the location of the distinctive peak in the subplot at the bottom of the column. However, these taxis dramatically reduced work hours in Weeks 2 and 3, as the peaks in the subplots in rows 2 and 3 in the leftmost column move "down". On the other hand, those working fewer hours (below 100 h per week) in Weeks 1 and 4 maintained a relatively stable schedule in Weeks 2 and 3. As a result, the joint distribution displays a similar right-skewed pattern with a single peak, as shown in the subplots on rows 2 and 3 on the leftmost column. *The above observation suggests that COVID-19 had a more disruptive impact on taxi drivers who used to work longer hours*. These are likely drivers staying up for lucrative late night rides that almost disappeared during the crisis.

5.2. Productivity analysis

As discussed in the previous section, taxis might have reduced their work hours for profitability. To further demonstrate this hypothesis, we proceed to analyze the productivity of taxis, which is considered as a surrogate of profitability. In this study, we measure taxi productivity using three metrics: number of occupied trips per week, average capacity utilization rate by time (CURT), and average search time. CURT is the ratio between the total time spent on serving occupied trips and the total work time, while the average search time is the average duration of search trips.

Fig. 12(a) illustrates the distributions of productivity metrics over the four weeks. Most results are expected, though a few are worth noting. First, the PDF of the number of occupied trips significantly skews to the left in Weeks 2 and 3, but to the right in Week 1. The mode in Weeks 2 and 3 is around 50, whereas that of Week 1 is around 260. In contrast, the distribution in Week 4 is rather symmetric,



(a) Off peak (b) Peak (c) Mid of day

Fig. 10. CDF of daily work hours (DWH) in different periods of day.

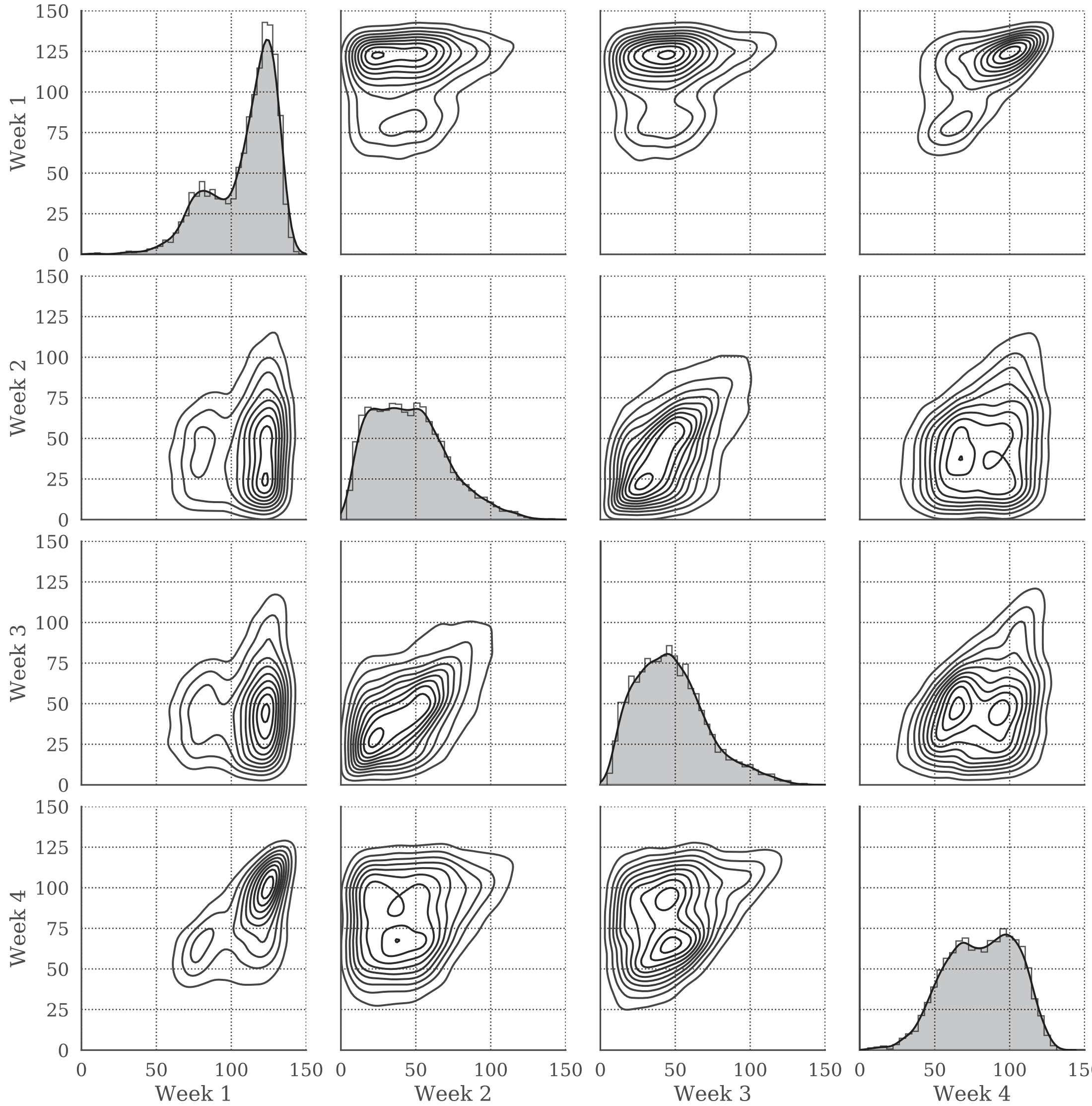
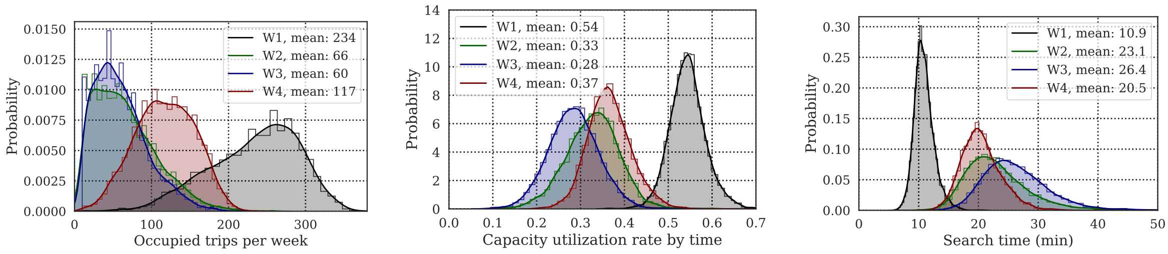


Fig. 11. Two-dimensional analysis of taxi weekly work hours (WWH). In each plot, both x and y axes represent WWH in one of the four weeks. The week number corresponding to each plot's axes can be read from the row (on the left) and column (at the bottom) indexes. Off-diagonal subplots are bivariate kernel density functions of WWH corresponding to the two different weeks on its axes, while diagonal plots show the PDFs of WWH in each week.



(a) Weekly occupied trips (b) Average capacity utilization rate by time (CURT) (c) Average search time

Fig. 12. Productivity metrics of the 5,021 taxis in the four weeks. (The mean value for each week is reported in each plot.).

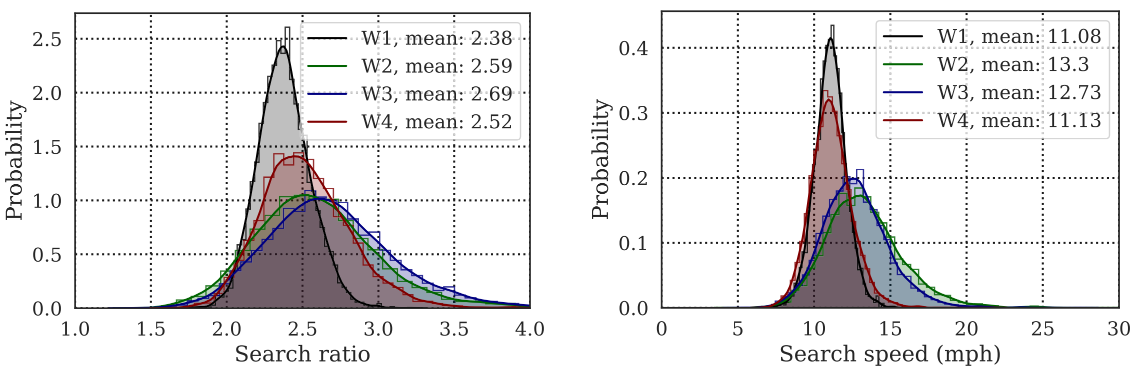
with a mode lying between Weeks 2, 3 and Week 1 (around 110). Also, the maximum number of weekly occupied trips is almost the same in Weeks 2, 3, and 4, though it is about 40% lower than that in Week 1. *Curiously, this gap suggests that COVID-19 had taken away some trips that taxi drivers could hardly make up by simply working harder, and the disappearance of those trips may be related to the restrictions that continued to impact some activities (e.g., entertainment and school) in Week 4.*

CURT and average search time essentially measure how much of a taxi's work time is actually profitable. These two metrics are closely related to each other: the longer the average search time, the lower the CURT. This relationship is demonstrated in Figs. 12(b) and 12(c). In Week 1, the distribution of CURT lies on the far right (with a mode around 0.55), and that of average search time lies on the far left (with a mode round 10 min), as expected. On average, taxis spent more than half of their working time serving passengers in Week 1. This percentage dropped to 28% in Week 3, when an average taxi spent almost half an hour to search for the next passenger, a 142% increase compared to Week 1. In Week 4, when taxis had recovered about 74.3% of their average work hours (see Fig. 9(a)), their productivity was still stuck at a very poor level, closer to the performance in Week 2 than to that in Week 1.

5.3. Search behaviors

To better quantify taxis' search efficiency, in this section, we introduce two measures: the average search ratio and the average search speed. The search ratio of a search trip is computed as the trip distance divided by the length of the straight line connecting the origin and the destination of the trip. The average search ratio and the average search speed of a taxi are obtained by taking average over all its search trips. Note that taxi drivers in Shenzhen can access e-hail platforms operated by Transportation Network Companies (TNCs) such as Didi Chuxing. Thus, an unknown number of trips recorded in the data might be brokered by TNCs. However, unlike the drivers that work exclusively for TNCs, taxi drivers have complete autonomy when it comes to accepting e-hail orders, and they do not pay commission fees. In other words, they still largely operate in the street-hail mode and only take e-hail orders that best fit their interests. On the flip side, however, this independence also means taxis are unlikely to get "good" orders from TNCs even in normal times, let alone when the overall demand is depressed by the pandemic. Thus, the efficiency of their operations can still be seen as closely associated with their own search strategies rather than TNCs' dispatching/matching strategies.

The PDFs of the two measures computed based on the 5,021 selected taxis are plotted in Fig. 13. For both search ratio and search speed, the mean and the lower bound are remarkably stable across the four weeks. The lower bound for the average search ratio is about 1.5, and that for the average search speed is 7.5 mph. The upper bound, however, has greater variances. In Week 1, there was



(a) Average search ratio (b) Average search speed (mph)

Fig. 13. Search behaviors of the 5,021 taxis in the four weeks. (The mean value for each week is reported in each plot.).

hardly any taxi with a search ratio higher than 3.0, whereas in the other weeks, the highest search ratio was close to 4.0. Thus, a fraction of taxis appeared to have experienced difficulty when searching passengers in Weeks 2 to 4. As a result, they tend to search more and make more winding search trips, which would drive up the search ratio. Fig. 13(b) indicates that a large portion of taxis had slightly improved the search speed in Weeks 2 and 3.While attributing this change to the improved traffic conditions during the lockdown seems reasonable, we note that subtle behavioral changes and the increase in the proportion of e-hail trips could also play a role, which, however, is much harder to discern with our data. Overall, these observed changes in search behaviors are modest and largely expected from the impact of COVID-19 on taxi market discussed in the previous sections.

6. Discussions

Having examined both demand and supply characteristics of the taxi data, we now conduct three in-depth analyses and discuss the results. In Section 6.1, we cluster the 5,021 taxis used in the supply analysis to look for structural patterns. The second analysis (Section 6.2) examines the taxi industry's level of service (LOS, measured by the expected passenger wait time) in different parts of the city. We then link the observed patterns of LOS changes to the taxi stimulus policy implemented by the city (Section 6.3). Finally, Section 6.4 discusses broader policy implications of our empirical findings.

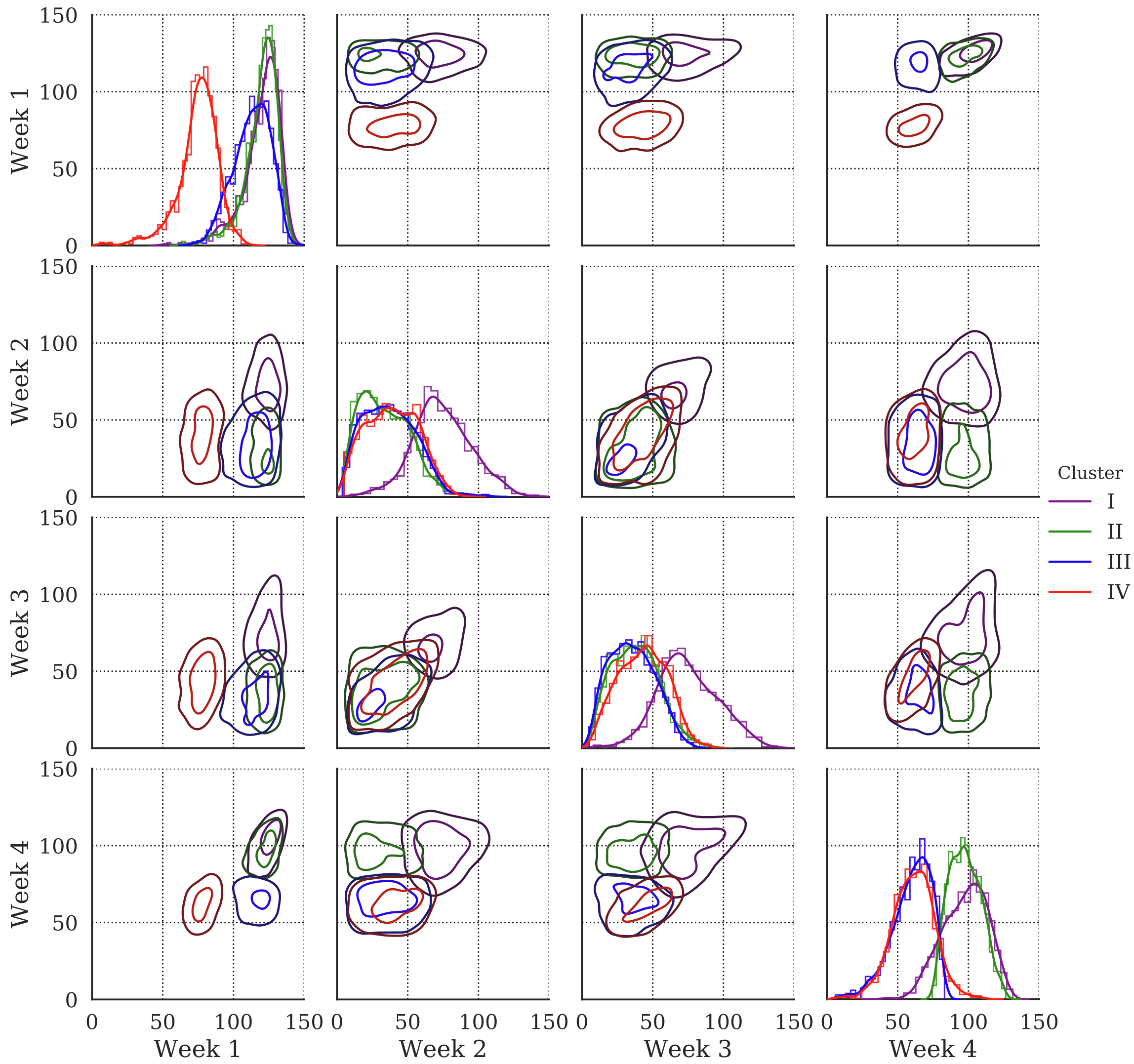


Fig. 14. Clustered two-dimensional analysis of taxi weekly work hours. In each plot, both x and y axes represent WWH in one of the four weeks. The week number corresponding to each plot's axes can be read from the row (on the left) and column (at the bottom) indexes. Off-diagonal subplots are bivariate kernel density functions of WWH corresponding to the two different weeks on its axes, while diagonal plots show the PDFs of WWH in each week.

6.1. Taxi clustering

Our extensive feature engineering exercises suggest weekly work hours (WWH) and the capacity utilization rate by time (CURT) are the most promising features for taxi clustering. This is not surprising given both features are subject to large variations throughout the analysis period. By computing WWH and CURT for each analysis week, we generate eight features for each taxi and normalize them into $[0,1]$. Then, we apply the K-means algorithm (Arthur and Vassilvitskii, 2006) to identify taxi groups with different operational patterns. K-means is a classic clustering method that aims to separate samples into a specified number of clusters such that the within-cluster sum of squares is minimized. The experiments suggest that the best result is achieved when the number of clusters is set to four. In what follows, we shall refer these clusters as I (1,221 taxis), II (1,556 taxis), III (1,210 taxis), and IV (1,034 taxis).

Fig. 14 repeats the 2-D analysis of Fig. 11, but does it for each cluster separately. With the clustering results, we can now see clearly that, in Week 1, Cluster I (purple) and Cluster II (green) are the most hard-working, Cluster III (blue) slightly lags behind, and Cluster IV (red) is a distant fourth (see the upper left corner subplot in Fig. 14). In Weeks 2 and 3, WWH of all clusters dropped, and for Clusters II and III, it dropped to the level of Cluster IV. In Week 4, while WWH of all clusters recovered (moved to the right), taxis in Cluster III worked roughly as hard as those in Cluster IV (recall the work intensity of these two clusters had a much greater difference in Week 1).

The above results suggest Cluster I consists of the most dedicated taxi drivers, who consistently worked the longest time throughout the crisis. Taxis in Cluster II are probably the most responsive to the crisis. While in general hard-working, they also strategically cut their work hours substantially when the pandemic torpedoed the business. Cluster IV is the most “laid back” group. Taxis in this group tend to work much less than the others, though their work hours were also affected by the pandemic. The most interesting is perhaps Cluster III. Taxis in this cluster worked significantly harder than those in Cluster IV in Week 1. However, once the pandemic started, they became as laid back as Cluster IV, and never recovered, even a month after the pandemic was contained (Week 4). It seems as if COVID-19 had permanently changed the work habit of Cluster III.

The off-diagonal subplots in Fig. 14 show that, for taxis in Clusters I and IV, the longer they worked in Weeks 1, 2 or 3, the more likely they would also work more in Week 4. Yet, this rule does not apply to Clusters II and III. Overall, the work schedule of Clusters II and III was more sensitive to the impact of COVID-19 than the other two.

Fig. 15 reports PDFs of the four clusters’ CURT, another feature used in clustering. For all clusters, the CURT distribution moves to the left (decreasing) from Week 1 to Weeks 2 and 3, before swinging back to the right (increasing) in Week 4. Cluster IV stands out for being the most productive group (highest CURT) in Week 1. A possible reason is that Cluster IV worked much less in the off-peak period (see Fig. 16). Since the off-peak demand is usually low, taxis working in this period need to spend more time to search passengers and hence often end up with lower CURT. Therefore, by reducing the work hours in the off-peak period, Cluster IV managed to achieve the highest CURT among all groups.

6.2. Level of service

In this study, we measure taxi LOS by the expected passenger wait time (EPWT). EPWT of street-hail taxi is mainly influenced by two local variables: vacant vehicle density Λ, which measures the supply in the local market, and the effective hail distance d, i.e., the maximum distance the passenger could see and hail a taxi. Following Zhang et al. (2019a), we estimate EPWT by

$$\mathrm{EPWT} = \frac{\delta}{\sigma \Lambda d v}, \tag{1}$$

where δ is a constant detour factor related to network topology, σ is a coefficient associated with each local market, and v is the average search speed.

While Λ and v can be directly calculated from taxi trajectories, d and σ are not observable and thus need to be calibrated from specific matching model. Here, we take the results reported in Zhang et al. (2019a), who calibrated the taxi matching model for each of the selected local markets (see Fig. 17). The EPWTs are computed for all local markets using Eq. (1) and then averaged for each core area.

Table 2 reports the average EPWTs in each core area across the four analysis weeks. In Week 1, downtown areas (A and B) have the lowest EPWT among the five core areas. LOS in all areas suffered a quite dramatic drop in Week 2. The hardest hits were the new high tech center (C) and two suburban areas (D and E), where EPWT almost tripled. In the downtown areas (A and B), EPWT increased at

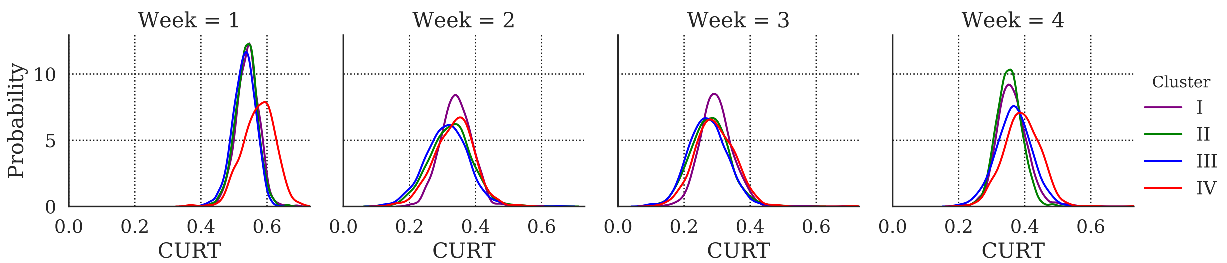


Fig. 15. Clustered PDF of average capacity utilization rate by time (CURT).

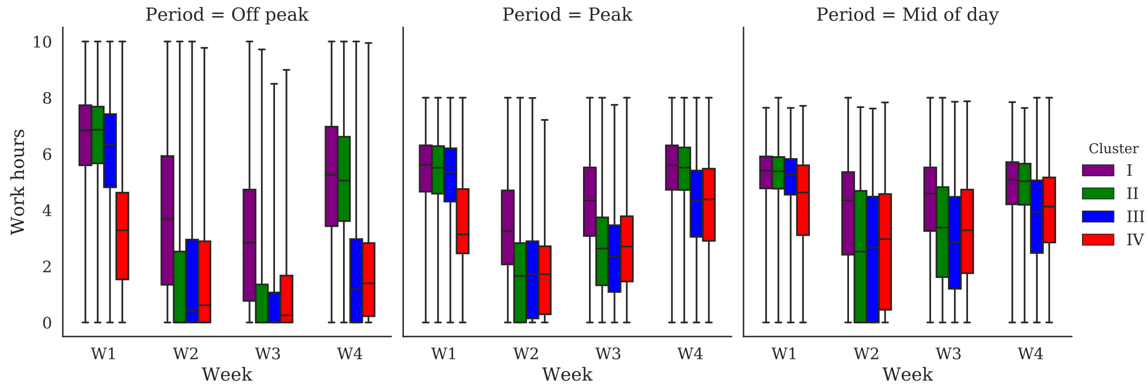


Fig. 16. Clustered box plots for daily work hours (DWH) by periods.

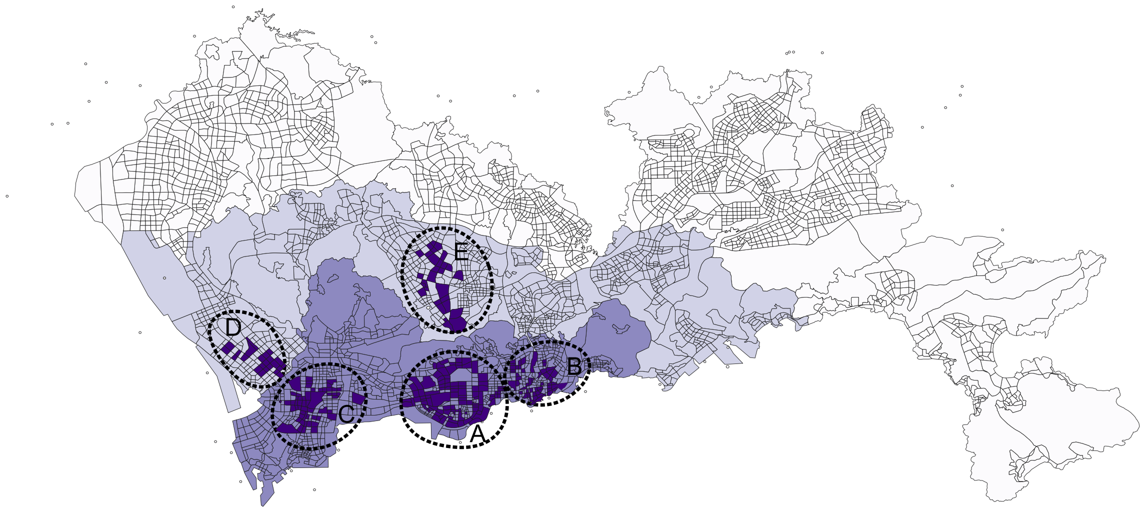


Fig. 17. Distribution of five selected core areas in Shenzhen (A and B are located in the Central Business District; C is located in the city's new high tech center; D and E are located in less densely developed suburban areas).

Table 2
Estimated passenger waiting time in the four weeks (min).

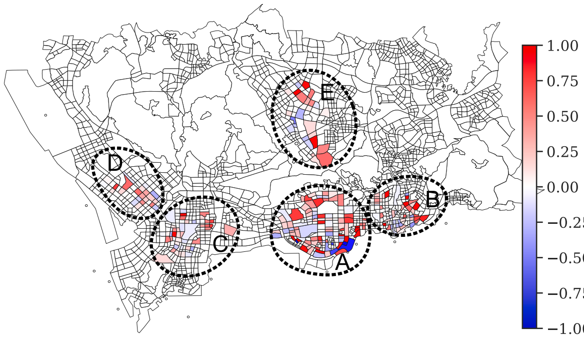
Core areas	A	B	C	D	E
Week 1	2.3	1.8	3.2	6.3	2.7
Week 2	4.4	2.7	9.6	17.6	7.4
Week 3	4.5	2.5	7.3	16.0	6.0
Week 4	2.0	1.5	2.9	5.2	2.3

least 50%. Although the pandemic was almost over in Week 3, LOS in most areas barely improved.

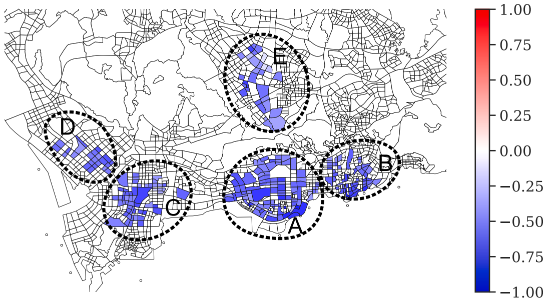
Perhaps the most intriguing finding from Table 2 is what happened to EPWT in Week 4. Unexpectedly, not only did LOS fully recover in all areas, it even exceeded the pre-COVID level, in some cases with significant margins (e.g., area D). Fig. 18 visualizes the change of taxi supply and demand in Week 4, relative to Week 1. It suggests that, while the demand was far from a full recovery in all local markets, the vacant taxi density in Week 4 had exceeded that in Week 1 in most local markets. Clearly, taxis were "oversupplied" in Week 4, if we assume the market in Week 1 was at a "normal" and efficient demand–supply equilibrium. How did this happen? We speculate that this phenomenon might have something to do with the city's stimulus policy described in Section 3. We present further evidence to support this connection in next section.

6.3. Impact of the stimulus policy

Right before Week 4, the Shenzhen government enacted a policy aiming to stimulate taxi supply. It offers a bonus of ¥50 to any taxi



(a) Vacant taxi density



(b) Taxi demand

Fig. 18. Changes in taxi supply and demand of local markets in Week 4 relative to Week 1 (±1.00 = ± 100%).

driver who operates at least 100 km or five hours a day. Judged by the exceedingly good LOS in Week 4, it is quite plausible that this policy had not only successfully overcome the potential problem of taxi shortfall, but also over-corrected it. We have seen indirect evidence supporting this conjecture before. While the total trips in Week 4 is less than half of the normal level, the average weekly work hours had recovered 75% for the 5,021 active taxis included in the supply analysis (see Fig. 9). Accordingly, these taxis suffered a much lower operational efficiency in Week 4 than Week 1: their average search time was twice as long, and their capacity utilization rate was 30% lower (see Fig. 12). Moreover, it is evident from Fig. 18 that the market balance decisively tilted towards over-supply across the board in Week 4. However, none of the above observations can be directly and unequivocally attributed to the stimulus policy itself. Indeed, there are alternative explanations to the oversupply issue. For example, perhaps the taxi drivers simply overestimated the demand, or were desperately seeking to boost their income.

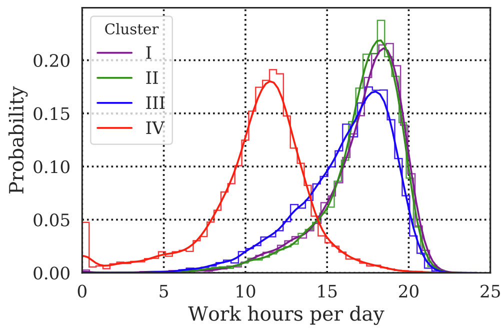
To find “direct” evidence, we begin by theorizing the potential impact of the stimulus policy on the taxi drivers’ behavior. The idea is rather simple. If some drivers were lured into the market by the bonus, they would at least try to stay as long as the threshold, i.e., 5 h a day. In other words, such a driver would not work just shy of five hours. Instead, he would continue to operate until he meet the requirement for bonus, even if he knew from experience that the extra operating time was almost certainly going to be wasted. If a significant portion of the taxi drivers behave this way, we can expect to see a lower concentration of taxi daily work hours (DWH) at a value slightly below the threshold. Since most taxis are actually operated by two drivers, the threshold is more likely to be around ten instead of five hours.

Fig. 19 compares the PDFs of average DWH in three weeks for the four taxi clusters obtained from the previous analysis. The patterns for Week 2 is very similar to that for Week 3, and thus excluded for brevity. Remarkably, Fig. 19(c) shows a “stimulus valley” in the PDFs for both Clusters I and II, at almost the exact location (i.e., right below 10 h/day) predicted by the above analysis. The existence of a valley at DWH around 10 h/day is a unique phenomenon of Week 4, as it cannot be found in any clusters in Fig. 19(a) or Fig. 19(b). Thus, it is more likely than not that the work schedules of the taxis in Clusters I and II were influenced by the stimulus policy. That these very taxis are also the most hard working is probably not a coincidence: if a taxi driver is inclined to work more, he might also be more disposed to aim at a higher income, and hence less likely to let go the bonus.

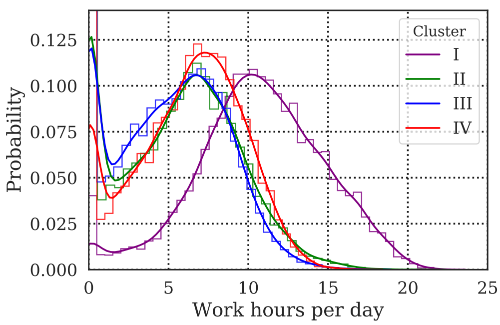
The above finding hence confirms the stimulus policy had contributed to the observed supply–demand imbalance in Week 4, although the magnitude of the impact is still difficult to measure, given the many other factors that might be at work. We leave to a future study a more quantitative analysis of supply-side policies for a taxi market disrupted by a major public health emergency.

6.4. Policy implications

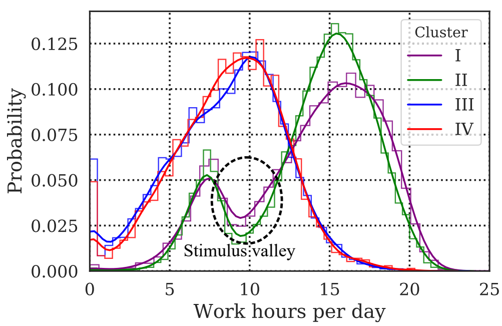
Motivated by the rapidly deteriorating taxi services at the peak of the crisis, the Shenzhen government intervened by offering taxi drivers a bonus if they meet certain daily work schedule requirement. This action no doubt contributed to a strong rebound of taxi supply in Week 4. However, the analysis presented in the previous section indicates that subsidizing taxi services in such a broad stroke had led to oversupply that helped maintain a level of service higher than that of a competitive market. If the policy aims to maintain an *adequate* level of taxi service, then it had created an unintended consequence. If, instead, the objective is to provide additional subsidies to protect taxi drivers from losing too much income, then the specific working hour requirement is not well justified, as it had only served to reduce overall efficiency. What lessons could we learn here? First and foremost, incentives aiming at boosting supply should more precisely target where the boost is most needed. In the case of Shenzhen, the incentive policy should probably reward taxi drivers for serving trips in morning rush hours and/or suburban areas, because that is when and where taxi trips recovered the fastest (see Figs. 4 and 5). Also, instead of tracking the total working hours, the incentive should be based on the number of served trips that meet these spatial–temporal requirements. Second, the taxi market conditions (e.g., average wait time, capacity utilization ratio) should be continuously and closely monitored so that whatever policies put in place can be adjusted according to empirical evidence. Of course, one should not attempt to adjust the policy too frequently, because it may create confusion and chaos. A weekly review seems a reasonable time framework. Had such a monitoring program existed, the government could have discovered the shortcoming of the incentive policy and reversed course earlier, which could literally save millions of dollars (recall that the city spent nearly ¥70 million



(a) Week 1



(b) Week 3



(c) Week 4

Fig. 19. Distribution of average daily work hours (DWH) for the four taxi clusters.

in total).

In the case of Shenzhen, taxi productivity had suffered a greater setback than ridership: it sank to the bottom right after the phased reopening kicked in, and was stuck at a dismal level even after the work resumption ratio reached 70% in the city. Such a low productivity is at least partially attributed to the traditional street hailing operation: cruising around and picking up passengers off streets. When the demand is severely depressed by lockdown orders (as in Weeks 2 and 3) or when the market is oversupplied (as in Week 4), street-hail is simply not an effective way to find passengers. To help taxi drivers, the government could encourage and aid them to switch to a centralized dispatching model. As mentioned before, while taxi drivers in Shenzhen have had access to TNCs' e-hail platforms, their priority is probably the lowest as they do not pay the commission fee. Thus, when the demand is low, taxis are unlikely to receive any TNC orders. A potential solution is to build a public dispatching platform shared by taxis. Interestingly, the Shenzhen government did launch such a platform on May 20, 2020[15], and reportedly a vast majority of the taxis had since adopted this service. Switching to e-hail alone may not be enough, however. If the demand is low, the waiting time between orders will be long regardless of the operational mode. In this case, taxis should be allowed to park at convenient locations, as much as needed, to avoid being forced to

[15] https://www.sohu.com/a/401558763_161795, in Chinese.

drive around without passengers. Such parking permissions would be easy to justify and implement when city streets are rendered much less crowded by lockdown orders.

7. Summary of findings

We have traced the plunge and rebound of the taxi market in Shenzhen, China through the COVID-19 lockdown, from the onset of the crisis to the reopening of the city. Our analysis is based on taxi GPS trajectory data collected in four separate weeks in the first quarter of 2020. We briefly summarize the main findings below.

On the demand side, 85% of the taxi ridership was lost due to the stay-at-home order. When the city began to reopen, the taxi demand recovered the fastest in the peak period when most commuters rush to work. However, even when the city was mostly reopened for business and work, the market's output was still 55% below normal. Notably, by this time, traffic congestion had returned to the pre-COVID level. In other words, taxi travel fell far behind the recovery of the overall vehicle trips in the city, suggesting that some travelers had substituted taxi (quite possibly also other mode of public transportation) with driving. The impact of the crisis on the taxi demand also displays noticeable spatial heterogeneity. In particular, the city center endured a more severe taxi demand contraction than the suburbs.

On the supply side, while all taxis significantly cut work hours due to the pandemic, those who used to work very hard were affected more. A large portion of taxis adjusted their work schedules to focus on serving peak-time demand, especially after the city began phased reopening. The taxi productivity, measured by the capacity utilization rate, plummeted during the pandemic and had a very slow recovery. Thus, not only did the taxis work fewer hours, they also generated less revenue per unit time. Although the taxi's level of service (i.e., average wait time) dropped precipitately at the beginning, it rebounded to exceed the pre-pandemic level toward the later phase of the recovery, thanks to the government's incentive policy.

The clustering analysis reveals four distinctive driver groups, including a dedicated group that always worked the longest hours, a laid back group that worked much less and especially disliked off-peak hours, and an adaptive group that adjusted work schedule vigilantly according to the evolution of the crisis. For the last group, which was the most affected, COVID-19 appears to have left a lasting mark on their work habit. Drivers in this group, which amount to about a quarter of the sample, had worked significantly less than what they used to, even after the city had largely reopened.

Based on the above empirical findings, we made the following policy recommendations. First, incentives aiming at boosting supply should more precisely target where the boost is most needed. Second, the taxi market conditions should be closely monitored to support and adjust policies. Finally, when the demand is severely depressed by lockdown orders or when the market is oversupplied, taxi drivers should be encouraged and aided to use more centralized dispatching modes.

Acknowledgements

The authors wish to thank Mr. Jiandong Qiu from Shenzhen Urban Transport Planning Center for providing the COST data used in this study. The research is supported by the US National Science Foundation under the award number CMMI 1922665.

Appendix A

Algorithm 1. Population-weighted relative changes in the number of occupied trips

Label all occupied trips by its starting time and origin area.
for *i* in *peak, mid of day, off peak* **do**
  for *j* in *city center, suburb, peripheral suburb* **do**
    Exact all occupied trips in time period *i* and origin area *j*.
    Count every TAZ's number of occupied trips in four weeks.
    Take Week 1 as the benchmark, calculate every TAZ's relative change in the number of occupied trips.
    Count number of people (by one thousand persons) that experienced the same relative change.
    Plot the cumulative population affected by relative changes from negative to positive.
  end for
end for

References

Ale-Ahmad, H., Mahmassani, H.S., 2020. Impact of COVID-19 on Taxi Operation in Chicago. URL: https://www.transportation.northwestern.edu/news-events/articles/2020/taxi-operations-during-covid-19.html.
Arthur, D., Vassilvitskii, S., 2006. k-means++: The advantages of careful seeding. Technical Report.
Baldwin, R., di Mauro, B.W., 2020. Economics in the Time of COVID-19. CEPR Press. URL: http://dln.jaipuria.ac.in:8080/jspui/bitstream/123456789/2757/1/Economics in the Time of COVID-19.pdf.

Cachon, G., Daniels, K., Lobel, R., 2017. The role of surge pricing on a service platform with self-scheduling capacity. Manufacturing and Service Operations Management 19, 368–384. https://doi.org/10.1287/msom.2017.0618.

Chapuis, R., Tadjeddine, K., David, C., Holmes, R., Knol, A., Speksnijder, L., Wolfs, K., Lotz, C., Stern, S., 2020. Restoring public transit amid COVID-19: What European cities can learn from one another. URL: https://www.mckinsey.com/industries/travel-logistics-and-transport-infrastructure/our-insights/restoring-public-transit-amid-covid-19-what-european-cities-can-learn-from-one-another.

Hu, Y., Barbour, W., Samaranayake, S., Work, D., 2020. Impacts of covid-19 mode shift on road traffic. arXiv preprint arXiv:2005.01610.

IBM, 2020. COVID-19 Is Significantly Altering U.S. Consumer Behavior and Plans Post-Crisis. Technical Report. IBM. URL: https://newsroom.ibm.com/2020-05-01-IBM-Study-COVID-19-Is-Significantly-Altering-U-S-Consumer-Behavior-and-Plans-Post-Crisis.

Ivanov, D., 2020. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transportation Research Part E: Logistics and Transportation Review 136, 101922.

Liu, D., Xue, L., Huang, T., 2020. 3 Ways China's Transport Sector Is Working to Recover from COVID-19 Lockdowns. URL: https://thecityfix.com/blog/3-ways-chinas-transport-sector-working-recover-covid-19-lockdowns/.

Liu, J., Han, K., Chen, X.M., Ong, G.P., 2019. Spatial-temporal inference of urban traffic emissions based on taxi trajectories and multi-source urban data. Transportation Research Part C: Emerging Technologies 106, 145–165.

Ma, H., Lu, H., Stathopoulos, A., Nie, Y., 2017. Characterization of Trip-Level Pace Variability Based on Taxi GPS Trajectory Data. Transportation Research Record 2667, 51–60.

Nie, Y.M., 2017. How can the taxi industry survive the tide of ridesourcing? Evidence from Shenzhen, China. Transportation Research Part C: Emerging Technologies 79, 242–256.

Oum, T.H., Wang, K., 2020. Socially optimal lockdown and travel restrictions for fighting communicable virus including COVID-19. Transportation Policy 96, 94–100.

Qian, X., Ukkusuri, S.V., 2021. Connecting urban transportation systems with the spread of infectious diseases: A Trans-SEIR modeling approach. Transportation Research Part B: Methodological 145, 185–211.

Sattenspiel, L., Dietz, K., et al., 1995. A structured epidemic model incorporating geographic mobility among regions. Mathematical biosciences 128, 71–92.

Sohrabi, C., Alsafi, Z., O'Neill, N., Khan, M., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, R., 2020. World health organization declares global emergency: A review of the 2019 novel coronavirus (covid-19). International Journal of Surgery 76, 71–76.

Tahlyan, D., Mahmassani, H.S., 2020. Chicago Mobility under COVID-19. URL: https://www.transportation.northwestern.edu/news-events/articles/2020/chicago-mobility-under-covid-19.html.

Tu, W., Li, Q., Fang, Z., Shaw, S.l., Zhou, B., Chang, X., 2016. Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach. Transportation Research Part C: Emerging Technologies 65, 172–189.

UBS, 2020. Where is traffic congestion in China rising and falling? Technical Report. UBS Evidence Lab. URL: https://www.ubs.com/global/en/investment-bank/evidence-lab/covid-19/2020/where-is-traffic-congestion-in-china-rising-and-falling.html.

Xie, J., Nie, Y.M., Liu, X., 2017. Testing the proportionality condition with taxi trajectory data. Transp. Res. Part B 104, 583–601.

Yuan, J., Zheng, Y., Xie, X., 2012. Discovering regions of different functions in a city using human mobility and POIs, in. In: Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 186–194.

Zhang, K., Chen, H., Yao, S., Xu, L., Ge, J., Liu, X., Nie, M., 2019. An efficiency paradox of uberization. Available at SSRN 3462912.

Zhang, K., Chen, Y., Nie, Y.M., 2019b. Hunting image: Taxi search strategy recognition using Sparse Subspace Clustering. Transportation Research Part C: Emerging Technologies 109, 250–266.

Zhang, X., Shao, Y., Sun, C., Long, J., An, J., Lin, Y., 2020. Data-Driven Pandemic Response and Delicacy Governance of Shenzhen Transportation. Urban Transport of China 4, 93–100.