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ABSTRACT

Dual Circulation and Population Mobility during the Pandemic in China*

We use high-frequency data from location-based mobile phone records to measure domestic air travel patterns of the Chinese population during the Covid-19 pandemic. The travel and tourism industry is a key driver of China's domestic economy and data from this industry helps serve as an objective proxy for domestic economic activity during the pandemic. Our results show that except for some periods of intense mobility restrictions, relative to travel patterns in 2019, mobility in fact increased in China from mid-2020 onwards. This increase in domestic air travel is likely due to a combination of factors: China's control and management of the Delta variant, China's new "dual circulation" development paradigm, and a pent-up demand for international travel that is not permitted.

JEL Classification: C31, I12, I18, R11, R41

Keywords: China, COVID-19, dual circulation, mobile phone data, mobility

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1 Introduction

Many economies around the world experienced severe downturns in 2020 following the outbreak of the Novel Coronavirus. Millions of people lost their jobs or had their wages cut. Millions of workers were also put on government-supported job retention schemes as parts of the economy, such as tourism and hospitality, came to a near standstill. In China, which was the first country to experience a large-scale Covid-19 outbreak in early 2020, there were also large disruptions to peoples' lives and the economy.

Yet, the only major economy to grow in 2020 was China. It registered a growth of 2.3%. Having life return to normal is a stark turnaround from the first half of 2020 and there are some suspicions that this is part of a coronavirus narrative engineered by the Chinese authorities. The relatively low death rate in the epicenter of China compared to some other Western countries such as Italy and Spain has raised doubts from a number of researchers and the media regarding the real death toll and severity of the crisis. Indeed, such suspicions have motivated researchers to use tools such as Benford's law, a commonly applied technique for the detection of data manipulation and fraud, to check if the Covid-19 case numbers in China are reliable (Koch and Okamura, 2020; Farhadi, 2021). These studies show that China's Covid-19 statistics satisfy Benford's law.

In terms of China's economic resilience during the pandemic, there has been considerably less attention placed on the fact that the Chinese government in 2020 adopted a newly introduced "dual circulation" development paradigm. This was an attempt to reduce reliance on the external sector due to the complexities and risks surrounding recovery from the pandemic shock and concerns regarding tensions in international relations (Huang et al., 2021a). The contribution of the dual circulation strategy in helping the Chinese economy recover quickly from the initial major outbreak of the Novel Coronavirus as well as subsequent minor outbreaks has not been explored in the literature. This is the question we seek to address in the paper.

Following the initial outbreak of the Covid-19 pandemic in Wuhan, the Chinese government locked down Wuhan and other cities in Hubei province on 23 January 2020. Other Chinese cities also quickly followed suit in varying degrees in introducing strict measures to restrict population mobility, to trace and isolate suspected Covid-19 patients as well as closing non-essential businesses.

Focusing on the initial outbreak, Li and Ma (2021) show that cities with larger bilateral migration flows and shorter travel distances with Hubei province, the epicentre of the outbreak, experienced a greater spread of Covid-19. Following the initial outbreak, many strict controls and countermeasures were adopted in China to prevent or control the disease from spreading. This included management measures, disinfection, environmental hygiene, personal protection and health promotion (Shen et al., 2020). Oka et al. (2021) use Baidu mobility data to show that the spread of the disease dropped substantially after local governments imposed various lockdown policies and introduced mobility restrictions across regions. Using real-time mobility data from Wuhan and detailed case data including travel history, Kraemer et al. (2020) find that the drastic control measures implemented in China had substantially mitigated the spread of Covid-19.

By August 2020, it appears that restaurant and bars in China had reopened and that restrictions on internal flights had eased substantially. There are accounts that most of the Chinese economy, including internal tourism, had returned to almost full operation.[1] Despite improvements in controlling the spread of Covid-19 infections with vaccines and decreasing mortality rates, China continues to attempt to contain the virus using very strict restrictions that include a combination of snap local lockdowns, mass testing, and strict quarantine measures. By the second half of 2021, with the rise of the highly infectious Delta variant (identified on 31 May 2021) and the Omicron variant (identified on 24 November 2021), while the rest of the world had given up on the goal of completely eliminating Covid-19, China remains the only country committed to pursuing a "Zero Covid" strategy.[2]

In essence, the dual circulation strategy aims for domestic economic circulation to play a leading role while international economic circulation acts as in a supporting role, boosting and supplementing the domestic development (Lin and Wang, 2021). Such a policy can play a major role in stimulating demand in the economy, especially for an economy the size of China. This can be of particular importance in a period of time when the economies around the world close their borders, such as what happened as a result of the Covid-19 outbreak. Dual circulation was mentioned by President Xi Jinping in his speeches in early 2020 and was formally proposed at the Fifth Plenary Session of the 19th Central Committee of the Communist Party of China in October 2020. It emphasizes domestic circulation as the major driving force of the Chinese economy so that the Chinese economy will be more resilient to external shocks. This includes encouraging Chinese citizens to travel more domestically. For example, to switch Chinese tourist spending abroad back to China, the Chinese government has cut import duties for many tourist-favored products. It has also opened up more duty-free stores and duty-free zones, like the Hainan duty-free zone established in June 2020 to attract more domestic tourists.[3]

[1] See https://www.nytimes.com/2020/08/23/world/asia/china-coronavirus-normal-life.html.

[2] See https://time.com/6104303/china-zero-covid/.

[3] See the article by Chi Lo entitled *"Dual Circulation" Is China's Strategic Pivot to Prepare for Long-Term Competition With the United States* in the Fall 2020 issue of the International Magazine. Available at: http://www.international-economy.com/TIE_F20_Lo_Scissors.pdf.

In this paper, we use objective data from mobile phone records to examine patterns of mobility of the Chinese population during the Covid-19 pandemic, which at approximately the same time, saw the introduction of China's dual circulation development paradigm. Our data measures the domestic air travel patterns of the Chinese population during the Covid-19 pandemic and are not based on any data reported by a government agency. The data comes from Tencent heatmap, which allows us to track almost the whole population at airports in most of the provincial capital cities in China. We are not aware of any research that has been based on this Tencent data. Population mobility here serves as an objective proxy measure for domestic economic activity in the Chinese economy.

Related to our work, Chen et al. (2021b) use location data from mobile phones to investigate empirically if there is any statistical relationship between air quality differences and population movement between pairs of Chinese cities on any given day. Such data have also previously been used to track the spread of Covid-19 in China and other countries around the world (Buckee et al., 2020; Grantz et al., 2020; Ilin et al., 2021; Oliver et al., 2020; Oka et al., 2021; Persson et al., 2021; Xiong et al., 2020). Our contribution is in terms of doing a detailed analysis of the dynamics of population mobility in several Chinese cities over the period January 2019 to May 2021. The extended time period we focus on in this study relative to prior studies allows us to go beyond estimating the short run effects of the Covid-19 outbreak on population mobility. It allows us to document how the dual circulation strategy, which is facilitated by China's Zero-Covid policy, provides a mitigating effect on the negative effects of Covid-19 outbreaks on domestic population flows.

Our main empirical strategy is to use a difference-in-differences approach to examine whether population mobility during 2020 and 2021 (following Covid-19 outbreaks in China) had changed substantially compared to 2019, which is a period prior to the pandemic outbreak.

In general, from our analysis of the location data from mobile phone devices that highlights the number of people at airports, we find that except for some periods of intense mobility restrictions, relative to mobility patterns in 2019, mobility in fact increased in China from mid-2020 onwards. In China, many people are taking flights again following any snap lockdowns or travel restrictions and the number of people at airports is actually higher than they were pre-pandemic.

The remainder of this article is organised as follows. Section 2 gives some background information of travel behavior during Covid-19 in China. Section 3 describes the data we use. Section 4 describes the empirical approach we use to analyse our data. Our results are described in Section 5. Finally, Section 6 gives the conclusions.

2 Background

2.1 Dual Circulation

China launched its new "dual circulation" strategy in May 2020 when Chinese President Xi Jinping first raised the idea that China will foster a new development paradigm. The meeting highlighted "the necessity to deepen supply-side structural reform, give full play to the advantages of the country's super-large market and the potential of domestic demand and construct a new development model (or pattern) featuring domestic and international dual circulations that complement each other."[4] This move reflects China's new worldview that an anti-globalization movement and increasing trade protectionism is forcing a structural shift in global supply chains, requiring a need to reduce reliance on the external sector in order to sustain stable growth and resilient investment. Due to tensions in international relations, for economic security, there appears to be a need for countries to pay more attention to the safety and integrity of industrial chains and supply chains. Furthermore, China is also facing the risks of the withdrawal of some foreign companies, a decline in foreign direct investment, and further decreases in foreign trade demand (Huang et al., 2021a).

Under the impact of the pandemic, countries have become fully aware of the potential risk, safety and risk variables of global supply chains that are excessively dispersed or concentrated in a certain region. For example, during the pandemic, pharmaceutical and medical equipment, electronic information and other key industries experienced serious global supply chain blockages or even broken chains (Huang et al., 2021b). Given the increasing challenges China faces in the uncertain global trade environment, with China's rising household incomes, the services sector accounting for a greater portion of its GDP, and with future economic growth likely to be driven by domestic consumption and investment, dual circulation appears to be the logical step in the evolution of the Chinese economy and to hedge against external risks (Zakić, 2021).

Jia (2021) highlights that, in fact, the focus on domestic circulation is in line with the expansion of domestic demand, which has been emphasized for many years in China. The current policy innovations are mainly reflected in considering domestic circulation as the mainstay. Lin (2021) states that from the economic perspective, China's proposal for fostering a new development pattern with domestic circulation as the foundation is in line with the basic laws of economic development. Despite many scholars who view China's economic development pattern as being based on an export-led growth model, the fact is that China's

[4] See "The standing committee of the Political Bureau of the CPC Central Committee held a meeting chaired by Xi Jinping," XinhuaNet 14 May 2020, available at: www.xinhuanet.com/politics/leaders/2020-05/14/c_1125986000.htm (in Chinese).

share of exports (as a percent of GDP) was generally increasing until 2006 but declined thereafter. In 2006, China's share of exports in its aggregate economic output reached its peak at 35.4%. By 2019, the export-to-GDP ratio had declined to 17.4%, meaning that 82.6% of GDP was circulating at home, and domestic circulation was already dominant in China's economy. Javed et al. (2021) argue that given China's high household savings rate, it is very likely that the dual circulation would promote a reduction in the savings rate and a surge in the private consumption rate.

In addition, as more and more industries in China have either narrowed the technological gap or moved to the global technological frontier, it is likely that China will increasingly rely on local innovation rather than technological transfer for its technological innovation and industrial upgrading. China's dual circulation development paradigm does not imply that exports and trade are unimportant as the Chinese government aims to continue to rely on external circulation to facilitate the expansion of domestic circulation and on the expansion of domestic circulation to reinforce external circulation (Lin and Wang, 2021). Put another way, the Chinese government foresees a strategy whereby the domestic and international circulation complement and support each other. It will continue to engage with foreign capital and technology to facilitate domestic development while simultaneously boosting local capabilities in order to minimize the impact of global volatility.

So far, limited assessments of the dual circulation strategy have been made but there are early indications that the internal circulation strategy has been successful, especially with tourism policies that have successfully promoted cross-provincial travel within China.[5] According to Zakić (2021), the main challenges in the implementation of the new development concept will be to expand domestic demand, have more equal regional development, increase domestic income, implement changes within the hukou system of household registration, increase the size of the high skilled labour force, change the culture of savings, reform the state-owned enterprises, and have more innovative development.

2.2 Travel Behaviour During Covid-19

The global travel industry has been hit hard during the pandemic. Many airlines, hotels and hospitality venues experienced steep declines in revenues. With regards to population mobility and travel, people are likely to become more risk averse after experiencing this pandemic. In China, even though the pandemic has been under control following the initial major outbreak through the use of strict measures, people may be less willing to travel than before due to an increase in risk aversion.

[5] See: https://think.ing.com/articles/chinas-internal-circulation-is-working.

Location data from smartphones can be useful to examine travel behavior and its relationship with Covid-19 outbreaks.[6] Brinkman and Mangum (2021) find using data on the movement of smartphones between U.S. counties that a doubling of new cases in a county led to a 3 to 4 percent decrease in trips to and from that county, and that travel between counties declined as Covid-19 cases rose. They find people responding to information on outbreaks by restricting their activity in rational ways –both in level and in direction. This "healthy fear" of the virus appears to provide motivation for social distancing and undertaking safety measures.

Following the end of the initial lockdown in early 2020 in Wuhan which lasted 76 days, economic activities largely resumed in China, including in the tourist industry. Based on the aggregate provincial-level sales data of attractions tickets from a leading travel agency in China, Li et al. (2021) find tourists' behaviors in China have been significantly reshaped by the pandemic. Specifically, they find that tourists avoid traveling to destinations with more reported confirmed cases relative to their places of origin, and that tourists prefer destinations close to home, especially local attractions. They find that in the Covid-19 recovery phase in China, short-distance and local trips appear to be dominant and have gained more popularity.

The papers that are most closesly related to our work are by Liu et al. (2021) and Tan et al. (2021). Using population flow data from Gaode Map from January to June 2019, and from December to June 2020, Liu et al. (2021) employ an event study analysis to examine the dynamics in population flows across cities in China. They focus on two distinct events, the lockdown and the reopening to shed light on the recovery of cities with different pandemic experiences, and to estimate the difference in population mobility between epicenter and non-epicenter cities. Their analysis is based on the aggregation of population inflows and outflows of cities during the event window of 5 weeks before the lockdown and 12 weeks after the reopening. They find that 12 weeks following the reopening of epicenter cities, population flows had still not returned to pre-pandemic levels. These results by Liu et al. (2021) suggest that by June 2020, the end of their study period, life in China had not returned to normal in cities where there were large Covid-19 outbreaks. However, among non-epicenter cities, cross-city mobility fully recovered to normal six weeks after the reopening started.

Similarly, Tan et al. (2021) analyzed aggregated human movement data recorded before, during and after the first wave of the Covid-19 outbreak in China. They use nationwide mobility data from China Unicom mobile phone users in China to examine the extreme

[6] Couture et al. (2021) investigate the reliability of smartphone movement data during the pandemic and provide guidance on potential benefits and relevant caveats when using smartphone movement data for economic research. Their work demonstrates the potential of smartphone movement data to quantify movement and social contact with high frequency and spatial precision.

fluctuations of population movements between 1 January to 29 February 2020. Their analysis revealed the changing spatio-temporal features of mobility and examined the impact of China's Covid-19 containment policies on domestic travel in 2020. They found that the population flow did not return to previous levels at the end of February 2020.

Both Liu et al. (2021) and Tan et al. (2021) focus on the first major wave of the outbreak in China in 2020. Our work differs from theirs in terms of the time period covered and objective. We examine mobility patterns in China from the start of 2019 to the second quarter of 2021 with twofold objectives. The first objective is to measure any potential effect of the dual circulation strategy on domestic travel behavior. The use of mobility data from 2019 before the start of the pandemic allows us to establish a benchmark regarding what "normal" mobility data in the absence of Covid-19 is. The second objective is to examine whether life in China following the recovery from the initial Covid-19 outbreak has become more normal. This indirectly addresses the issue of whether Covid-19 case number statistics in China are reliable, as large population movements are unlikely to be taking place if the virus is still a big threat to peoples' health.

3 Data

3.1 Mobility Data

Location-based service (LBS) data that traces human mobility patterns in the literature typically come from anonymised real-time location records of mobile phone users (Schläpfer et al., 2021; Liu et al., 2021). In China, the mobile phone penetration rate is very high and mobile phone data is usually high frequency in both the time and spatial dimensions.[7] However, Kishore et al. (2020) highlight that it is important to be clear what fraction of the population are represented in these data, because location data from smartphones are typically only captured for a subset of the population that uses a particular application and provides consent to share location services. Due to privacy concerns, the data on phone users available to researchers is often restricted and limited in space and time. It is also usually provided by one of many telecom operators providing mobile services in the country. If available, a common trade-off of obtaining and using nationally representative data on mobile phone users and their migration trajectories is to sacrifice the frequency and granularity features of the data (Tan et al., 2021; Wang et al., 2019).

A second type of LBS data is based on real-time migration flows recorded by mapping

[7]The percentage of the population in China owning a smartphone was 63.4% in 2020 according to Newzoo's Global Mobile Market Report (see https://newzoo.com/insights/rankings/top-countries-by-smartphone-penetration-and-users/)

apps on mobile phones such as Baidu map (which is the predominant mapping app used in China and similar to Google map). For example, recent studies have used Baidu city-pair migration data to analyze Covid-19 issues on the city variables in China (Fang et al., 2020; Oka et al., 2021). These data are usually more aggregated in nature (e.g. aggregated by prefecture cities), making it less appropriate to track population flows at specific transportation hubs.

Tencent is a dominant market leader in China and its software products are widely used. Its communication software products include WeChat (a multi-purpose instant messaging, social media and mobile payment app) and QQ (an instant messaging software service and web portal). The demographic characteristics of registered WeChat users span across various social classes and age groups. WeChat is one of the main ways people communicate in China. Out of the total WeChat users in China, 25% belong to the age group of 25 to 30 years while another 13.8% of users are aged between 31 and 35 years. The largest age demographic (33.5%) is composed of users below 24 years. This is closely followed by users over 41 years who constitute 19.1% of the total. About 43% of WeChat users are female, while about 57% of accounts are male. It is reported that the average monthly active users for WeChat was more than 1.2 billion users in December 2020.[8]

The travel and tourism industry has become a key driver of China's domestic economy since the 1980s, after market liberalisation and the opening up of China. Both the nation's growing domestic middle class and accommodating government policies have helped it grow exponentially over the past four decades. In 2019, the industry contributed to about 11 per cent of the China's total gross domestic product.[9] The Covid-19 outbreak affected many industries, especially the aviation market. With the closure of its borders and strict restrictions, both the number of flights and passengers dropped significantly in China shortly following the Wuhan outbreak. These changes have important implications for the Chinese economy.

In this paper, we use domestic air travel patterns of the Chinese population measured using LBS data as an objective proxy for domestic economic activity during the pandemic. The Tencent LBS team has made available two types of LBS products. The first product captures pairwise city migration flows of Tencent product users. This is similar to data from mapping apps provided by other companies (such as Baidu or Gaode Map used in Fang et al. (2020); Liu et al. (2021); Zhuang et al. (2020)). The second LBS product is the Tencent heatmap product. This new data allows us to track almost the whole population

[8]See https://brewinteractive.com/wechat-statistics/.

[9]See https://www.scmp.com/economy/china-economy/article/3145468/how-has-chinas-travel-industry-been-hurt-coronavirus-pandemic.

within a particular airport.[10] In our work, we utilise the Tencent LBS heatmap product that covers all active Tencent software users at airports of most of the provincial capital cities in China. Compared to mobile phone signaling data and data from mapping apps on mobile phones, the Tencent LBS heatmap is more representative of the population and useful for studying population counts in specific locations due to its granularity. We are not aware of any research that has been based on this Tencent data.

Our high frequency data set spans the period 1 January 2019 to 31 May 2021, covering five minute intervals during each day.[11] For our analysis, we collapsed the data into daily level data for each airport. In total, there are 17 airports recorded in the Tencent LBS heatmap. This data primarily comprises of airports in key capital and tourism cities (see Table A1 for a list of the airports and Figure A1 for a map of where they are located). For each airport, we have collapsed our population data by hour of the sample year (2019 - 2021) and plotted the average hourly trend in Figure A2. As expected, Beijing Capital International Airport has the greatest number of people at the airport at all hours of the day. This is followed by Changsha, Jinan, Shenyang, Tianjin, and the tourist cities Sanya and Haikou. This closer examination of the high resolution data from Tencent heatmap illustrates the features of our analysis data set. In general, population counts peaked at all the airports in our sample in the afternoon.

The data for our sample cities are representative of the populations in each of the cities and our data capture almost all of the human mobility flows within each of the airports examined. However, as our data set only covers major airports in China, the external validity of our findings is limited. Our use of standard errors that are clustered by city for the analysis reflect this sampling concern.

3.2 Data on Outbreaks and Tourism

Covid-19 daily case counts are collected from the China National Health Commission, which provides daily updates on the number confirmed dead and the number of recovered Covid-19 cases in each city.[12]

We define a major outbreak as having taken place if the confirmed Covid-19 cases have spread across at least five provinces and a lockdown was implemented. Following this def-

[10] We had previously accessed these data from: https://heat.qq.com/heatmap.php. However, since around October 2021, these data are no longer available and Tencent currently uses this data for helping with the control of Covid-19 outbreaks only.

[11] At the time when we retrieved the Tencent heatmap data (in March 2020), the Tencent LBS team had only made the 2019 and 2020 data available. From October 2021 onwards, this heatmap product was no longer made available to the public.

[12] These data are available at: http://www.nhc.gov.cn/.

inition, there were two major Covid-19 national outbreaks and several minor outbreaks in China over the period January 2019 to May 2021. We focus on two major outbreaks. The first one was the initial outbreak that started on 23 January 2020, and the second one was an outbreak that started on 17 December 2020. To gauge the domestic sentiment and reactions towards the outbreaks, we collected data from the index in the Baidu search engine that measured searches related to Covid-19. Baidu search index is similar to Google Trends (the dominant search service outside of China) and has been widely applied by economists.[13] The key words we searched for are "epidemic", "lockdown", "pneumonia" and "virus" (The corresponding Chinese words used in the keyword search are "疫情", "封城", "肺炎" and "病毒", respectively, and the search covered the period from January 2019 to May 2021).

In addition, to augment our focus on domestic travel behavior, we also collected tourism data from the local Bureau of Culture and Tourism for two famous tourist cities, Hainan and Sanya. These data help to further provide an indication of the behavior of domestic travellers in response to the various Covid-19 outbreaks.

3.3 Summary Statistics and Population Mobility Patterns

The Covid-19 case numbers in China over the period January 2020 to May 2021 are depicted in Figure 1a. The scale of the initial Wuhan outbreak in late January 2020 clearly dominates all other outbreaks in China during that period. In Figure 1b, we therefore focus on the period March 2020 to May 2021 to get a better sense of the minor outbreaks that occurred in China. Following the tapering down of the initial Wuhan outbreak, by April 2020, it can be seen that Covid-19 was well contained in China, with only a few cases being detected. Collectively, Figures 1a and 1b show that the major Covid-19 outbreak in China occurred in January 2020, followed by smaller outbreaks in June 2020 and January 2021.

Covid-19 severely affected the mobility of the Chinese population, especially during the initial lockdown period. China had also closed its borders to nearly all travellers in March 2020, when the pandemic started spreading in Europe. This effectively halted the inflow of international tourists into China.

Figure 2a shows the raw trends of log population counts at airports in China in our data set. In 2019, there is a small drop in population counts during the Chinese Spring Festival as a result of a week long public holiday where business travel is halted. The drop in 2020 during the Chinese Spring Festival was considerably more severe as it coincided with the Wuhan lockdown that was implemented two days before 2020 Spring Festival. The figure

[13] One recent example is Fang et al. (2020) who used data from the Baidu index to document the extent of panic following the Wuhan lockdown. They found that the number of searches on Covid-related words had increased immediately.

shows that population counts dropped significantly till mid-February but gradually recovered after that.

Beyond the issue of the recovery from population counts following the early 2020 Covid-19 outbreak, particularly noteworthy in Figure 2a is a significant and clear change in the mean levels of population counts around the middle of 2020. This change in mean levels happens to coincide with President Xi Jinping introducing the dual circulation strategy in a speech in May 2020, which was widely publicised in the Chinese media. The fact that this new mean level of population counts is observed in 2021 (see Figure 2b), even following a Covid-19 outbreak in early 2021, is suggestive of a dual circulation effect.[14] From March 2021, the population counts at the airports in our sample are all considerably higher than they were as compared to 2019 (see Figure A3). The fast rebound that occurred for the 2021 outbreak might be because local government officials had learnt from their previous experiences with containing the spread of the virus. In other words, the implementation of the "Zero Covid" policy had been refined and executed more precisely over time. This makes it easier to control any outbreaks and helps people to more quickly return to their normal daily routines.

The domestic or internal circulation component of the dual circulation strategy likely plays a role in stimulating domestic travel through a mechanism that involved government stimulus packages. Under the new Covid-19 travel restrictions following the initial outbreak, for all onshore arrivals, the China border force required a 14 day hotel stay plus an additional 14 days of quarantine at home. Not surprisingly, this led to a large reduction in outbound travel which affected the travel industry adversely. Hence, as part of the dual circulation strategy and to help increase domestic travel demand, the central and provincial governments launched a series of stimulus plans involving the provision of digital consumption coupons and free tourism tickets.

Figure A4 illustrates the change in tourist numbers in Haikou and Sanya (two of the most popular tourist destinations in Hainan Province and China) in response to the shock of Covid-19. During the Wuhan lockdown (February 2020), the number of travellers decreased dramatically. After mid-2020 when Covid-19 was under control in China, the number of tourists increased and soon reached the levels seen in 2019. Furthermore, the number of tourists visiting Haikou and Sanya in early 2021 surpassed the levels seen over the same period

[14] Zhang et al. (2021) use airline ticket data from the TravelSky Departure Control System and find that the domestic air travel passenger volume had a reversal after reaching the bottom in February 2020 and recovered to 90% of the 2019 level during the National Day holiday period in October 2020. However, their data does not cover all domestic air passengers because some low-cost airlines are not connected to the TravelSky system. This possibly explains why they do not detect a shift in the mean level in late 2020 that is visible in the Tencent data.

for 2019. Together with our data on population counts at airports, these descriptive statistics are suggestive that the dual circulation strategy has led to higher levels of population mobility within China.

The severity of the Covid-19 outbreak in China can also be indirectly inferred from internet searches related to the virus. In Figure 3, we plot the frequency of the four keyword searches from the Baidu search engine previously mentioned. The spike in January 2021 for the term "epidemic" reinforces the evidence from Figure 1b that a second relatively large outbreak occurred at that time. Similarly, the relatively low incidence of keyword searches for terms related to Covid-19 outbreaks in most other months suggests that till the period June 2021, following the initial outbreak, the Chinese people were generally not too worried about Covid-19.

4 Empirical Strategy

We employ a difference-in-differences (DID) design to estimate the effect of Covid-19 outbreaks in China on population mobility. As Covid-19 outbreaks occurred in China in 2020 and 2021, we use both these years as the treated years. To control for seasonal patterns of the demand for air travel unrelated to the Covid-19 outbreak, we use 2019 as the untreated year, which helps construct the counterfactual trend of travel patterns in 2020 and 2021.

Such a difference-in-differences approach is similar to the approach used in Chen et al. (2021a) who use high-frequency offline spending transactions data in China to estimate the change in consumption during the initial period of the pandemic relative to the counterfactual change in spending based in 2019. Chen et al. (2022) adopt a similar approach in using 2018-2019 as untreated years for comparisons to the post-pandemic period to estimate the effects of Covid-19 on the demand for public transport in Taiwan.[15]

To investigate the dynamic impact on the mobility, we estimate the following equation:

$$
\begin{aligned}
Log\_Mobility_{i,d} &= \sum_{w=-3}^{w=20} \gamma_w \times Treated_y \times Week_w \\
&+ \sum_{w=-3}^{w=20} \alpha_w \times BaiduIndex_i \times Week_w + \lambda_i + \lambda_d + Holiday_d + \epsilon_{i,d},
\end{aligned}
$$

in which $Log\_Mobility_{i,d}$ indicates the natural logarithm of population counts in the airport in city i on day d; $Treated_y$ is equal to one if the observation is in treated year (depending

[15] It is also consistent with how the travel industry in China assesses its current state. See, for example, this report from trip.com, a leading travel service provider in China: https://www.trip.com/newsroom/trip-com-group-2021-may-day-travel-data-reveals-record-growth/.

on which outbreak we analyse, the treated year can be 2020 or 2021) and zero otherwise; $Week_w$ is defined relative to the outbreak date and takes a value of one if the outbreak falls in that week (i.e. $Week_0 = 1$ is defined as the next 7 days starting from the treatment date) and zero otherwise; λ_i are city fixed effects, λ_d is a vector of time-related dummy variables, including year, week of year, and day of week fixed effects to control for seasonality or any time-varying factors of mobility. The $Holiday_d$ variable takes a value of one if day d falls on a public holiday and is zero otherwise.[16] We also include interaction terms between the 7-day (before the treatment date) average value of the Baidu Index and week dummies. The coefficients of interest, γ_w, capture the change in log population counts in week w relative to the outbreak.

In the analysis of the outbreak in 2020, the dummy variable $Treated_y$ is defined as one for all observations in 2020, and zero otherwise, and the dummy variables $Week_w$ are defined for the week relative to the Wuhan lockdown date (23 January 2020).[17] For instance, $Week_0$ takes a value of one if the observations falls in the period from 23 to 29 January 2020.

With respect to the outbreak in 2021, the exact treatment date is not very clear due to its scale. Unlike the Wuhan outbreak in 2020, which was an unprecedented incident, people likely started adapting to their "new normal" lives in the second half of 2020. After June 2020 when the Wuhan outbreak was put under control by the authorities, there were only a few small Covid-19 outbreaks in China (with the number of cases generally smaller than 100). As these local outbreaks were all contained using strict measures, population mobility was not greatly impacted compared to the very first outbreak. The outbreak in late 2020/early 2021 started with a small number of cases (fewer than 10 from 17-25 December 2020), but then started spreading faster with the peak number of cases in a day (135 cases) occurring on 14 January 2021. Hence, we choose three different treatment dates: 17 December 2020[18], 26 December 2020[19] and 5 January 2021[20] as there is no single large spike in Covid-19 cases to focus on as the treatment date. For analysing the outbreak in 2021, the same equation used previously is again estimated, with a notable difference being that the dummy variables

[16]The public holidays include the New Year, Spring Festival, Tomb Sweeping Festival, Labor Day Holiday, Dragon Boat Festival, National Day Holiday, and the Mid-Autumn Festival.

[17]While there were rumours regarding the Novel Coronavirus at the end of December 2019 and early January 2020, the Chinese government did not take it seriously until 23 January 2020, when they implemented the lockdown. The Chinese citizens also did not pay any attention to the new virus until then, so population mobility was not impacted before this date. Note that the Spring Festival, one of the most important holidays in China, was only two days after 23 January 2020. Domestic travel before the Spring Festival is usually very heavy as many migrants make their annual visits to their home provinces.

[18]This is the first day of the outbreak (the two previous days had recorded zero cases).

[19]This is the day when the number of Covid-19 cases went beyond 10. Generally, having 10 Covid-19 cases in a day in China can be regarded as a serious outbreak.

[20]This is when the number of Covid-19 cases recorded was larger than 20.

$Week_w$ are now defined relative to each of the three respective treatment dates listed above.

In theory, the DID analysis can be conducted by comparing data for 2018/2019 and 2020/2021. Unfortunately, the Tencent data are only available from the beginning of 2019. Therefore, the analysis for the January 2021 outbreak using January 2019 as the control period can only show results for the post-treatment period.[21] To help ensure that the parallel trend assumption is satisfied, we conduct a separate analysis of the pre-treatment period by comparing data of the December/January period of 2020/2021 with that of 2019/2020 instead of 2018/2019 (for which data is not available in Table A4). This alternative pre-trend analysis is possible because the December/January period of 2019/2020 is pre-Covid-19 and arguably reflects a valid counterfactual of population counts without Covid-19.

5 Results

The results from the DID analysis examining the effect of the January 2020 outbreak are plotted in Figure 4.[22] The outbreak occurs in week 0, while the pre-outbreak period is defined as weeks -3 to -1 and the post-outbreak period is defined as weeks 1 to 20, with $Week_{-1}$ set as the reference week. The top left plot presents results from a base specification which includes controls for city fixed effects, week of year fixed effects, year fixed effects, holiday fixed effects, and day of week fixed effects. The plots in other three panels include the same set of fixed effects but also further adds controls based on the frequency of keyword searches from the Baidu search engine.

Statistical significance levels in the table are provided based on robust standard errors. As an alternative way of performing statistical inference due to the clustered nature of the data, p-values clustered at the city level using the wild bootstrap proposed by Cameron et al. (2008) are also computed. Bold coefficients in the table indicate that there is at least 10% statistical significance using both approaches.

There are two main insights from Figure 4. First, the estimated coefficients for weeks -3 and -2 are small and statistically insignificant, suggesting that trends in the number of airline passengers in the treated year (2020) and untreated year (2019) were similar before

[21]The pre-period analysis for the January 2021 outbreak will require data from 2018 which is not available. This is because the treatment date of the control group is chosen such that the distance between the date and the Spring Festival is maintained. For example, as 5 Jan 2021 and 12 Feb 2021 (the first day of Spring Festival 2021) are 38 days apart, the hypothetical treatment date of the control group for the 5 Jan 2021 outbreak is 38 days away from 5 February 2019 (the first day of Spring Festival 2019), which is 30 Dec 2018. The corresponding hypothetical treatment dates using 17 December 2020 and 26 December 2020 as the outbreak start dates will therefore be even earlier in December 2018 and result in more missing data for the analysis.

[22]Detailed results can be found in Table A2.

the Covid-19 outbreak. Second, the estimated coefficients are negative and statistically significant for weeks 0 to 18, reaching a peak in week 3 and gradually dissipating after that. This pattern is similar across the specifications in all four plots. These results correspond to the descriptive evidence in Figure 1a, where it can be seen that the initial gap in the lines closed by June 2020, which is approximately 18 weeks after the outbreak in January 2020. The DID event study analysis in Figure 4 does not extend past 20 weeks and therefore does not reveal the change in the mean levels in log population counts that is visible in Figure 1a.

The results of the effects of the 2021 outbreak are presented in Figure 5.[23] Although a similar DID event study analysis is conducted, recall that due to data constraints resulting from the unavailability of data before 2019 to construct the counterfactual, only results for the post-treatment period can be estimated. Furthermore, the post-treatment weeks where effects can be estimated also vary depending on which of the treatment dates (17 December 2020, 26 December 2020, 5 January 2021) is used. The availability of data for post-treatment weeks also affects the reference weeks that are used in all three plots in Figure 5. In the top right panel, the reference week is week 0, in the top left panel, it is week 1, while in the bottom left panel, it is week 3.[24]

For the 2021 outbreak, the estimated coefficients reveal that the recovery in the post-treatment period was considerably faster than the recovery for the 2020 outbreak. Using 5 January 2021 as the treatment date, the results in the top right panel suggest that by week 8, most of the negative effects of the Covid-19 outbreak on population mobility had dissipated. Furthermore, as early as week 12, positive effects began to emerge. These positive effects most likely arise due to the dual circulation strategy that led to policies to help boost domestic travel. The pattern of results in the plots in the top right panel and bottom left panel largely mimic the results in the top left panel, even though the reference week used in both cases now involve post-treatment weeks.

6 Conclusions

Following the end of the nationwide lockdown, travel returned to normal in many parts of China. In many cities where there were few or no Covid-19 cases, there were actually more people at the airports compared to the same period in 2019. The world's busiest airports in

[23] Detailed results can be found in Table A3.

[24] The results of the pre-trends analysis comparing data of the December/January period of 2020/2021 with that of 2019/2020 (instead of 2018/2019 for which data is not available) are shown in Table A4. The significant coefficients in the pre-trend period could arise here because of a difficulty in assigning a true start date for the January 2021 outbreak. As it is not the first time a Covid-19 outbreak is happening in China, people could have been starting to take safety precautions once a few cases were detected as there were already a handful of cases being detected from late November 2020 onwards.

the world by passenger traffic reveal that ten Chinese cities were among the top 20 in the ranking list in 2020 as compared to only three among the top 20 in 2019.[25] Our findings on population mobility suggests that data on Covid-19 cases in China are reliable as large population movements are unlikely to be taking place if the virus is still a big threat to people's health.

In this paper, we use high-frequency data from location-based mobile phone records from Tencent, a market leader in communications software in China, to measure domestic air travel patterns of the Chinese population during the Covid-19 pandemic. Compared to the existing literature that uses mobile phone data, the location data we use in this paper is more representative of the Chinese population in terms of the demographical coverage, as well as spatial and temporal resolutions. While much research has focused on the impact of Covid-19 in China, we are not aware of any papers that have focused on analysing the effect of the introduction of the dual circulation strategy in China. This a new development strategy which places domestic circulation as the foundation of the economy, and with external circulation or foreign trade and investments playing a supportive and complementary role. In light of the stress on global supply chains during the pandemic, the introduction of this new economic strategy appears to be a timely one.

In our analysis, we focus on the travel and tourism industry, which is a key driver of China's domestic economy and data from this industry helps serve as an objective proxy for domestic economic activity during the pandemic. Our results show that except for some periods of intense mobility restrictions, relative to travel patterns in 2019, mobility in fact increased in China from mid-2020 onwards to May 2021 (the end of our sample period). This increase in domestic air travel is likely due to a combination of factors: the success of China's strict controls on virus transmission, China's new dual circulation development paradigm, and a pent-up demand for international travel that is not permitted.

As the pandemic continues to evolve, it remains to be seen how the dual circulation strategy will impact the Chinese economy, especially if more infectious strains like the Omicron Covid-19 variant make it more difficult for authorities to maintain a Zero-Covid policy.

[25] See https://en.wikipedia.org/wiki/List_of_busiest_airports_by_passenger_traffic.

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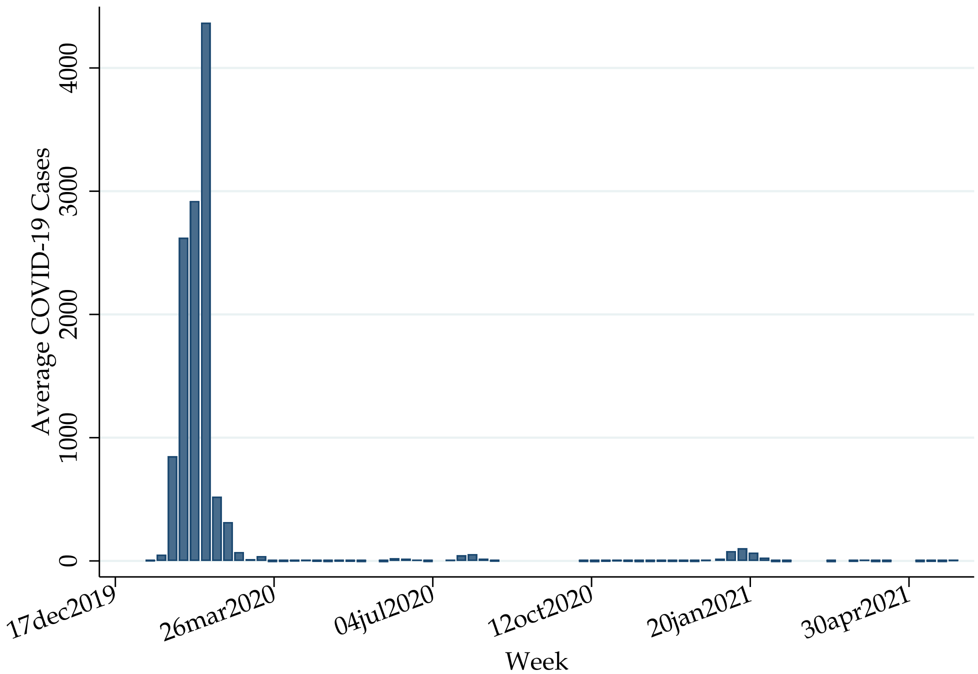
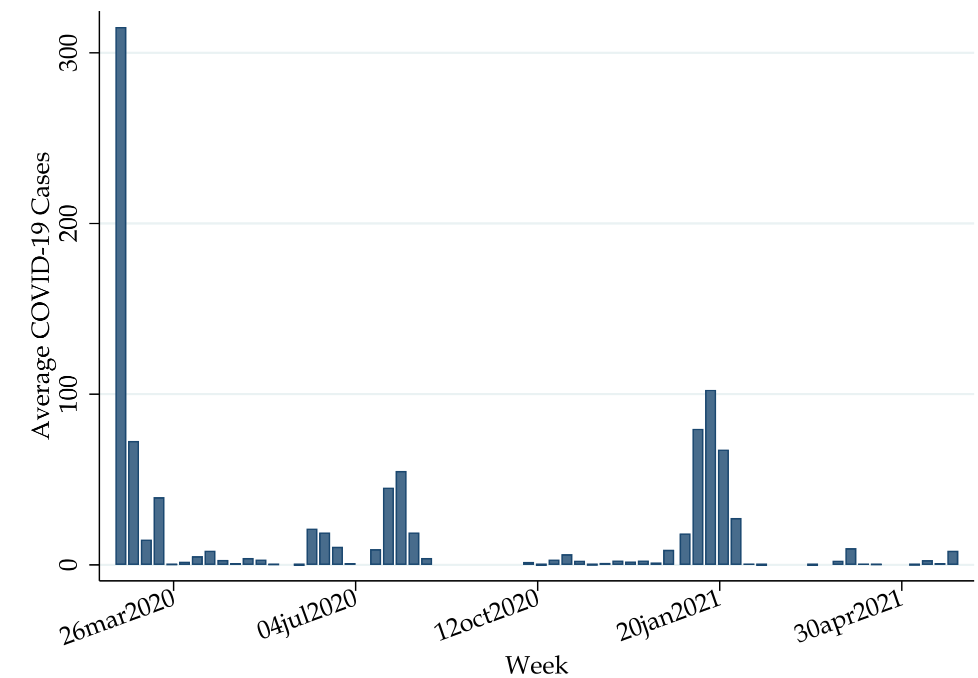


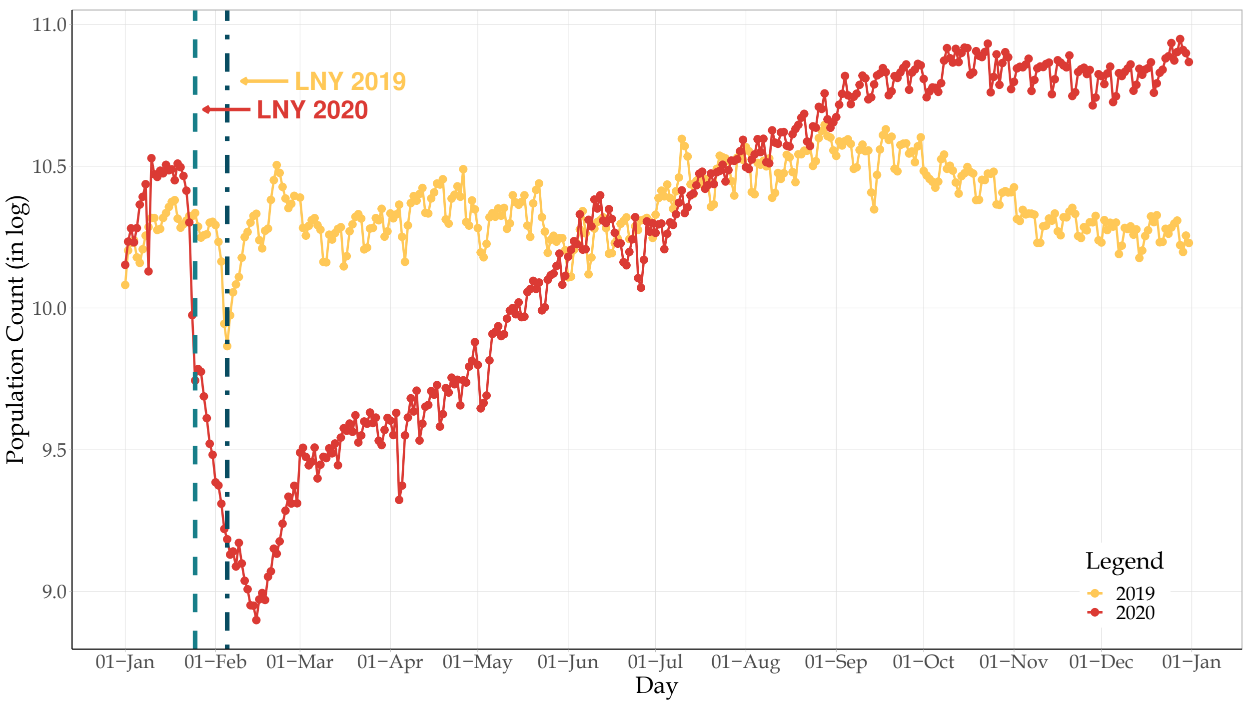
(a) January 2020 to May 2021



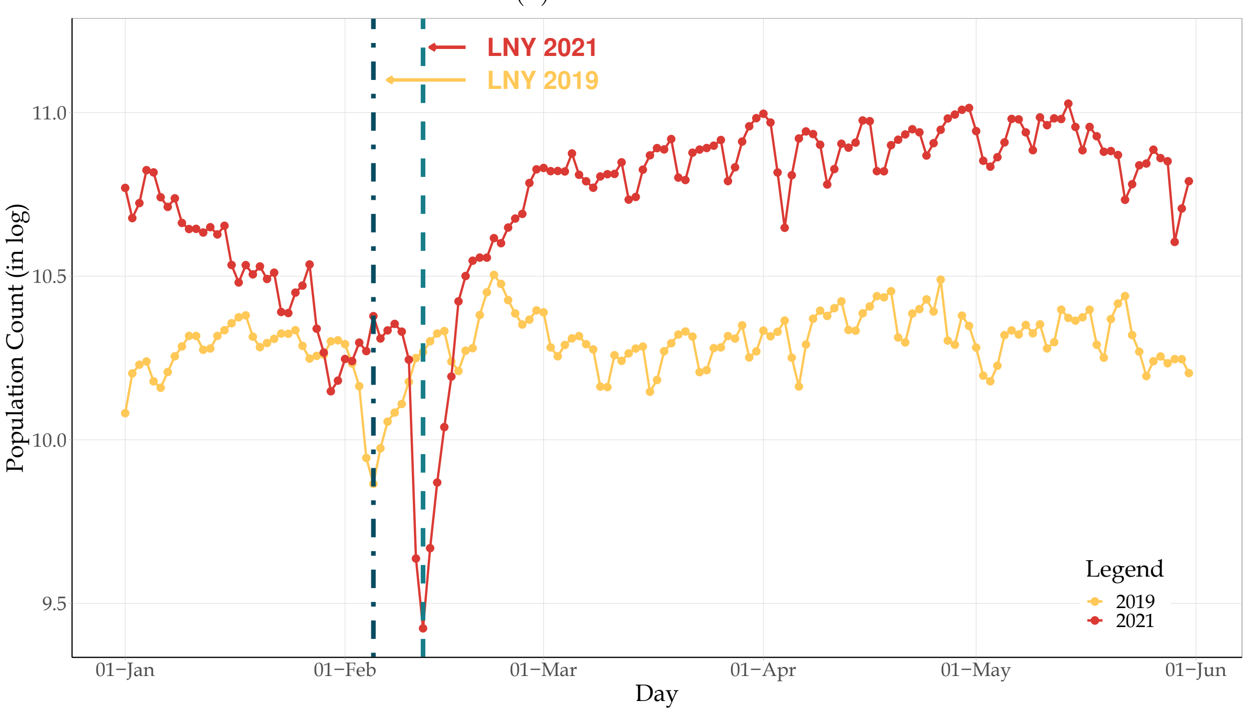
(b) March 2020 to May 2021

Figure 1: Covid-19 Cases in China

Notes. Week is based on the calendar year. Week 1 is counted from 01 January to 07 January of the year. Hence, week 52 will have more than 7 days.



(a) 2019 vs. 2020



(b) Jan-May 2019 vs. Jan-May 2021

Figure 2: Log Population Counts at Airports in China

Notes. Data for the 17 airports listed in Table A1 are used to create the plots. We exclude Xianyang and Shanghai in this figure due to missing values in some periods.

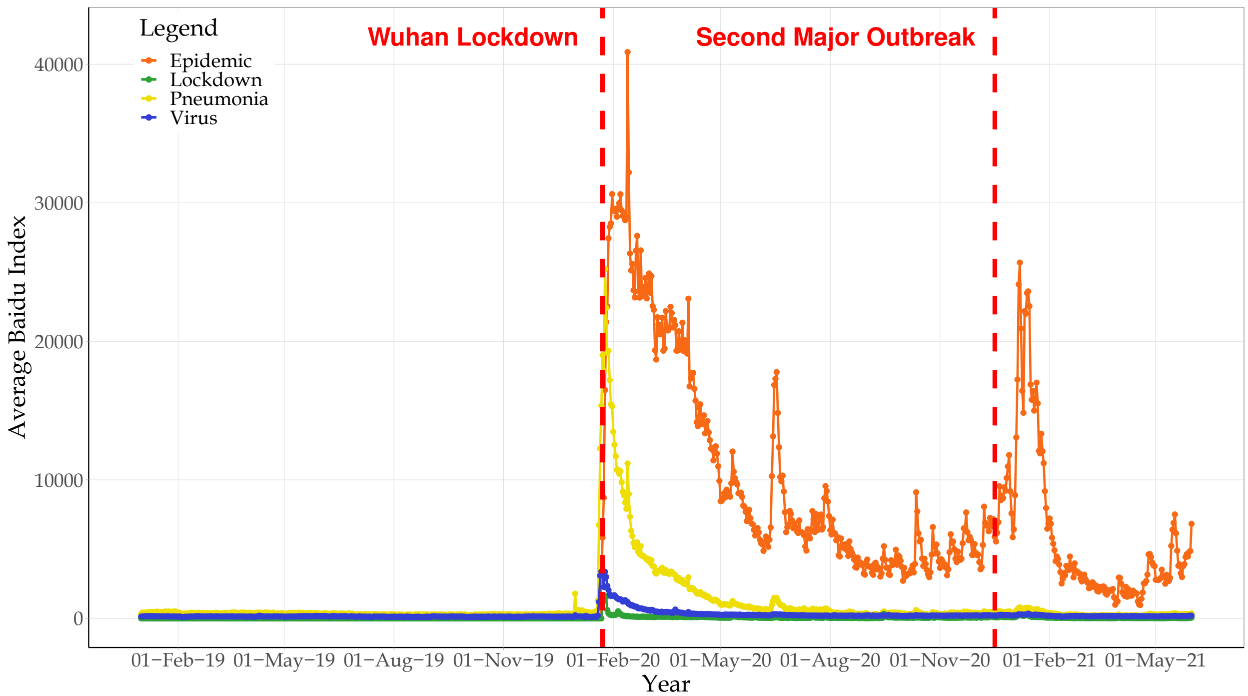


Figure 3: Plot of Baidu Search Index Terms January 2019 to May 2021

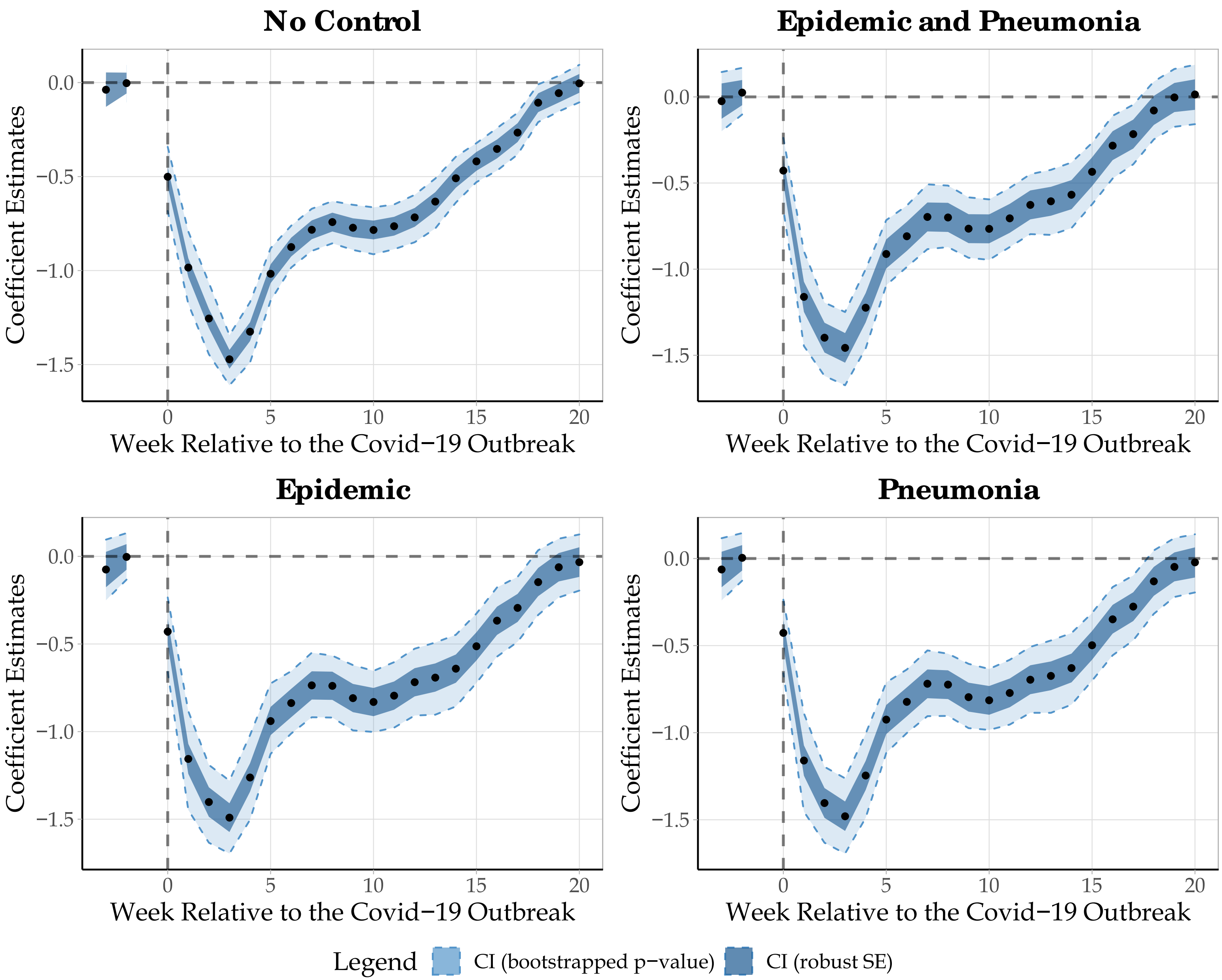


Figure 4: Coefficient Plot - Difference-in-Differences Estimates for 2020 Relative to 2019

Notes. Statistics in this plot come from the results in Table A2. All regression results depicted include city FE, week of year FE, year FE, holiday FE, and day of week FE. The top left plot is the base specification. The top right plot includes controls for epidemic and pneumonia keyword frequency searches in Baidu. The bottom left and right plots control only for epidemic and

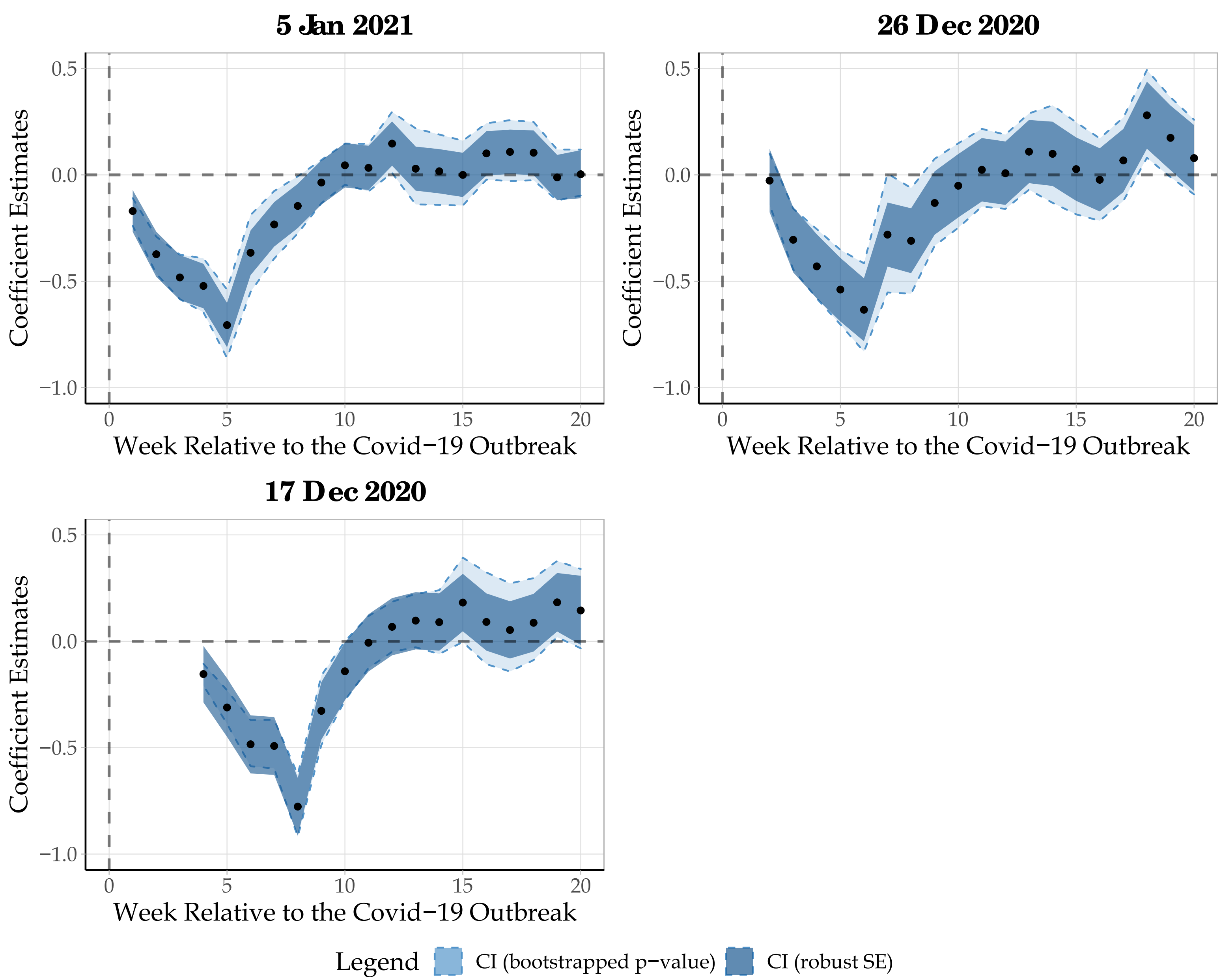


Figure 5: Coefficient Plot - Difference-in-Differences Estimates for 2021 Relative to 2019

Notes. Statistics in this plot come from the results Table A3. All regression results depicted include city FE, week of year FE, year FE, holiday FE, and day of week FE, as well as controls for epidemic and pneumonia keyword frequency searches in Baidu. The top left plot assumes a treatment date of 5 January 2021, the top right plot a treatment date of 26 December 2020, and

Online Appendix

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Table A1: List of Airports in China for the Analysis Sample

Airport	**City**
Shanghai Hongqiao International Airport	Shanghai
Beijing Capital International Airport	Beijing
Tianjin Binhai International Airport	Tianjin
Sanya Phoneix International Airport	Sanya*
Haikou Meilan International Airport	Haikou
Shijiazhuang Zhengding International Airport	Shijiazhuang
Taiyuan Wusu International Airport	Taiyuan
Jieyang Chaoshan International Airport	Jieyang*
Shenyang Taoxian International Airport	Shenyang
Jinan Yaoqiang International Airport	Jinan
Xining Caojiabao Airport	Haidong*
Urumqi Diwopu International Airport	Urumqi
Lanzhou Zhongchuan Airport	Lanzhou
Hohhot Baita International Airport	Hohhot
Xi'an Xianyang International Airport	Xianyang*
Guiyang Longdongbao International Airport	Guiyang
Changsha Huanghua International Airport	Changsha

Notes. Asterisk denotes non-capital cities.

Table A2: Difference-in-Differences Estimates for 2020 Relative to 2019

	(1)	(2)	(3)	(4)
Treated x Dummy Week = -3	-0.038	-0.025	-0.075	-0.063
	(0.047)	(0.052)	(0.052)	(0.052)
	-	[0.748]	[0.704]	[0.733]
Treated x Dummy Week = -2	-0.003	0.025	-0.003	0.004
	(0.028)	(0.037)	(0.037)	(0.037)
	[0.947]	[0.703]	[0.948]	[0.942]
Treated x Dummy Week = 0	**-0.501*** **	**-0.428*** **	**-0.429*** **	**-0.427*** **
	(0.026)	(0.037)	(0.037)	(0.037)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 1	**-0.984*** **	**-1.161*** **	**-1.156*** **	**-1.160*** **
	(0.026)	(0.045)	(0.043)	(0.044)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 2	**-1.255*** **	**-1.398*** **	**-1.402*** **	**-1.404*** **
	(0.026)	(0.044)	(0.043)	(0.044)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 3	**-1.472*** **	**-1.457*** **	**-1.491*** **	**-1.480*** **
	(0.026)	(0.044)	(0.042)	(0.043)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 4	**-1.325*** **	**-1.224*** **	**-1.262*** **	**-1.246*** **
	(0.025)	(0.043)	(0.042)	(0.043)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 5	**-1.017*** **	**-0.912*** **	**-0.940*** **	**-0.925*** **
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 6	**-0.875*** **	**-0.809*** **	**-0.837*** **	**-0.823*** **
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 7	**-0.783*** **	**-0.697*** **	**-0.736*** **	**-0.719*** **
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 8	**-0.742*** **	**-0.700*** **	**-0.739*** **	**-0.724*** **
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 9	**-0.772*** **	**-0.765*** **	**-0.809*** **	**-0.796*** **
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 10	**-0.784*** **	**-0.766*** **	**-0.831*** **	**-0.814*** **
	(0.026)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]

	(1)	(2)	(3)	(4)
Treated x Dummy Week = 11	**-0.764*****	**-0.705*****	**-0.795*****	**-0.772*****
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 12	**-0.717*****	**-0.627*****	**-0.718*****	**-0.696*****
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 13	**-0.633*****	**-0.606*****	**-0.692*****	**-0.674*****
	(0.026)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 14	**-0.509*****	**-0.568*****	**-0.641*****	**-0.629*****
	(0.026)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 15	**-0.419*****	**-0.435*****	**-0.513*****	**-0.498*****
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 16	**-0.353*****	**-0.283*****	**-0.367*****	**-0.349*****
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 17	**-0.266*****	**-0.216*****	**-0.294*****	**-0.276*****
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.000]	[0.012]	[0.001]	[0.000]
Treated x Dummy Week = 18	**-0.107*****	-0.079*	-0.147***	-0.131***
	(0.025)	(0.043)	(0.041)	(0.042)
	[0.023]	[0.450]	[0.120]	[0.179]
Treated x Dummy Week = 19	-0.056**	-0.003	-0.062	-0.048
	(0.026)	(0.043)	(0.041)	(0.042)
	[0.256]	[0.970]	[0.506]	[0.662]
Treated x Dummy Week = 20	-0.004	0.014	-0.033	-0.022
	(0.026)	(0.045)	(0.043)	(0.044)
	[0.927]	[0.911]	[0.724]	[0.832]
Observations	5,712	5,712	5,712	5,712
R-squared	0.968	0.970	0.969	0.969
Controls	No	Epidemic and Pneumonia	Epidemic	Pneumonia

Notes. Robust standard errors clustered by city are in parentheses. Bootstrapped p-values clustered at the city level using the wild bootstrap proposed by Cameron et al. (2008) using 1000 replications are reported in square brackets. Bold coefficients indicate that there is at least 10% statistical significance for both the robust SEs and the bootstrapped p-values. All regressions include city FE, week of year FE, year FE, holiday FE, and day of week FE. "-" means test statistics cannot be computed. *, ** and *** denote significance at 10%, 5% and 1%. The treatment date is 23 Jan 2020.

Table A3: Difference-in-Differences Estimates for 2021 Relative to 2019

	(1)	(2)	(3)
Treated x Dummy Week = 1	**-0.170*** **		
	(0.050)		
	[0.000]		
Treated x Dummy Week = 2	**-0.373*** **	-0.027	
	(0.054)	(0.076)	
	[0.000]	[0.661]	
Treated x Dummy Week = 3	**-0.482*** **	**-0.305*** **	
	(0.054)	(0.078)	
	[0.000]	[0.000]	
Treated x Dummy Week = 4	**-0.522*** **	**-0.430*** **	**-0.154** **
	(0.053)	(0.077)	(0.068)
	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 5	**-0.706*** **	**-0.539*** **	**-0.311*** **
	(0.053)	(0.076)	(0.070)
	[0.000]	[0.000]	[0.000]
Treated x Dummy Week = 6	**-0.366*** **	**-0.634*** **	**-0.484*** **
	(0.054)	(0.075)	(0.070)
	[0.001]	[0.000]	[0.000]
Treated x Dummy Week = 7	**-0.233*** **	**-0.281*** **	**-0.492*** **
	(0.053)	(0.077)	(0.069)
	[0.001]	[0.060]	[0.000]
Treated x Dummy Week = 8	**-0.146*** **	**-0.310*** **	**-0.777*** **
	(0.053)	(0.078)	(0.069)
	[0.043]	[0.007]	[0.000]
Treated x Dummy Week = 9	-0.036	-0.132*	**-0.327*** **
	(0.053)	(0.076)	(0.069)
	[0.510]	[0.268]	[0.004]
Treated x Dummy Week = 10	0.045	-0.051	**-0.141** **
	(0.053)	(0.076)	(0.069)
	[0.309]	[0.622]	[0.050]
Treated x Dummy Week = 11	0.033	0.024	-0.007
	(0.053)	(0.076)	(0.069)
	[0.518]	[0.792]	[0.910]
Treated x Dummy Week = 12	**0.147*** **	0.008	0.068
	(0.053)	(0.076)	(0.069)
	[0.034]	[0.925]	[0.243]
Treated x Dummy Week = 13	0.029	0.109	0.097
	(0.053)	(0.076)	(0.069)
	[0.780]	[0.232]	[0.107]

	(1)	(2)	(3)
Treated x Dummy Week = 14	0.017	0.099	0.090
	(0.053)	(0.077)	(0.069)
	[0.840]	[0.453]	[0.237]
Treated x Dummy Week = 15	-0.000	0.027	**0.182*** **
	(0.053)	(0.076)	(0.069)
	[0.997]	[0.827]	[0.056]
Treated x Dummy Week = 16	0.101*	-0.023	0.091
	(0.053)	(0.076)	(0.068)
	[0.131]	[0.854]	[0.489]
Treated x Dummy Week = 17	0.108**	0.068	0.053
	(0.053)	(0.076)	(0.069)
	[0.147]	[0.494]	[0.653]
Treated x Dummy Week = 18	0.104*	**0.280*** **	0.087
	(0.054)	(0.080)	(0.069)
	[0.135]	[0.007]	[0.439]
Treated x Dummy Week = 19	-0.012	**0.174** **	**0.183*** **
	(0.054)	(0.077)	(0.070)
	[0.874]	[0.062]	[0.025]
Treated x Dummy Week = 20	0.003	0.079	0.145*
	(0.058)	(0.079)	(0.083)
	[0.973]	[0.351]	[0.153]
Treatment Date	5-Jan-21	26-Dec-20	17-Dec-20
Observations	4,947	4,658	4,267
R-squared	0.921	0.919	0.916

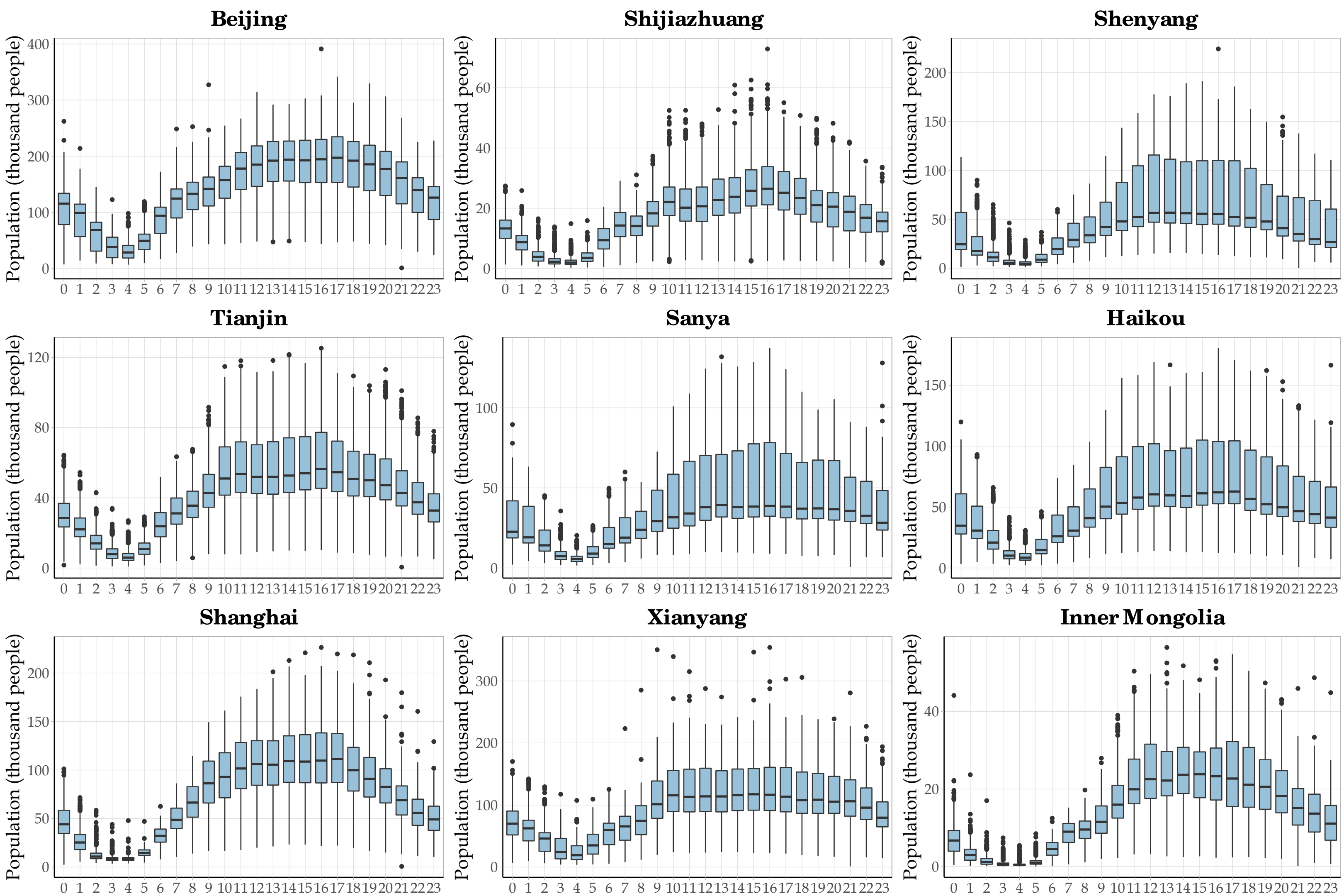
Notes. Robust standard errors clustered by city are in parentheses. Bootstrapped p-values clustered at the city level using the wild bootstrap proposed by Cameron et al. (2008) using 1000 replications are reported in square brackets. Bold coefficients indicate that there is at least 10% statistical significance for both the robust SEs and the bootstrapped p-values. All regressions include city FE, week of year FE, year FE, holiday FE, day of week FE, and Baidu index of keywords “pneumonia” and “epidemic”. *, ** and *** denote significance at 10%, 5% and 1%. The treatment date is either 5 Jan 2021, 26 Dec 2020 or 17 Dec 2020 (columns 1-3 respectively).

Table A4: Pre-trends Analysis for Difference-in-Differences Estimates for 2021 using 2020

	(1)	(2)	(3)
Treated x Dummy Week = -5	**-0.161****	-0.077	0.282***
	(0.072)	(0.050)	(0.096)
	[0.001]	[0.145]	[0.303]
Treated x Dummy Week = -4	**-0.183*****	-0.050	-0.083
	(0.067)	(0.046)	(0.052)
	[0.000]	[0.227]	[0.000]
Treated x Dummy Week = -3	**-0.232*****	-0.052	-0.065
	(0.056)	(0.040)	(0.046)
	[0.000]	[0.027]	[0.000]
Treated x Dummy Week = -2	**-0.136****	-0.016	-0.048
	(0.041)	(0.030)	(0.036)
	[0.001]	[0.031]	[0.000]
Treated x Dummy Week = 0	0.017	**0.112*****	0.001
	(0.046)	(0.029)	(0.036)
	[0.498]	[0.000]	[0.942]
Observations	1,344	1,344	1,232
R-squared	0.961	0.978	0.980
Treatment Date	5-Jan-21	26-Dec-20	17-Dec-20

Notes. Robust standard errors clustered by city are in parentheses. Bootstrapped p-values clustered at the city level using the wild bootstrap proposed by Cameron et al. (2008) using 1000 replications are reported in square brackets. Bold coefficients indicate that there is at least 10% statistical significance for both the robust SEs and the bootstrapped p-values. All regressions include city FE, week of year FE, year FE, holiday FE, day of week FE, and Baidu index of keywords "pneumonia" and "epidemic". *, ** and *** denote significance at 10%, 5% and 1%.

Figure A1: Location of the Airports in the Sample


Beijing
Shijiazhuang
Shenyang
Tianjin
Sanya
Haikou
Shanghai
Xianyang
Inner Mongolia
Population (thousand people)

(cont.)

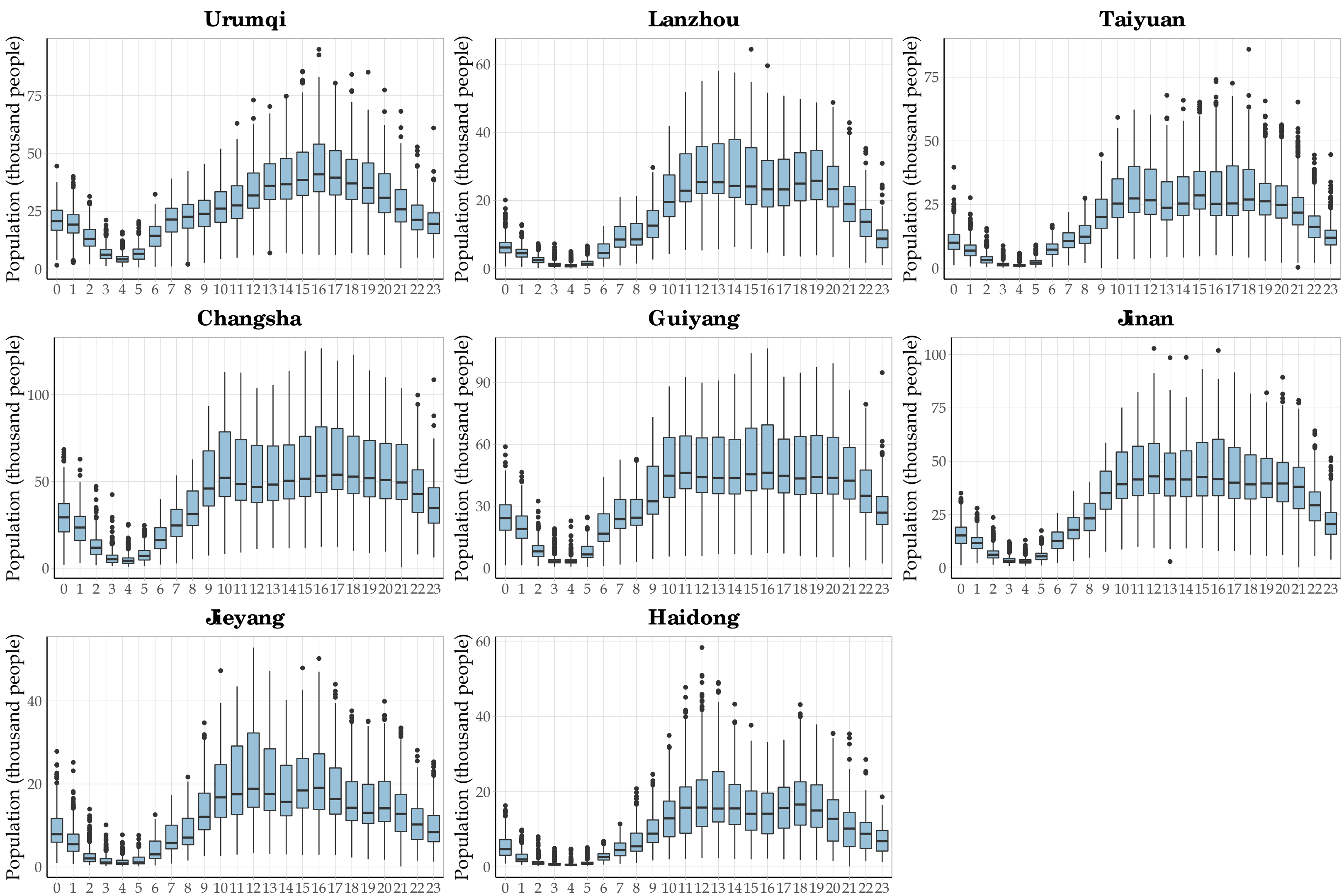
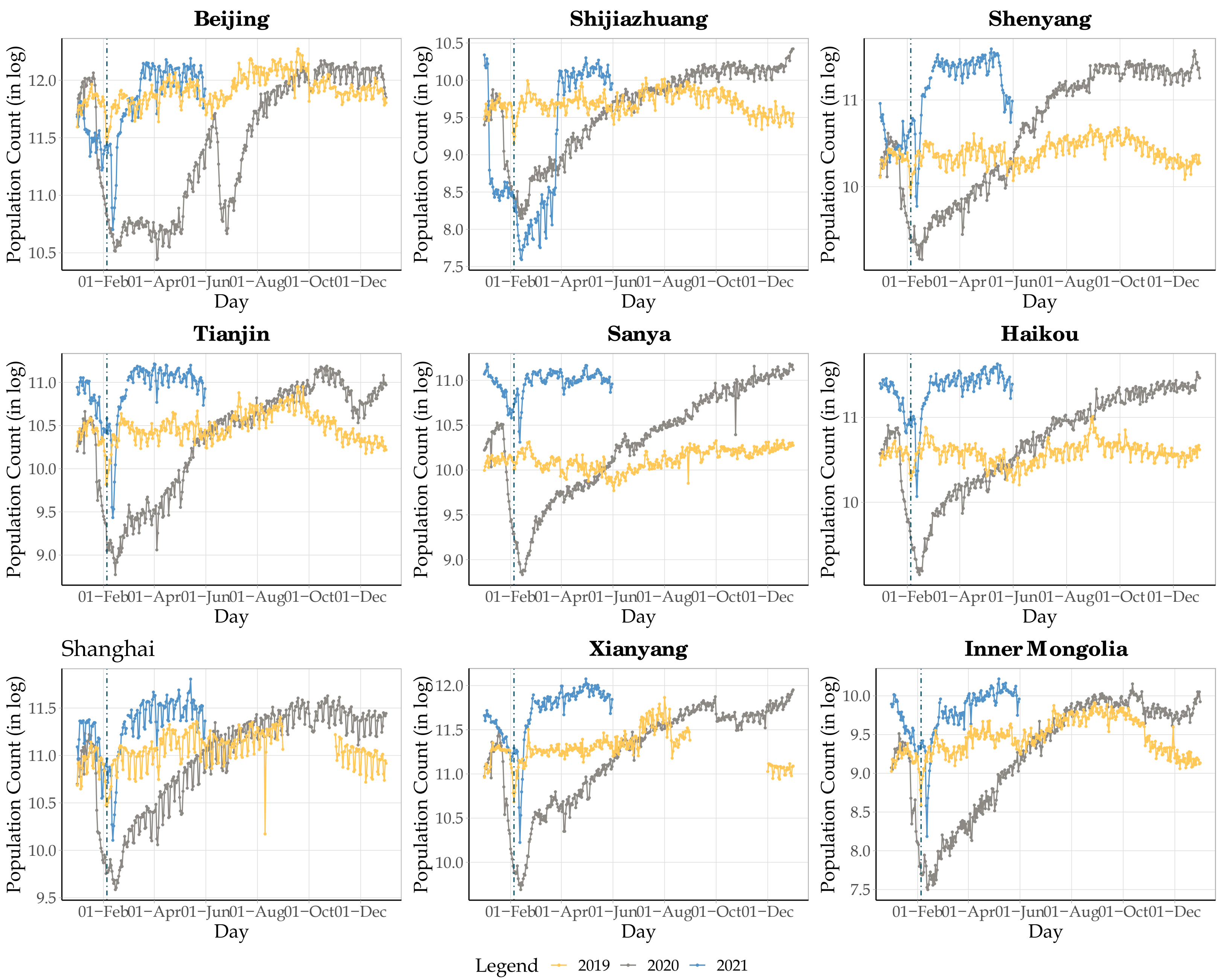


Figure A2: Boxplot of Average Population Counts by Hour of the Day and Airport

Notes. The data period is 01 Jan 2019 to 31 May 2021. The data in the plots are at the daily level (collapsed from the raw 5-minute level data). There are missing values for Shanghai during 1 September - 30 October 2019 and Xianyang during 1 September - 30 November 2019.


Beijing
Shijiazhuang
Shenyang
Tianjin
Sanya
Haikou
Shanghai
Xianyang
Inner Mongolia
Population Count (in log)
01−Feb
01−Apr
01−Jun
01−Aug
01−Oct
01−Dec
Day
Legend
2019
2020
2021

(cont.)

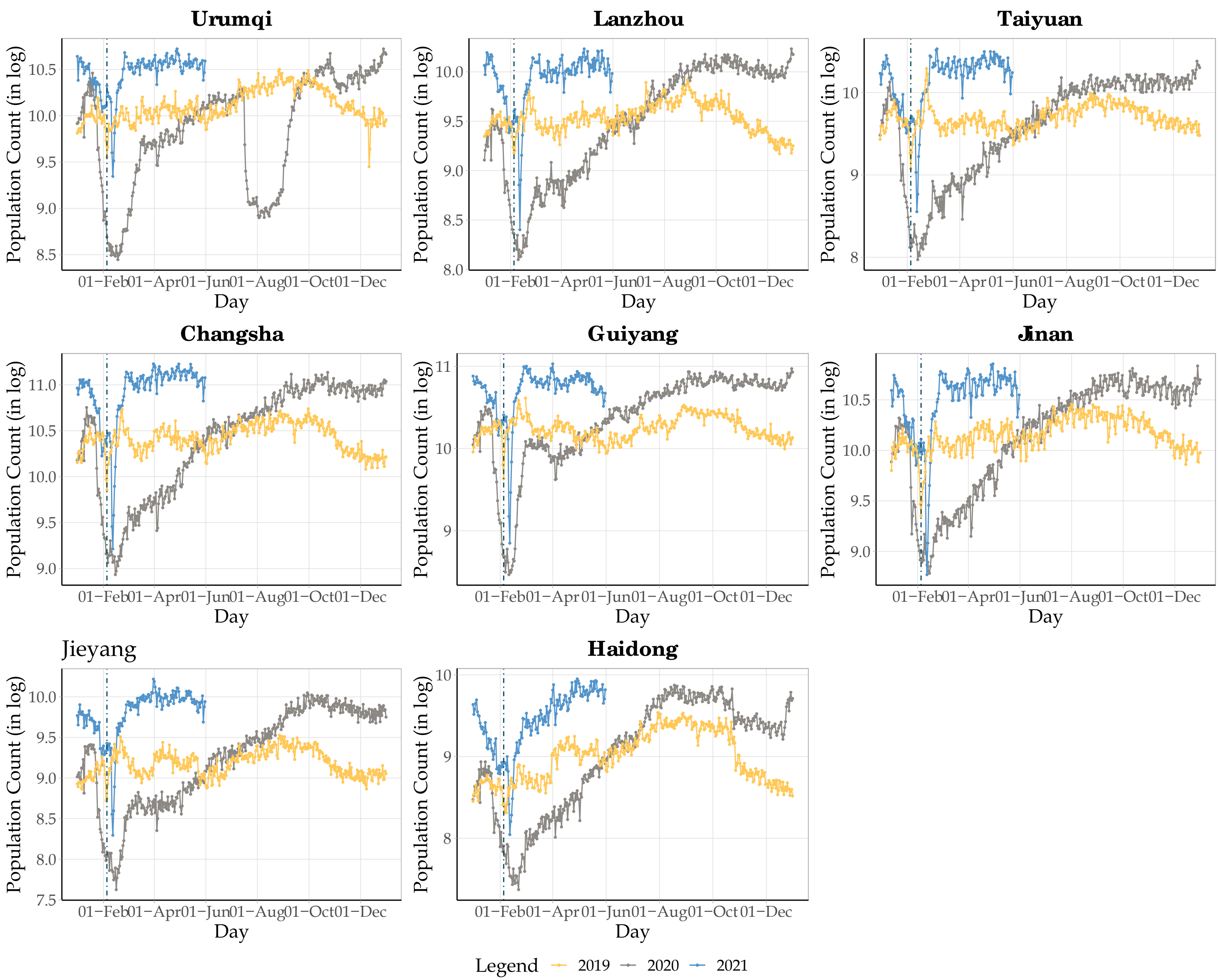
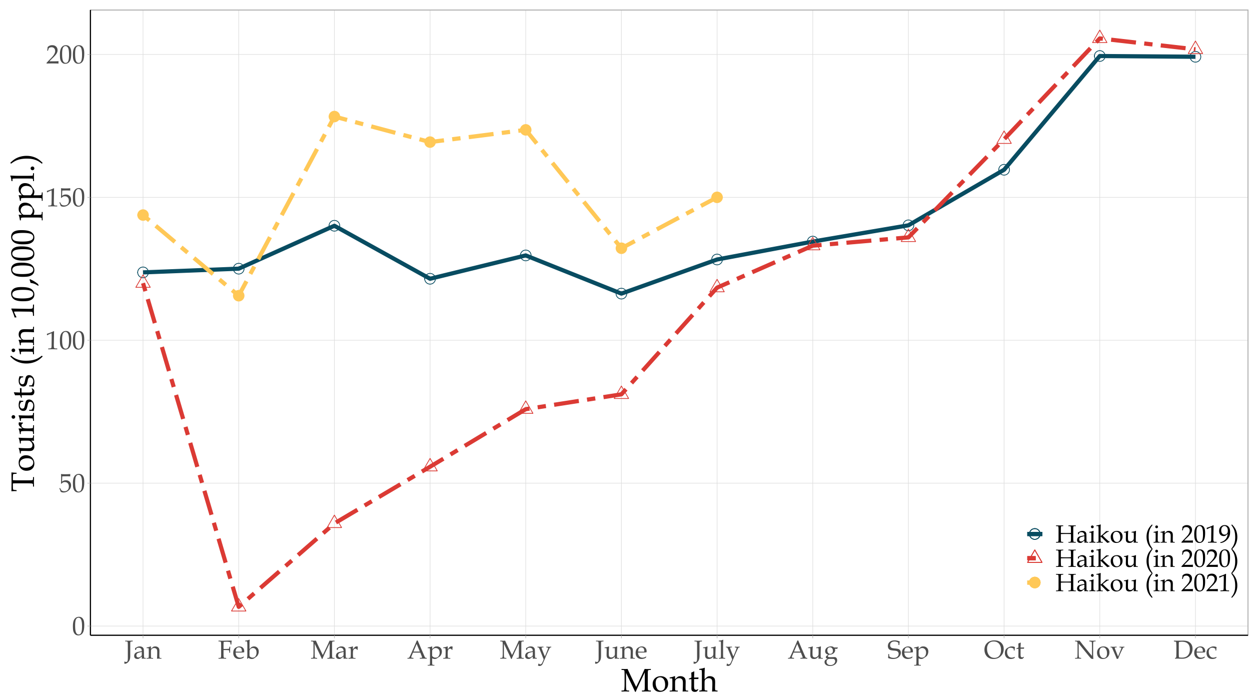
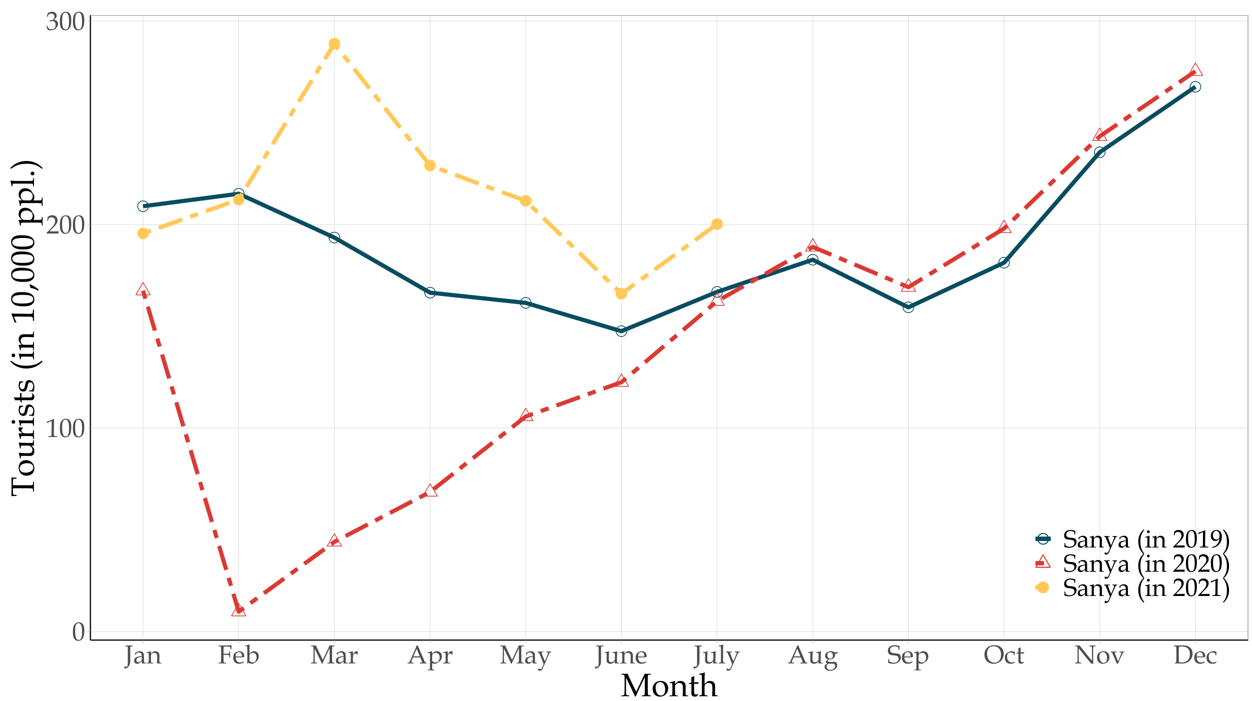


Figure A3: Log Population Counts at Each Airport in China



(a) Popular Tourist City: Haikou



(b) Popular Tourist City: Sanya

Figure A4: Monthly Tourists Visits in the Major Tourist Cities