Airbnb, COVID-19 Risk and Lockdowns: Local and Global Evidence♣

Maggie R. Hu
Chinese University of Hong Kong
Email: maggiehu@cuhk.edu.hk

Adrian D. Lee
Deakin University
Email: Adrian.Lee@deakin.edu.au

Latest draft: December 2020

♣ We thank Sudipto Dasgupta, Michael Zheng Song, participants at HKIAPS COVID-19 Webinar Series, seminar participants at Deakin University and Wollongong University for helpful comments and suggestions.

Airbnb, COVID-19 Risk and Lockdowns: Local and Global Evidence

Abstract

The COVID-19 pandemic has triggered an unprecedented crisis in the travel industry and short-term rental market. We study the impact of COVID-19 on global Airbnb booking activity from three aspects: the initial Wuhan lockdown, local COVID-19 cases, and local lockdowns. Using reviews and cancellations as proxies for Airbnb bookings, we find that local lockdowns result in a 57.8% fall in global booking activities, with an 8.8% fall after the Wuhan lockdown. Every doubling of newly infected cases is associated with a 4.16% fall in bookings. The sensitivity of bookings to COVID-19 decreases with geographic distance to Wuhan, and increases with government stringency of lockdown policies as well as human mobility within a market. Using London, United Kingdom as a case study, we find private rooms experience over 20% more cancellations than entire homes, consistent with host fears of infection. On the supply side, we find stable listings volume and lower booking price. Hosts charge an infection risk premium of 5.2% for letting private rooms relative to entire homes. Our study provides insights for hosts and policymakers to formulate recovery plans in a post COVID-19 economy.

Key words: Airbnb, Travel activity, COVID-19, lockdown, confinement orders, social distancing

JEL Classification Code: R30, L83, L85

1. Introduction

The onset of COVID-19 is one of the most dramatic changes in recent history. Within only a few months of the first detected case, it has brought our world to a standstill with unparalleled and unforeseen impact on our lives, our economies, and our societies. Governments around the world have implemented various containment measures, such as travel bans and lockdowns, to prevent the spread of the disease. These travel restrictions and associated disruptions have created a direct and huge impact on travel activities. The United Nations World Tourism Organization (UNWTO)[1] declared the travel industry to be one of the hardest-hit by the outbreak of the coronavirus disease (COVID-19), with impacts on both travel supply and demand, particularly in China, the world's leading outbound market in spending. According to a report released by the U.S. Travel Association and Oxford Economics, the U.S. is expected to suffer a $519 billion decline in direct travel spending, translating to $1.2 trillion in lost economic output, which is nine times worse than the financial impact of 9/11. These numbers highlight COVID-19's devastating impact on the travel and tourism sector.

Although governments around the world have put in place social distancing advice and lockdown measures, there is also anecdotal evidence of people acting carelessly or selfishly, ignoring government advice. In addition, there is no consensus on what constitutes the most appropriate measure to address public health concerns without undue disruption to social wellbeing. A variety of approaches have been implemented to deal with the infectious spread of COVID-19 around the world. For some people, being able to experience nature or exercise outdoors is an essential part of daily life, which is significantly disrupted due to lockdown measures. At the beginning of the COVID-19 pandemic, most people treated COVID-19 as nothing more than a seasonal flu. They were inattentive to COVID-19 and did not heed preventive measures (such as social distancing). Many only started to pay attention when the rise in

[1] Source: https://www.unwto.org/news/unwto-underscores-tourisms-importance-for-covid-19-recovery-in-meeting-with-the-king-of-spain

COVID-19 casualties in their local region became alarming. On the other end of the spectrum, as this infectious disease is transmitted rapidly and invisibly, many people develop anxiety and excessive fear of the disease, and opt to practice the strongest possible form of social distancing and cut off all non-essential travel activities to prevent infection.

Despite the heightened situation of COVID-19 and various lockdown measures, it is not obvious how people will adjust their travel behavior, particularly considering the different attitudes towards the disease (Barrios et al., 2021; Goolsbee and Syverson, 2021). In this paper, we study how people adjust their travel behavior with respect to government lockdown polices and also the outbreak situation in their local region. We infer people's attitude towards COVID-19 by examining their reaction to the news of newly confirmed infection cases or the initiation of lockdown policies. We expect travel activities to reduce substantially if people perceive a heightened threat of infection. Meanwhile, we expect all travel activities should plummet to minimal essential level if the government lockdown policies are fully effective. These questions are of great importance to the tourism industry as well as the economy as a whole, enabling industry practitioners to gain a comprehensive understanding of the damage done to the tourism industry globally. This study also provides insights for policy makers to formulate recovery plans to revive the hospitality industry.

We base our analysis on the travel activities of the world's largest accommodation booking platform, Airbnb. Airbnb has grown into one of today's top communities and platforms for tourists to book unique homes and experiences. According to Airbnb, the company now has over 7 million accommodations worldwide and over 50,000 handcrafted activities, across over 220 countries and regions, amounting to over 750 million Airbnb guest arrivals[2], which is more than the top five hotel brands combined.[3] Since the onset of the outbreak, the number of Airbnb listings on offer has remained

[2] https://news.airbnb.com/fast-facts/
[3] https://www.businessinsider.com/airbnb-total-worldwide-listings-2017-8

relatively steady but the number of bookings has plummeted due to travel bans and health concerns, according to the vacation-rental site AirDNA[4]. The reduction in bookings is most significant in COVID-19 epicenters. For example, the number of bookings in Beijing[5] shrank from 40,508 in early January to only 1,655 reservations in the first week of March. These lost bookings had a devastating impact on Airbnb's revenue, as seen from the recent layoff of about a quarter of its work force.

As the global travel and tourism sector grinds to a halt, many owners of short-term or holiday rental homes on Airbnb, especially those with large mortgages, are struggling to maintain their income and keep their business. Faced with low demand, hosts are expected to adjust the listing price if they choose to continue with their business amidst the outbreak. Many may exit the short-term rental market for long-term leasing, as the future is uncertain for the short-term leasing market. We study how hosts adjust listing price and volume based on demand changes as the pandemic evolves over time.

We utilize scraped data from the Airbnb website from January 1, 2019 to Mar 31, 2020, including detailed review comments of each stay experience, cancellation postings at the listing level, and monthly snapshots of booking prices of each accommodation. To measure the intensity of travel activities, we use the number of reviews and cancellation rates as proxies. We also collect detailed data on the event dates of major lockdowns and/or travel bans in each Airbnb market. In addition, we collect the daily count of COVID-19 cases in local Airbnb markets. As the city of Wuhan is the original epicenter of the COVID-19, the Wuhan lockdown served as the first alert to the world regarding the severity of the epidemic situation. We start by analyzing whether the news of the Wuhan lockdown caused travelers worldwide to cancel their travel plans. With travel restrictions around the world becoming stricter as the pandemic evolved globally, we also look at the specific date of lockdowns or travel bans in each specific market. As the first case signals the onset of the virus and potential spread afterwards, we expect people would

[4] Source: Business Insider. https://www.businessinsider.com/airbnb-city-bookings-drop-coronavirus-2020-3
[5] Note that for Airbnb data in China, only Beijing and Hong Kong are available.

be more cautious (due to increasing risk of infection in the local region) after the initial outbreak in the local market.

Based on a sample of 98 Airbnb markets across 30 countries around the world, we document negative effects of COVID-19 on travel activity due to three separate causes: 1) the initial Wuhan lockdown shock; 2) new cases of COVID-19 infections in local markets; and 3) government policies on lockdown and travel bans. We employ the difference-in-differences (DID) test as our main empirical method, where travel activities in 2020 serve as the treatment group and those in 2019 as the control group. The difference between 2020 and 2019 is the first difference and the difference between pre- and post-event date is the second difference. The events include the Wuhan lockdown on January 23, 2020, COVID-19 outbreaks in local markets, and travel bans in local markets, corresponding to the three causes mentioned above.

First, we examine the effect of the Wuhan lockdown on travel activities around the world. Our DID estimation result reveals that there is a -8.8% fall in booking activity (proxied by daily Airbnb reviews) after the Wuhan lockdown relative to the pre-Wuhan lockdown period. Host cancellation as a percentage of review count increases by 0.55% after the Wuhan lockdown or 20% more than pre-lockdown, consistent with the observed reduction in travel activities (from reduced reviews).

The next effect we examine is the severity of the COVID-19 outbreak in local Airbnb markets in terms of newly confirmed cases. We find that every doubling of new local COVID-19 cases in the prior day is associated with a 4.16%[6] fall in travel activities the next day. We also find similar effects of COVID-19 cases on cancellations, with cancellation increasing by 15.46%[7] with a doubling of local COVID-19 cases.

[6] Table 2 Panel A Column 6 *Treat*Post*NewCase coefficient* is -0.06 in. So ln(2)*-0.06= -0.0416 or -4.16% change.
[7] Table 2 Panel B Column 6 *Treat*Post*NewCase* coefficient of 0.223. ln(2)*0.223=0.1546

Third, we look at the effect of local government lockdown policies including local lockdowns and travel bans, where the earlier date of these two polices is used in the analysis. Local lockdowns are associated with a 57.8%[8] fall in booking activity on average and an increase in cancellations of 4.5-fold.[9] In dollar terms, we estimate the immediate aftermath of the COVID-19 Wuhan lockdown on global Airbnb bookings to be -$634 million in Q1 2020 (or -$6.97 million per day post Wuhan lockdown), given Airbnb's publicly reported Q1 2019 total booking value of $9.4B and an estimated average stay of 4.3 nights. Every doubling of local COVID-19 cases in all local Airbnb markets is associated with an additional -$4.34 million per day loss in booking revenues.

We then explore the channels behind the sensitivity of booking activity to COVID-19 risks. We propose three main channels, including geographic distance to Wuhan, government stringency of COVID-19 policies, and human mobility within Airbnb markets. First, with respect to distance, we expect that the further away the market is from Wuhan, the lower the market's sensitivity to the Wuhan lockdown shock. Second, for regions with greater government stringency of lockdown policies, travel activity is expected to drop more in response to these interventions. Third, markets with greater mobility pose a heightened threat of infection. As a result, booking activity is expected to drop to a greater extent due to the higher infection risk. We document consistent evidence in all three channels.

Inbound travel bans may explain the reduced Airbnb booking activity. We further account for the effect of inbound travel restriction by separating the previous lockdown measure into two variables: inbound ban and confinement. For each Airbnb market each day, we define inbound ban as the percentage of the top 10 international tourists banned due to COVID-19 inbound travel restrictions from the Airbnb market. We expect inbound ban to be negatively related to booking activity as foreign guests are unable to enter. Consistent with our expectation, we find that a full inbound ban is associated with a fall of 46.6%

[8] Table 2 Panel A Column 6 *Treat*Post*Lockdown* coefficient of 0.578.
[9] Table 2 Panel B Column 6 *Treat*Post*Lockdown* coefficient of 4.482.

of reviews and an increase of 6.27 times the number of cancellations, greater than the effect of confinement. The results suggest that in terms of lockdown effects, inbound travel bans have a stronger effect on booking activity than local confinement/lockdown measures.

Our global results may be biased by cross-country differences in estimating the effects of COVID-19, including how COVID-19 cases are detected/recorded and different levels of COVID-19 management and testing (Hasell et al., 2020). We provide more detailed evidence on COVID-19's effects at a more granular level by conducting a case study of London's 33 boroughs. We start with testing whether the outbreaks in each borough and borough-level COVID-19 cases result in lower Airbnb booking activity. We further investigate whether Airbnb supply and booking prices are affected by COVID-19 and whether the effect differs between entire home and private room listings. We expect private room listings to be more negatively affected, as both hosts and guests would be reluctant to share residence during an outbreak, compared with entire homes. We find consistent evidence that booking activity declines sharply after the outbreak in each borough as proxied by reviews. And as the outbreak evolves over time, bookings drop to a greater extent with the reduction of reviews increasing each week after the initial outbreak. The reduction in reviews is particularly higher in boroughs with more COVID-19 cases. We also find that the cancellation rate is about 20% higher for private rooms compared to entire homes, consistent with host fears of infection.

Next, we examine supply side effect in terms of active listing volume and booking prices. We find that the supply of active listings on Airbnb is stable and unaffected by COVID-19 with respect to local lockdown policies or new cases of infection. This result implies that the reduced booking activity we document above is mainly due to shrinking demand. To further examine the impact on booking price, we study the booking price adjustment over time by comparing the current listing price of the same unit with its price one month ago. We find on average, booking prices are reduced by 6.1% in response to the outbreak, and the drop is more pronounced in areas with greater COVID-19 severity, implying hosts actively adjust the listing price downward in an attempt to improve booking revenue, given the negative demand shock. Moreover, we document room type heterogeneity that the price reduction of private rooms is 5.2% less than entire homes, suggesting private room hosts charge a positive risk premium for sharing their residence with potentially infected guests.

We also look at the dynamics of listing price adjustment with respect to different time horizons and find that hosts offer discount of 12.1%, 5.9%, 2.9% for booking dates in the next first, second and third month, respectively, whereas no significant discount is offered for dates in the fourth month. We observe the price discount and its sensitivity to COVID-19 severity have a pattern of being monotonically higher in more recent dates, and lower in more distant future, which offers important insights on hosts' revenue management strategies with respect to the option value to wait for each available date of their listings. Hosts offer greater discount for nearby dates to increase revenue, as the option to wait is close to zero. However, they set higher price for future days given the higher option value to wait, in case of a speedy market recovery.

Last, we examine whether professional hosts respond differently to the COVID-19 situation than non-professional hosts. We find that professional hosts offer greater discounts with higher local COVID-19 severity relative to non-professionals, consistent with the rationale that professional hosts are more experienced in assessing market demand and maximizing listing revenue by adjusting price (Li, Moreno and Zhang, 2016; Gibbs et al., 2018). We further compare the price discount of professional host in private rooms and entire units and find that professional hosts of private rooms offer greater discount than non-professional hosts, implying non-professional hosts of private rooms are more concerned about infection risk than professionals and charge a risk premium accordingly.

Our paper makes the following contributions. Our study is amongst the first to document empirical evidence on the impact of COVID-19 on travel activities around the world. Utilizing listing level travel data on the largest travel platform, Airbnb, we provide a comprehensive understanding of the impact of COVID-19 on the demand and supply dynamics of bookings. On the demand side, we find people reduce their travel activities in response to three factors: the Wuhan lockdown, the severity of spread in their local geographic area, and local lockdown.

On the supply side, we document that the volume of active listing is stable, while listing prices see a substantial discount. We also document room type heterogeneity by showing hosts of private rooms charge higher prices relative to entire homes as infection risk premium. We also provide evidence that hosts respond to the pandemic by strategic adjusting booking prices based on the occupancy status of the listing and the option value of booking dates, implying hosts' income smoothing and revenue maximization incentives.

Second, we examine the heterogeneous sensitivity of travel activity towards the pandemic outbreak. Overall, we observe similarity in terms of reduced travel in all Airbnb markets, suggesting fear of virus spread. There are also varying degrees of sensitivities across regions with the initial Wuhan lockdown depending on geographic proximity to the epicenter and sensitivity to local COVID-19 cases and lockdowns.

Third, our paper also contributes to our understanding of whether lockdown policies are successful in limiting human mobility and reducing the spread during the crisis. Our results provide an estimate of how human behavior, specifically, bookings and cancellations on the Airbnb platform, responds to perceived risks of contracting the disease. The results shed light on the role of government announcements in affecting people's travel behavior. Engle, Stromme and Zhou (2020) estimate how individual mobility is affected by local disease prevalence and restriction orders to stay-at-home, and document an official stay-at-home restriction order corresponds to reducing mobility by 7.87%. Chinazzi et al. (2020) find that the Wuhan lockdown was able to reduce the cases by 10% in cities outside Wuhan.

Our paper documents evidence from the perspective of travel activities on Airbnb. In particular, we find that the reduction in travel activities is most pronounced in regions that are geographically close to an outbreak and which also have local cases, even with the absence of lockdowns.

Last, this paper contributes to a rapidly evolving field regarding the impact of COVID-19 on the economy and various industries. Ramelli and Wagner (2020) document stock price reactions to COVID-19 as the outbreak evolved over time in different regions. Chen, Qian and Wen (2020) study the impact of COVID-19 on consumption after the outbreak started in China and document a sharp decline in spending. Gormsen and Koijen (2020) examine the impact of COVID-19 on stock price and dividend future and derive growth expectations for a recession. Our paper is the first to study the impact of COVID-19 on the travel industry, utilizing detailed listing level travel data from the largest travel platform (Airbnb). Our findings provide insights to inform recovery policies for the travel and hospitality industry.

The paper is structured as follows. Section 2 provides the institutional background on Airbnb reviews. Section 3 describes the data and methodology, and Section 4 reports the main results. Section 5 conducts a case study of London’s boroughs and Section 6 concludes.

2. Institutional background

2.1. Airbnb reviews and COVID-19 related cancellation policies

Reviews are an essential part of the Airbnb experience, with both host and guests able to leave a review or privately message each other. Guests are encouraged to write a review on the Airbnb platform to share their experience of the stay (for example, they can comment on the cleanliness of the place, personal touches from the host, or convenience of the location). In addition to a written review, guests are also asked to provide star ratings. Airbnb relies on the review and rating system to provide feedback to the hosts and encourage a higher standard of quality and hospitality. Moreover, future guests also rely on the feedback when they choose from various listings. Note that reviews are optional; the host and guest both have 14 days to review each other.

Cancellation can be initiated by either guests or hosts. Hosts normally incur a cancellation fee if they cancel a booking. Most of the time, hosts do not initiate the cancellation as they lose booking revenue and incur a penalty fee. Note that host penalties do not apply to guest-initiated cancellations - if a guest cancels a reservation, the refund amount is determined by the host's cancellation policy and how close the cancellation is to the impending trip.

Since the World Health Organization (WHO) declared the outbreak of COVID-19 a global pandemic on March 11, 2020, the outbreak has evolved rapidly. The travel industry has been hit especially hard by the spread of the coronavirus, including Airbnb. Across the world, Airbnb bookings have tanked. Bookings across Europe collapsed in March, dropping 80% compared to the previous week in the week beginning March 9, and another 10% on top of that in the week of March 16. In the U.S., where virus response lagged, the figures for falls in booking are uneven, but scarcely less dramatic. By the middle of March, bookings in New York City, San Francisco and Seattle had already dropped more than 50% compared to the week beginning January 5, with drops of over 35% in Washington, D.C., and Chicago[10].

Governments around the world have taken swift actions to slow the spread of the disease. In response, Airbnb provides an extenuating circumstances policy to protect guests and hosts from unforeseen circumstances that arise after booking. In general, reservations for stays and Airbnb Experiences made on or before March 14, 2020, with a check-in date between March 14, 2020 and May 31, 2020, are covered by the policy and may be canceled before check-in. Reservations for stays and

[10] The information is sourced from AirDNA.

Airbnb Experiences made after March 14, 2020 in general fall outside Airbnb's extenuating circumstances policy, as COVID-19 was declared a pandemic, and its consequences are no longer unforeseen or unexpected. Therefore, travelers should be responsible for their decisions.

The special policy Airbnb implemented under the situation of a fast-evolving pandemic has antagonized hosts who suffered loss from booking revenues. Brian Chesky, the founder of the company, explained Airbnb's dilemma in a public statement on March 30, 2020[11]: "If we allowed guests to cancel and receive a refund, we knew it could have significant consequences on your livelihood. But we couldn't have guests and hosts feel pressured to put themselves into unsafe situations and create an additional public health hazard."

2.2 Literature on COVID-19, social distancing, and human mobility

As the COVID-19 pandemic evolved over time, lockdown measures have been promoted by local authorities. However, we do not know to what extent these lockdown measures cause individuals to alter their mobility in response to government orders. Nor do we know how they adjust travel behavior when perceived risks of COVID-19 increase, even in the absence of no compulsory government lockdown orders. Utilizing location data from Unacast, Engle et al. (2020) find that a rise of local infection rate from 0% to 0.003% is associated with a reduction in mobility by 2.31%. An official stay-at-home restriction order corresponds to reducing mobility by 7.87%.

To understand how travel and quarantine influence the dynamics of the spread of COVID-19, Chinazzi et al. (2020) apply a global metapopulation disease transmission model to epidemiological data from China. They find that the travel quarantine introduced in Wuhan on 23 January 2020 only delayed epidemic progression by 3 to 5 days within China, but international travel restrictions did help to slow

[11] Source: "A Letter to Hosts" from Airbnb Newsroom. Airbnb, March 30, 2020. https://news.airbnb.com/a-letter-to-hosts/

spread elsewhere in the world until mid-February. Modeling results also indicate that sustained 90% travel restrictions to and from mainland China only modestly affect the epidemic trajectory unless combined with a 50% or higher reduction of transmission in the community.

Fang, Wang and Yang (2020) find that the Wuhan lockdown reduced inflow into Wuhan by 76.64%, outflows from Wuhan by 56.35%, and within-Wuhan movements by 54.15%. They conjecture that COVID-19 cases would be 64.81% higher in the 347 Chinese cities outside Hubei province, and 52.64% higher in 16 non-Wuhan cities inside Hubei, if there was no Wuhan lockdown.

Kraemer et al. (2020) use real-time mobility data from Wuhan and detailed case data to ascertain the impact of control measures. Their evidence shows that the spatial distribution of COVID-19 cases in China was well explained by human mobility data at the early stage of the epidemic. Following the implementation of control measures, this correlation dropped, and growth rates became negative in most locations. They conclude that the drastic control measures implemented in China substantially mitigated the spread of COVID-19.

There is hot debate over the benefits and costs of public health measures that limit interpersonal contact or restrict travel and mobility. In a context where individual compliance has collective benefits, but full enforcement is costly and controversial, the effectiveness of these unprecedented lockdown measures is unclear. Briscese et al. (2020) study how intentions to comply with the self-isolation restrictions introduced in Italy to mitigate the COVID-19 epidemic respond to the length of their possible extension. Based on a survey of a representative sample of Italian residents (N=894), they find that respondents are more likely to express the intention to reduce compliance, and are less willing to increase their self-isolation effort if negatively surprised by a given hypothetical extension. These intentions are stronger among respondents who reported high compliance with the isolation prescriptions.

3. Data and method

3.1 Data

Airbnb review data is scraped from the Airbnb website for various Airbnb markets as provided by Inside Airbnb[12]. Inside Airbnb provides scraped data snapshots from Airbnb.com at periodic intervals, usually monthly. As each snapshot only has live listings at that point in time, we collate all snapshots during our sample period and remove duplicate reviews to ensure that any removed listing reviews are obtained.[13] The review data contains individual reviews with listing ID, reviewer ID, date of review, and reviewer comments. We use reviews as a proxy for the number of bookings. We further collect cancellations from reviews which are automated postings. The comments of such reviews read "The host canceled this booking X days before arrival. This is an automated posting." Such reviews are also removed when counting total daily reviews in an Airbnb market.

We obtain daily COVID-19 cases and deaths data for Airbnb markets[14] from John Hopkins University Coronavirus Center Github[15]. We use the most granular level COVID-19 case data available for the Airbnb market (e.g. for Beijing, China we use Beijing cases). To measure COVID-19 cases per capita, we obtain the most recent population estimates from the Australian Bureau of Statistics (for Australian states), Statistics Canada (for Canadian provinces), US Census (for US counties) and from www.worldometers.info for Beijing, Hong Kong and at the country level for all other countries. We obtain lockdown dates initially from the Aura Vision website[16] and manually verify the lockdown dates with alternative news sources. Lockdown dates are defined as the start of government lockdown orders where residents in the Airbnb market are only allowed to go out for food or essential services. We obtain

[12] http://insideairbnb.com/get-the-data.html

[13] There may still be loss of listing reviews if some listings are permanently removed between monthly snapshots. Our results are qualitatively similar when using all snapshots or just the latest snapshot.

[14] Airbnb markets comprise listings that represent a geographical area (which may be a city, region, province, state, county or country). No market overlaps.

[15] https://github.com/CSSEGISandData/COVID-19

[16] https://auravision.ai/covid19-lockdown-tracker/

travel ban dates from www.restrictions.info and manually verify with alternative news sources. A travel ban is defined as when non-residents are banned from entering a country. For Europe, we define the ban as the date when non-EU or non-Schengen citizens are banned and for the U.S., we use the date when visas were no longer being processed.

Appendix 1 reports the various Airbnb markets that we use. For each market we report the first COVID-19 case date, lockdown date, travel ban date, and last scrape date of the Airbnb market. Our sample starts from Jan 2019 and ends in March 2020. Overall, we use 98 Airbnb markets across 30 countries. Many lockdown or travel ban dates are towards the end of the sample period.

We make use of Airbnb listings and calendar data for analysis of London, United Kingdom at the local government (borough level). The listings and calendar data are monthly snapshots. Listings contains data on listing price, borough location, host characteristics (such as whether they are a 'superhost'[17]), and listing characteristics (such as how many people the listing accommodates, property type, and room type), and a list of amenity features. For each listing, the calendar shows the booking price for future dates, where available. London borough daily COVID-19 cases are from the UK government's COVID-19 website (https://coronavirus.data.gov.uk/).

3.2 Method

We employ two proxies to measure booking activities as we do not observe direct booking records[18] from the scraped Airbnb data: *Reviews* and *Cancel_pct*. *Reviews* is the daily number of Airbnb

[17] Superhost is a designation that Airbnb assigns to hosts that meet certain requirements such as a high guest rating and promptly answering guest enquiries.
[18] Fradkin, Grewal and Holtz (2020) find that about 69% of bookings are reviewed, based on their proprietary Airbnb bookings dataset. Barron, Kung and Proserpio (2020) also use reviews as a proxy for booking activity due to unavailability of booking data.

reviews, less automated cancellation postings[19] for each Airbnb market. *Cancel_pct* is the daily number of automated cancellation postings in the review data as a percentage of *Reviews*. We also create adjusted measures *Adj_Reviews* and *Adj_Cancel_pct* by dividing *Reviews* and *Cancel_pct* by their daily pre-period average (before Jan 23, 2020 for 2020 sample and before Jan 23, 2019 for 2019 sample). The adjustments provide an ease of interpretation of the booking activity measures as the percentage change of booking measures between the pre- and post-periods.

Figure 1 shows the total daily number of *Reviews* (Panel A) and Cancellation percentage *Cancel_pct* (Panel B) across all Airbnb markets against the daily number of new COVID-19 cases per 1,000 people for all Airbnb markets from Jan 2020 to Mar 2020. We also denote periods of the COVID-19 outbreak as per Ramelli and Wagner (2020), namely Incubation, Outbreak, and Fever periods. Figure 1 Panel A shows that *Reviews* tend to peak on Sundays, which is consistent with guests checking out on Sundays in preparation for the working week. During the incubation period, *Reviews* fall from the start of January but are stable during the Outbreak period in February. Meanwhile, daily COVID-19 infections only start increasing during the Outbreak period. As daily COVID-19 cases rapidly increase during the Fever period, we see a sizeable fall in daily *Reviews* to almost zero in the final weeks of March. The pattern for *Cancel_pct* is noticeably more stable, ranging from 0.5% to 1.5% of *Reviews* during both the Incubation and Outbreak periods. It is only during the Fever period in mid-March that cancellations increase exponentially, which corresponds to the large drop in *Reviews*. From Mar 21 onwards, there were no more automated host cancelation messages across markets, which is due to Airbnb's changed cancellation policy after Mar 14[20]. As such for all results related to cancellations, we use a truncated sample prior to Mar 21, 2020.

[19] These reviews are left on the host's feedback and are automated postings to the effect of "The host canceled this reservation X days before arrival. This is an automated posting" whenever a host cancels the booking of a guest.
[20] https://www.airbnb.com.au/help/article/2701/extenuating-circumstances-policy-for-the-coronavirus-COVID-1919

[--- INSERT FIGURE 1 ABOUT HERE ---]

To get a better view of the immediate aftermath of the Wuhan lockdown on Jan 23, 2020, Figure 2 plots daily *Reviews* (Panel A) and *Adj_Reviews* (Panel B) for Asian Airbnb markets (all are cities) and the equally-weighted rest of world average from Jan 1, 2020 to Mar 31, 2020. In Figure 2 Panel A we find Beijing, Singapore, and Tokyo have higher daily *Reviews* than the rest of the world pre-Wuhan lockdown. The higher reviews suggest that these Airbnb markets are large and active. Just prior to the Wuhan lockdown, we can already see a sizeable fall in *Reviews* for Beijing, which gradually drop to almost zero by mid-February. This overall 95% drop in bookings has been documented by an analytical website www.airdna.co[21]. While *Reviews* in Beijing fall, all other Asian markets have stable *Reviews* until mid-February when the markets began to fall. The rest of world average however remains relatively stable and even increases slightly until mid-March, suggesting that the impact of the Wuhan lockdown was subdued outside of Asia.

[--- INSERT FIGURE 2 ABOUT HERE ---]

Figure 2 Panel B uses *Adj_Reviews* and depicts a similar pattern. Prior to the Wuhan lockdown, *Adj_Reviews* of Asian cities follows very closely the trend pattern of the rest of world average. Post-Wuhan lockdown, we find that Beijing drops to almost zero by mid-February with the other Asian markets following suit in the beginning of March, exhibiting levels below the rest of world average. The rest of world average fluctuates around 1 until mid-March, suggesting that *Reviews* persist at a level similar to that observed during the Pre-Wuhan lockdown period for the rest of the world. The figures show that China was hit hardest by booking activity with other Asian markets following suit due to the COVID-19 outbreak spreading to neighboring Asian countries. Meanwhile, the rest of the world was

[21] https://www.airdna.co/blog/coronavirus-impact-on-global-short-term-rental-markets

largely unaffected in the immediate aftermath of the Wuhan lockdown. By late March, the average *Adj-_Reviews* for the Asian markets and the rest of world average converge due to the worldwide lockdowns.

To estimate the effect of the three factors, including the Wuhan lockdown, local COVID-19 cases, and local lockdown policies, we estimate the following regression model using the diff-in-diff approach:

$$Y_i = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log(1 + NewCase_{i,t-1}) + \beta_4 Treat * Post_j * Lockdown_i + \mu_i + \tau_t + \varepsilon_{it} \quad \text{--- (1)}$$

Where Y_i is *Reviews*, *Adj_Reviews*, *Cancel_pct* or *Adj_Cancel_pct* for Airbnb market *i* for day *t*. Treat is a dummy of 1 if the review was made in 2020; 0 otherwise. Post is a dummy of 1 if the review was made on or after Jan 23, 2020 (Wuhan lockdown date) for the 2020 sample and on or after Jan 23, 2019 for the 2019 sample. *NewCase* is the prior day's number of new COVID-19 cases at the most granular level for market *i*. μ_i are Airbnb market fixed effects, τ_t represent the day-of-week and the month of year fixed effects. *Lockdown* is a dummy of 1 if the date is after either the start of lockdown orders or travel ban, whichever is earlier; 0 otherwise. The sample is from Jan 2019 to Mar 2019 (control period) and from Jan 2020 to Mar 2020 (treatment period).

The model utilizes the diff-in-diff strategy in Chen et al. (2020) and Fang et al. (2020) by using year 2019 as the control period and comparing Airbnb booking activity before and after the event of the Wuhan lockdown on Jan 23rd of year 2019 and year 2020. We also include additional post treatment variables of local COVID-19 cases and the initiations of local lockdowns to analyze the effect of COVID-19 infections and lockdowns on Airbnb markets.

Table 1 reports summary statistics of Airbnb booking activity variables for the entire sample and by year, pre- and post- period. Table 1 Panel A reports the summary statistics for *Reviews*. The average daily *Reviews* in 2019 is 351.89, and 291.33 in 2020, depicting a fall in Airbnb booking activity.

Comparing pre with post-period in 2019, *Reviews* increase from an average of 343.08 in the pre- period to 354.74 in the post-period. In 2020 however, *Reviews* fall from an average of 359.67 in the pre-period to 269.54 post-period, indicating a clear reduction of travel activities globally.

In terms of cancellation, *Cancel_pct* is observed to be lowest at 1.68% of reviews before the Wuhan lockdown in 2020, and highest at 2.95% in 2020 after the Wuhan lockdown. During 2019, the pre- and post-period *Cancel_pct* are of similar magnitude (between 1.75% and 1.83%). Had 2020 been similar to 2019, we would expect an increase in reviews and similar cancellations pre- versus post-Wuhan lockdown. Altogether, the summary statistics on reviews and cancellation show that after the Wuhan lockdown in 2020, there is a fall in Airbnb booking activity with lower reviews and an increase in cancellations.

[--- INSERT TABLE 1 ABOUT HERE ---]

Table 1 Panel C formally tests whether the difference in booking measures pre- and post-period, and between 2019 and 2020 samples, are statistically significant. We find that for 2019, reviews are relatively stable; where there is an increase in *Reviews* of 11.65 from pre- to post-Wuhan lockdown period, the result is statistically insignificant. The fall in *Cancel_pct* from pre- to post-period in 2019 of -0.08 is also statistically insignificant.

We then examine reviews in year 2020 and find that the difference in *Reviews* between pre- and post-period is -90.13, statistically significant at the 1% level. The difference in *Cancel_pct* between pre- and post-period in 2020 is 1.27, statistically significant at the 1% level. The pre-post differences between 2020 and 2019 (the diff-in-diff) are also statistically significant at the 1% level. The diff-in-diff measures are -101.78 (*Reviews*) and 1.35 (*Cancel_pct*), both with 1% statistical significance. This implies that due to the Wuhan COVID-19 lockdown shock, there is a daily average drop of 101.78 reviews in each Airbnb market and an increase of 1.35% in cancellations (as a percentage of daily reviews). Based on the 2020 pre-period mean measures of 359.67 for reviews and 1.68 for cancellations, this represents a fall of 28.30% in *Reviews* and an 80.35% increase in cancellations, respectively.

We present the correlation matrix of variables for the 2020 sample in Table 1 Panel D. *Reviews* is negatively correlated to all other variables, implying that when *Reviews* drop, cancellations go up. Further, reviews go down when there is an increase in the prior day's COVID-19 cases in a city. *Cancel_pct* is positively related to all explanatory variables. *Lockdown* is also highly positively correlated with *NewCase* of 0.70. *NewCase* is also highly correlated to *NewDeaths*, our alternative local COVID-19 cases measure.

4. Empirical analysis of the global Airbnb market

4.1 Baseline results of COVID-19's impact on bookings activity

Table 2 reports our baseline regression results on the impact of the three COVID-19 events, i.e., Wuhan lockdown shock, daily local COVID-19 cases, and local lockdown policies. Panel A presents the effect on reviews and Panel B on cancellations. Overall, we find effects on all three COVID-19 events for both reviews and cancellations. Including all three events improves the explanatory power of both booking activity measures in comparison to only using one effect alone.

Reviews is used as the dependent variable in the first three columns of Panel A, and *Adj_Reviews* in the last three columns. We find that the effects from the three events are all negative and statistically significant for both reviews and adjusted reviews. For all three models, *Treat* is positive and weakly statistically significant, which implies the number of reviews in 2020 is greater on average than that of 2019. The coefficients on *Post* are negative and statistically significant for Columns 2 and 3, although statistically insignificant in Column 1, which indicates the Feb-Mar periods tend to have lower reviews than the Jan period for all markets around the world. In Column 1, the coefficient of *Treat*Post* is -

101.937 (1% statistically significant), indicating there is a drop of around 102 daily reviews after the Wuhan lockdown (on average) for each Airbnb market. The effect is comparable to the univariate diff-in-diff of -101.78 in Table 1 Panel C. In Columns 4-6, *Adj_Reviews* is used as the dependent variable to examine the fall in bookings as a percentage relative to the pre-period, with specifications equivalent to that of Columns 1-3. We find the coefficient on *Treat*Post* is -0.307, implying a 30.7% fall in daily reviews compared with the pre-period, consistent with the result regarding the number of reviews in Column 1 and the percentage estimate of 28.30% fall in Table 1.

[--- INSERT TABLE 2 ABOUT HERE ---]

Next, we include the logarithm of the number of new infection cases the previous day into the regression. When including the previous day's new cases in Column 2 with *NewCase* (Column 5 using *Adj_Reviews*), we find that the effect of the Wuhan lockdown becomes smaller, with a coefficient of – 30.841 on *Treat**Post (-0.100 for *Adj_Reviews*), both statistically significant at the 1% level. Our result implies that travel activities, as proxied by reviews, are affected by both the Wuhan lockdown shock and also local COVID-19 infection cases. Note that the reduction in the Wuhan lockdown effect by over half after controlling for local COVID-19 cases differs to Chen et al. (2020), who find that the effect of the Wuhan lockdown on spending is not reduced in magnitude after controlling for local COVID-19 cases. The difference in comparison reveals different sensitivity to COVID-19 between day-to-day spending and booking activity.

We also observe that the adjusted R-squared in Column 2 and Column 5 increases after including local COVID-19 cases, indicating that local COVID-19 cases contribute to the higher explanatory power of booking activity. The coefficient of *NewCase*[22] is -41.084 in Column 2; namely, for every doubling

[22] As an alternative to *NewCase* we use the infections per 1,000 of population version *Log(1+NewCase_percapita)* in Internet Appendix Table IA1 Panel A and COVID-19 deaths in the prior day Log(1+NewDeaths) in Panel B and find qualitatively similar results with the full model across booking activity measures.

of *COVID-19* cases, there is a reduction of 28.48 (=ln(2)*-41.084) reviews each day per Airbnb market. For *Adj_Reviews*, the coefficient in Column 5 implies 8.32% (=ln(2)*-0.12) decrease in reviews per doubling of new cases in the prior day. The full model includes lockdown of local Airbnb markets subsequent to the Wuhan lockdown (Columns 3 and 6). The coefficient for *Lockdown* is -167.104 (-0.578 for *Adj_Reviews*), which means that daily reviews fall by 167.104 or by 57.80%. The falls are larger than the Wuhan lockdown shock and are consistent with Airbnb markets having almost no booking activity once lockdown occurs.

To offer a rough estimate of the effect of the Wuhan lockdown on global Airbnb bookings, we use Airbnb's publicly reported total booking value of $9.4 billion and total nights booked in Q1 2019 of 91 million nights, respectively[23]. We also assume the average booking is 4.3 nights based on Statista estimates of average nights of stay in Europe and the US from 2015-2018[24]. Based on our full model estimate of the Wuhan lockdown effect of -0.088 (Table 2 Panel A Column 6)[25], our estimate of the lost bookings revenue is $634 million[26] during our sample period (or $6.97 million per day) due to the Wuhan lockdown alone in Q1 2020. Doubling the COVID-19 cases in all local Airbnb markets of the prior day is associated with an additional -$4.34 million[27] lost bookings, globally.

In Table 2 Panel B, the effects of cancellations are consistent[28] with all variables of interest largely being statistically significant. The initial Wuhan lockdown shock as measured by the *Treat*Post* coefficient implies that cancellations increase by 1.473% as a percentage of daily reviews (Column 1) or by 78.7% relative to the pre-period, (Column 4). When including *NewCase* in Columns 2 and 5, the

---

[23] https://www.pymnts.com/earnings/2019/airbnb-total-booking-value-soars-30-percent-year-over-year/

[24] https://www.statista.com/statistics/796534/average-number-of-nights-per-airbnb-booking-us-europe/

[25] There is a further assumption here that the drop in reviews is similar to the drop in bookings. We think it is reasonable to assume that the review behavior of those that decide to travel post Wuhan lockdown is similar to those that stop traveling.

[26] The calculation of the lost bookings revenue is as follows: -0.088 *Post*Treat* coefficient*69 days*235,142 bookings per day* $444.18 per booking = -$634.187 million

[27] As *NewCase* coefficient is -0.06, the estimated loss of booking revenue is ln(2)*(-0.06)*235,142 bookings per day* $444.18 per booking= -$4.34 million

[28] We also use just the total number of cancellations and find qualitatively similar results in Internet Appendix Table IA1 Panel C.

coefficient of *Treat*Post* becomes weaker in magnitude. The *NewCase* coefficient of 0.804 (0.517 for *Adj_Cancel_pct*) implies that every doubling of COVID-19 cases in the local market in the prior day would lead *Cancel_pct* to increase by 0.56% of reviews (=ln(2)*0.804, or lead *Cancel_pct to* increase by 35.84% (=ln(2)*0.517) compared with the pre-period). The coefficients for *NewCase* are statistically significant across all models.

In Columns 3 and 6 where all three COVID-19 effects are included, local lockdowns of Airbnb markets are associated with dramatic increases in cancellations. The *Lockdown* coefficient for both *Cancel_pct* and *Adj_Cancel_pct* are relatively large (6.663 and 4.482, respectively) and statistically significant. The coefficients imply lockdowns increase cancellations by 6.67% of total daily reviews or a total increase of 448% compared to the pre-period. Using the full regression, we also observe that the relationship between local COVID-19 cases and cancellations is halved, with coefficients of *Treat*Post*NewCase* of 0.384 (Column 3 for *Cancel_pct*) and 0.223 (Column 4 for *Adj_Cancel_pct*). This set of results implies that excluding the lockdown effect overestimates the sensitivity of cancellations to local COVID-19 cases.

In summary, we document separate effects of the initial Wuhan lockdown, local COVID-19 cases, and local lockdowns across booking measures. In particular, when including all three effects, local COVID-19 cases and lockdowns improve the explanatory power of booking activity compared to accounting for the Wuhan outbreak shock alone.

4.2 Sensitivity of Airbnb booking activity to COVID-19 pandemic

In prior sections, we document that COVID-19 pandemic negatively affects global booking and travel activities through three channels: the initial Wuhan lockdown shock, local cases, and local lockdowns. We now investigate factors that may cause Airbnb markets to vary in sensitivity to COVID-

19 effects. The COVID-19 literature finds proximity to the Wuhan outbreak, government policy stringency, and mobility factors explain COVID-19 infection and related phenomena. As such, we test whether such factors explain the sensitivity to the COVID-19 effects that we document.

As a first look, Table 3 Panel A reports the correlation of our booking activity and COVID-19 effect variables with potential explainers: *Wuhan_Distance*, *Gov_Stringency*, *Mobility_Rec*, and *Mobility_Parks*[29]. *Wuhan_Distance* is the distance of an Airbnb market to Wuhan, in thousands of kilometers (about 621 miles). *Gov_Stringency* is an index of government policy stringency[30] towards COVID-19 lockdown measures (such as school/workplace closures, cancelling public events, and stay-at-home requirements). The index is collected from the Oxford COVID-19 Government Response Tracker (OxCGRT)[31]. *Mobility_Rec*[32] is a daily index of mobility trends to retail and recreation locations (such as restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters). *Mobility_Parks* is a daily index of mobility trends to park areas (such as local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens). Mobility measures are obtained from Google COVID-19 community mobility reports. *Gov_Stringency*, *Mobility_Rec* and *Mobility_Parks* are standardized. The correlation statistics sample is from Feb 15, 2020 to Mar 20, 2020 (representing the start of the mobility data sample and before Airbnb stops reporting host cancellations).

We find *Wuhan_Distance* is positively correlated to *Adj_Reviews*, with a correlation coefficient of 0.13, indicating markets further away from Wuhan have higher reviews. The correlation of *Wuhan_Distance* to *Adj_Cancel_Pct* is -0.01, close to uncorrelated. *Gov_Stringency* is negatively correlated to *Adj_Reviews*, with a correlation coefficient of -0.42, and positively correlated to *Adj_Cancel_Pct*, with a correlation coefficient of 0.35, indicating that *Gov_Stringency is* negatively

[29] We provide descriptive statistics of these four explainer variables in Internet Appendix Table IA2.
[30] The index is available at the country level for all countries.
[31] Hale et al. (2020) detail the method in constructing the index.
[32] The mobility measures are generally available at the same level as the Airbnb market. They are only missing for Beijing, China.

associated with booking activities. Similarly, the two mobility measures, *Mobility_Rec* and *Mobility_Parks*, are positively corelated to booking activities.

To analyze the sensitivity of booking activity to the three COVID-19 variables, we run the following regression using the post-Wuhan lockdown sample from Jan 23, 2020 to Mar 31, 2020:

$$Y_i = a + \beta_0 Measure_i + \beta_1 Measure_i * Log\big(1 + NewCase_{i,t-1}\big) + \beta_2 Measure_i * Lockdown_i + \beta_3 Log(1 + NewCase_{i,t-1}) + \beta_4 Lockdown_i + \mu_i + \tau_t + \varepsilon_{it} \qquad \text{--- (2)}$$

Where Y_i denotes our booking activity measures *Adj_Reviews* and *Adj_Cancel_pct*. *Measure* is either *Wuhan_Distance*, *Gov_Stingency*, *Mobility_Rec* or *Mobility_Parks*. We control for local COVID-19 cases, *NewCase*, Airbnb market fixed effects, and time fixed effects. We utilize the post-Wuhan lockdown sample rather than the diff-in-diff sample for parsimony, as we are primarily interested in determining the sensitivity of booking activities to COVID-19. Our coefficients of interest are β_0 (sensitivity to Wuhan lockdown shock attributable to *Measure*), β_1 (sensitivity to local COVID-19 cases), and β_2 (sensitivity to local lockdown). Note that we test for individual interaction effects as appropriate to the hypotheses we test.

Zheng et al. (2020) study COVID-19 infections within China and find the distance between Wuhan and other cities is inversely associated with the number of COVID-19 cases in that city, and the correlation becomes increasingly stronger after February 1^{st}. Therefore, to understand the mechanism of the sensitivity of booking activity to the Wuhan lockdown shock, we analyze the distance of an Airbnb market to the initial COVID-19 epicenter, Wuhan. We model the effect of distance using Equation 2 with *Wuhan_Distance*, controlling for *NewCase* and *Lockdown*. We expect the coefficient of *Wuhan_Distance* to be positive and statistically significant as Airbnb markets further away from Wuhan are less affected by the Wuhan lockdown shock.

We find that the distance to Wuhan has an attenuating effect on the sensitivity of booking activity to the Wuhan lockdown shock in Table 3 Panel B. In Column 1, we regress *Adj_Reviews* without *Wuhan_Distance* and find both *NewCase* and *Lockdown* are negative and statistically significant, confirming our baseline results with the shortened sample. In Column 2 we find a positive and statistically significant coefficient for *Wuhan_Distance* of 0.072. The coefficient implies 7.2% higher daily reviews per 1,000 kilometers away from Wuhan compared to during the pre-Wuhan lockdown period between Jan 1, 2020 and Jan 22, 2020. In Columns 3 and 4, we run the same regression for *Adj_Cancel_pct* and find insignificant results implying no reduction in cancellations with further distance from Wuhan due to the Wuhan lockdown shock. These results are consistent with baseline findings of a positive and statistically insignificant effect on cancellations for the initial Wuhan lockdown shock.

[--- INSERT TABLE 3 ABOUT HERE ---]

The stringency of a government's COVID-19 lockdown measures may also affect booking activity and sensitivity of booking activity to COVID-19 local cases and local lockdown. For example, Frey, Chen and Presidente (2020) use the OxCGRT government policy stringency index and find that for the same level of government policy stringency, democratic governments were more effective in reducing geographic mobility than autocratic governments in managing COVID-19. To test whether government policy stringency affects COVID-19 sensitivity, we include the interaction of *Gov_Stringency* with either *NewCase* or *Lockdown* and other control variables (as we use in Equation 2).

Table 3 Panel C reports results for the interaction effects of *Gov_Stringency* with local COVID-19 cases or local lockdowns. Firstly, looking at the coefficient of *Gov_Stringency* across all models we find a negative statistically significant coefficient for *Adj_Reviews* and a positive coefficient for *Adj_Cancel_pct*. As expected, we find that booking activity decreases with higher government stringency on COVID-19 management. *NewCase* and *Lockdown* remain significant and have smaller magnitudes which implies *Gov_Stringency* absorbs some of the explanatory power of the COVID-19 effect variables. In Column 1, the interaction variable *Gov_Stringency*NewCase* is negative and statistically significant with a value of -0.01. This variable implies that for a given level of COVID-19 cases, a one standard deviation increase in government policy stringency further reduces the sensitivity to COVID-19 cases by -0.01. The effect is large as the coefficient of *NewCase* is only -0.015. Panel B shows that the coefficient of *GovStringency*Lockdown* is -0.075 and statistically significant, which implies that while lockdown clearly affects booking activity, more stringent COVID-19 management policies increase the severity of the lockdown effect on booking activity. For *Adj_Cancel_pct*, we find only base level effects for *Gov_Stringency* and no interaction effects.

A further consideration is whether mobility in an Airbnb market affects sensitivity to local COVID-19 cases. For example, Kraemer et al. (2020) find human mobility data helps to explain the spatial distribution of COVID-19 in China. Mobility is positively associated with COVID-19 cases, as it could facilitate contagion; thus, guests have greater fears of increased infection risk with more mobility. We therefore hypothesize that travel activity in areas with greater mobility will have greater sensitivity to COVID-19. To test our hypothesis, we use the model in Equation 2 and add the interactions of *NewCase* and our two mobility measures, *Mobility_Rec* or *Mobility_Parks*. For example, if higher mobility with local COVID-19 cases affects booking activity, then we expect a negative correlation for *NewCase* Mobility_Rec* (or *Mobility_Parks)* when the dependent variable is *Adj_Reviews*.

Table 3 Panel D reports results for the interaction term of mobility and local COVID-19 cases. Consistent with the rationale that higher mobility areas have more booking activity, we find a positive relationship between Airbnb booking activity and contemporaneous mobility measures *Mobility_Rec* and *Mobility_Parks*. For *Adj_Reviews*, we find a negative coefficient for the interaction between *NewCase* and mobility measures. This negative interaction effect implies that guests fear local COVID-19 cases more in highly mobile areas due to potential for COVID-19 spread than in low mobility areas. Regarding the *Adj_Cancel_pct* regression in Column 3, we also find that *Mobility_Rec*NewCase* is positive and statistically significant, indicating higher host cancellations in more mobile areas and higher local COVID-19 cases for retail and recreation areas. However, in Column 4 *Mobility_Parks*NewCase* is positive and statistically insignificant.

Overall, we find evidence that booking activity sensitivity to COVID-19 effects may be partially explained by geographic distance to Wuhan (for the initial Wuhan lockdown shock), government policy stringency (for local COVID-19 cases and local lockdown), and mobility (for local COVID-19 cases).

4.3 Inbound travel bans and local confinement/lockdown orders

In prior sections, we use a broad measure of lockdown, which is defined as the earliest date of travel ban or local lockdown order. Besides confinement measures captured by the local lockdown variable, countries have implemented travel bans to prevent spread from inbound travelers. Different countries have utilized a range of inbound travel bans to deal with COVID-19 over time. For example, some countries and regions implemented a staggered travel ban (e.g. Australia and Singapore) while others such as Schengen Area members like Germany only banned non-Schengen countries. The differences in how countries implemented inbound travel bans may explain the effects of our COVID-19 measures on Airbnb booking activity.

In this section, we further account for the effect of inbound travel restriction and separate the previous lockdown measure into two variables: inbound travel ban and local confinement. To obtain detailed information on inbound travel bans for each country, we collect the dates when inbound tourists were banned by the host countries from sources including restrictions.info and news articles. For each Airbnb market, we rank tourist arrival by nationality based on the 2019 statistics and obtain the top 10 countries of inbound tourists[33] from official travel statistics for each host country. We then compute the total percentage of the top 10 international tourists banned from the market.

We run the following regression by including the inbound travel ban effect:

$$Y_i = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\left(1 + NewCase_{i,t-1}\right)$$
$$+\beta_4 Treat * Post_j * Inbound\_Ban_{it} + \beta_5 Treat * Post_j * Confinement_i + \mu_i + \tau_t + \varepsilon_{it} \qquad \text{--- (3)}$$

Where *Inbound_Ban* is the percentage of international tourists banned due to COVID-19 inbound travel restrictions from market *i* on day *t*. The percentage is based on the 2019 (or most recent if not available) market share of inbound tourists for the top 10 inbound countries. *Confinement* is a dummy of 1 for after the date of the start of local lockdown measures; 0 otherwise. We expect *Inbound_Ban* to be negatively related to booking activity due to foreign guests being unable to enter.

Table 4 reports our results including *Inbound_Ban* and *Confinement* measures for our Airbnb booking activity measures. Across all measures, *NewCase* remains statistically significant which implies booking activity remains sensitive to local COVID-19 cases even when accounting for inbound travel bans. *Treat*Post* remains robust except for *Cancel_pct* which is no longer statistically significant.

[--- INSERT TABLE 4 ABOUT HERE ---]

We find *Inbound_Ban* to be statistically significant across all booking measures. The coefficients imply that a full inbound ban is associated with a fall of 45.2% of reviews (Column 2) and 6 times increase in the number of host cancellations (Column 4). These effects are stronger than that of *Confinement,* which is associated with a fall of 22.9% in reviews and 2.743 times increase in host

[33] For countries which report less than ten inbound tourist origin countries, we use all countries available. If 2019 statistics are not available, we use the most recent year's statistics. Note that some countries only report overnight stays by inbound countries, and we calculate the share of inbound tourists from a country based on the overnight stay statistics for these countries.

cancellations. The results suggest that in terms of lockdown effects, inbound travel bans have a stronger effect on booking activity than local confinement/lockdown measures.

5. Local evidence based on London borough analysis

In this section, we test the effect of COVID-19 on Airbnb bookings, supply, and prices at the borough[34] level in London, United Kingdom (UK). Studying a particular city alleviates concerns that cross-city differences in COVID-19 case measurement and COVID-19 management efforts (e.g. social distancing guidelines) may contaminate results. We choose London as it is the third most popular international tourist destination in the world according to the 2019 Mastercard Global Destination Cities Index[35], there is daily COVID-19 data available at the borough level, and the United Kingdom had no restrictions on air travel during our study period (until March 23, 2020 when the UK lockdown was announced). A further advantage of borough level analysis is that we may further incorporate listing level data to the analysis. As such, we further examine whether the type of accommodation (entire home or private rooms) matters and also the effect of COVID-19 on listing volume and prices. We focus on entire homes and private room accommodation types as they comprise the dominant form of accommodation in London. Figure 3 shows the daily *Reviews* by room type in London and demonstrates that entire homes and private rooms have much larger volume than hotel rooms or shared rooms. [36]

[--- INSERT FIGURE 3 ABOUT HERE ---]

We also investigate whether there is a differential impact of COVID-19 on entire homes versus private rooms. Hosts are expected to be more reluctant to let private rooms as they risk sharing their home with COVID-19 infected guests.[37] Guests may also be reluctant to book private rooms, opting for

---

[34] A borough is similar to a local government area.

[35] https://newsroom.mastercard.com/wp-content/uploads/2019/09/GDCI-Global-Report-FINAL-1.pdf

[36] We also check if some listings change room type due to COVID-19. Between Jan 2020 and Mar 202, we find 740 listings or 0.57% of the sample changed room type from the prior month. This suggests most listings retain the same room type.

[37] There is also the possibility that hosts delist/block out dates for private rooms in preparation for working from home. However, it was only towards the end of the sample on Mar 16, 2020 that the UK Prime Minister Boris Johnson advised

entire homes with less contact with the host and others. However, the supply of entire homes is unlikely to change due to COVID-19 as hosts have minimal contact with guests. To examine this potential differential effect between these two home types, we examine the change in booking activity, listing volume, and booking prices in response to COVID-19, and test whether it affects private rooms to a greater extent than entire homes in London in the following sections.

5.1 Reviews and cancellations in London

Having established a relationship between COVID-19 cases and booking activity in a global setting, we now test whether such sensitivity exists within the boroughs of London and differs between room types. To make better use of our borough level data, we use a staggered dynamic diff-in-diff regression. The regression design is distinct from our prior global diff-in-diff regression in setting the shock as the date of each borough's initial outbreak rather than the Wuhan outbreak. We therefore measure the impact of the local COVID-19 shock rather than the global shock. The control group is now the period prior to the borough's initial infection (rather than the borough's own past year's booking activity), providing a robustness check of COVID-19's effects.[38] The dynamic staggered diff-in-diff regression also allows us to test for the heterogenous effects of COVID-19 over time after a borough's initial outbreak. This is in contrast to the global regression, which only tests for an average treatment effect over time. We estimate the following staggered dynamic regression:

---

people to work from home (https://www.bbc.com/news/uk-51917562). Prior to the UK lockdown, there were no mobility restrictions.

[38] For robustness we apply the global sample diff-in-diff strategy to the London data and report coefficient estimates in Internet Appendix Table IA4. For Reviews in Panel A, we find similar results with a fall in bookings after the first COVID-19 case in the UK (Column 1) and negative sensitivity to borough local COVID-19 cases (Column 2). We further find a larger drop in private room reviews than entire homes post UK COVID-19 outbreak (Column 3). However, there is no statistical difference to local COVID-19 between entire home and private rooms (Column 4). For *Cancel_pct* in Panel B, we find a weak positive coefficient for *NewCase* in Column 2 results with private room cancellations being more sensitive to local COVID-19 cases than entire homes (Column 4).

$$Y_{b,r} = a + \sum_{w=-3^-}^{w=3^+} \beta_w * Week_w + \rho_r + \mu_b + \tau_t + \varepsilon_{bt} \qquad \text{--- (4)}$$

Where $Y_{b,r}$ is either Log(1+*Reviews*) or Log(1+*Cancel*).[39] *Reviews* is the total daily number of Airbnb reviews (less automated host cancellation postings). *Cancel* is the total daily number of cancellations. Both variables are statistics for London borough *b* and room type *r* (entire home or private room). $Week_w$ are dummies of 1 if the date is in the *w*-th week (seven-day intervals) relative to the week of the first recorded COVID-19 case (week zero) in the borough, zero otherwise. *Week* $w=-3^-$ is a dummy of 1 for days three weeks before week zero. *Week* $w=3^+$ is a dummy of 1 for days three weeks after week zero. We omit the week dummy for week $w=0$, the week of the initial COVID-19 case in the borough, as the week 0 effect is used as the base effect. Note that there is a delay between the stay and the review, which is normally at the end of the stay (given the average 2019 Airbnb stay is 4.3 nights[40]). Those guests that review during the outbreak week (week 0) either have stayed prior to the outbreak or just when the outbreak occurs and so have little time to cancel or delay, so we expect week 0 bookings to be stable and not affected by COVID-19, hence using it as the base effect.

Next, we include additional explanatory variables to the base regression, *NewCase* and *Private*. Log(*NewCase*) is the logarithm of the prior day's number of new COVID-19 cases in borough *b*. *Private* is a dummy of one if the room type is a private room; 0 otherwise. ρ_r denotes room type fixed effects, μ_b are borough fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. Review and listing data are from Inside Airbnb. Daily COVID-19 cases at the borough level are collected from coronavirus.data.gov.uk. The sample comprises Airbnb reviews for the London market

[39] We use log measures rather than raw measures so that we are able to interpret the coefficients as percentage differences.
[40] See Section 4.1 on Statista estimates of average nights of stay in Europe and the US from 2015-2018.

from Jan 1, 2020 to Mar 23, 2020 (before the UK lockdown announcement). Reviews are matched to listings in the same month to obtain borough and room type.

The staggered diff-in-diff regression is similar to the setting in Aggarwal and Schenone (2019) and Lin, Liu and Manso (2020) except that the final week extends to the end of the sample. For this identification strategy to be valid, the treatment (i.e. the initial outbreak in each borough) must be assigned randomly and there should be no reverse causality between treatment and outcome variables. Appendix 2 lists the dates of the first COVID-19 cases for each of the 33 boroughs of London and the region each borough is in. Appendix 3 presents the London map, illustrating the location and boundary of each borough as well as the pattern of infection during Mar 2020. It is a legitimate concern that outbreaks of COVID-19 may be non-random if initial spread is by close contact (i.e. community transmission). As such, we may expect the first COVID-19 cases in each borough to be preceded by the first COVID-19 cases in boroughs within the same region or adjacent boroughs.

To test whether this is the case, we conduct a runs test using a time series of dummies denoting whether the first case in a borough was immediately preceded by a first case in a borough in the same region, zero otherwise. We also use an alternative dummy specification for if the prior outbreak was in an adjacent borough. The *z*-statistic and the critical *p*-values of the tests are 0.17 and 0.62, respectively (statistically insignificant), which confirms the first COVID-19 cases in each borough are indeed random.[41] We therefore find validity in our experimental design.

Table 5 reports our results for *Log(1+Reviews)* in Panel A and *Log(1+Cancel)* in Panel B. For both panels, we estimate Equation 4 in Column 1, with the interaction between the dynamic treatment and *NewCase* in Column 2, interaction with *Private* in Column 3, and both interaction of *NewCase* and *Private* in Column 4. The four coefficients on $Week_{-3}$ to $Week_{-1}$ are all statistically insignificant for all

[41] See tabulated results in Internet Appendix IA3.

models, indicating the reduction in booking only starts after the outbreak and the diff-in-diff model passes the parallel trends assumption. That is, we establish that there is no difference in *Reviews* or *Cancel* for control and treatment groups prior to initial outbreaks, controlling for observables. This further implies that booking activity in the week of the outbreak is similar to prior weeks as there is little time for guests to alter their travel arrangements immediately following the outbreak.

[--- INSERT TABLE 5 ABOUT HERE ---]

For Table 5 Panel A, we find effects consistent with our global study of COVID-19 effects, namely falls in *Reviews* after the shock from the initial COVID-19 outbreak in a borough ($Week_1$ to $Week_{3+}$) and negative sensitivity to prior day new COVID-19 cases in a borough ($Week_w$*NewCase*). However, we find no evidence that private room reviews experience greater falls from COVID-19 outbreaks or have greater sensitivity to COVID-19 cases than entire home reviews.

In Table 5 Panel A Column 1, we document a fall in daily reviews after the first recorded COVID-19 case in the borough, with all $Week_1$ to $Week_{3+}$ coefficients being statistically significant at the one percent level. We also observe the magnitude of the fall increases with more weeks after the first case. For example, $Week_1$'s coefficient is -0.175 (implying an approximate 17.5% fall in *Reviews* compared to the initial week of the COVID-19 outbreak), monotonically decreasing as the week number increases, with $Week_{3+}$'s coefficient being -0.603.

When including the prior day's local COVID-19 cases in Column 2, we find that the coefficients of $Week_1$ *to* $Week_{3+}$'s interaction with *NewCase* are all negative and statistically significant and the coefficients of the initial outbreak effect $Week_w$ are all statistically insignificant except $Week_2$ which is positive and weakly significant.[42] The interaction effects of week dummies and number of confirmed

[42] The positive coefficient for $Week_2$ of 0.071 is economically small relative to the coefficient for $Week_2$**NewCase of -0.305*. For example, with just one case in the prior day, there is a ln(2)*-0.305 = -0.2114 or about 21.14 percent fall in reviews which is much larger than the 0.071 or about 7.1% increase of reviews during Week 2 if there are no prior day COVID-19 cases.

cases becomes more severe in the latter weeks. For example, *$Week_1$*NewCase* is -0.168 and is -0.283 for *$Week_{3+}$*NewCase*, increasing in magnitude. The result implies that with time passing since the borough's initial outbreak, booking activity sensitivity increases with new COVID-19 cases. In Columns 3 and 4 where we include interactions for *Private,* we find statistically insignificant effects, which suggests that the effect of local COVID-19 cases on reviews is not statistically different between entire homes and private rooms.

For Table 5 Panel B using *log (1+Cancel*), Column 1 shows a positive and statistically significant effect of initial outbreak at the borough level. Column 2 includes interaction with local COVID-19 severity and these effects are positive and statistically significant from Week 2 onwards, implying that cancellation rates go up due to a COVID-19 outbreak in the borough and the increase in cancellations is sensitive to local COVID-19 cases. For Column 3 where we interact the treatment with *Private,* we find positive and statistically significant coefficients for *$Week_2$*Private* (0.112) and *$Week_{3+}$*Private* (0.307). The result implies that there is significantly more cancellation of between 11.2% to 30.7% for private rooms after a borough's initial outbreak, relative to entire homes. This finding is consistent with hosts of private rooms being more fearful of becoming infected by guests as they share the space and hence hosts are more likely to cancel the bookings. For Column 4 where we have interaction of both private and local COVID-19 cases, we find statistically significant $Week_2$*Private and $Week_{3+}$*Private and insignificant differences in *$Week_w$*NewCase*Private*.

For robustness, we also conduct the same analysis using the entire home and private rooms sample in separate regressions and using seemingly unrelated regressions (SUR). SUR allows us to test whether individual coefficients for private rooms sample regression statistically differ to the same coefficient in the entire homes sample using chi-squared tests. The results are presented in Internet Appendix Table IA5. Consistent with the results in Table 5 Panel A, reviews for both entire homes and private rooms react negatively to an initial outbreak or local COVID-19 severity (Internet Appendix

Table IA5 Panel A). Also consistent to the pooled results, individual coefficients are not statistically different between the entire home and private room sample. For cancellations in Internet Appendix Table IA5 Panel B, we find positive and statistically significant effects after the initial outbreak for the private room sample (Column 2) and for both room types for local COVID-19 cases (Panel 3 and 4). Consistent to the pooled results, for column 2 *Week 2* and *Week* 3^{+} coefficients are larger and statistically different for private rooms than entire homes.

Overall, we show evidence of review activity affected by both a borough's initial COVID-19 outbreak and local COVID-19 outbreaks, with the effect increasing over time. We also show that cancellations increase for private rooms but not for entire homes, consistent with hosts being fearful of contact with potentially infected COVID-19 guests.

5.2 Supply side effect: number of active listings

In this section, we focus on the supply side effect by examining how the total volume of active Airbnb listing responds to the COVID-19 pandemic. We use monthly Airbnb listings snapshots (which contain individual Airbnb listing information for a day in each month) with the last snapshot being on Mar 15, 2020 prior to the UK lockdown announcement. Figure 4 reports the monthly total number of listings by room type in London from Jan 2019 to Mar 2020. Listings are stable over time with only a very slight decline during the COVID-19 outbreak between Jan 2020 and Mar 2020.

[--- INSERT FIGURE 4 ABOUT HERE ---]

As we only have monthly snapshots, we use a similar diff-in-diff strategy for our global analysis to test for the effect of COVID-19 on listings. Here we only consider active listings as it is known that many listings are inactive (Zervas, Proserpio and Byers (2017). We run the following regression:

$$Log(N\_Active_{b,r}) = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\,(1 + NewCase_{b,t-1}) + \beta_4 Treat * Private + \beta_5 Post_j * Private + \beta_6 Treat * Post_j * Private + \beta_7 Treat * Post_j * Private * Log\big(1 + NewCase_{b,t-1}\big) + \rho_r + \mu_b + \tau_t + \varepsilon_{bt} \quad \text{--- (5)}$$

Where *N_Active* is the number of active listings in borough *b* for room type *r* (entire home or private room). A listing is deemed active if there was a review for it in the prior three months. *Treat* denotes whether the date of the listing is in 2020. *Post* denotes the date of the listing is on or after Jan 31, 2020 (first COVID-19 case in the United Kingdom) for the 2020 sample and is on or after Jan 31, 2019 for the 2019 sample.

Table 6 reports our results on the number of active listings. We find no statistical association between listing volume and COVID-19 shock or local COVID-19 cases, as seen from the insignificant coefficient on *Treat*Post*NewCase*. We further examine the supply difference between private rooms and entire homes, by interacting with the *Private Room* dummy. We find there is also no statistical difference regarding the effect of COVID-19 on entire homes versus private listings volume as seen from the insignificant coefficient on *Treat*Post*NewCase*Private*. In Internet Appendix Table IA6, we perform separate regressions for the entire homes only sample (Columns 1 and 3) and private rooms only sample (Column 2 and Column 4). We find the coefficients on *Treat*Post* and *Treat*Post*NewCase* are statistically insignificant in most models. Further, the coefficients in the entire homes sample are not statistically different to the sample of private rooms, implying there is no significant evidence of listing supply reduction or difference between the entire home sample and not the private rooms sample, consistent with the result in Table 6.

[--- INSERT TABLE 6 ABOUT HERE ---]

5.3 Booking price adjustments in London

To study COVID-19's effect on booking prices, we examine booking price adjustment over time, by comparing the current month's prices with future booking prices for each listing for a given monthly snapshot. Figure 5 plots the median booking price for a given future calendar date based on monthly snapshots from Dec 2019 to Mar 2020, with information on booking prices extending to Jul 2020. We observe that booking prices for dates one month ahead tend to be lower than the booking price for same dates based on the prior month's calendar snapshot. It is especially clear when we compare the median prices in the calendar month of Mar 2020 snapshot to the Feb 2020 snapshot. For the Mar 2020 snapshot, the median booking price in Mar 2020 is £70/night whereas for the same date using the Feb 2020 snapshot, the price is about £85 or over 20% higher. We term this price difference the *Calendar Gap* and use it as a measure of booking price discounts in response to COVID-19 across boroughs.

[--- INSERT FIGURE 5 ABOUT HERE ---]

5.3.1 Price adjustment one week ahead

We first analyze listing price adjustment based on monthly snapshot, focusing on the first week head of each snapshot. We run the following regression based on a diff-in-diff strategy, using daily listing price data for the 3 months from Jan to Mar in both 2019 and 2020.

$$
\begin{aligned}
Log(CalGap_{i,t,t+k}) \quad & \text{--- (6)} \\
= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j \\
* Log\left(1 + NewCase_{b,t-1}\right) + \beta_4 Treat * Private + \beta_5 Post_j \\
* Private + \beta_6 Treat * Post_j * Private + \beta_7 Treat * Post_j \\
* Private * Log\left(1 + NewCase_{b,t-1}\right) + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}
\end{aligned}
$$

Where $CalGap_{i,t,t+k}$ is listing *i's* booking price at the date *t+k* from monthly snapshot *t*, divided by date *t+k*'s booking price in the previous month's snapshot. We remove the listing if the prior month's room type is different. We use the first week's booking price from the monthly snapshot, so *k*=0 to 6 days.

Our evidence on price adjustment is presented in Table 7, which is consistent with the falling booking prices pattern in Figure 5. In Table 7 Panel A using the full sample of Airbnb listings in London market, we find the coefficient on *Treat*Post* is negative and statistically significant with a value of -0.061 (Column 1), implying a 6.1% fall in the booking price, compared with the same day of the last month post UK COVID-19 outbreak. In Column 2, the coefficient on *Treat*Post*NewCase* is significantly negative at -0.023, implying -1.59% (=ln(2)*-0.023) lower booking prices (relative to the previous snapshot) per doubling of the prior day's local COVID-19 cases.

[--- INSERT TABLE 7 ABOUT HERE ---]

The coefficient of *Treat*Post*Private* is positive and statistically significant with a value of 0.052 (Column 3), which indicates that the price reduction of private rooms is about 5.2% less than entire homes, with respect to the initial COVID-19 shock in UK. The result is consistent with the rationale that private room hosts are more concerned about the infection risk from Airbnb guests and therefore charge an infection risk premium compared with entire units. In Column 4, we interact *Private* with *NewCase* and find the coefficient on *Treat*Post*Private*NewCase* is 0.015, statistically significant at the 10% level. This result implies that private room booking prices are less sensitive to local COVID-19 cases than entire homes. The private room sensitivity is about half that of entire homes as the coefficient for *Treat*Post*NewCase* is -0.030 (statistically significant at the 1% level).

5.3.2 Price adjustment further ahead

The above tests use changes in listing prices one week ahead of the most recent snapshot. Next we test booking price adjustments in windows further ahead of time using booking prices in the next four months. The intuition is that listing prices for dates in more distant future are less likely to be affected by COVID-19 situation. As seen in Figure 5, hosts tend to set normal market price for dates in the distant future, consistent with hosts hoping the market will recover in the future. However, an anticipated prolonged effect of COVID-19 may cause hosts to lower prices for dates in the more distant future, especially with greater local COVID-19 severity. Furthermore, private room hosts could be more concerned about infection risk, so they would offer less discounts due to COVID-19 relative to entire homes. To test these conjectures, we run the regression in the below equation, using monthly average calendar gap as the dependent variable.

$$
\begin{aligned}
Log(CalGapAvg_{i,t+j,t+k}) &= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j \\
&* Log\left(1 + NewCase_{b,t-1}\right) + \beta_4 Treat * Private_i + \beta_5 Post_j * Private_i \\
&+ \beta_6 Treat * Post_j * Private_i + \beta_7 Treat * Post_j * Private_i \\
&* Log\left(1 + NewCase_{b,t-1}\right) + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}
\end{aligned} \quad \text{--- (7)}
$$

Where *CalGapAvg* is the average *CalGap* for listing i between month $t+j$ and month $t+k$. We use four windows in the next four months after the snapshot time t: t+0 to t+29, t+30 to t+59, t+60 to t+89 and t+90 to t+119. Our sample includes 6-months listing price data in Jan to Mar 2019 and 2020. These windows represent the average booking price adjustment in the first, second, third and fourth month from the current time of the listing, respectively.

Table 8 reports the regression results, which are in general consistent with using the shorter daily window in Table 7. The coefficients on *Treat*Post* are all negative in the four windows, and monotonically declining the further into the future from -0.121 (1% statistically significant) to -0.023 (statistically insignificant), indicating that the discount is 12.1% for dates in the next month, while no significant discount is offered for dates in the fourth month after.

[--- INSERT TABLE 8 ABOUT HERE ---]

We also examine whether hosts of private rooms and entire units react differently to COVID-19 risk by adding in interaction terms with the private dummy. We find that the coefficients on *Treat*Post*Private*Log(1+New_Case*$_{t-1}$*)* in the four models are all positive and statistically significant, implying that hosts of private rooms charge an infection risk premium for greater COVID-19 severity, relative to entire units, consistent with the result in Table 7. Overall, our analysis shows that hosts adopt dynamic pricing strategy where dates in near future have deeper discounts than those in more distant future, consistent with higher value of the option to wait for future dates with potential recovery of the market (McAfee and Velde, 2006).

5.4 Booking price adjustments of professional and non-professional hosts

A distinct feature of Airbnb and other markets that follow a "sharing economy" paradigm are that there exists a mixture of professional and non-professional service providers. Professionals are seen as being better at profit maximizing and reacting to market conditions (e.g. Li et al., 2016; Gibbs et al., 2018). The number of Airbnb listings likely to be operated by hospitality professionals grew 36% last year, more than three times the increase in listings for rentals of spare rooms, according to AirDNA.[43] In our sample, professional hosts, defined as those that manage multiple listings, make up 58.87%, 59.29% and 58.29 of listings in the full, entire home and private rooms samples, respectively.

In this section, we test whether professional hosts react differently to the COVID-19 outbreak than non-professional ones. We anticipate that professional hosts may adjust booking prices according to the local COVID-19 situation when demand for short-term accommodation drops in response to COVID-19 severity, while non-professionals are less likely to do so. To test the pricing difference

[43] Source: https://www.theinformation.com/articles/influx-of-professional-hosts-tests-airbnbs-message

between professional versus non-professional Airbnb hosts, we run the following regression using the full sample of listings, as well as two subsamples for entire homes and private rooms:

$$
\begin{aligned}
Log(CalGap_{i,t,t+k}) &= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j \\
&* Log(1 + NewCase_{b,t-1}) + \beta_4 Treat * Private_i + \beta_5 Post_j * Pro_i \\
&+ \beta_6 Treat * Post_j * Pro_i + \beta_7 Treat * Post_j * Pro_i \\
&* Log(1 + NewCase_{b,t-1}) + \beta_8 * Pro + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}
\end{aligned} \quad \text{--- (8)}
$$

Where *Pro* is a dummy of one if the host has multiple listings under his or her management, and 0 otherwise, following the definition of *Pro* in Li et al. (2016).[44] We expect professional hosts react to COVID-19 by adjusting price down further to maximize revenue, relatively to non-professional ones. That is, we expect *Treat*Post*Pro* and *Treat*Post*Pro*Log(1+NewCase)* to be both negative and statistically significant.

We report the regression results in Table 9. Across all three columns, the coefficients on *Treat*Post*Pro*Log(1+NewCase)* are all negative and statistically significant, indicating that professionals offer greater discount in response to local COVID-19 severity than nonprofessionals, consistent with professional hosts being more experienced in gauging demand and adjusting price to maximize revenue. *Treat*Post*Pro* is only negative and statistically significant for the private room sample, suggesting professional hosts of private rooms respond to the initial outbreak by offering greater discount than non-professional hosts, consistent with non-professional hosts of private rooms having great infection risk concern than professionals and charge a risk premium accordingly.

We also test the difference between private rooms versus entire homes using SUR test, and the test results are indicated in the last column. Consistent with the COVID-19 risk premium result in prior sections, we find that *Treat*Post* is more negative for the entire room sample and statistically different

[44] We find qualitatively similar results using a professional host definition of having five or more listings at the same time.

to the private room sample. *Treat*Post*Pro* is not statistically different between entire room and private room samples, suggesting that non-professional hosts with private room listings reduce booking prices less than hosts with entire homes due to the initial COVID-19 outbreak shock. Overall, we show professional hosts are more responsive in making price adjustments than non-professional hosts in response to the effects of COVID-19. This result is consistent with professional hosts being more experienced with the hospitality industry and more attuned to market conditions, hence reacting to varying demand during the pandemic in order to maximize revenue.

[--- INSERT TABLE 9 ABOUT HERE ---]

6. Conclusion

COVID-19 is arguably the most disruptive event to travel activities since World War II. In this paper, we document the effects of COVID-19 using travel booking information from the largest accommodation sharing platform, Airbnb. Utilizing daily reviews and cancellations as proxies for booking activity, we find that Airbnb market booking activity is negatively affected by three COVID-19 related factors: the initial Wuhan lockdown shock, local COVID-19 cases, and local lockdowns/travel bans. Our results demonstrate that all three factors have an economically and statistically significant impact on booking activities. Specifically, the shock of the Wuhan lockdown leads to an 8.8% fall in booking activity globally. Every doubling of new local COVID-19 cases in the prior day is associated with a 4.16% fall in bookings the next day. Moreover, local lockdowns cause a 57.8% fall in booking activity on average and an increase in cancellations of 4.5-fold.

We explain the sensitivity of booking activity to COVID-19 risks using geographic distance to Wuhan, government stringency of COVID-19 policies, and human mobility within Airbnb markets. We find sensitivity to the initial Wuhan lockdown shock decreases with increasing distance from Wuhan, consistent with geographic proximity of infection risk. Local COVID-19 case sensitivity increases with more stringent COVID-19 policies, consistent with the severity of COVID-19 increasing guest fears of staying in a market. Highly mobile areas that also have a higher number of local COVID-19 cases also increases sensitivity, consistent with guest fears of infection due to potential spread in highly mobile areas. Finally, local lockdown sensitivity increases with more stringent COVID-19 management policies, consistent with such policies making it more difficult for guests to travel.

Examining the data at the local government level of the 33 boroughs of London, UK, we document that both the initial outbreak in a borough and local borough cases have a negative impact on reviews, consistent with our global evidence. We find that reviews for both entire homes and private rooms are similarly affected by COVID-19. Interestingly, we find higher cancellation activity for private rooms than entire homes for local borough COVID-19 cases, consistent with host fears of being in contact with COVID-19 infected guests.

On the supply side, we find that Airbnb supply remains steady amidst the pandemic, and hosts adopt dynamic pricing strategy by adjusting booking prices downward in response to COVID-19 outbreak and severity in local Airbnb market. In terms of room type heterogeneity, we find hosts of private rooms charge a positive price premium relative to entire units, consistent with private room hosts demanding a risk compensation for hosting potentially infected guests in shared accommodation. We also document dates in near future have deeper discounts than those in more distant future, consistent with the higher option value of future dates. We also compare professional versus non-professional hosts, and find professionals adjust prices by offering greater discounts in response to local COVID-19 severity.

Our findings suggest that the COVID-19 pandemic has had a significant adverse impact on the tourism market, attributable to travelers' infection concerns as well as government lockdown measures in response to COVID-19. Our findings shed light on understanding the demand and supply factors crucial to eventual recovery of the tourism industry. Relaxation of lockdowns/travel bans would provide the largest boost for all regions, although reducing local COVID-19 cases and fear of infection is just as important to attract guests.

References

Aggarwal, R.K., Schenone, C., 2019. Incentives and Competition in the Airline Industry. The Review of Corporate Finance Studies 8, 380-428.

Barrios, J.M., Benmelech, E., Hochberg, Y.V., Sapienza, P., Zingales, L., 2021. Civic capital and social distancing during the Covid-19 pandemic. Journal of Public Economics 193, 104310.

Barron, K., Kung, E., Proserpio, D., 2020. The effect of home-sharing on house prices and rents: Evidence from Airbnb. Marketing Science, forthcoming

Briscese, G., Lacetera, N., Macis, M., Tonin, M., 2020. Compliance with COVID-19 Social-Distancing Measures in Italy: The Role of Expectations and Duration. Working paper, NBER

Chen, H., Qian, W., Wen, Q., 2020. The impact of the COVID-19 pandemic on consumption: Learning from high frequency transaction data. Working paper, Xiamen University

Chinazzi, M., Davis, J.T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., y Piontti, A.P., Mu, K., Rossi, L., Sun, K., 2020. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 368, 395-400.

Engle, S., Stromme, J., Zhou, A., 2020. Staying at Home: Mobility Effects of Covid-19. Working paper, University of Wisconsin - Madison

Fang, H., Wang, L., Yang, Y., 2020. Human mobility restrictions and the spread of the Novel Coronavirus (2019-nCoV) in China. Journal of Public Economics 191, 104272.

Fradkin, A., Grewal, E., Holtz, D., 2020. Reciprocity in Two-sided Reputation Systems: Evidence from an Experiment on Airbnb. Working Paper, Boston University

Frey, C.B., Chen, C., Presidente, G., 2020. Democracy, Culture, and Contagion: Political Regimes and Countries Responsiveness to Covid-19. Covid Economics 18, 222-235.

Gibbs, C., Guttentag, D., Gretzel, U., Yao, L., Morton, J., 2018. Use of dynamic pricing strategies by Airbnb hosts. International Journal of Contemporary Hospitality Management 30, 2-20.

Goolsbee, A., Syverson, C., 2021. Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. Journal of Public Economics 193, 104311.

Gormsen, N.J., Koijen, R.S., 2020. Coronavirus: Impact on stock prices and growth expectations. Working paper, University of Chicago

Hale, T., Petherick, A., Phillips, T., Webster, S., 2020. Variation in government responses to COVID-19. Working paper, Blavatnik School of Government Oxford University 31

Hasell, J., Mathieu, E., Beltekian, D., Macdonald, B., Giattino, C., Ortiz-Ospina, E., Roser, M., Ritchie, H., 2020. A cross-country database of COVID-19 testing. Scientific Data 7, 345.

Kraemer, M.U.G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D.M., du Plessis, L., Faria, N.R., Li, R., Hanage, W.P., Brownstein, J.S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O.G., Scarpino, S.V., 2020. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science, eabb4218.

Li, J., Moreno, A., Zhang, D., 2016. Pros vs joes: Agent pricing behavior in the sharing economy. Working paper, University of Michigan

Lin, C., Liu, S., Manso, G., 2020. Shareholder litigation and corporate innovation. Management Science, forthcoming

Ramelli, S., Wagner, A., 2020. Feverish Stock Price Reactions to COVID-19. Review of Corporate Finance Studies, forthcoming

Zervas, G., Proserpio, D., Byers, J.W., 2017. The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. Journal of Marketing Research 54, 687-705.

Zheng, R., Xu, Y., Wang, W., Ning, G., Bi, Y., 2020. Spatial transmission of COVID-19 via public and private transportation in China. Travel Medicine and Infectious Disease 34, 101626.

Appendix 1: Dates of lockdown measures in Airbnb sample areas

The appendix reports the individual Airbnb market data that we use in the paper and as scraped by the Inside Airbnb website. Lockdown dates are obtained from Aura Vision's lockdown tracker and manually verified. First COVID-19 Case is the first COVID-19 case in the Airbnb market as recorded by the John Hopkins University Coronavirus Resource Center. Lockdown date is the start of quarantine measures in the Airbnb market. Travel ban date is the start of travel bans for the country. Last Airbnb scrape date is when Inside Airbnb last collected listings and reviews data for the Airbnb market. COVID-19 measure level is the level of COVID-19 cases used for that Airbnb market (e.g. city, county, state, etc.)

Country	Airbnb Market Name	First COVID-19 Case Date	Lockdown Date	Travel Ban Date	Last Airbnb Scrape Date	Airbnb Market Level	COVID-19 Measure Level
Argentina	Buenos Aires	2020-03-03	2020-03-19	2020-03-15	2020-04-26	City	National
Australia	Barossa Valley	2020-02-01	2020-03-23	2020-03-20	2020-04-26	Region	State
Australia	Barwon South West	2020-01-26	2020-03-23	2020-03-20	2020-04-28	Region	State
Australia	Melbourne	2020-01-26	2020-03-23	2020-03-20	2020-04-18	City	State
Australia	Northern Rivers	2020-01-26	2020-03-23	2020-03-20	2020-04-29	Region	State
Australia	Sydney	2020-01-26	2020-03-23	2020-03-20	2020-04-15	City	State
Australia	Tasmania	2020-03-02	2020-03-23	2020-03-20	2020-04-15	State	State
Australia	Western Australia	2020-02-29	2020-03-23	2020-03-20	2020-04-20	State	State
Austria	Vienna	2020-02-25	2020-03-16	2020-03-26	2020-04-19	City	National
Belgium	Antwerp	2020-02-04	2020-03-18	2020-03-21	2020-04-28	City	National
Belgium	Brussels	2020-02-04	2020-03-18	2020-03-21	2020-04-19	City	National
Belgium	Ghent	2020-02-04	2020-03-18	2020-03-21	2020-04-27	City	National
Belize	Belize	2020-03-23	2020-04-03	2020-04-03	2020-04-30	National	National
Brazil	Rio De Janeiro	2020-02-26	.	2020-03-30	2020-04-20	City	National
Canada	Montreal	2020-02-28	2020-03-13	2020-03-18	2020-04-20	City	Province
Canada	New Brunswick	2020-03-11	.	2020-03-18	2020-04-30	Province	Province
Canada	Ottawa	2020-01-26	2020-03-24	2020-03-18	2020-04-30	City	Province
Canada	Quebec City	2020-02-28	2020-03-13	2020-03-18	2020-04-17	City	Province
Canada	Toronto	2020-01-26	2020-03-24	2020-03-18	2020-04-09	City	Province
Canada	Vancouver	2020-01-28	.	2020-03-18	2020-04-17	City	Province
Canada	Victoria	2020-01-28	.	2020-03-18	2020-04-30	City	Province
Chile	Santiago	2020-03-03	2020-03-19	2020-03-19	2020-04-27	City	National
China	Beijing	2020-01-22	.	2020-03-28	2020-04-29	City	City
China	Hong Kong	2020-01-23	.	2020-03-28	2020-04-29	City	City
Czech Republic	Prague	2020-03-01	2020-03-16	2020-03-16	2020-04-29	City	National
Denmark	Copenhagen	2020-02-27	2020-03-13	2020-03-14	2020-04-28	City	National
France	Bordeaux	2020-01-24	2020-03-17	2020-03-20	2020-04-22	City	National
France	Lyon	2020-01-24	2020-03-17	2020-03-20	2020-04-27	City	National
France	Paris	2020-01-24	2020-03-17	2020-03-20	2020-04-15	City	National
Germany	Berlin	2020-01-27	2020-03-23	2020-03-19	2020-04-17	City	National
Germany	Munich	2020-01-27	2020-03-20	2020-03-19	2020-04-25	City	National
Greece	Athens	2020-02-26	2020-03-23	2020-03-19	2020-04-21	City	National
Greece	Crete	2020-02-26	2020-03-23	2020-03-19	2020-04-30	Region	National
Greece	South Aegean	2020-02-26	2020-03-23	2020-03-19	2020-04-28	Region	National
Greece	Thessaloniki	2020-02-26	2020-03-23	2020-03-19	2020-04-21	City	National
Ireland	Dublin	2020-02-29	2020-03-27	.	2020-04-23	City	National

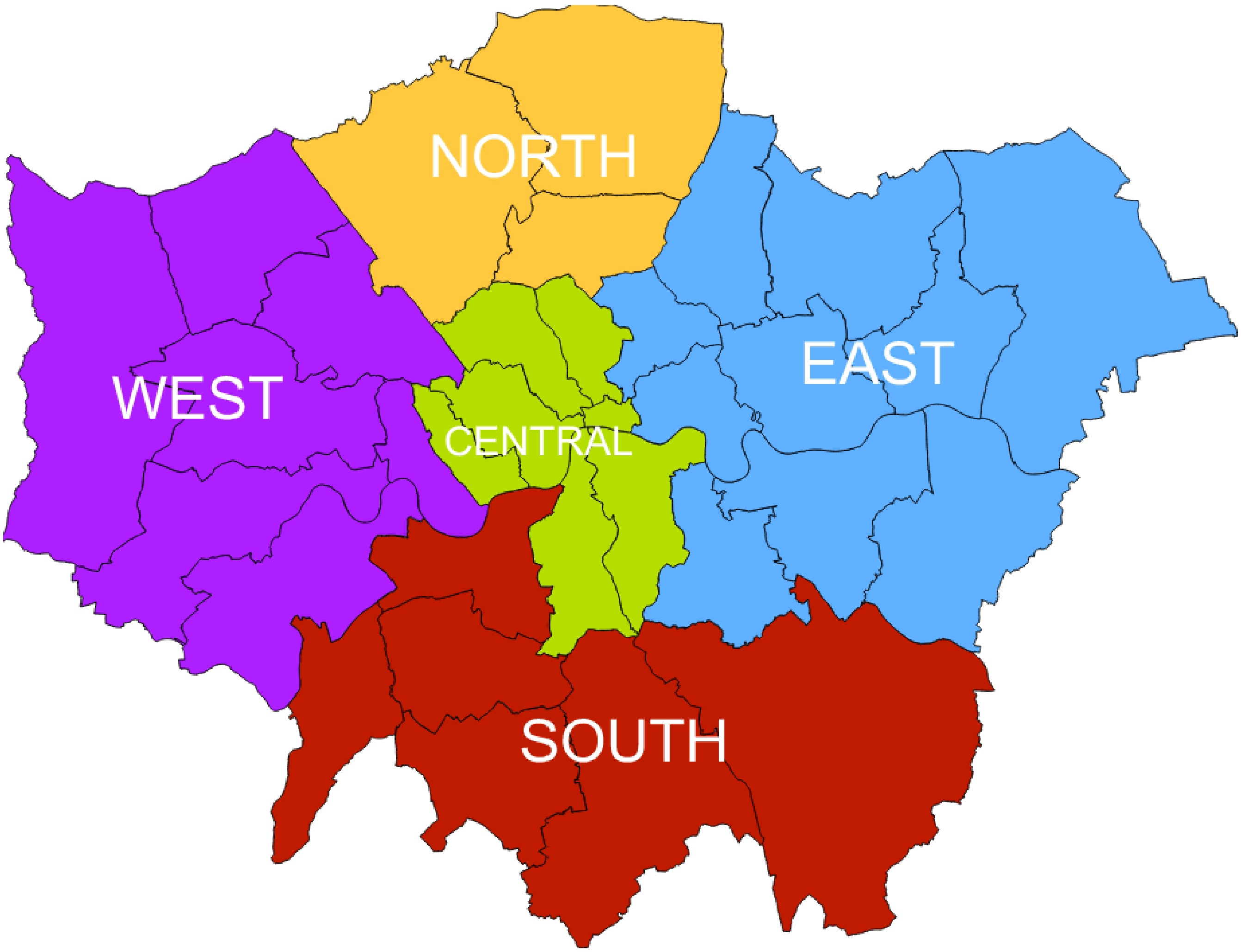
Country	Airbnb Market Name	First COVID-19 Case Date	Lockdown Date	Travel Ban Date	Last Airbnb Scrape Date	Airbnb Market Level	COVID-19 Measure Level
Italy	Bergamo	2020-01-31	2020-03-09	2020-03-09	2020-04-28	City	National
Italy	Bologna	2020-01-31	2020-03-09	2020-03-09	2020-04-30	City	National
Italy	Florence	2020-01-31	2020-03-09	2020-03-09	2020-04-30	City	National
Italy	Milan	2020-01-31	2020-03-09	2020-03-09	2020-04-29	City	National
Italy	Naples	2020-01-31	2020-03-09	2020-03-09	2020-04-30	City	National
Italy	Puglia	2020-01-31	2020-03-09	2020-03-09	2020-04-30	Region	National
Italy	Rome	2020-01-31	2020-03-09	2020-03-09	2020-04-29	City	National
Italy	Sicily	2020-01-31	2020-03-09	2020-03-09	2020-04-30	Region	National
Italy	Venice	2020-01-31	2020-03-09	2020-03-09	2020-04-29	City	National
Japan	Tokyo	2020-01-22	2020-04-07	2020-04-03	2020-04-28	City	National
Mexico	Mexico City	2020-02-28	2020-03-21	2020-03-21	2020-04-23	City	National
Norway	Oslo	2020-02-26	2020-03-12	2020-03-13	2020-04-30	City	National
Portugal	Lisbon	2020-03-02	2020-03-19	.	2020-04-29	City	National
Portugal	Porto	2020-03-02	2020-03-19	.	2020-04-23	City	National
Singapore	Singapore	2020-01-23	2020-04-07	2020-03-23	2020-04-26	National	National
South Africa	Cape Town	2020-03-05	2020-03-26	2020-03-26	2020-04-26	City	National
Spain	Barcelona	2020-02-01	2020-03-14	2020-03-16	2020-04-16	City	National
Spain	Euskadi	2020-02-01	2020-03-14	2020-03-16	2020-04-30	Region	National
Spain	Girona	2020-02-01	2020-03-14	2020-03-16	2020-04-30	City	National
Spain	Madrid	2020-02-01	2020-03-14	2020-03-16	2020-04-17	City	National
Spain	Malaga	2020-02-01	2020-03-14	2020-03-16	2020-04-30	City	National
Spain	Mallorca	2020-02-01	2020-03-14	2020-03-16	2020-04-23	Region	National
Spain	Menorca	2020-02-01	2020-03-14	2020-03-16	2020-04-30	Region	National
Spain	Sevilla	2020-02-01	2020-03-14	2020-03-16	2020-04-30	City	National
Spain	Valencia	2020-02-01	2020-03-14	2020-03-16	2020-04-28	City	National
Sweden	Stockholm	2020-01-31	.	2020-03-19	2020-04-28	City	National
Switzerland	Geneva	2020-02-25	2020-03-17	2020-03-19	2020-04-28	City	National
Switzerland	Vaud	2020-02-25	2020-03-17	2020-03-19	2020-04-23	Region	National
Taiwan	Taipei	2020-01-22	.	2020-03-19	2020-04-30	City	National
The Netherlands	Amsterdam	2020-02-27	2020-03-16	2020-03-20	2020-04-16	City	National
Turkey	Istanbul	2020-03-11	2020-04-11	2020-03-28	2020-04-28	City	National
United Kingdom	Bristol	2020-01-31	2020-03-24	.	2020-04-25	City	National
United Kingdom	Edinburgh	2020-01-31	2020-03-24	.	2020-04-27	City	National
United Kingdom	Greater Manchester	2020-01-31	2020-03-24	.	2020-04-20	City	National
United Kingdom	London	2020-01-31	2020-03-24	.	2020-04-14	City	National
United States	Asheville	2020-03-18	2020-03-30	2020-03-19	2020-04-30	City	County
United States	Austin	2020-03-26	2020-04-02	2020-03-19	2020-04-20	City	County
United States	Boston	2020-02-01	2020-03-24	2020-03-19	2020-04-14	City	County
United States	Broward County	2020-03-07	2020-04-03	2020-03-19	2020-04-25	County	County
United States	Cambridge	2020-03-06	2020-03-24	2020-03-19	2020-04-28	City	County
United States	Chicago	2020-01-24	2020-03-21	2020-03-19	2020-04-23	City	County
United States	Clark County NV	2020-03-05	2020-03-20	2020-03-19	2020-04-28	County	County
United States	Columbus	2020-03-28	2020-03-23	2020-03-19	2020-04-25	City	County
United States	Denver	2020-03-06	2020-03-26	2020-03-19	2020-04-30	City	County

Country	Airbnb Market Name	First COVID-19 Case Date	Lockdown Date	Travel Ban Date	Last Airbnb Scrape Date	Airbnb Market Level	COVID-19 Measure Level
United States	Hawaii	2020-03-10	2020-03-25	2020-03-19	2020-04-09	City	County
United States	Jersey City	2020-03-08	2020-03-21	2020-03-19	2020-04-30	City	County
United States	Los Angeles	2020-01-26	2020-03-19	2020-03-19	2020-04-14	City	County
United States	Nashville	2020-03-08	2020-04-02	2020-03-19	2020-04-21	City	County
United States	New Orleans	2020-03-11	2020-03-23	2020-03-19	2020-04-09	City	County
United States	New York City	2020-03-02	2020-03-22	2020-03-19	2020-04-08	City	County
United States	Oakland	2020-03-03	2020-03-19	2020-03-19	2020-04-21	City	County
United States	Pacific Grove	2020-03-17	2020-03-19	2020-03-19	2020-04-29	City	County
United States	Portland	2020-03-11	2020-03-23	2020-03-19	2020-04-14	City	County
United States	Rhode Island	2020-03-01	2020-03-30	2020-03-19	2020-04-30	State	County
United States	Salem OR	2020-03-08	2020-03-23	2020-03-19	2020-04-22	City	County
United States	San Diego	2020-02-11	2020-03-19	2020-03-19	2020-04-22	City	County
United States	San Francisco	2020-03-05	2020-03-19	2020-03-19	2020-04-07	City	County
United States	Santa Clara County	2020-01-31	2020-03-19	2020-03-19	2020-04-22	County	County
United States	Santa Cruz County	2020-03-10	2020-03-19	2020-03-19	2020-04-30	County	County
United States	Seattle	2020-01-22	2020-03-25	2020-03-19	2020-04-23	City	County
United States	Twin Cities MSA	2020-03-12	2020-03-27	2020-03-19	2020-04-14	City	County
United States	Washington DC	2020-03-16	2020-04-01	2020-03-19	2020-04-21	City	County

Appendix 2: Timeline of first COVID-19 cases by borough and region in London

Date	Borough	Region
11/02/2020	Lewisham	East
13/02/2020	Ealing	West
16/02/2020	Barnet	North
17/02/2020	Enfield	North
19/02/2020	Hackney	East
23/02/2020	Islington	Central
	Redbridge	East
25/02/2020	Southwark	Central
27/02/2020	Kensington and Chelsea	Central
28/02/2020	Brent	West
	Hounslow	West
29/02/2020	Kingston upon Thames	South
1/03/2020	Barking and Dagenham	East
	Bromley	South
	Merton	South
	Wandsworth	South
	Westminster	Central
2/03/2020	Camden	Central
	Hillingdon	West
3/03/2020	Harrow	West
	Lambeth	Central
4/03/2020	Hammersmith and Fulham	West
	Sutton	South
	Tower Hamlets	East
5/03/2020	Waltham Forest	East
6/03/2020	Havering	East
	Richmond upon Thames	West
7/03/2020	Croydon	South
	Greenwich	East
8/03/2020	Haringey	North
9/03/2020	Bexley	East
	Newham	East
20/03/2020	City of London	Central

Appendix 3: Map of London boroughs and regions

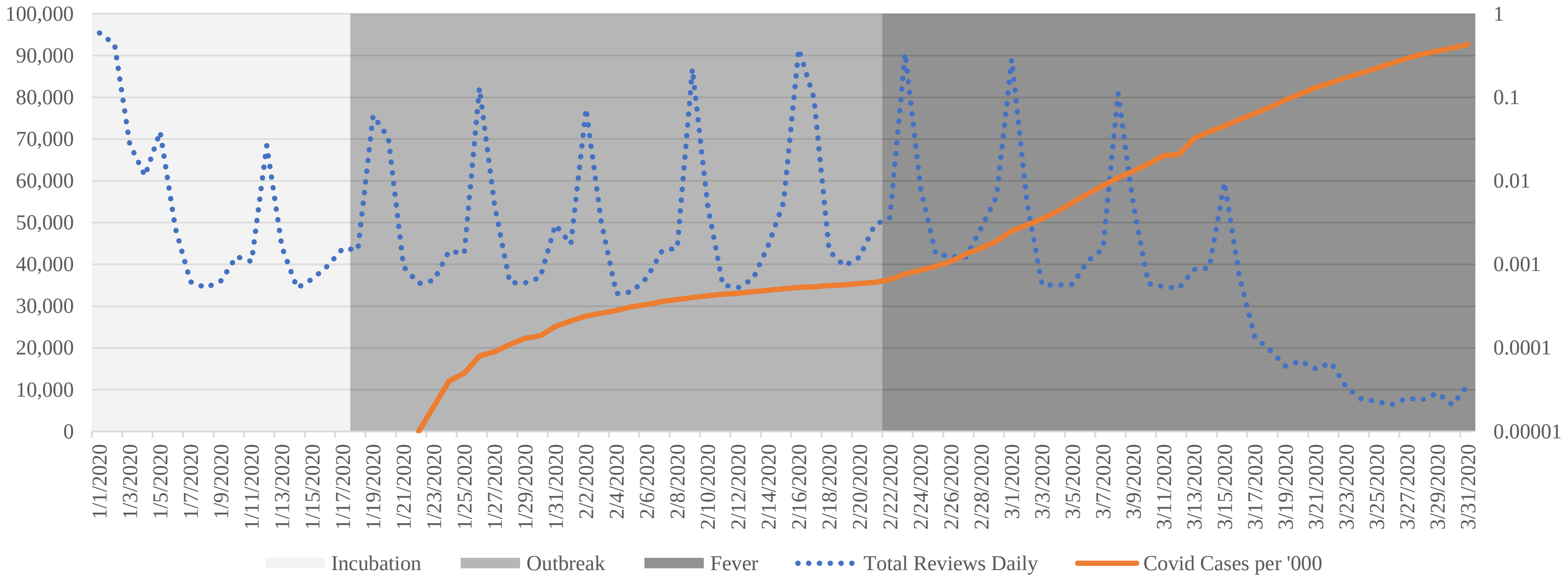


Source: Wikimedia

Figure 1: Number of Airbnb reviews and COVID-19

The figures report the daily Airbnb reviews as scraped by Inside Airbnb website for select major Airbnb markets, against the cumulative COVID-19 cases per 1,000 population of sample Airbnb major cities and regions (from John Hopkins University COVID-19 Center Github). Panel A reports daily Airbnb reviews against COVID-19 per 1,000. Panel B reports daily Airbnb cancellations as a percentage of daily reviews against daily COVID-19 per 1,000. Daily COVID-19 per 1,000 is on the right axis and in log scale. The shaded periods are from Ramelli and Wagner (2020).

Panel A: Total daily Airbnb reviews and daily COVID-19 cases per 1,000



Panel B: Daily Airbnb cancellations as percentage of reviews and daily COVID-19 cases per 1,000

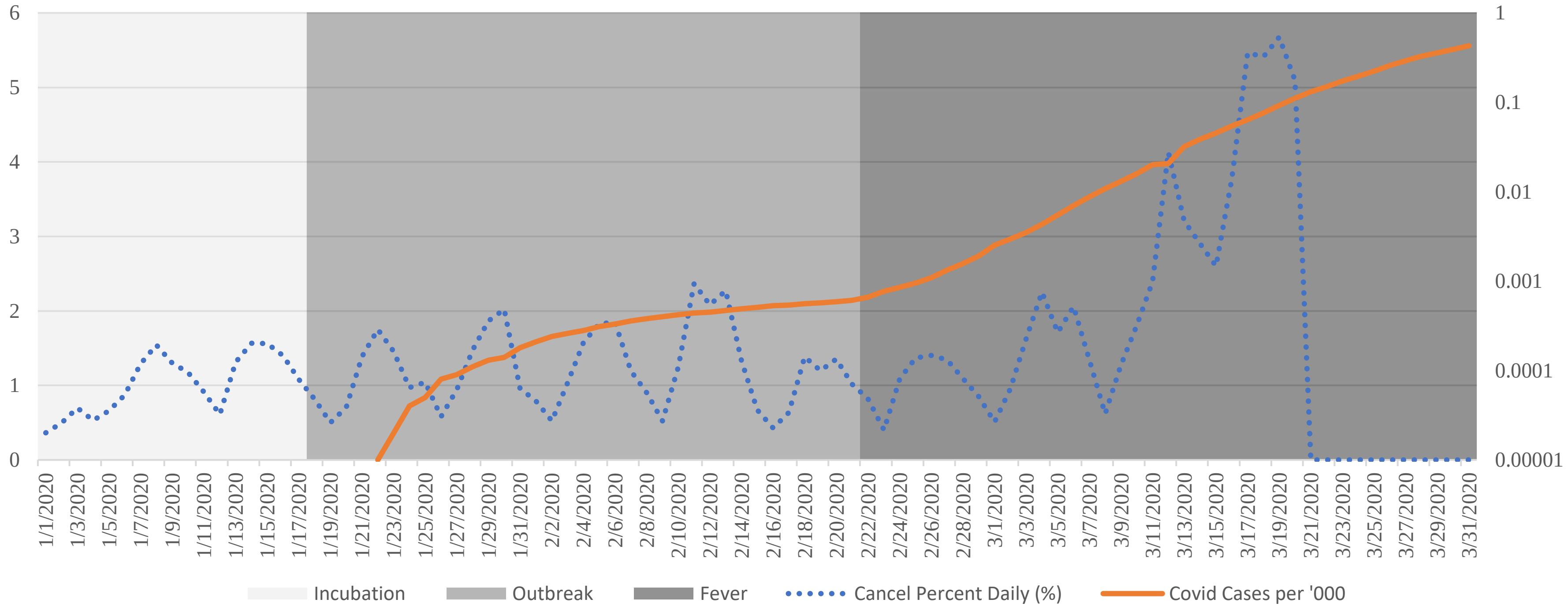
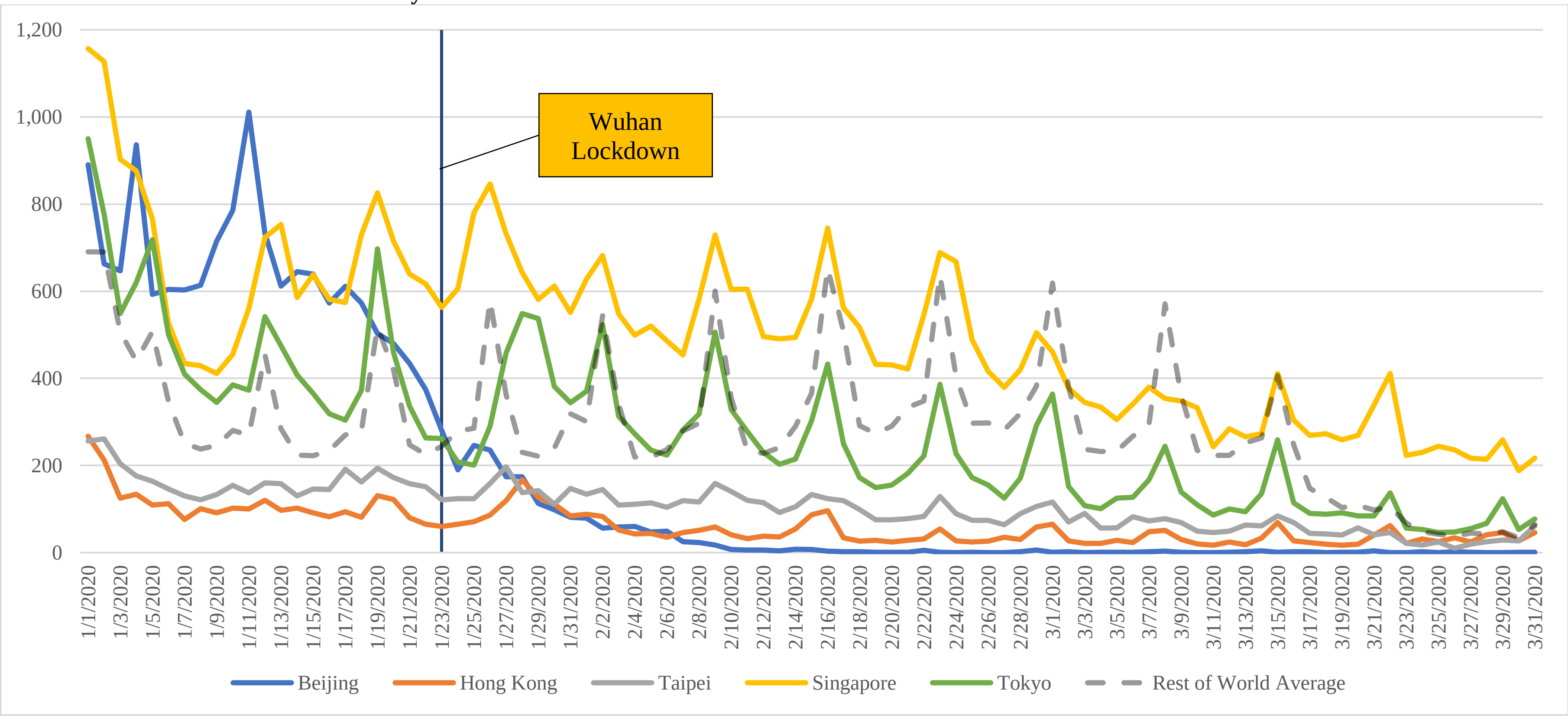


Figure 2: Number of Airbnb reviews and COVID-19

The figures report the daily Airbnb reviews over time from Jan 1, 2020 to Mar 31, 2020 for Asian cities against the equally weighted average daily Airbnb reviews of all other Airbnb markets. Reviews which are automated cancellations are removed. Data is obtained from the Inside Airbnb website. Panel A reports daily reviews. Panel B reports daily reviews divided by the pre-Wuhan lockdown average daily reviews.

Panel A: Asian cities vs. rest of world daily Airbnb reviews



Panel B: Asian cities vs. rest of world daily Airbnb reviews adjusted for pre-period average

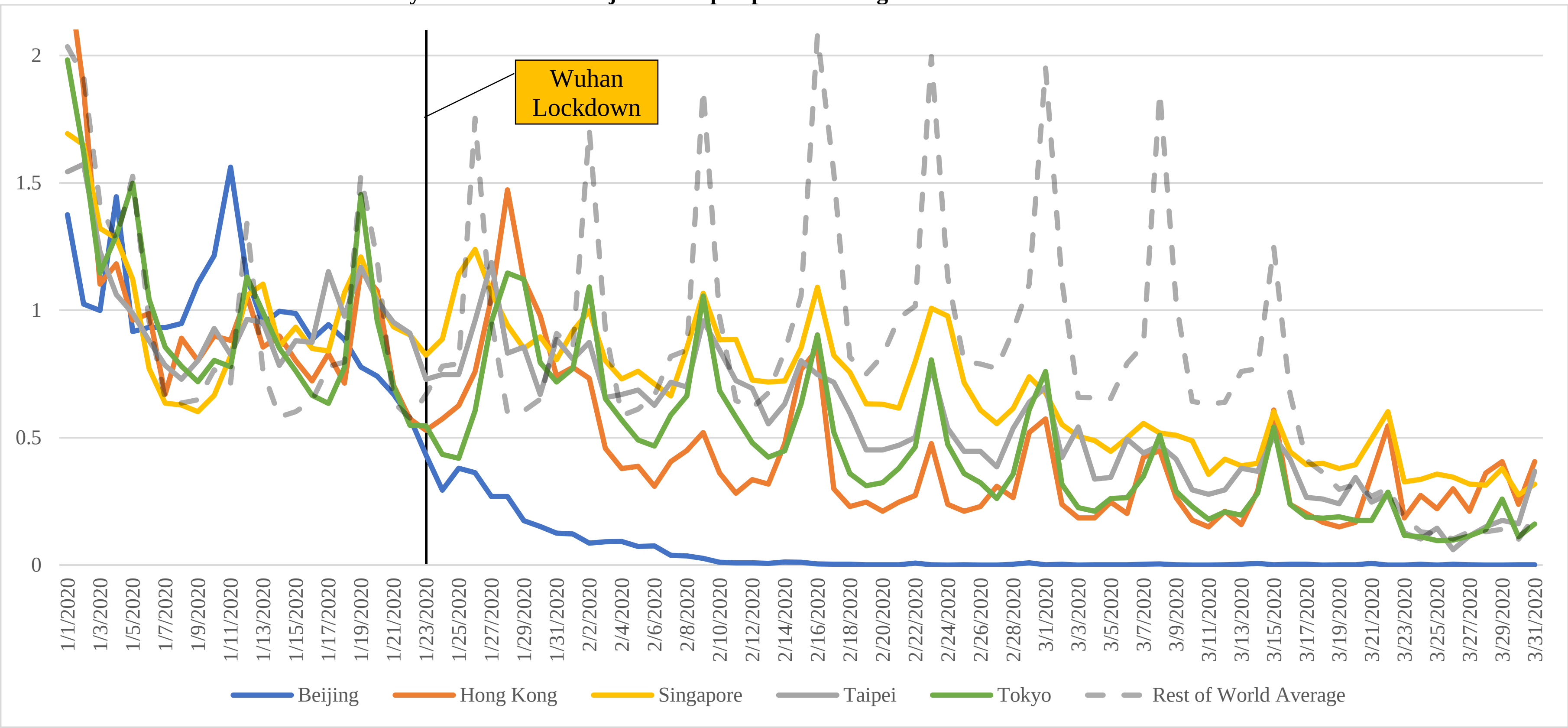


Figure 3: Reviews by room type in London

The figure reports the total daily number of reviews by room type in London between Jan 1, 2020 and Mar 23, 2020. Data is sourced from scraped monthly listings from the Inside Airbnb website.

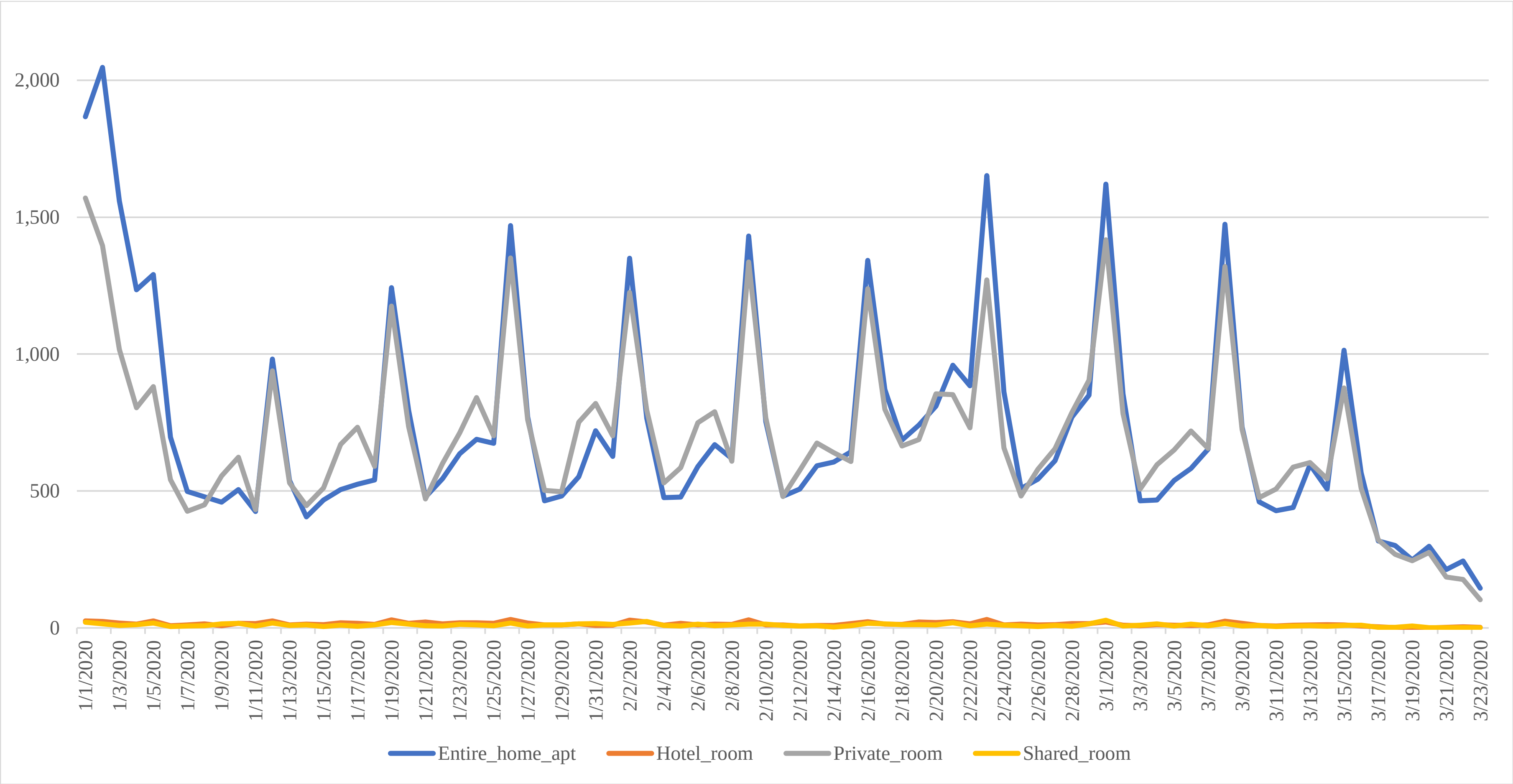


Figure 4: Number of listings by room type in London

The figure reports the total daily number of reviews by room type in London between Jan 2020 and Mar 2020. Data is sourced from scraped monthly listings from the Inside Airbnb website.

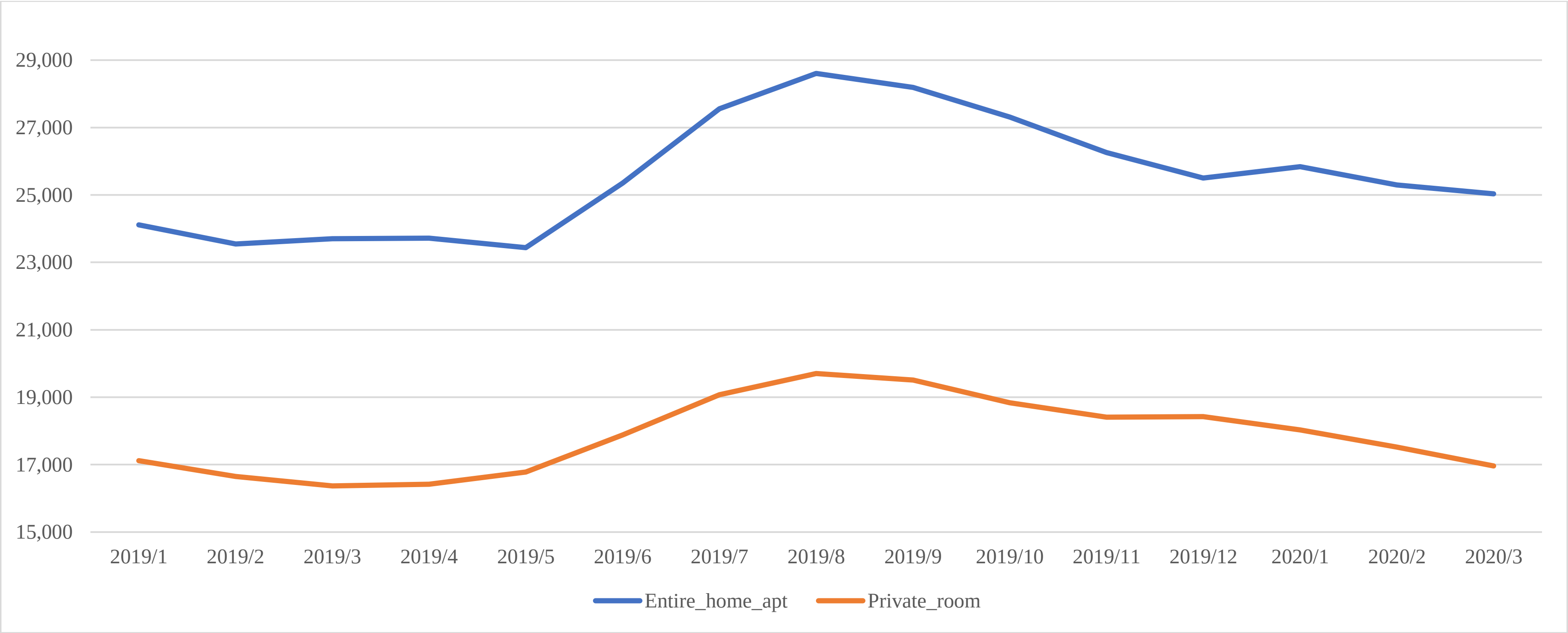


Figure 5: Daily median future booking prices of active listings at different points in time in London

The figure reports the median booking prices in future dates in London from monthly snapshots between Dec 2019 and Mar 2020 for booking dates until 31st July 2020. Data is sourced from scraped monthly listings from the Inside Airbnb website.

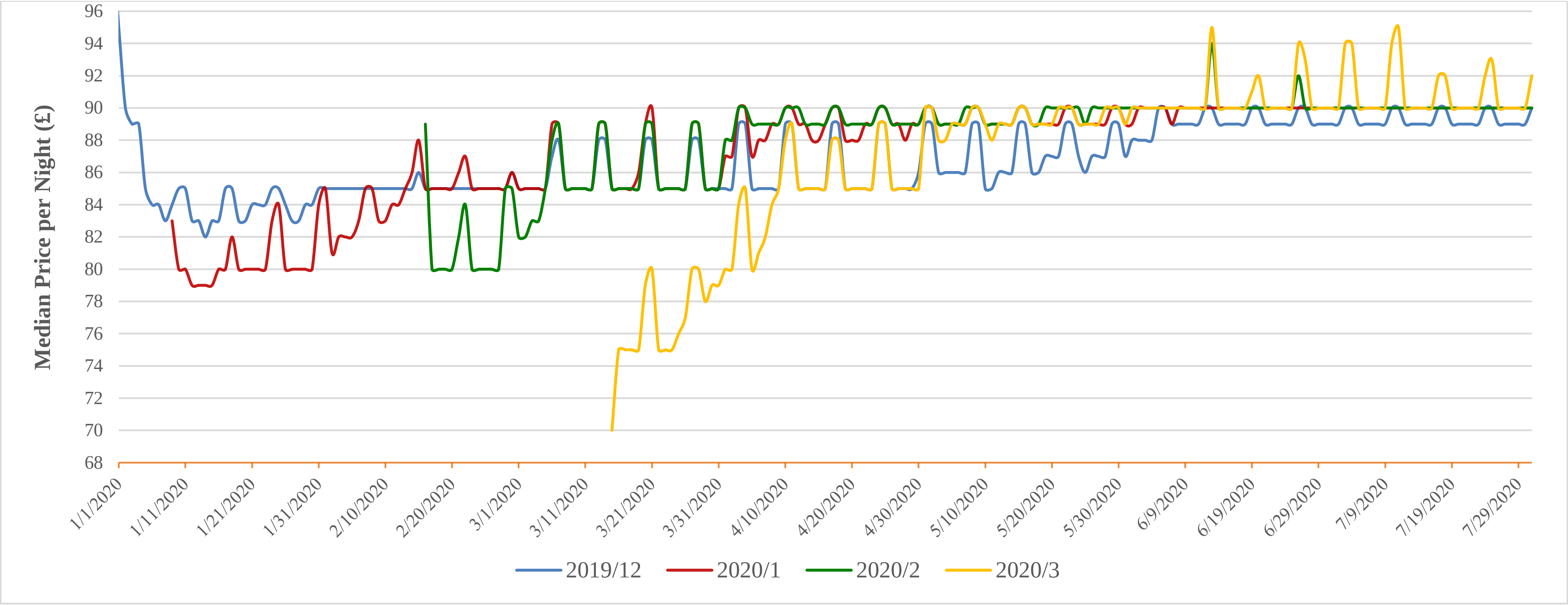


Table 1: Descriptive statistics

This table reports various summary statistics of Airbnb reviews across markets. *Reviews* is the daily number of Airbnb reviews in an Airbnb market less automated cancellation reviews. Details of Airbnb markets are presented in Appendix 1. *Cancel_pct* is the daily number of automated cancellations divided by the daily *Reviews* as a percentage. 2019 Pre is the period from Jan 1, 2019 to Jan 23, 2019. 2019 Post indicates the period from Jan 23, 2019 to Mar 31, 2019. 2020 Pre indicates the period from Jan 1, 2020 to Jan 22, 2020. 2020 Post is the period from Jan 23, 2020 to Mar 31, 2020 (Mar 20, 2020 for *Cancel_pct* due to changes in Airbnb reporting). Panel A reports basic summary statistics for *Reviews*. Panel B reports basic summary statistics for *Cancel_pct*. Panel C reports difference tests of daily average *Reviews* and *Cancel_pct* between the pre- and post-periods, as well as the difference-in-difference between 2019 and 2020. Panel D reports the correlation matrix of key variables. *t*-stats are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Descriptive statistics for *Reviews*

Year	Sample	Mean	Std Dev	Q1	Median	Q3	N
2019	All	351.89	396.07	93	235	455.5	8820
	Pre	343.08	411.47	82	219	436.0	2156
	Post	354.74	390.94	96	240	462.0	6664
2020	All	291.33	358.11	56	166	392.0	8918
	Pre	359.67	405.57	85	223	497.5	2156
	Post	269.54	338.74	49	148	366.0	6762

Panel B: Descriptive statistics for *Cancel_pct*

Year	Sample	Mean	Std Dev	Q1	Median	Q3	N
2019	All	1.77	6.10	0.19	0.81	1.87	8820
	Pre	1.83	8.86	0.00	0.67	1.69	2156
	Post	1.75	4.89	0.24	0.86	1.92	6664
2020	All	2.60	8.39	0.30	1.10	2.57	7840
	Pre	1.68	5.17	0.16	0.76	1.82	2156
	Post	2.95	9.30	0.36	1.25	2.87	5684

Panel C: Difference-in-difference test of Airbnb booking activities

	2019 Pre	2019 Post	2019 Post - Pre	2020 Pre	2020 Post	2020 Post - Pre	Diff-in-Diff
Reviews	343.08	354.74	11.65	359.67	269.54	-90.13***	-101.78***
			(1.19)			(-10.23)	(-7.72)
Cancel_pct	1.83	1.75	-0.08	1.68	2.95	1.27***	1.35***
			(-0.55)			(6.00)	(5.27)

Panel D: Correlation of key variables using 2020 sample

	Correlation	1)	2)	3)	4)	5)	6)	7)
1)	Reviews	1.00						
2)	Cancel_pct	-0.10	1.00					
3)	Post	-0.11	0.04	1.00				
4)	Lockdown	-0.24	0.03	0.21	1.00			
5)	Log(1+NewCase)	-0.23	0.09	0.32	0.70	1.00		
6)	Log(1+NewCase_percapita)	-0.19	0.01	0.16	0.62	0.65	1.00	
7)	Log(1+NewDeaths)	-0.21	0.06	0.20	0.69	0.85	0.67	1.00

Table 2: Reviews and cancellations regression

This table estimates the following full regression and nested versions of:

$$Y_i = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log(1 + NewCase_{i,t-1}) + \beta_4 Treat * Post_j * Lockdown_i + \mu_i + \tau_t + \varepsilon_{it}$$

Where Y_i is either *Reviews*, the daily number of Airbnb reviews (less automated cancellation postings) or *Cancel_pct*, the percentage of cancellations over *Reviews* for Airbnb market *i*. The *Adj* prefix represents adjusted reviews where *Reviews* or *Cancel_pct* are divided by the daily pre-period average (before Jan 23, 2020 for 2020 sample and before Jan 23, 2019 for 2019 sample). *Treat* is a dummy of 1 if the review was made in 2020; 0 otherwise. *Post* is a dummy of 1 if the review was made on or after Jan 23, 2020 (Wuhan lockdown date) for the 2020 sample and on or after Jan 23, 2019 for the 2019 sample. *NewCase* is the prior day's number of new COVID-19 cases at the finest level for market *i*. μ_i are Airbnb market fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. *Lockdown* is a dummy of 1 for after the date of either the start of lockdown orders or travel ban, whichever is earlier; 0 otherwise. Review data is from Inside Airbnb. COVID-19 data is from the John Hopkins University COVID-19 Research Center Github. The sample is from Jan 1, 2019 to Mar 31, 2019 and from Jan 1, 2020 to Mar 31, 2020 (Mar 20, 2020 for *Cancel_pct* and *Adj_Cancel_pct* due to changes in Airbnb reporting of cancellations). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Reviews/adjusted reviews

	(1)	(2)	(3)	(4)	(5)	(6)
Y:	Reviews	Reviews	Reviews	Adj_Reviews	Adj_Reviews	Adj_Reviews
Treat	16.164*	16.215*	16.333*	-0.001	-0.001	-0.001
	(9.200)	(9.371)	(9.362)	(0.017)	(0.018)	(0.017)
Post	1.027	-32.790***	-35.287***	0.017	-0.081***	-0.090***
	(7.904)	(7.535)	(7.387)	(0.020)	(0.018)	(0.018)
Treat*Post	-101.937***	-30.841***	-27.148**	-0.307***	-0.100***	-0.088***
	(12.828)	(10.966)	(10.889)	(0.026)	(0.027)	(0.026)
Treat*Post*NewCase		-41.084***	-23.866***		-0.120***	-0.060***
		(4.640)	(4.806)		(0.005)	(0.005)
Treat*Post*Lockdown			-167.104***			-0.578***
			(22.576)			(0.028)
Constant	554.249***	561.335***	559.417***	1.681***	1.702***	1.695***
	(25.952)	(22.308)	(22.878)	(0.031)	(0.039)	(0.037)
Airbnb Market F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,738	17,738	17,738	17,738	17,738	17,738
R-squared	0.713	0.735	0.741	0.349	0.420	0.447
Adj. R-squared	0.711	0.734	0.740	0.345	0.416	0.444

Panel B: Cancellations as percentage of total reviews/adjusted cancellation percentage

	(1)	(2)	(3)	(4)	(5)	(6)
Y:	Cancel_pct	Cancel_pct	Cancel_pct	Adj_Cancel_pct	Adj_Cancel_pct	Adj_Cancel_pct
Treat	-0.161	-0.159	-0.153	-0.007	-0.005	-0.005
	(0.257)	(0.257)	(0.252)	(0.081)	(0.085)	(0.082)
Post	-0.277	0.177	0.246	0.005	0.298**	0.302***
	(0.240)	(0.220)	(0.212)	(0.124)	(0.116)	(0.115)
Treat*Post	1.473***	0.516*	0.554*	0.787***	0.172	0.204
	(0.338)	(0.302)	(0.296)	(0.161)	(0.144)	(0.142)
Treat*Post*NewCase		0.804***	0.384***		0.517***	0.223**
		(0.146)	(0.104)		(0.102)	(0.090)
Treat*Post*Lockdown			6.663***			4.482***
			(1.195)			(0.580)
Constant	2.445***	2.406***	3.513***	0.223	0.198	0.232
	(0.319)	(0.282)	(0.260)	(0.282)	(0.246)	(0.242)
Airbnb Market F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,660	16,660	16,660	16,660	16,660	16,660
R-squared	0.124	0.137	0.141	0.075	0.100	0.123
Adj. R-squared	0.118	0.132	0.136	0.069	0.094	0.117

Table 3: Explaining Airbnb booking activity sensitivity to COVID-19 risk factors

The table estimates variants of the following regression:

$$Y_i = a + \beta_0 Measure_i + \beta_1 Measure_i * Log\left(1 + NewCase_{i,t-1}\right) + \beta_2 Measure_i * Lockdown_i + \beta_3 Log(1 + NewCase_{i,t-1}) + \beta_4 Lockdown_i + \mu_i + \tau_t + \varepsilon_{it}$$

Where Y_i is either *Adj_Reviews*, the daily number of Airbnb reviews (less automated cancellation postings) or *Adj_Cancel_pct*, the percentage of cancellations over *Reviews* for Airbnb market *i*. The *Adj* prefix represents adjusted reviews where *Reviews* or *Cancel_pct* are divided by the daily pre-period average between Jan 1, 2020 and Jan 23, 2020. *Measure* is either *Wuhan_Distance*, *Mobility_Rec*, *Mobility_Parks*, or *Gov_Stringency*. *Wuhan_Distance* is the distance of an Airbnb market to Wuhan, in thousands of kilometers. *Gov_Stringency* is a daily index of government policy stringency towards COVID-19 lockdown measures (such as school/workplace closures, cancelling public events, and stay-at-home requirements). *Mobility_Rec* is a daily index of mobility trends to retail and recreation locations (such as restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters). *Mobility_Parks* is a daily index of mobility trends to park areas (such as local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens). All *Measure* variables except for *Wuhan_Distance* are standardized. *NewCase* is the prior day's number of new COVID-19 cases at the finest level for market *i*. μ_i are Airbnb market fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. *Lockdown* is a dummy of 1 for after the date of either the start of lockdown orders or travel ban, whichever is earlier; 0 otherwise. Review data is from Inside Airbnb. COVID-19 data is from the John Hopkins University COVID-19 Research Center Github. Mobility measures are from Google COVID-19 community mobility reports. *Government Stringency Index* is from Hale et al. (2020). The sample is from Jan 23, 2020 to Mar 31, 2020 (Mar 20, 2020 for *Adj_Cancel_pct* due to changes in Airbnb reporting of cancellations). For regressions using mobility data the sample starts from Feb 15, 2020 when data availability starts. Panel A reports the correlation statistics for variables. Panel B reports regression results using Wuhan distance. Panel C reports results using mobility or government policy stringency measures interacted with local COVID-19 cases or local lockdown. Panel D reports results using mobility interacted with local COVID-19 cases. Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Wuhan lockdown shock and distance from Wuhan (Jan 23, 2020 to Mar 20, 2020)

		1)	2)	3)	4)	5)	6)	7)	8)
1)	Adj_Reviews	1.00							
2)	Adj_Cancel_pct	-0.27	1.00						
3)	NewCase	-0.32	0.23	1.00					
4)	Lockdown	-0.33	0.33	0.52	1.00				
5)	Wuhan_Distance	0.13	-0.01	-0.19	-0.02	1.00			
6)	Gov_Stringency	-0.42	0.35	0.70	0.66	-0.24	1.00		
7)	Mobility_Rec	0.42	-0.35	-0.67	-0.76	0.13	-0.78	1.00	
8)	Mobility_Parks	0.38	-0.18	-0.41	-0.41	0.09	-0.43	0.63	1.00

Panel B: Wuhan lockdown shock and distance from Wuhan

Y:	(1) Adj_Reviews	(2) Adj_Reviews	(3) Adj_Cancel_pct	(4) Adj_Cancel_pct
Wuhan_Distance		0.072***		0.142
		(0.012)		(0.190)
NewCase	-0.043***	-0.043***	0.072	0.072
	(0.005)	(0.005)	(0.102)	(0.102)
Lockdown	-0.549***	-0.549***	4.221***	4.221***
	(0.024)	(0.024)	(0.545)	(0.545)
Constant	1.524***	0.940***	0.647***	-0.504
	(0.044)	(0.089)	(0.215)	(1.459)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market S.E.	Yes	Yes	Yes	Yes
Observations	6,944	6,944	5,822	5,822
R-squared	0.594	0.594	0.184	0.184
Adj. R-squared	0.588	0.588	0.168	0.168

Panel C: Government stringency and local COVID-19 cases/local lockdown interaction

Y:	(1) Adj_Reviews	(2) Adj_Reviews	(3) Adj_Cancel_pct	(4) Adj_Cancel_pct
Gov_Stringency*NewCase	-0.010**		-0.028	
	(0.004)		(0.147)	
Gov_Stringency*Lockdown		-0.075**		1.123
		(0.037)		(1.072)
Gov_Stringency	-0.147***	-0.151***	1.688***	1.603***
	(0.022)	(0.022)	(0.442)	(0.286)
NewCase	-0.015*	-0.025***	-0.104	-0.138
	(0.008)	(0.006)	(0.071)	(0.100)
Lockdown	-0.328***	-0.247***	2.576***	0.884
	(0.038)	(0.060)	(0.651)	(1.456)
Constant	1.338***	1.338***	2.729***	2.677***
	(0.046)	(0.045)	(0.538)	(0.389)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market S.E.	Yes	Yes	Yes	Yes
Observations	6,944	6,944	5,822	5,822
R-squared	0.604	0.604	0.196	0.197
Adj. R-squared	0.598	0.597	0.181	0.181

Panel D: Mobility and local COVID-19 cases interaction

Y:	(1) Adj_Reviews	(2) Adj_Reviews	(3) Adj_Cancel_pct	(4) Adj_Cancel_pct
Mobility_Rec*NewCase	-0.010***		0.227**	
	(0.003)		(0.100)	
Mobility_Rec	0.319***		-2.520***	
	(0.030)		(0.539)	
Mobility_Parks*NewCase		-0.012***		0.099
		(0.004)		(0.072)
Mobility_Parks		0.144***		-0.487***
		(0.022)		(0.164)
NewCase	-0.023***	-0.053***	-0.027	0.143
	(0.005)	(0.006)	(0.100)	(0.092)
Lockdown	-0.163***	-0.449***	2.361***	4.283***
	(0.036)	(0.028)	(0.614)	(0.628)
Constant	1.372***	1.573***	2.929***	1.048***
	(0.052)	(0.058)	(0.489)	(0.255)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market S.E.	Yes	Yes	Yes	Yes
Observations	4,644	4,594	3,533	3,496
R-squared	0.649	0.633	0.251	0.232
Adj. R-squared	0.641	0.624	0.227	0.208

Table 4: Robustness check with inbound travel bans and local lockdown measures

This table estimates the following full regression and nested versions of:

$$Y_i = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log(1 + NewCase_{i,t-1}) + \beta_4 Treat * Post_j * Inbound\_Ban_{it} + \beta_5 Treat * Post_j * Confinement_i + +\mu_i + \tau_t + \varepsilon_{it}$$

Where Y_i is either *Reviews*, the daily number of Airbnb reviews (less automated cancellation postings) or *Cancel_pct*, the percentage of cancellations over *Reviews* for Airbnb market *i*. The *Adj* prefix represents adjusted reviews where *Reviews* or *Cancel_pct* are divided by the daily pre-period average (before Jan 23, 2020 for 2020 sample and before Jan 23, 2019 for 2019 sample). *Treat* is a dummy of 1 if the review was made in 2020; 0 otherwise. *Post* is a dummy of 1 if the review was made on or after Jan 23, 2020 (Wuhan lockdown date) for the 2020 sample and on or after Jan 23, 2019 for the 2019 sample. *NewCase* is the prior day's number of new COVID-19 cases at the finest level for market *i*. μ_i are Airbnb market fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. *Inbound_Ban* is the percentage of international tourists banned from market *i* on day *t* due to COVID-19 inbound tourist restrictions. The percentage is based on the 2019 (or most recent if 2019 is not available) market share of inbound tourists for the top 10 inbound countries. *Confinement* is a dummy of 1 for after the date of the start of local confinement/lockdown measures; 0 otherwise. Review data is from Inside Airbnb. COVID-19 data is from the John Hopkins University COVID-19 Research Center Github. The sample is from Jan 1, 2019 to Mar 31, 2019 and from Jan 1, 2020 to Mar 31, 2020 (Mar 20, 2020 for *Cancel_pct* and *Adj_Cancel_pct* due to changes in Airbnb reporting of cancellations). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

	(1)	(2)	(3)	(4)
Y:	Reviews	Adj_Reviews	Cancel_pct	Adj_Cancel_pct
Treat	16.345*	-0.001	-0.153	-0.004
	(9.150)	(0.016)	(0.250)	(0.080)
Post	-38.723***	-0.101***	0.446**	0.470***
	(7.173)	(0.017)	(0.206)	(0.109)
Treat*Post	-19.726**	-0.063**	0.137	-0.138
	(9.972)	(0.025)	(0.253)	(0.135)
Treat*Post*NewCase	-26.143***	-0.074***	0.437***	0.283***
	(4.619)	(0.005)	(0.098)	(0.083)
Treat*Post*Inbound_Ban	-137.202***	-0.452***	7.657***	6.007***
	(30.153)	(0.036)	(2.895)	(1.395)
Treat*Post*Confinement	-80.064***	-0.229***	4.876***	2.743***
	(26.562)	(0.034)	(1.778)	(0.751)
Constant	551.993***	1.671***	3.670***	0.372
	(26.701)	(0.031)	(0.342)	(0.331)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes
Observations	17,738	17,738	16,660	16,660
R-squared	0.742	0.446	0.146	0.135
Adj. R-squared	0.741	0.443	0.140	0.129

Table 5: London boroughs reviews and cancellations regression

This table estimates the following base regression and variations of:

$$Y_{b,r} = a + \sum_{w=-3^-}^{w=3^+} (\beta_{w1}\, Week_w + \beta_{w2}\, Week_w * Log\big(1 + NewCase_{b,t-1}\big) + \beta_{w2}\, Week_w * Private_i) + \rho_r + \mu_b + \tau_t + \varepsilon_{bt}$$

Where $Y_{i,r}$ is either Log(1+*Reviews*) or Log(1+*Cancel*). *Reviews* is the total daily number of Airbnb reviews (less automated cancellation postings). *Cancel* is the total daily number of cancellations. Both variables are statistics for London borough *b* and room type *r* (entire home or private room). $Week_w$ are dummies of 1 if the date is in the *w*-th week (seven-day intervals) relative to the week of the first recorded COVID-19 case (week zero) in the borough, zero otherwise. *Week* $w=-3^-$ is a dummy of 1 for days three weeks before week zero. Week $w=3^+$ is a dummy of 1 for days three weeks after week zero. The omitted dummy is for week $w=0$, the week starting from the first recorded COVID-19 case in the borough. The omitted dummy is for the week starting from the first recorded COVID-19 case in the borough. We include further interaction variables to the base regression, *NewCase* and *Private*. *NewCase* is the prior day's number of new COVID-19 cases in borough *b*. *Private* is a dummy of one if the room type is a private room; 0 otherwise. ρ_r are room type fixed effects, μ_b are borough fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. Review and listing data are from Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample comprises London Airbnb reviews from Jan 1, 2020 to Mar 23, 2020 (before the UK lockdown announcement). The *Cancel* sample ends at Mar 20, 2020 as Airbnb stops reporting cancellations after this date. Reviews are matched to listings in the same month to obtain room type. Panel A reports coefficients using *Log(1+Reviews*) as the dependent variable. Panel B reports coefficients using *Log(1+Cancel*) as the dependent variable. Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Log reviews regression

	(1)	(2)	(3)	(4)
	Dependent variable: Log(1+Reviews)			
$Week_{-3-}$	-0.025	-0.026	-0.004	-0.004
	(0.027)	(0.028)	(0.045)	(0.045)
$Week_{-2}$	0.021	0.033	0.059	0.071
	(0.031)	(0.030)	(0.049)	(0.048)
$Week_{-1}$	0.005	0.012	0.006	0.014
	(0.028)	(0.027)	(0.045)	(0.044)
$Week_{1}$	-0.175***	0.022	-0.186***	-0.002
	(0.034)	(0.038)	(0.053)	(0.060)
$Week_{2}$	-0.453***	0.071*	-0.385***	0.034
	(0.059)	(0.041)	(0.070)	(0.065)
$Week_{3+}$	-0.603***	-0.027	-0.634***	-0.196
	(0.081)	(0.108)	(0.095)	(0.139)
$Week_{1}$*NewCase		-0.168***		-0.157***
		(0.030)		(0.050)
$Week_{2}$*NewCase		-0.305***		-0.244***
		(0.032)		(0.043)
$Week_{3+}$*NewCase		-0.283***		-0.209***
		(0.049)		(0.057)
$Week_{-3-}$*Private			-0.043	-0.043
			(0.062)	(0.063)
$Week_{-2}$*Private			-0.077	-0.077
			(0.059)	(0.060)
$Week_{-1}$*Private			-0.003	-0.003
			(0.055)	(0.055)
$Week_{1}$*Private			0.021	0.047
			(0.066)	(0.085)
$Week_{2}$*Private			-0.135	0.074
			(0.112)	(0.108)
$Week_{3+}$*Private			0.061	0.340
			(0.156)	(0.206)
$Week_{1}$*NewCase*Private				-0.023
				(0.067)
$Week_{2}$*NewCase*Private				-0.122
				(0.075)
$Week_{3+}$*NewCase*Private				-0.149
				(0.093)
Constant	1.290***	1.291***	1.273***	1.274***
	(0.065)	(0.066)	(0.066)	(0.068)
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	5,412	5,412	5,412	5,412
R-squared	0.819	0.825	0.819	0.825
Adj. R-squared	0.818	0.823	0.818	0.823

Panel B: Log cancellations

	(1)	(2)	(3)	(4)
	Dependent variable: Log(1+Cancel)			
$Week_{-3-}$	-0.011	-0.011	-0.011	-0.011
	(0.026)	(0.026)	(0.031)	(0.031)
$Week_{-2}$	-0.014	-0.016	0.001	-0.001
	(0.027)	(0.028)	(0.037)	(0.037)
$Week_{-1}$	-0.018	-0.019	-0.005	-0.006
	(0.025)	(0.024)	(0.036)	(0.036)
$Week_{1}$	0.054*	0.024	0.031	-0.018
	(0.027)	(0.037)	(0.034)	(0.055)
$Week_{2}$	0.081**	-0.025	0.025	-0.129**
	(0.034)	(0.041)	(0.049)	(0.060)
$Week_{3+}$	0.131***	0.015	-0.023	-0.128**
	(0.049)	(0.065)	(0.052)	(0.055)
$Week_{1}$*NewCase		0.027		0.043
		(0.026)		(0.038)
$Week_{2}$*NewCase		0.069***		0.101***
		(0.024)		(0.032)
$Week_{3+}$*NewCase		0.061**		0.055**
		(0.026)		(0.026)
$Week_{-3-}$*Private			-0.001	-0.001
			(0.030)	(0.030)
$Week_{-2}$*Private			-0.030	-0.030
			(0.040)	(0.040)
$Week_{-1}$*Private			-0.025	-0.025
			(0.044)	(0.044)
$Week_{1}$*Private			0.047	0.084
			(0.052)	(0.070)
$Week_{2}$*Private			0.112*	0.209***
			(0.059)	(0.078)
$Week_{3+}$*Private			0.307***	0.286***
			(0.071)	(0.100)
$Week_{1}$*NewCase*Private				-0.033
				(0.046)
$Week_{2}$*NewCase*Private				-0.064
				(0.044)
$Week_{3+}$*NewCase*Private				0.013
				(0.045)
Constant	0.047	0.049	0.053	0.055
	(0.040)	(0.040)	(0.043)	(0.044)
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	5,280	5,280	5,280	5,280
R-squared	0.296	0.298	0.300	0.302
Adj. R-squared	0.290	0.291	0.293	0.294

Table 6: Active listings volume regression

The table reports diff-in-diff coefficient estimate results for individual Airbnb active listings in London boroughs for monthly listings snapshots:

$$
\begin{aligned}
Log(N\_Active_{b,r}) &\\
&= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\ (1 + Newcase_{b,t-1}) + \beta_4 Treat \\
&* Private_i + \beta_5 Post_j * Private_i + \beta_6 Treat * Post_j * Private_i + \beta_7 Treat * Post_j * Private_i \\
&* Log\big(1 + Newcase_{b,t-1}\big) + \rho_r + \mu_b + \tau_t + \varepsilon_{bt}
\end{aligned}
$$

Where *N_Active* is the number of active listings in borough b for room type *r* (entire home or private room). A listing is active if there was a review for it in the prior three months. *Treat* is a dummy of 1 if the listing is made in 2020; 0 otherwise. *Post* is a dummy of 1 if the listing is made on or after Jan 31, 2020 (first COVID-19 case in the United Kingdom) for the 2020 sample and after Jan 31, 2019 for the 2019 sample. *Private* is a dummy of one if the room type is a private room; 0 otherwise. *NewCase* is the prior day's number of new COVID-19 cases in borough b. ρ_r are room type fixed effects, μ_i are Borough fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. Listings data is from Airbnb as data scraped by Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample comprises London Airbnb listing monthly snapshots between Jan 1, 2019 to Mar 23, 2019 and from Jan 1, 2020 to Mar 23, 2020 (before the UK lockdown announcement). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

	(1)	(2)	(3)	(4)
Y:	Log(N_Active)	Log(N_Active)	Log(N_Active)	Log(N_Active)
Treat	0.077	0.077	0.069	0.069
	(0.064)	(0.065)	(0.076)	(0.076)
Post	-0.043***	-0.043***	-0.059	-0.059
	(0.009)	(0.009)	(0.045)	(0.045)
Treat*Post	-0.000	0.043	0.029	0.083
	(0.013)	(0.115)	(0.046)	(0.127)
Treat*Post*NewCase		-0.029		-0.044
		(0.077)		(0.083)
Treat*Private			0.016	0.016
			(0.091)	(0.092)
Post*Private			0.032	0.032
			(0.090)	(0.090)
Treat*Post*Private			-0.058	-0.080
			(0.091)	(0.098)
Treat*Post*Private*NewCase				0.029
				(0.053)
Constant	4.256***	4.252***	4.264***	4.261***
	(0.202)	(0.202)	(0.203)	(0.204)
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.911	0.911	0.911	0.911
Adj. R-squared	0.901	0.901	0.901	0.900

Table 7: London calendar price adjustment regression

The table reports regression coefficient estimates for the following regression:

$$
\begin{aligned}
Log(Cal\_Gap_{i,t,t+k}) \; &= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\big(1 + NewCase_{b,t-1}\big) \\
&+ \beta_4 Treat * Private_i + \beta_5 Post_j * Private_i + \beta_6 Treat * Post_j * Private_i \\
&+ \beta_7 Treat * Post_j * Private_i * Log\big(1 + NewCase_{b,t-1}\big) + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}
\end{aligned}
$$

Where *Cal_Gap* is the booking price for the date *k* days ahead of snapshot *t*, divided by the same date's booking price in the previous month's snapshot for listing *i*. We remove the listing if the prior month's room type is different. We use *k* for between 0 and 6 (first week's booking price schedule for the month's snapshot). *Treat* is a dummy of 1 if the listing is made in 2020; 0 otherwise. *Post* is a dummy of 1 if the listing is made on or after Jan 31, 2020 (first COVID-19 case in the United Kingdom) for the 2020 sample and on or after Jan 31, 2019 for the 2019 sample. *Private* is a dummy of one if the room type is a private room; 0 otherwise. *NewCase* is the prior day's number of new COVID-19 cases in borough *b*. $X_{h,i}$ represents individual listing level characteristics including the experience of the host, whether the host is a superhost, the property type (apartment, house, etc.), number of people the listing accommodates, number of beds and baths and a host of amenity dummies. ρ_r are room type fixed effects, μ_i are borough fixed effects, and τ_t represents event time t+*k (k=0 to 6 days)* fixed effects, the day-of-week fixed effects and the month-of-year fixed effects. Calendar schedule and listings data are from Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample comprises London Airbnb listing monthly snapshots between Jan 1 to Mar 23, 2019 and from Jan 1 to Mar 23, 2020 (before the UK lockdown announcement). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

	(1) Log(Cal_Gap)	(2) Log(Cal_Gap)	(3) Log(Cal_Gap)	(4) Log(Cal_Gap)
Treat	0.021***	0.021***	0.033***	0.033***
	(0.005)	(0.005)	(0.006)	(0.006)
Post	0.032***	0.042***	0.052***	0.062***
	(0.008)	(0.007)	(0.009)	(0.008)
Treat*Post	-0.061***	-0.041***	-0.084***	-0.059***
	(0.007)	(0.008)	(0.008)	(0.009)
Treat*Post*NewCase		-0.023***		-0.030***
		(0.005)		(0.007)
Treat*Private			-0.027***	-0.027***
			(0.007)	(0.007)
Post*Private			-0.046***	-0.046***
			(0.009)	(0.009)
Treat*Post*Private			0.052***	0.041***
			(0.010)	(0.010)
Treat*Post*Private*NewCase				0.015*
				(0.008)
Constant	-0.037	-0.037	-0.051	-0.050
	(0.033)	(0.033)	(0.033)	(0.033)
Listings Characteristics	Yes	Yes	Yes	Yes
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	1,438,319	1,438,319	1,438,319	1,438,319
R-squared	0.072	0.074	0.073	0.076
Adj. R-squared	0.072	0.074	0.073	0.076

Table 8: London average calendar price adjustment regression

The table reports regression coefficient estimates for the following regression:

$$Log(CalGapAvg_{i,t+j,t+k}) = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * \mathrm{Log}(1 + NewCase_{b,t-1}) + \beta_4 Treat * Private_i + \beta_5 Post_j * Private_i + \beta_6 Treat * Post_j * Private_i + \beta_7 Treat * Post_j * Private_i * Log(1 + NewCase_{b,t-1}) + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}$$

Where *CalGapAvg* is the average *Cal_Gap* between $t+j$ and $t+k$. *Cal_Gap* is booking price date *x (x=j,…, k)k* days ahead of snapshot *t*, divided by the booking price on the same day of the previous month for listing *i*. We remove the listing if the prior month's room type is different. We use four windows: t+0 to t+29, t+30 to t+59, t+60 to t+89 and t+90 to t+119 to examine the time-varying price adjustment in the next few months. *Post* is a dummy of 1 if the listing is made on or after Jan 31, 2020 (first COVID-19 case in the United Kingdom) for the 2020 sample and on or after Jan 31, 2019 for the 2019 sample. *Private* is a dummy of 1 if the room type is a private room; 0 otherwise. *NewCase* is the prior day's number of new COVID-19 cases in borough *b*. $X_{h,i}$ represents individual listing level characteristics including the experience of the host, whether the host is a superhost, the property type (apartment, house, etc.), number of people the listing accommodates, number of beds and baths and a host of amenity dummies. ρ_r are room type fixed effects, μ_i are borough fixed effects, and τ_t listing snapshot day-of-week and month-of-year fixed effects. The sample comprises London Airbnb listing monthly snapshots between Jan 1 to Mar 23, 2019 and from Jan 1 to Mar 23, 2020 (before the UK lockdown announcement). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Y: $Log(Cal\_GapAvg_{i,t+j,t+k})$	(1) t+0 to t+29	(2) t+30 to t+59	(3) t+60 to t+89	(4) t+90 to t+119
Treat	0.034***	0.013*	0.008	0.015**
	(0.008)	(0.007)	(0.007)	(0.007)
Post	0.061***	0.032***	0.023***	0.014*
	(0.009)	(0.008)	(0.007)	(0.007)
Treat*Post	-0.121***	-0.059***	-0.029**	-0.023
	(0.019)	(0.016)	(0.014)	(0.015)
Treat*Post* $NewCase_{t-1}$	0.004	-0.001	-0.003	-0.002
	(0.006)	(0.004)	(0.003)	(0.003)
Treat*Private	-0.023***	-0.008**	-0.010***	-0.008**
	(0.005)	(0.003)	(0.004)	(0.003)
Post*Private	-0.036***	-0.020***	-0.020***	-0.018***
	(0.006)	(0.004)	(0.003)	(0.003)
Treat*Post*Private	0.034***	0.016***	0.019***	0.020***
	(0.006)	(0.004)	(0.004)	(0.005)
Treat*Post*Private*$NewCase_{t-1}$	0.014***	0.012***	0.007***	0.004**
	(0.004)	(0.002)	(0.002)	(0.002)
Constant	-0.019	-0.005	-0.008	0.002
	(0.019)	(0.011)	(0.008)	(0.008)
Listings Characteristics	Yes	Yes	Yes	Yes
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	211,346	210,936	205,120	204,662
R-squared	0.062	0.017	0.008	0.010
Adj. R-squared	0.061	0.016	0.006	0.009

Table 9: London calendar price adjustment with professional host interaction regression

The table reports regression coefficient estimates for the following regression:

$$
\begin{aligned}
Log(Cal\_Gap_{i,t,t+k}) \\
&= a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\big(1 + NewCase_{b,t-1}\big) + \beta_4 Treat \\
&\quad * Private_i + \beta_5 Post_j * Pro_i + \beta_6 Treat * Post_j * Pro_i \ + \beta_7 Treat * Post_j * Pro_i \\
&\quad * Log\big(1 + NewCase_{b,t-1}\big) + \beta_8 * Pro + \gamma X_{h,i} + \rho_r + \mu_i + \tau_t + \varepsilon_{it}
\end{aligned}
$$

Where *Cal_Gap* is the booking price for the date *k* days ahead of snapshot *t*, divided by the same date's booking price in the previous month's snapshot for listing *i*. We remove the listing if the prior month's room type is different. We use *k* for between 0 and 6. *Treat* is a dummy of 1 if the listing is made in 2020; 0 otherwise. *Post* is a dummy of 1 if the listing is made on or after Jan 31, 2020 (first COVID-19 case in the United Kingdom) for the 2020 sample and on or after Jan 31, 2019 for the 2019 sample. *Pro* is a dummy of one if the host has multiple listings; 0 otherwise. *NewCase* is the prior day's number of new COVID-19 cases in borough b. $X_{h,i}$ represents individual listing level characteristics including the experience of the host, whether the host is a superhost, the property type (apartment, house, etc.), number of people the listing accommodates, number of beds and baths and a host of amenity dummies. ρ_r are room type fixed effects, μ_i are borough fixed effects, and τ_t represents event time t+*k (k=0 to 6 days)* fixed effects, the day-of-week fixed effects and the month-of-year fixed effects. Calendar schedule and listings data are from Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample comprises London Airbnb listing monthly snapshots between Jan 1 to Mar 23, 2019 and from Jan 1 to Mar 23, 2020 (before the UK lockdown announcement). Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively. In Column 3, *a, b, c* denote that the coefficient for the private room sample is statistically different to the same coefficient for the entire room sample using a chi-squared test at the 1, 5 and 10 percent level, respectively.

	(1) Log(Cal_Gap)	(2) Log(Cal_Gap)	(3) Log(Cal_Gap)
Treat	0.022***	0.036***	0.007**a
	(0.004)	(0.006)	(0.003)
Post	0.027***	0.044***	0.009**a
	(0.005)	(0.005)	(0.004)
Treat*Post	-0.037***	-0.061***	-0.005*a
	(0.005)	(0.005)	(0.003)
Treat*Post*NewCase	-0.003	-0.002	-0.005**
	(0.002)	(0.003)	(0.002)
Treat*Pro	-0.004	-0.005	-0.005
	(0.009)	(0.012)	(0.007)
Post*Pro	0.024***	0.023**	0.021***
	(0.008)	(0.011)	(0.006)
Treat*Post*Pro	-0.005	0.005	-0.015**
	(0.009)	(0.012)	(0.006)
Treat*Post*Pro*NewCase	-0.036***	-0.044***	-0.027***c
	(0.006)	(0.007)	(0.007)
Constant	-0.012	-0.023	0.002
	(0.033)	(0.062)	(0.038)
Sample	Full	Entire Homes	Private Rooms
Listings Characteristics	Yes	Yes	Yes
Borough F.E.	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes
Observations	1,438,319	839,790	598,529
R-squared	0.084	0.083	0.075
Adj. R-squared	0.083	0.083	0.075

Internet Appendix Table IA1: Robustness using alternative definition of key variables

This table uses alternative specifications of Equation 1's regression. Panel A uses NewCase_percapita as an explanatory variable rather than *NewCase*. *NewCase_percapita* is defined as the logarithm of 1 plus the number of daily new cases per 1,000 population in the prior day for the Airbnb market. Panel B reports regression using *NewDeaths*, which is defined as the logarithm of the number of new deaths due to COVID-19 in the prior day. Panel C reports regression using total number of cancellations (Columns 1 to 3) and total number of cancellations adjusted for the pre-period average (Columns 4 to 6) as the dependent variable. The sample is from Jan 1, 2019 to Mar 31, 2019 and from Jan 1, 2020 to Mar 31, 2020 (Mar 20, 2020 for *Cancel_pct* and *Adj_Cancel_pct* due to changes in Airbnb reporting of cancellations).

Panel A: Using alternative specification for new cases per 1,000 population

	(1)	(2)	(3)	(4)
Y:	Reviews	Adj_Reviews	Cancel_pct	Adj_Cancel_pct
Treat	16.405*	-0.001	-0.159	-0.005
	(9.349)	(0.017)	(0.257)	(0.080)
Post	-25.264***	-0.065***	0.050	0.217*
	(7.304)	(0.019)	(0.226)	(0.112)
Treat*Post	-48.980***	-0.143***	0.860***	0.392***
	(11.616)	(0.027)	(0.316)	(0.137)
Treat*Post*NewCase_percapita	-910.839**	-1.942***	42.905	13.609
	(421.502)	(0.497)	(27.385)	(18.233)
Treat*Post*Lockdown	-217.985***	-0.721***	6.741***	4.968***
	(27.744)	(0.028)	(1.098)	(0.780)
Constant	555.679***	1.686***	2.496***	0.252
	(24.695)	(0.033)	(0.294)	(0.254)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes
Observations	17,738	17,738	16,660	16,660
R-squared	0.738	0.438	0.147	0.120
Adj. R-squared	0.736	0.435	0.141	0.114

Panel B: Using alternative specification for new deaths

	(1)	(2)	(3)	(4)
Y:	Reviews	Adj_Reviews	Cancel_pct	Adj_Cancel_pct
Treat	16.388*	-0.001	-0.166	-0.010
	(9.425)	(0.017)	(0.264)	(0.077)
Post	-26.759***	-0.069***	0.003	0.204*
	(7.262)	(0.019)	(0.221)	(0.111)
Treat*Post	-45.970***	-0.134***	0.892***	0.376***
	(11.495)	(0.027)	(0.307)	(0.131)
Treat*Post*NewDeaths	-22.222**	-0.062***	-0.025	0.092
	(9.567)	(0.006)	(0.165)	(0.115)
Treat*Post*Lockdown	-210.249***	-0.673***	0.150	-0.251
	(24.915)	(0.026)	(0.402)	(0.300)
Constant	558.221***	1.693***	2.389***	0.246
	(23.560)	(0.036)	(0.275)	(0.257)
Airbnb Market F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes
Observations	17,738	17,738	17,738	17,738
R-squared	0.739	0.441	0.110	0.057
Adj. R-squared	0.737	0.438	0.105	0.051

Panel C: Total cancellations and adjusted total cancellations instead of *Cancel_pct*

	(1)	(2)	(3)	(4)	(5)	(6)
Y:	Cancel	Cancel	Cancel	Adj_Cancel	Adj_Cancel	Adj_Cancel
Treat	0.355*	0.355*	0.357*	-0.003	-0.003	-0.003
	(0.208)	(0.208)	(0.207)	(0.061)	(0.061)	(0.061)
Post	0.255	0.330**	0.366**	0.158**	0.168**	0.168**
	(0.176)	(0.164)	(0.163)	(0.074)	(0.076)	(0.075)
Treat*Post	0.521*	0.363	0.366	0.197*	0.177*	0.180*
	(0.288)	(0.259)	(0.258)	(0.103)	(0.106)	(0.106)
Treat*Post*NewCase		0.133*	0.140*		0.017	-0.017
		(0.073)	(0.082)		(0.024)	(0.027)
Treat*Post*Lockdown			0.018			0.520*
			(0.670)			(0.305)
Constant	6.757***	6.750***	7.307***	0.751***	0.750***	0.754***
	(0.873)	(0.884)	(0.879)	(0.113)	(0.112)	(0.111)
Airbnb Market F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,660	16,660	16,660	16,660	16,660	16,660
R-squared	0.675	0.675	0.668	0.075	0.075	0.076
Adj. R-squared	0.672	0.673	0.666	0.069	0.069	0.070

Internet Appendix Table IA2: Descriptive statistics of sensitivity factors

This table provides summary statistics for COVID-19 effect sensitivity factors that we use in Table 3 Table 3. *Wuhan_Distance* is the distance of an Airbnb market to Wuhan, in thousands of kilometers. *Gov_Stringency* is a daily index of government policy stringency towards COVID-19 lockdown measures such as school/workplace closing, cancelling public events, stay at home requirements, etc, obtained from Hale et al. (2020). *Mobility_Rec* is a daily index of mobility trends to retail and recreation locations like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. *Mobility_Parks* is a daily index of mobility trends to park areas like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. The mobility data is available from Feb 15, 2020. Mobility measures are from Google COVID-19 community mobility reports. Variables are displayed in raw form. We also include the country average of *Gov_Stringency, Mobility_Rec, and Mobility_Parks* for easy reference.

Variable	Mean	Std. Dev.	Min	Max	Obs
Wuhan_Distance	9.34	2.76	0.54	19.65	6,944
Gov_Stringency	27.67	29.07	0.00	100.00	6,944
Mobility_Rec	-21.25	31.81	-96.00	87.00	4,644
Mobility_Parks	-5.81	38.44	-93.00	202.00	4,594

Internet Appendix Table IA3: Runs test for first COVID-19 cases in each London borough

It is a legitimate concern that outbreaks of COVID-19 may be non-random if initial spread is by close contact (i.e. community transmission). As such, we may expect the first COVID-19 cases in each borough to be preceded by the first COVID-19 cases in boroughs within the same region or adjacent boroughs. To test this hypothesis, we conduct a runs test using a time series of dummies denoting whether the first case in a borough was immediately preceded by a first case in a borough in the same region (North, South, East, West or Inner London), zero otherwise. We also use an alternative dummy specification for if the prior outbreak was in an adjacent borough. The table reports the number of runs, the *z*-statistic and the critical *p*-values of the runs tests with the null that the series of dummies for each specification are random. See Appendix 2 for the first case dates in each London borough and borough regions. The COVID-19 cases data are from coronavirus.data.gov.uk.

Runs test variable	Number of Runs	*z*-statistics	*p*-value	N
Prior first case outbreak in borough in same region	13	-1.37	0.17	32
Prior first case outbreak adjacent to borough	11	-0.50	0.62	32

Internet Appendix Table IA4: London reviews and cancellations diff-in-diff regression

The table estimate the following regression in Column 2 and nested version in Column 1:

$$Y_{b,r} = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log(1 + NewCase_{b,t-1}) + \rho_r + \mu_b + \tau_t + \varepsilon_{b,t}$$

and estimates the following regression in Column 4 and nested version in Column 3:

$$\begin{aligned} Y_{b,r} = a + \beta_0 Treat + \beta_1 Post_j + \beta_2 Treat * Post_j + \beta_3 Treat * Post_j * Log\,(1 + NewCase_{b,t-1}) + \beta_4 Treat * Private \\ + \beta_5 Post_j * Private + \beta_6 Treat * Post_j * Private + \beta_7 Treat * Post_j * Private \\ * Log(1 + NewCase_{b,t-1}) + \rho_r + \mu_b + \tau_t + \varepsilon_{b,t} \end{aligned}$$

Where $Y_{i,r}$ is either *Adj_Reviews* or *Adj_Cancel_pct*. *Reviews* is the total daily number of Airbnb reviews (less automated cancellation postings) or *Cancel_pct*, the percentage of cancellations over *Reviews* for London borough *b* and room type *r* (entire home or private room). The *Adj* prefix represents adjusted reviews where *Reviews* or *Cancel_pct* are divided by the daily pre-period average (in Jan 2020 for 2020 sample and in Jan 2019 for 2019 sample). *Treat* is a dummy of 1 if the review was made in 2020; 0 otherwise. *Post* is a dummy of 1 if the review was made on after Jan 31, 2020 (first COVID-19 case in United Kingdom) for the 2020 sample and after Jan 31, 2019 for the 2019 sample. *Private* is a dummy of one if the room type is a private room; 0 otherwise. *NewCase* is the prior day's number of new COVID-19 cases in borough *b*. ρ_r are room type fixed effects, μ_b are Borough fixed effects, τ_t represent the day-of-week fixed effects and month-of-year fixed effects. Review and listing data are from Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample are London Airbnb reviews from Jan 1 to Mar 23, 2019 and from Jan 1 to Mar 23, 2020 (before the UK lockdown announcement). The *Cancel* sample ends at Mar 20, 2020 as Airbnb stops reporting cancellations after this date. Reviews are matched to listings in the same month to obtain room type. Panel A reports results for *Adj_Reviews* and Panel B for *Adj_Cancel_pct*. Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively.

Panel A: Adjusted reviews

	(1)	(2)	(3)	(4)
Y:	Adj_Reviews	Adj_Reviews	Adj_Reviews	Adj_Reviews
Treat	-0.006	-0.007	-0.007	-0.007
	(0.009)	(0.009)	(0.012)	(0.012)
Post	0.101**	0.034	0.045	-0.022
	(0.041)	(0.040)	(0.041)	(0.040)
Treat*Post	-0.164***	-0.043	-0.105***	0.015
	(0.025)	(0.027)	(0.037)	(0.039)
Treat*Post*NewCase		-0.244***		-0.242***
		(0.011)		(0.016)
Treat*Private			0.001	0.001
			(0.017)	(0.017)
Post*Private			0.112***	0.112***
			(0.032)	(0.032)
Treat*Post*Private			-0.117**	-0.115**
			(0.048)	(0.053)
Treat*Post*Private*NewCase				-0.003
				(0.021)
Constant	1.657***	1.646***	1.674***	1.663***
	(0.064)	(0.068)	(0.062)	(0.067)
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	10,758	10,758	10,758	10,758
R-squared	0.184	0.208	0.186	0.210
Adj. R-squared	0.181	0.205	0.182	0.206

Panel B: Adjusted cancellation percentage

Y:	(1) Adj_Cancel_pct	(2) Adj_Cancel_pct	(3) Adj_Cancel_pct	(4) Adj_Cancel_pct
Treat	-0.036	-0.035	-0.140	-0.135
	(0.242)	(0.243)	(0.357)	(0.358)
Post	-0.021	0.150	0.239	0.413
	(0.554)	(0.583)	(0.687)	(0.708)
Treat*Post	0.562	0.282	1.068	1.078
	(0.596)	(0.720)	(1.140)	(1.323)
Treat*Post*NewCase		0.621*		-0.053
		(0.370)		(0.544)
Treat*Private			0.205	0.197
			(0.478)	(0.479)
Post*Private			-0.512	-0.512
			(0.556)	(0.556)
Treat*Post*Private			-0.996	-1.575
			(1.179)	(1.295)
Treat*Private*NewCase				1.332***
				(0.503)
Constant	1.082***	1.116***	0.705**	0.737**
	(0.343)	(0.331)	(0.318)	(0.315)
Borough F.E.	Yes	Yes	Yes	Yes
Room type F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Market-Year S.E.	Yes	Yes	Yes	Yes
Observations	9,337	9,337	9,337	9,337
R-squared	0.012	0.013	0.013	0.014
Adj. R-squared	0.008	0.008	0.008	0.009

Internet Appendix Table IA5: London boroughs reviews and cancellations by room type

This table estimates the below regression by room type (entire home or private room) using seemingly unrelated regressions:

$$Y_{b,r} = a + \sum_{w=-3^-}^{w=3^+} (\beta_{w1}\, Week_w + \beta_{w2}\, Week_w * Log\big(1 + NewCase_{b,t-1}\big)) + \mu_b + \tau_t + \varepsilon_{bt}$$

Where $Y_{i,r}$ is either *Log(1+Reviews*) or *Log(1+Cancel*). *Reviews* is the total daily number of Airbnb reviews (less automated cancellation postings). *Cancel* is the total daily number of cancellations. Both variables are for London borough b and room type r. $Week_w$ are dummies of 1 if the date is in the w-th week (seven-day intervals) relative to the week of the first recorded COVID-19 case (week zero) in the borough, zero otherwise. *Week* $w=-3^-$ is a dummy of 1 for days three weeks before week zero. Week $w=3^+$ is a dummy of 1 for days three weeks after week zero. The omitted dummy is for week $w=0$, the week starting from the first recorded COVID-19 case in the borough. The omitted dummy is for the week starting from the first recorded COVID-19 case in the borough. *NewCase* is the prior day's number of new COVID-19 cases in borough b. μ_b are borough fixed effects, and τ_t represent the day-of-week fixed effects and month-of-year fixed effects. Review and listing data are from Inside Airbnb. Daily COVID-19 cases at the borough level are from coronavirus.data.gov.uk. The sample comprises London Airbnb reviews from Jan 1, 2020 to Mar 23, 2020. The *Cancel* sample ends at Mar 20, 2020 as Airbnb stops reporting cancellations after this date. Panel A reports coefficients using Log(1+*Reviews*) as the dependent variable. Panel B reports coefficients using Log(1+*Cancel*) as the dependent variable. Standard errors are in parentheses. ***, **, * signifies statistical significance at the 1, 5 and 10 percent level, respectively. *a, b, c* denote that the coefficient for the private room sample is statistically different to the same coefficient for the entire room sample using a chi-squared test at the 1, 5 and 10 percent level, respectively.

Panel A: Reviews regression by room type

	(1)	(2)	(3)	(4)
Y:	Log(1+Reviews)	Log(1+ Reviews)	Log(1+Reviews)	Log(1+Reviews)
$Week_{-3-}$	-0.066	0.016	-0.062	0.010
	(0.040)	(0.033)	(0.043)	(0.033)
$Week_{-2}$	0.016	0.025	0.033	0.032
	(0.047)	(0.036)	(0.046)	(0.036)
$Week_{-1}$	-0.026	0.035	-0.015	0.040
	(0.046)	(0.031)	(0.044)	(0.030)
$Week_{1}$	-0.168***	-0.183***	0.065	-0.022
	(0.056)	(0.039)	(0.059)	(0.048)
$Week_{2}$	-0.365***	-0.540***	0.116**	0.026
	(0.075)	(0.086)	(0.055)	(0.060)
$Week_{3+}$	-0.531***	-0.675***	-0.081	0.028
	(0.105)	(0.122)	(0.158)	(0.133)
$Week_{1}$*NewCase			-0.199***	-0.137***
			(0.048)	(0.036)
$Week_{2}$*NewCase			-0.281***	-0.328***
			(0.043)	(0.046)
$Week_{3+}$*NewCase			-0.217***	-0.350***
			(0.063)	(0.065)
Constant	1.342***	1.490***	1.335***	1.499***
	(0.049)	(0.037)	(0.053)	(0.037)
Sample	Entire Homes	Private Rooms	Entire Homes	Private Rooms
Borough F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	2,706	2,706	2,706	2,706
R-squared	0.870	0.863	0.874	0.870
Adj. R-squared	0.868	0.860	0.872	0.868

Panel B: Host cancellations regression by room type

	(1)	(2)	(3)	(4)
Y:	Log(1+Cancel)	Log(1+Cancel)	Log(1+Cancel)	Log(1+Cancel)
$Week_{-3-}$	-0.036	0.014	-0.036	0.014
	(0.038)	(0.038)	(0.038)	(0.037)
$Week_{-2}$	-0.026	-0.002	-0.029	-0.003
	(0.039)	(0.038)	(0.040)	(0.038)
$Week_{-1}$	-0.022	-0.013	-0.024	-0.014
	(0.037)	(0.033)	(0.037)	(0.032)
$Week_{1}$	0.032	0.076*	-0.001	0.049
	(0.035)	(0.042)	(0.055)	(0.049)
$Week_{2}$	0.018	0.144****b*	-0.093	0.044*c*
	(0.052)	(0.037)	(0.060)	(0.042)
$Week_{3+}$	0.021	0.241****a*	-0.051	0.081
	(0.050)	(0.047)	(0.047)	(0.091)
$Week_{1}$*NewCase			0.030	0.024
			(0.039)	(0.034)
$Week_{2}$*NewCase			0.073**	0.065**
			(0.034)	(0.032)
$Week_{3+}$*NewCase			0.036	0.086**
			(0.022)	(0.037)
Constant	0.010	-0.027	0.013	-0.026
	(0.044)	(0.037)	(0.045)	(0.037)
Sample	Entire Homes	Private Rooms	Entire Homes	Private Rooms
Borough F.E.	Yes	Yes	Yes	Yes
Weekday and Month F.E.	Yes	Yes	Yes	Yes
Borough-Room Type-Year S.E.	Yes	Yes	Yes	Yes
Observations	2,640	2,640	2,640	2,640
R-squared	0.425	0.203	0.427	0.205
Adj. R-squared	0.415	0.188	0.416	0.190