The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data*

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Abstract: We use daily transaction data in 214 cities to study the impact of COVID-19 on consumption after China's outbreak in late January 2020. Based on difference-in-differences estimation, daily offline consumption—via UnionPay card and QR scanner transactions—fell by 32%, or 18.57 million RMB per city, during the twelve-week period. Spending on goods and services were both significantly affected, with a decline of 33% and 34%, respectively; within finer categories, dining & entertainment and travel saw the greatest dip of 64% and 59%. The consumption decrease is prevalent across cities with the largest drop occurring in the epicenter Wuhan (by 70%). Consumption responded negatively to the day-to-day changes in epidemic severity while distancing measures remained stable. Consumption had rebounded back to the baseline level by the end of March but dropped to -20% in early April due to the elevated risk of a second wave of infections. We infer that China's offline consumption decreased by over 1.22 trillion RMB in the three-month post-outbreak period, or 1.2% of China's 2019 GDP. Our estimates suggest a significant economic benefit of containing the virus through a lessened consumption decrease and a faster consumption recovery.

Keywords: COVID-19, coronavirus, pandemic, consumption, economic impact, policy response, fiscal stimulus, transaction data

JEL codes: E21, E62, E61

1. Introduction

On March 11, 2020, the World Health Organization announced COVID-19 outbreak as pandemic. By late-April 2020, COVID-19 had infected more than 2.88 million people worldwide in 210 countries, with over 198,000 deaths. Countries around the globe have increasingly implemented strict public health measures to respond to the outbreak. These measures range from social distancing to a complete lockdown, invariably constraining economic activities with serious ramifications. Many governments have rolled out gigantic fiscal stimulus packages, as large as over 10% of the country's GDP, to help combat the negative economic consequences of COVID-19. New support packages will likely be added as we delve further into the pandemic.

An ongoing policy debate centers on finding adequate measures that balance public health efforts to contain the coronavirus spread with considerations to neutralize the economic impact. Public health measures that enforce strict distancing and mobility restrictions incur a significant cost to the economy. A major economic woe is firms' immediate cashflow pressure from the sudden halt in economic activities, leading to massive unemployment and business shutdown that feed back into aggregate demand. However, downplaying public health interventions also carries serious economic consequences. Knowledge is inconclusive concerning the transmission mode, rate of spread, and lethality, and no effective medical cure of the novel coronavirus exists, making projecting the course of the pandemic difficult. The huge uncertainty directly hurts consumers' willingness to consume when they feel unsafe and anxious, even with no imminent threat of economic security. The reduction in consumer demand as a direct result of the pandemic will therefore create a rippling effect on the macroeconomy. Consequently, a prolonged pandemic outbreak will weaken demand and delay economic recovery. Such intricacies add to the challenge of policy responses, compounded by the lack of a good understanding of the magnitude and source of the problem due to the unprecedented nature of the crisis in the past century.

This paper provides direct evidence on the immediate economic impact of COVID-19, drawing upon China's experience to date. China offers a good setting to assess the economic impact of COVID-19. It was the first country to experience a large-scale outbreak, starting in January 2020, which renders a sufficiently long post-outbreak period and thus statistical power for us to obtain credible estimation. By mid-April, China had reported 82,341 COVID-19 cases with 3,342 deaths. Significant geographic variation exists in the epidemic exposure across cities: the epicenter city, Wuhan, accounts for 61% of the total reported cases, whereas 33 cities had reported 0 cases by the mid of April. The Chinese government implemented draconian measures to contain the spread, including locking down Wuhan on Jan 23, 2020. Other cities also used strict measures to distance the population, and to trace and isolate suspected COVID-19 patients as well as closing non-essential service businesses, which other infected countries or regions subsequently adopted to a varying degree. Moreover, China reported no new local infections on March 19 and gradually relaxed the lockdown and mobility restriction measures since late February. This also provides an opportunity to study the path of economic recovery, both during and after stringent public health measure enforcement.

We focus on the impact of COVID-19 on consumption, which accounts for over 42% of China's GDP in the last decade (source: People's Bank of China, National Bureau of Statistics). We gain access to the universe of consumer spending transactions at offline merchants using bank cards and mobile QR codes (i.e., linked to e-wallets in Alipay and Wechat pay), captured by UnionPay's POS machines and QR scanners. UnionPay is the one of China's largest payment service provider for offline spending serving over 1 billion people in the country (source: People's Bank of China). In 2019, the total offline consumer spending recorded by UnionPay covers 30% of China's total retail consumption offline (source: China UMS and National Bureau of Statistics). While E-Commerce has experienced accelerating growth in recent years, offline consumption still constitutes 76% of China's overall retail consumption (source: National Bureau of Statistics). In addition, with brick-and-mortar retailers as major employers in the economy, studying offline consumption provides a sharper assessment of the economic impact of COVID-19.

We collect daily offline consumption at the city level from January 1 to April 14 2020 for 214 prefecture-level cities, which cover 92% of China's 2018 GDP and 90% of the country's urban population. In addition to total spending, we observe consumption by type (goods vs. services) and by category (daily necessities, durable goods, discretionary goods, dining & entertainment, travel-related, and others). For the empirical analysis, we use the Wuhan lockdown date (January 23, 2020) as the start of the outbreak and compare the consumption before and after. To capture the counterfactual consumption pattern, we use the same period data in 2019 as the benchmark group. Instead of using the same calendar date to divide the 2019 sample, we use the lunar calendar to define the event date to account for the seasonal variation in consumption related to the CNY period. January 23, 2020 was the day before CNY eve, and thus we use the corresponding lunar calendar date in 2019 as the cutoff to define the before and after period. In the difference-in-differences regressions, we include city, event-day, and day-of-week fixed effects to absorb unobserved city and time heterogeneity.

Our objective is two-fold. The first is to use the transaction-based consumption measure to document and quantify the immediate impact of COVID-19 on aggregate consumption. How large is the consumption decrease? For what type and categories of consumption do we observe the greatest effect? How persistent is the impact and how soon did the recovery start? The second goal is to investigate the pattern of the consumption impact across space and over time in relation to the occurrence and severity of the epidemic outbreak. We exploit the data's high frequency and large cross section to detect the consumption response to day-to-day changes in the epidemic development, whereas macroeconomic conditions and distancing measures varied at a (much) lower frequency. Thus, we can learn about the direct effect of the epidemic severity on consumption.

After the coronavirus outbreak, China's consumption took a severe hit. Looking at the raw consumption data, the average difference in total offline consumption for the 214 cities in sample is 8.06 billion RMB per day in 2020 after the outbreak. However, part of the decrease may capture the seasonal variation in spending during the CNY period. We use the difference-in-differences regression to estimate the change in consumption relative to the counterfactual change in spending based on 2019 data. The regression result suggests cities witnessed a decline in their offline consumption by 18.57 million RMB per day, on average, or 32% in percentage terms. This finding translates into a total decrease of 329.84 billion RMB in the twelve-week post-outbreak period.

If other offline consumption experienced a similar rate of decrease, and using the fact that UnionPay captures 30% of China's offline consumption and that our sample covers 90% of the urban population, we infer a total decrease in China's offline consumption of 14.72 billion RMB per day, or 1.22 trillion RMB during the twelve-week post-outbreak period. As a reference, the country's total GDP in 2019 was 99.10 trillion RMB. Note the number likely represents a lower-bound estimate, because consumption using cash presumably could be more severely affected. We also provide a coarse estimate of the online-spending response to the COVID-19 outbreak to be -13%. Given the 76% share of offline consumption in China, we infer the total consumption in

China declined 27% twelve weeks after the outbreak.

Spending on goods and services were both significantly affected, with a decline of 33% and 34%, respectively. Within goods, durable spending fell the most—by 35%—followed by discretionary items (e.g., apparel and shoes) with a decrease of 29%. Regarding services, dining & entertainment and travel-related spending experienced significant decreases of 64% and 59%, respectively. Their large decreases are likely related to the intervention measures in place, which imposed mobility restrictions and closed non-essential services.

We observe a prevalent consumption decrease across the 214 cities in our sample: the median city experienced a decrease of 33% with over 90% of the 214 cities saw a consumption decrease of more than 20%. Notably, the consumption effect is stronger in more-exposed cities (after controlling for city's size and dependence on service and export industries). The epicenter city, Wuhan, witnessed a 70% decrease in its offline consumption during the twelve-week post-outbreak period. We also study the effect for the 20 cities that received the highest inflow of Wuhan residents during the two-week period before the outbreak. These cities were at a higher risk of importing cases and spreading the disease; accordingly, offline consumption decreased by 11% more in these more-exposed cities than the rest of the cities in our sample. For the cities reporting 0 cases (as of mid-April), the decrease in offline consumption was 12% less than cities with positive COVID-19 cases in the same time window. Geographically, using heatmaps, we show the greatest consumption decline was concentrated in cities closer to Wuhan and a few other cities, which all had more COVID-19 cases.

The cross-sectional findings reveal a compelling pattern between epidemic severity and changes in city consumption. It is likely attributable to the consequences of the distancing and mobility-restriction measures, either by physically constraining people's shopping opportunities or through affecting income and job security. In addition, the epidemic disease can induce uncertainty and anxiety and change consumers' willingness to spend, absent mobility restrictions and for those without imminent income loss concerns. To enlighten the latter channel, we leverage the high frequency data to examine how daily consumption in each city responded to the one-day lagged indicators of the epidemic in the same city, while controlling for city and time fixed effects. The epidemic measures, including the number of COVID-19 cases, hospital capacity, and the COVID-19 death toll in the city, not only gauge the day-to-day change in severity, but also capture changing uncertainty on the length and trajectory of the city's epidemic exposure. At the same time, we note that relevant distancing and mobility-restriction measures as well as macroeconomic conditions were more persistent in the sample period, allowing us to isolate the direct effect of the epidemic.

Results suggest a strong negative sensitivity of consumption to within-city changes in the outbreak severity. Doubling the infected cases in a city was followed by a 4.9% greater decrease in the same-city offline consumption. In addition, rising numbers heightened the concern about hospital capacity: when a city was among the 30 cities with the highest COVID-19 cases relative to the city's hospital bed capacity, city offline consumption dropped by an additional 5%. Similarly, doubling the city's COVID-19 deaths led to an additional 8.3% decrease in consumption. The negative association between consumption and epidemic intensity is not driven by Wuhan, nor does it coincide with each city's implementation of mobility-restriction measures (that limit people's spending opportunities). We also find the consumption sensitivity to epidemic severity to be equally strong, both qualitatively and quantitatively, across all spending categories. In sum, these results suggest the consumer demand responds promptly to uncertainty regarding the pandemic's trajectory.

Turning to the evolution of the consumption change over time, we find the decline in consumption started immediately after Wuhan lockdown. On average, city offline consumption fell by 6.6% during the immediate week after Wuhan lockdown, before reaching the largest decline (59%-66%) in the next three weeks after the outbreak. Notably, the consumption change became less negative starting from the fifth week, when the epidemic curve showed sign of flattening. By the end of eight weeks, the consumption decrease shrank to 33%, a 33% improvement relative to the lowest consumption decline. By the end of March (i.e., ten weeks after the outbreak), consumption had fully rebounded since the difference-in-differences estimate is not statistically distinguishable from zero. The recovery is evident for both the goods and services consumption types yet spending on dining & entertainment as well as on travel-related show much weaker rebounds than spending on discretionary items and durable goods. It's important to note that we observe a very similar recovery pattern by restricting to the period before cities downgraded from the highest level of emergency public health alerts and responses (i.e., the regime corresponding to the most stringent restriction measures), which underscores the consumption recovery as a direct response to the improvement in the public health situation.

However, consumption fell again, to 20% and 16% below the baseline level, in the first two weeks of April. This retreat echoes the rising concern over a potential second wave of infections, mostly driven by imported and asymptomatic cases. The day-to-day consumption responses in April indeed demonstrates a strong negative relationship with the one-day lagged number of new cases, including the asymptomatic cases that the government started to report since the beginning of April. Since most cities relaxed their mobility restrictions measures by April, this evidence highlights the importance of epidemic containment in the economic recovery.

We further illustrate this point by showing the overall consumption decline and recovery across 214 cities during the twelve-week period. More specifically, at the epicenter, Wuhan's consumption decrease started immediately and remained persistently large—down by 75%-87% in the second to the eighth week, followed by a slow recovery with its consumption still down by 52% by the end of the sample period. Several mega cities, including Guangzhou, Beijing, and Shanghai, saw a visible resurgence of COVID-19 cases near the end of the sample period and a large consumption decline subsequently. In addition, cities with a higher service industry concentration or export dependence showed a very similar consumption recovery path as cities less reliant on service and export industries. We cannot reject the null hypothesis that the consumption rebound by the end of March and the subsequent dip in early April differ between the two sets of cities, while the economic consequences continued to unravel, especially after the concurrent global pandemic development. Therefore, this result provides further support that China's consumption decline and recovery traces the progress in epidemic containment.

What do we learn from these results? First, the consumption consequences are grave. It responded immediately and was hit hard across the board. Heavily exposed cities, such as Wuhan, saw their offline consumption reduced by close to 70% during a twelve-week period. Strict public health measures, which significantly restricted people's physical activities and halted many businesses, are likely an important factor. The findings thus highlight the importance of policymakers using prompt and adequate interventions to alleviate the negative impact especially on the more affected sectors such as retail and certain service industries. Our finding implies China lost over 1.2% of the entire country's 2019 GDP through offline consumption in the twelve-week post-outbreak period, providing an informative ballpark estimate of the effect magnitude, as many countries start to go through the same experience.

Second, the consumption pattern also shows a strong negative sensitivity to the day-to-day change in the severity of the public health crisis. When the public health situation worsened, consumption plummeted as well. Such a relationship is not explained by the mobility-restriction measures or macroeconomic conditions that varied at a much lower frequency in the period. We observe an encouraging trajectory of consumption recovery starting from the second month after the outbreak, as the epidemic curve started to stabilize. When indicators of a potential second wave of infections in China emerged in April, consumption immediately fell again by a significant margin, even though most cities had relaxed the mobility restriction measures by then. These findings suggest management of the public health crisis is crucial for reinvigorating our economy. When consumers' demand retreats from the pandemic-induced uncertainty, economic relief programs, which focus on injecting liquidity in the economy, may result in a limited effect and even risk being unsustainable.

We use our estimates to provide a more quantitative assessment on the economic benefit of containment of the coronavirus spread. First, we identify, for each city, the first day the number of newly recovered cases exceeded the number of newly confirmed cases. We use the correlation between the city-level days-to-turning-point and the average first-month consumption decrease as well as the size of consumption recovery (consumption effect in the last second month minus the first month effect) to back out the consumption implication of the speed to contain the spread. Controlling for the city population, a 10-day reduction in the time for newly recovered cases to exceed newly infected cases lessens the first-month consumption decrease by 3% and increases the second-month consumption recovery by 4.1%. Similarly, controlling for the level of infected cases, cities with zero COVID-19 deaths on average had 4.5% smaller consumption decrease in the first post-outbreak month and 4.6% greater consumption recovery in the second month.

Our contributions to the literature are two-fold. A large literature finds the economic consequences of diseases are significant (e.g., Fan, Jamison, and Summers, 2016). Specifically, large-scale viral diseases have a significant long-term impact on GDP and per-capita income (Bloom and Mahal, 1997; Sachs and Malaney, 2002), human capital accumulation (Young, 2005; Almond, 2006; Bleakley, 2007), house prices, and urban landscape (Ambrus, Field, and Gonzalez, 2020). Given the glaring concern over the COVID-19 pandemic, economists have started to identify and estimate the potential economic impact (e.g., Atkeson, 2020; Barro, Usua, and Weng, 2020;

Gormsen and Koijen, 2020). We use high frequency transaction-based consumption data to quantify the aggregate consumption impact of COVID-19 and relate it to the epidemic severity both in the cross section and over time.[1]

This paper also contributes to the debate over the benefits and costs of public health measures that limit interpersonal contact or restrict traffic. Greenstone and Nigam (2020) and Fang, Wang, and Yang (2020) find such measures are effective in containing the virus' spread. Research also shows the intervention measures mitigate the negative economic consequences (Correia, Luck and Verner, 2020; Duan, Wang, and Yang; 2020; Li, Qin, Wu, and Yan, 2020). Others caution about the cost-effectiveness of social distancing (Adda, 2016) or show direct and indirect economic costs of such interventions (Chen, He, Hsieh, and Song, 2020; Eichenbaum, Rebelo, and Trabandt, 2020). Our results imply a large risk of reduced consumer demand in face of the huge uncertainty regarding the disease, cautioning policies that weigh stimulating economic activities over public health effort to contain the pandemic. To put the uncertainty aspect in perspective, the epidemiology literature is far from reaching a conclusion about the transmission mode of this novel coronavirus (Ferretti et al., 2020; Wong, Leo, and Tan, 2020), the spread rate (Li et al., 2020; Wu, Leung, and Leung, 2020), morbidity and mortality (Li et al., 2020; Tian et al., 2020), and the existence of an effective vaccine or medical cure (Cao et al., 2020).

2. Data and Empirical Methodology

2.1.Consumption data

Our dataset is a daily city-level offline consumption dataset obtained from China UnionPay Merchant Services Corporation (hereafter China UMS), the largest bankcard acquiring and professional service supplier in China. The daily offline consumption is calculated as the sum of all spending through China UMS POS machines or QR scanners for each city during our sample period. Given their recent adoption of QR scanner machines, China UMS not only records spending transactions through POS machines, but it can also capture a significant share of offline spending transactions through mobile QR codes (i.e., spending linked to e-wallets of Alipay or

[1] Our paper is more broadly related to the large literature on the consumption response to income or macroeconomic shocks (see review by Jappelli and Pistaferri, 2010). Recent literature uses high frequency and transaction-based consumption data and document significant consumption responses (e.g., Agarwal, Liu, and Souleles, 2007; Agarwal and Qian, 2014, 2017; Gelman et al., 2014, Di Maggio et al. 2017).

WeChat pay accounts). China UMS focuses on offering service to offline merchants. According to the recent statistics provided by China UMS, by the end of 2019, China UMS had set up a national service network, serving close to 8 million offline merchants in various types of offline spending categories, such as department stores, restaurants, hotels, air travel, finance and taxation, logistics, health care, and so on. In 2019, China UMS completed 12.7 billion transactions, with a transaction volume of 15 trillion RMB. Of those transactions, 9 trillion RMB capture offline spending, which covers about 30% of China's total offline retail consumption (source: China Bureau of Statistics).

Our sample covers 214 prefecture-level cities in China, with an urban population above 1 million in 2017. These cities account for about 92% of China's 2018 GDP and close to 90% of China's urban population in 2017. The sample period is from January 1, 2020, to April 14, 2020, with January 23, 2020 (when Wuhan lockdown was implemented) defined as the start of the outbreak. To capture the counterfactual consumption pattern, we use the same data from January 12, 2019, to April 26, 2019, as the benchmark group, and evaluate the impact on consumption through a DID regression approach. Note we match the sample in 2019 and 2020 by the lunar calendar instead of the calendar date to capture the seasonality variation in consumption related to CNY. Accordingly, we use February 3, 2019 (one day before CNY Eve similar to January 23, 2020), as the cut-off date to define the before and post period for 2019. Besides total consumption, we collect the city-level aggregated consumption for six detailed consumption categories: durable goods, daily necessities, discretionary items, dinning & entertainment, travel-related service, and others. We also combine them into two broad consumption types: goods and services; see Table A1 for the detailed classification of each type.

Our dataset offers several advantages for studying consumption. First, relative to surveyed consumption datasets, our sample covers almost 90% the country's urban population and provides high-frequency, up-to-date, transaction-based information about consumers' offline spending before and after the outbreak of COVID-19. While official statistics reported aggregate consumer spending on a periodic basis, our data offer a much more granular view at high frequency and for each city using actual spending transactions. Second, instead of relying on one specific bank or financial institution, our dataset covers credit cards and debit cards issued by Chinese commercial banks or financial institutions that carry the UnionPay logo, as well as mobile payment transactions captured by UnionPay scanner machines. In sum, our data can capture offline consumption behavior representative of China during such an unprecedented public health crisis. Admittedly, our dataset does not cover the offline consumption through POS machines or QR scanners that are not operated by China UMS. However, such measurement error will not change our main conclusion if the distribution and use of POS machines or QR scanners of different service providers do not considerably change in the short period around the COVID-19 outbreak.

2.2.Data on China's COVID-19 outbreak

We download the dataset on China's COVID-19 from CSMAR database. The daily cumulative confirmed cases, cumulative deaths, and cumulative recovered cases for each infected city are updated daily by the National Health Commission of China or province-level Health Commissions since January 21, 2020. In addition, we collect city characteristics, such as population, GDP, industry composition, and number of hospital beds from China City Statistical Yearbook, China Urban Construction Statistical Yearbook, and CEIC database. The Wuhan migrant-flow data are obtained from Baidu (http://qianxi.baidu.com/). The implement dates of control policies for each city are obtained from Fang et al. (2020).

2.3.Summary statistics

Table 1 presents the summary statistics of daily offline consumption. Based on the event date of each year, we divided the sample in 2019 and 2020 into two periods: the pre-period and the post-period.

Panel A reports the summary statistics for the 2019 sample (control group). The average city-level daily offline consumption for the whole sample period, the pre-period, and the post-period are 75.23, 89.89, and 71.35 (units: million RMB), respectively. Relative to the pre-period, the post-period fell by 18.55 million RMB, or 21%. The median of the daily offline consumption for the three sample periods is 32.62, 42.28, and 30.44. Compared to the pre-period, the median for the post-period decreased by 11.84 million RMB, or 28%. The decrease likely reflects a seasonal consumption pattern associated with CNY.

Panel B reports the summary statistics for the 2020 sample (treated group). The average city-level daily offline consumption for the whole sample period, the pre-period, and the post-period is 33.64, 63.41, and 25.74 (units: million RMB), respectively. Relative to the pre-period, the post-period fell by 37.67 million RMB, or 59%. The median of daily offline consumption for the full-, pre-, and post-period sample periods is 12.89, 27.63, and 10.19, respectively. Compared to the pre-period, the median for the post-period decreased by 17.44 million RMB, or 63%. Compared with the percentage change before and after the event date in 2019, we see an additional 38% decrease in 2020 based on mean, and 35% based on median.

Panel C further reports the mean difference of offline consumption between the pre-period and the post-period by consumption type and category. First, the mean differences (post-pre) are negative, with statistical significance for all types and categories in 2019 and 2020. In 2019, daily consumption of goods fell by 11.05 million RMB, on average, or 18%, while the daily consumption of services fell by 7.50 million RMB, or 26%. In 2020, the decrease in goods consumption expanded to 23.73 million RMB, or 58%. The change in services consumption is -13.94 million RMB, or 63%, more severe than the type of goods.

For more detailed consumption categories, we focus on describing the percentage changes in 2020. Within goods, discretionary items fell the most, by 71%. Within services, dining & entertainment fell the most by 79%. Based on the percentage changes relative to 2019, the top three categories are dining & entertainment (67%), travel-related (64%), and durable goods (42%).

[Insert Table 1 about Here]

[Insert Figure 1 about Here]

To view the time-series pattern of daily offline consumption, Figure 1 presents time-series plots of the raw data for the full sample for Wuhan, Hubei province, and outside Hubei Province. The findings can be summarized as follows. First, the daily offline-consumption series in 2020 (red line) is always below that of 2019 (blue dash line), and the gap widens in the post period. The level difference at the beginning of 2020 relative to the same period in 2019 largely reflects consumers' transition to online spending, but the incremental part of the gap in the post period should be contributed to the shock of the COVID-19 outbreak event.[2] Second, the daily offline consumption

[2] The important identifying assumption for our analysis is that the market share of UnionPay-captured spending does not vary in a short horizon. We compared the monthly total spending amount captured by UnionPay with the monthly total retail consumption reported by National Bureau of Statistics and indeed find a consistent share in the first four months of 2019. Moreover, UnionPay's offline share does not exhibit a significant decline after the outbreak, relative

fell by a significant amount in the post period for 2019 and 2020, likely due to CNY, since the 2019 time series quickly rebounded. On the other hand, the time series of 2020 (red line) stayed persistently low for an extended period of time, which to a large extent captures the consumption impact of COVID-19. Third, compared to the plots for all cities and cities outside Hubei, Wuhan and Hubei were severely hit and recovered very slowly after the COVID-19 outbreak.

We report the summary statistics of city's characteristic variables in Table A2. Among the 214 cities in sample, 9.4% are ranked into top 20 cites by Wuhan migrant inflow before the COVID-19 outbreak. Only 2.3% cities reported zero cases (N=5). The mean of the total number of COVID-19 cases (excluding asymptomatic cases, by April 13) is 367, whereas the median and 90% quantile are 32 and 836, implying a skewed infection intensity across cities.[3] The mean of the average active cases per 100 hospital beds, *Average PTB*, is 0.22, whereas the median and 90% quantile are 0.03 and 0.9, respectively. *Average PTB* is less than 1 for most cities, far below the extreme situations including Wuhan (16.4), Ezhou (5.5), Xiaogang (4.5), illustrated in Figure A1. The average death as of April 13, 2020 toll over the post period is 15.

2.4.Empirical Methodology

Using the implementation of the Wuhan lockdown (Jan. 23, 2020) as the start of the COVID-19 outbreak (Fang et al., 2020), we evaluate the impact of COVID-19 on daily offline consumption with the following difference-in-differences regression approach:

$$Y_{i,t} = \alpha_i + \delta_t + \beta_{post} Treat \cdot post + \epsilon_{i,t} \tag{1}$$

where the dependent variable, $Y_{i,t}$, is the daily spending amount (in millions RMB), which is winsorized at the 1st and 99th percentile to remove the effect of outliers. To estimate the percentage changes, we also use the daily spending amount divided by the pre-period average spending as the dependent variable.[4] α_i captures the individual fixed effects to absorb time-invariant factors at the city level. The dummy variable *Treat* is defined as 1 for 2020 sample observations, and 0 otherwise. *Post* is defined as 1 for post periods after January 23, 2020, for 2020 samples, and for

to the change in 2019.

[3] China's National Health Commission only started to report asymptomatic cases, at the national level (as opposed to the city level), from April 1, 2020.

[4] The log-transformed approach for estimating percentage changes only works for small changes.

post periods after February 3, 2019, for 2019 samples. δ_t is a vector of time-related dummy variables to control for the time-varying trend of daily consumption. Specifically, we include the day of week and the distance to CNY fixed effects. β_{post} captures the average response to the COVID-19 outbreak event.

To investigate the dynamic evolution of the impact, we further estimate the following specified regressions:

$$Y_{i,t} = \alpha_i + \delta_t + \sum_{j=0}^{K} \beta_j Treat \times post_j + \epsilon_{i,t} \tag{2}$$

where $post_j$ is the dummy variable defined for a specific period after the event date, and the coefficient β_j estimates the impact on offline consumption during the corresponding post period.

In addition, we investigate the heterogeneity of the impact across cities or over time by adding interaction terms into equation (1) as follows:

$$Y_{i,t} = \alpha_i + \delta_t + \beta_{post} Treat \times post + \beta_{post \times Interactive} Treat \times post \times D_{Interactive} + \epsilon_{i,t} \tag{3}$$

The new coefficient $\beta_{post \times Interactive}$ captures the extra average impact of the COVID-19 outbreak for the group defined by the interactive term, relative to the benchmark group.

All equations are estimated using ordinary least squares (OLS), and standard errors are clustered at the city level.

3. Main Results

3.1.The average effect on consumption

We begin by estimating the average effect on daily offline consumption and report the results in Table 2. Panel A presents the estimated results of equation (1) with the offline spending amount (in millions RMB) as the dependent variable. Column 1 shows the estimated results for the total spending of all consumption types and categories. The coefficient of the interactive term *treat*post* is -18.57, which statistically significant at the 1% level, implying a decrease of 18.57 million RMB in daily offline consumption on average for each city, relative to the counterfactual path without the COVID-19 outbreak event. Columns 2 and 3 report the estimated results by two consumption types. On average, the daily offline goods consumption fell by 12.47 million RMB, whereas daily services spending decreased by 6.16 million RMB, for each city. The dummy variable *treat* is significantly negative for all offline consumption, offline goods consumption and offline services consumption, which likely reflects the ongoing transition from offline to online spending of Chinese consumers in recent years.

Panel B reports the estimation results of equation (1) with the spending amount divided by the pre-period average as the dependent variable. Again, column 1 shows the estimated results for total offline spending, where the difference-in-differences coefficient is -0.32. The estimate is statistically significant at the 1% level, indicating a 32% decrease in offline consumption on average during the post period in 2020, relative to the counterfactual path in 2019. From columns 2 and 3, we see the offline goods and services consumption decreased by a comparable amount in percentage terms (33% vs. 34%).

[Insert Table 2 about Here]

The overall analysis confirms the outbreak of COVID-19 severely hit the average offline consumption. However, one may wonder what category of offline consumption has suffered the most from the shock. Table 3 reports the estimated results with the dependent variable defined as the spending amount of each category divided by pre-period average category spending. Columns 1-6 report the results for daily necessities, discretionary items, durable goods, dining & entertainment, travel-related, and others (see Table A1 for classification of these categories). For all categories, the difference-in-differences coefficients are significantly negative, implying the COVID-19 outbreak hurt all consumption categories. According to the magnitude of the impact, dinning & entertainment fell the most, by 64%, followed by travel-related with a decrease of 59% and the durable goods with 35%. The spending category least affected is daily necessities (-15%), as consumers still had to meet their basic needs. During outbreak periods, most cities in Mainland China decided to close non-essential service businesses, keeping supermarkets and pharmacies open. Additionally, consumers moved their grocery shopping to online retailers (Chen et al., 2020). Overall, the large impact on entertainment & dining as well as travel is in part explained by the strict travel and distancing measures that many cities adopted that closed many service businesses.

[Insert Table 3 about Here]

3.2.The aggregate impact

In our sample, 214 cities account for 90% of China's urban population, and UnionPay captures 30% of China's offline consumption. Our previous finding thus suggests that if other offline consumption experienced a similar rate of decrease, the total decrease in China's offline consumption is 14.72 billion RMB per day (=18.57 million*214/(0.9*0.3)), or 1.22 trillion RMB (=14.72billion*83) during the twelve-week post-outbreak period. As a reference, the country's total GDP in 2019 was 99.10 trillion RMB. Note 1.22 trillion RMB likely represents a lower-bound estimate, because consumption using cash presumably is more severely affected (retrieving cash is more affected by mobility restrictions and transacting via cash also raises potential of virus spreading).

One plausible hypothesis lies in the substitution from shopping offline to online as a result of COVID-19 (e.g., grocery shopping). Note first that offline still constituted 76% of total consumption in China in 2019 (source: National Bureau of Statistics), which implies online spending would have to increase by an unrealistic amount to completely offset the massive decrease in offline consumption that we document. In addition, the lockdown or strict travel restrictions also limit the capability of E-commerce to serve consumption needs due to their large impact on distribution network and logistics (Luohan Academy, 2020). To provide a better assessment, we utilize the online spending data captured by the online payment platform ChinaPay (held by UnionPay) and compare the online spending response relative to that of offline spending in 2020. Although ChinaPay is not the dominant payment provider for online spending, it has grown steadily in recent years with about 5% of the online spending market share.

We focus on the top 30 Chinese cities ranked by GDP in the analysis to alleviate the concern about ChinaPay's weaker coverage in small cities. In addition, these 30 cities account for 44% of China's GDP in 2018. We compare the percentage change in online spending in these 30 cities around the COVID-19 outbreak, relative to the percentage change in offline consumption during the same period in 2020. To the extent that the use of ChinaPay's online payment service does not change in the short window around COVID-19, difference-in-differences estimate can be interpreted as the incremental percentage change in online spending relative to the percentage change in offline consumption. The regression coefficient reported in Table A3 of the Internet Appendix is 0.31 and is statistically significant at the 1% level. This finding suggests online spending increased by 31% relative to the percentage change in consumption offline after the outbreak. We use equation (1) to separately estimate these 30 cities' offline consumption impact (-0.44). Thus, online spending also decreased, even though much less than offline spending, by 13% (=0.31-0.44). If we extrapolate this estimate as representative, given the 76% share of offline consumption in China, we infer the total consumption in China had experienced a decrease of 27% twelve weeks after the outbreak.

3.3.The role of the exposure intensity: across cities

The negative consumption impact is large and prevalent among the 214 cities in our sample. The median city experienced a consumption decrease of 33% and more than 90% of the 214 cities saw a consumption decrease of more than 20%. In the following, we investigate the impact heterogeneity across cities with different exposure to COVID-19. Table 4 reports the estimated results of equation (3) with three different dummy variables: *Wuhan city*, *Top20 Wuhan inflow cities*, and *City with 0 cases*. *Wuhan city* is defined as 1 for Wuhan. *Top20 Wuhan inflow cities* is defined as 1 for the top 20 cities receiving migrants from Wuhan between January 10 and January 24 of 2020 according to the Baidu migration index. *City with 0 cases* is defined as 1 for cities without confirmed COVID-19 cases as of April 13, 2020.

Column 1 shows the estimation results with *Wuhan city* interacting with *treat* and *post* dummies. The estimated coefficient of the interactive term is -0.38 with statistical significance, implying an additional 38% decrease in daily offline consumption in Wuhan compared to non-Wuhan cities. Column 2 reports the result for *Top20 Wuhan inflow cities*. The estimated coefficient of the interactive term is -0.11 with statistical significance; that is, the daily offline consumption for these top 20 cities had an additional 11% decrease compared to other cities (excluding Wuhan). Column 3 reports the estimated results for *City with 0 cases*. The estimated coefficient of the interactive term is 0.12, with statistical significance, implying a 12% less negative response to the COVID-19 outbreak for these cities without confirmed cases. More generally, we find that cities with higher per-capita COVID-19 cases (as of April 13, 2020) experienced a larger consumption decline, after controlling for the city's GDP reliance on service and export industries (column 4).

[Insert Table 4 about Here]

We further demonstrate the negative relationship between the impacts on offline consumption and city exposure to COVID-19 in Figure 2. Panel A displays the simple scatterplot between the city-level percentage change in offline consumption and the number of COVID-19 cases as of April 13, 2020. The percentage change in the city-level daily offline consumption is estimated from equation (1) with city dummy variables interacting with *treat* and *post*, and the dependent variable defined as spending amount divided by the pre-period average. The regression line fitted in the plot shows a significantly negative coefficient with an R-square of 0.23, implying a 23% variation in the impact across cities can be explained by the variation in the total number of COVID-19 cases.

Panel B presents heatmaps about the geographic distribution of percentage changes in offline consumption in comparison to the total number of COVID-19 cases (excluding asymptomatic cases) at the end of the sample period.[5] The plot in the bottom shows the COVID-19 cases concentrated in Wuhan and nearby cities in the Hubei province. As of April 13, 2020, Wuhan had 50,008 cases, or 61% of the total cases in Mainland China (82,249), and the top 10 cities are all in the Hubei province, collectively accounting for about 79% of total cases in the country. Outside of Hubei, only 7 cites (Chongqing, Wenzhou, Shenzhen, Beijing, Shanghai, Guangzhou and Mudanjiang) had more than 300 cases. The top figure shows wide variation in the impact across cities. We can find some close associations between these two distributions. For example, Wuhan and 10 other Hubei cities are all listed in the cities with percentage changes larger than 40%. In general, the geographical pattern reinforces the evidence that the more serious the COVID-19 exposure, the larger the impact on offline consumption.

[Insert Figure 2 about Here]

3.4. Within-city variation in exposure

The cross-sectional findings reveal a compelling pattern between epidemic severity and changes in city consumption. It is likely attributable to the consequences of the distancing and mobility-restriction measures, either by physically constraining people's shopping opportunities or through

[5] We also provide the geographical distribution of other measures of the COVID-19 exposure in Figure A1 of the Internet Appendix, including the percentage of Wuhan migrant's inflow in a city, the number of active cases per 100 hospital beds and the total COVID-19 death toll as of April 13, 2020. We see a very similar pattern.

affecting income and job security. In addition, the epidemic disease can induce uncertainty and anxiety and change consumers' willingness to spend, absent mobility restrictions and for those without imminent income loss concerns. To sharpen the interpretation, and especially to shed light on the latter hypothesis, we leverage the high frequency data to examine how daily consumption in each city responds to the day-to-day changes in the epidemic severity in the same city while controlling for city and time fixed effects. We note that mobility-restriction measures as well as the macroeconomic conditions (e.g., unemployment) were much more persistent in the sample period.

We examine this hypothesis by estimating equation (3) using three proxies of COVID-19 intensity— *log*(*1+newcase*), *PTBtop*, and *log*(*1+deaths*)—as interactive variables to capture their impacts. *newcase* is the one-day lagged number of newly confirmed patients. The dummy variable *PTBtop* is defined as 1 if the city's *PTB* is among the top 30 on this date, whereas *PTB* is the one-day lagged number of active patients per 100 hospital beds in the city. *deaths* is the one-day lagged number of COVID-19 deaths. These measures gauge the day-to-day change in the epidemic severity, which also correlates with changing uncertainty on the length and trajectory of the city's epidemic exposure.

Column 1 of Table 5 shows the results by using the number of new cases of COVID-19 as a proxy (*log*(*1+newcase*)). The result suggests doubling the infected cases in a city led to a 4.9% greater reduction in offline consumption. Column 2 shows the estimated result for *PTBtop.* The result suggests the city incurred an additional 5% decrease in offline consumption when it was among the 30 cities with the highest hospital-capacity constraints. Column 3 shows that doubling the COVID-19 death toll in a city led to an additional 8.3% decrease of offline consumption. In summary, we find evidence of a much stronger decrease in offline consumption in response to the increase in new cases, increasing stress on the hospital system and the increase in COVID-19 deaths in the city.

[Insert Table 5 about Here]

For robustness, we repeat the above regression analysis by excluding Wuhan city and controlling for mobility-restriction polices that were implemented during the sample period (Fang et al., 2020).[6] The coefficients of the interactive term for different within city intensity measures are all significantly negative, indicating that the findings about the stronger negative response to the rising of COVID-19 intensity, are not driven by Wuhan, nor explained away by the reduced purchase opportunities after cities implemented stricter mobility-restriction measures (Table A4). In unreported results, we also find the consumption sensitivity to epidemic severity to be equally strong, both qualitatively and quantitatively, across all spending categories. To the extent that price adjustment (e.g., due to logistic pressure) would presumably be more pronounced in groceries and other daily necessities, the effect is unlikely explained by consumers' response to price. In sum, these results suggest consumer demand responds promptly to uncertainty regarding the pandemic's trajectory.

3.5.The dynamics of the consumption response

To study the dynamic pattern of the offline-consumption response to COVID-19, we estimated equation (2), with twelve dummy variables, *post0*, *post1*, …, *post11*, interacting with the *treat* dummy variable. Whereas the dummy variable *post0* is defined for the sample period [0, 6] after the event date, *post1*, …, *post11* are defined for the subsequent eleven weeks after the event date.

Figure 3 presents the estimated effect of the week-by-week percentage change in daily total offline consumption during the twelve-week post period. We observe a pattern with an accelerated decline in the first four weeks and a gradual recovery starting from the second month. Particularly, city offline consumption fell by 6.6% during the first week after Wuhan lockdown, and by 59%, 66%, and 65% for the next three weeks. The consumption change became less negative, with only 42% decrease in the fifth week when the epidemic curve started to flatten. The consumption decrease had shrank to 33% by the end of the second month, with a 33% improvement from the lowest offline consumption decline.[7] For the third month, we first observe a peak at the end of March (i.e., ten weeks after the outbreak), when the consumption has fully rebounded as the difference-in-differences estimate is not statistically distinguishable from zero. It's important to note that we

[6] We also use an alternative proxy based on the dates when cities activated and lifted the highest level of public health emergency alerts and responses in the nation's public health management system. The results remain very similar: within each public health management regime, we observe a strong negative consumption response to day-to-day change in epidemic severity.

[7] To examine the significance of the recovery, we conduct F-test on the hypotheses about the equality of coefficients of two adjacent periods. The equality of coefficients for *post3* and *post4* is rejected with p-values smaller than 0.001, confirming the recovery of offline consumption since the fifth week.

observe a very similar recovery pattern by restricting to the period before cities downgraded from the highest level of emergency public health alerts and responses (i.e., the regime corresponding to the most stringent restriction measures), which underscores the consumption recovery as a direct response to the improvement in the public health situation (see Figure A2).

However, consumption fell again, to 20% and 16% below the baseline level respectively, in the first two weeks of April. This retreat echoes the rising concern over a potential second wave of infections, mostly driven by imported and asymptomatic cases. The day-to-day consumption responses in April presented in Figure A3 indeed demonstrated a strong negative relationship with the one-day lagged number of new cases, after including the asymptomatic cases that the government started to report since the beginning of April.[8] Since most cities had relaxed their mobility restrictions measures by April, this evidence highlights the importance of epidemic containment in driving economic recovery.

[Insert Figure 3 about Here]

Figure 4 shows the dynamic offline consumption responses by consumption type and category. In general, we observe a similar pattern for goods consumption and services consumption. The key difference is that services consumption recovered earlier but at a lower speed than goods consumptions. Within goods, daily necessities decreased much less than discretionary items and durable goods but the latter showed a much stronger recovery. Durable goods spending took a more severe hit than spending on discretionary items in the first three weeks and recovered later but at a greater rate. Within services, spending on both dining & entertainment and travel-related services lost more than 80% in the second week, and show much weaker rebounds than spending on discretionary items and durable goods.

[Insert Figure 4 about Here]

We further illustrate this point by showing the overall consumption decline and recovery across 214 cities during the twelve-week period. Figure 5 presents the heatmaps for three post-periods: [0, 27], [28, 55], and [56, 82]. Visually, we observe a trend that the red color, reflecting the magnitude of impact, is dark for most cities on the map in the first month, and then becomes much

[8] We also confirm the visual correlation using a regression analysis.

lighter for most areas in the second month, with some cities even showing positive changes in the third month. Exceptions to the strong recovery include Wuhan and several other places, which struggled with a large negative consumption impact by the end of the twelve-week period. For example, Wuhan's consumption decrease started immediately and remained persistently large—down by 75%-87% in the second to the eighth week, followed by a slow recovery with its consumption still down by 52% by the end of the sample period. Several mega cities, including Guangzhou, Beijing, and Shanghai, saw a visible resurgence of COVID-19 cases near the end of the sample period and a large consumption decline subsequently (Figure A4).

[Insert Figure 5 about Here]

In addition, cities with a higher service industry concentration or export dependence showed a very similar consumption recovery path as cities less reliant on service and export industries (Figure 6). Specifically, we cannot reject the null hypothesis that the consumption rebound by the end of March and the subsequent dip in early April differ between the two sets of cities, while the economic consequences continued to unravel, especially after the concurrent global pandemic development. Therefore, this result provides further support that China's consumption decline and recovery traces the progress in epidemic containment.

[Insert Figure 6 about Here]

4. Conclusion

We use high-frequency, transaction-based consumption data to study the impact of COVID-19 in the three-month post-outbreak period. Offline consumption dropped by an average of 32% in China. It responded immediately and was hit hard across the board. Heavily exposed cities, such as Wuhan, saw their offline consumption reduce by 70% during the twelve-week period. Even cities with no reported COVID-19 cases experienced a large decrease in their offline consumption for weeks. The findings thus highlight the importance of policymakers using prompt and adequate interventions to alleviate the negative impact, especially on the more affected sectors such as retail and certain service industries. Our finding implies China lost over 1.2% of the entire country's 2019 GDP through offline consumption in the twelve-week period, providing an informative ballpark estimate of the effect magnitude, as many countries start to go through the same experience.

Furthermore, the consumption pattern also shows a strong negative sensitivity to the severity of the public health crisis. When the public health situation worsened, consumption plummeted as well. On the other hand, consumption witnessed strong signs of recovery starting from the second month after the outbreak, in accordance with a gradual stabilizing trend of COVID-19. This finding suggests management of the public health crisis is crucial for reinvigorating our economy. When consumer demand retreats from uncertainty, economic relief programs may result in a limited effect absent an effective public health intervention to contain the spread. Our estimates suggest a significant economic benefit of containing the virus through a lessened consumption decrease and a faster consumption recovery.

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Figure 1: Daily Offline Consumption: Raw Data

Note: The daily total offline consumption is calculated as the sum of all spending through UnionPay Merchant Service (UMS) POS machines and QR scanners for each city-day. Our sample covers 214 prefecture-level Chinese cities with more than one million urban population. The sample period for 2019 is from Jan.12, 2019 to April 26, 2019, and the sample period for 2020 is from Jan. 1, 2020 to April 14, 2020. The event date is defined as January 23, 2020 (the date when Wuhan lockdown was implemented), while the event date of 2019 is defined as February 3, 2019, one day before the Chinese New Year's Eve as well. The vertical line indicates the date of January 23, 2020. The red solid line displays the time series of total daily spending of the sample period in 2020, while the blue dash line for 2019.

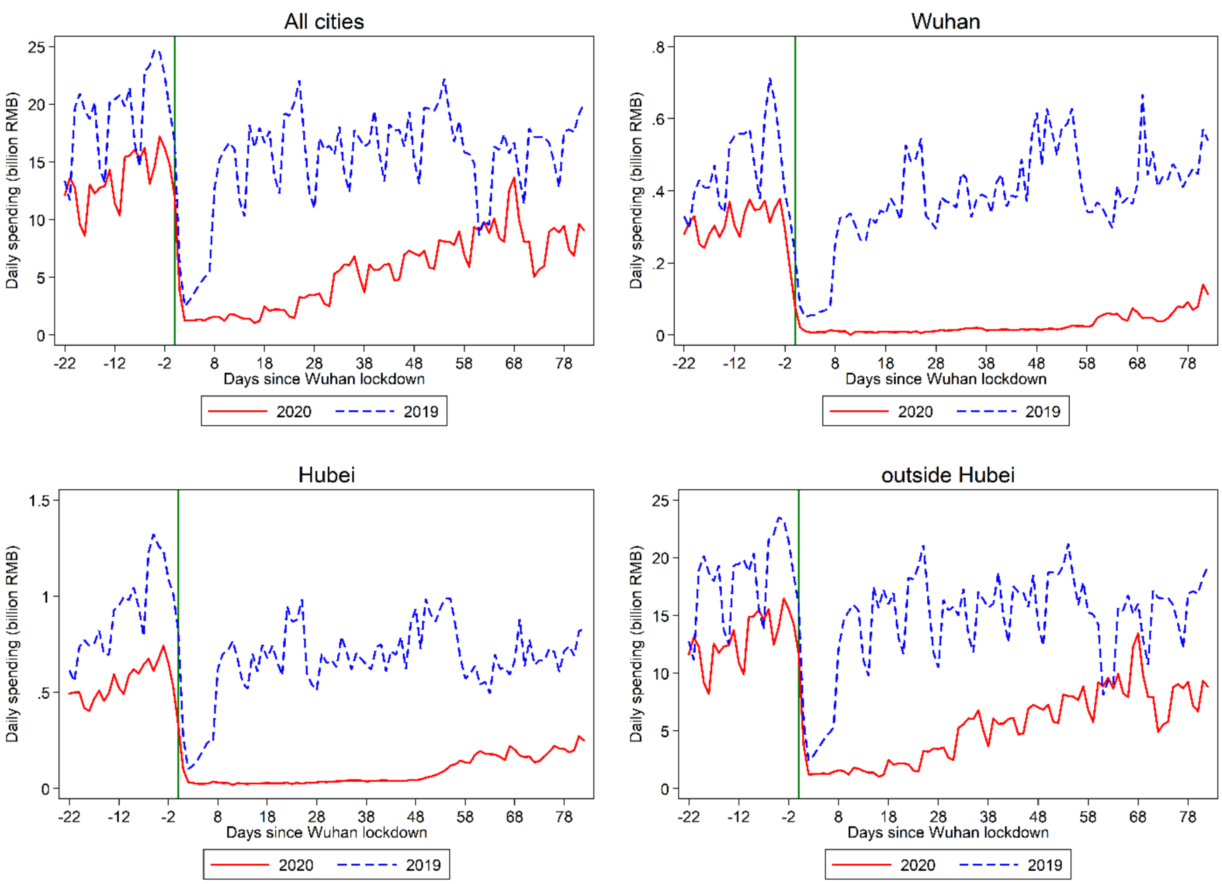
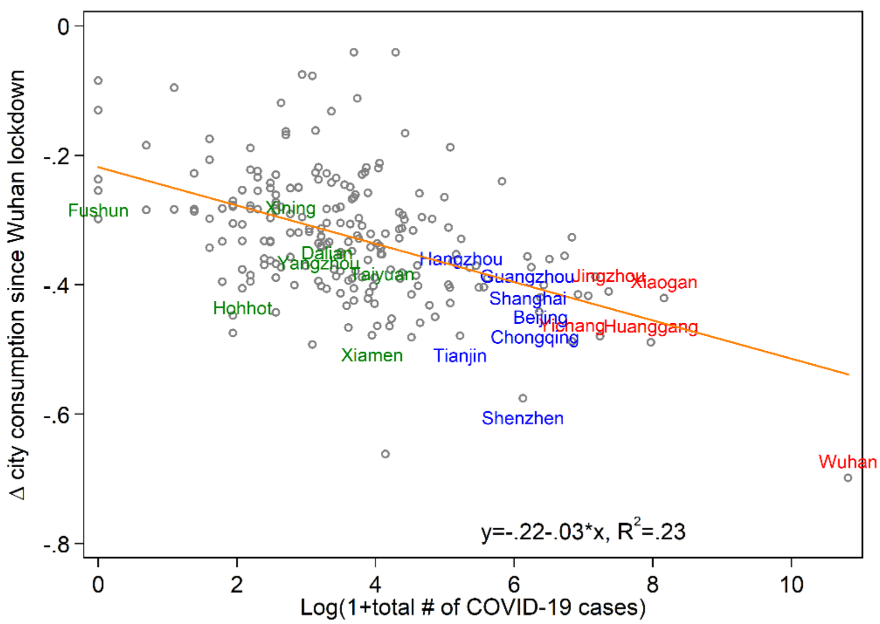


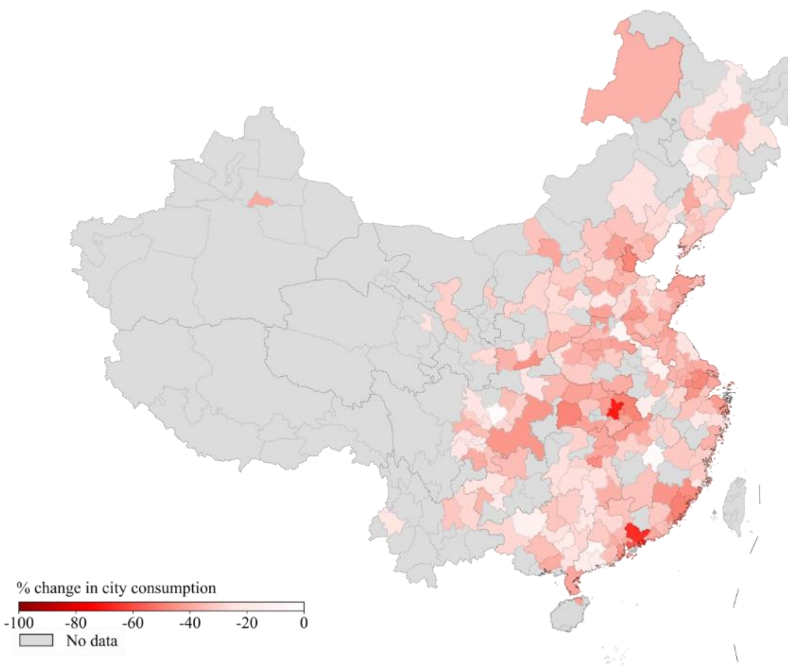
Figure 2: The Offline Consumption Response across Cities

Note: This figure shows the impact of COVID-19 on offline consumption across cities. Percentage change in daily offline consumption is the difference-in-differences regression coefficients, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. Panel A displays scatterplot between the percentage change in offline consumption and the total number of COVID-19 cases (excluding asymptomatic cases) as of April 13, 2020. We also include the fitted line in the scatterplot. Panel B presents heatmaps showing the geographic distributions of both offline consumption changes and the number of total COVID-19 cases (excluding asymptomatic cases) as of April 13, 2020.

Panel A: Percentage change of city consumption and total # COVID-19 cases



Panel B: Geographic distribution of offline consumption change



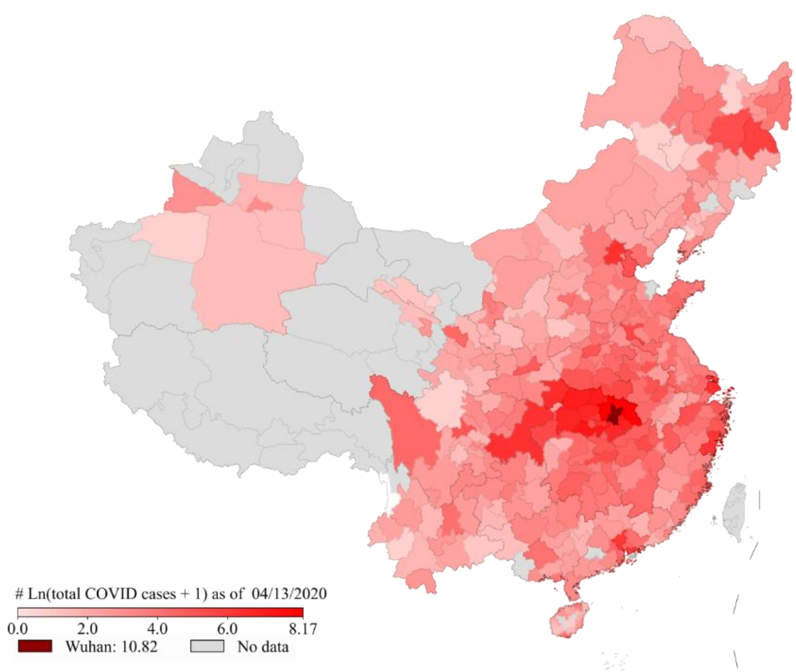


Figure 3: The Dynamic Offline Consumption Response

Note: This figure presents the dynamic offline consumption response. Percentage change in daily offline consumption is the regression coefficients estimated from the difference-in-differences regression on twelve dummy variables, *post0*, *post1*, …, *post11*, interacting with the *treat* dummy variable, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variables *post0* is defined for the sample period [0, 6] after the event date, whereas *post1*, …, *post11* are defined for the subsequent eleven weeks after the event date. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020 (the date when Wuhan lockdown was implemented), whereas the event date for 2019 is defined as February 3, 2019, one day before the 2019 Chinese New Year's Eve. The blue line displays the percentage changes of daily offline consumption, with shaded area indicating 95% confidence intervals. *Total # of COVID-19 cases* is the total COVID-19 cases (excluding asymptomatic cases) at the end of the event week.

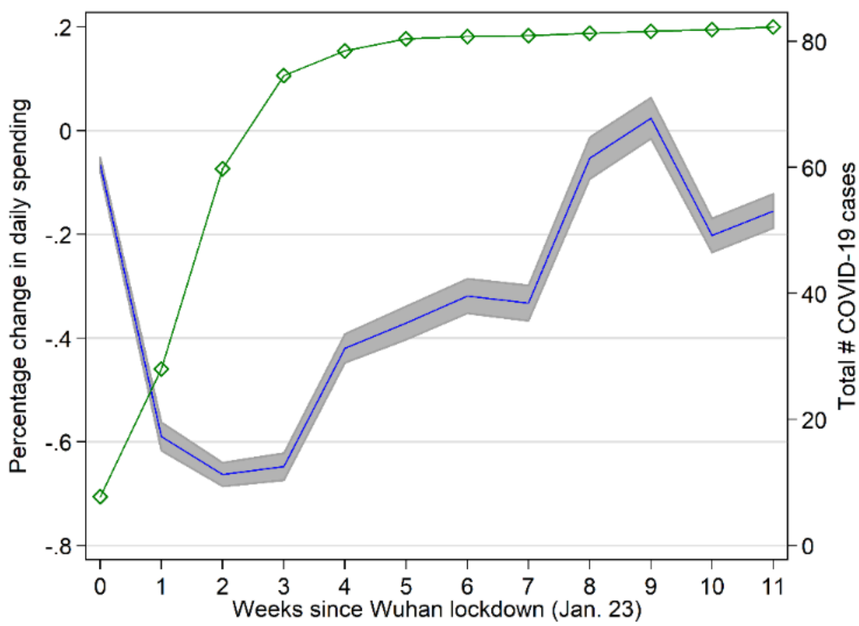
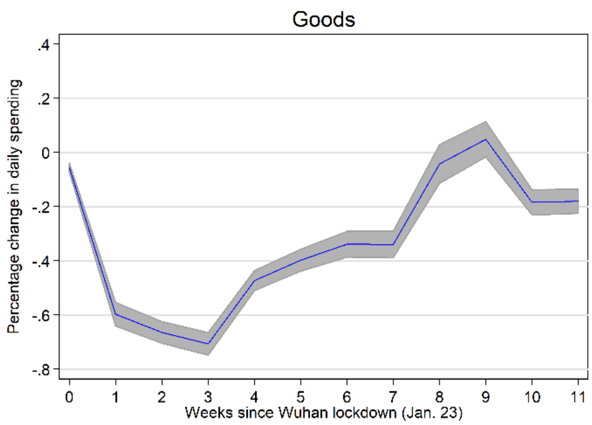
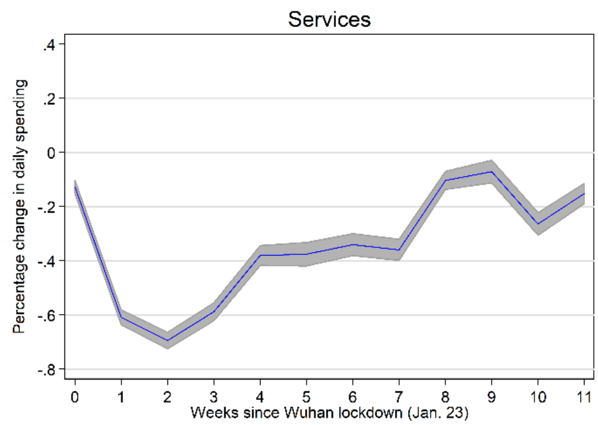


Figure 4: Offline Consumption Changes over Time: By Category

Note: These figures present the dynamic offline consumption response by categories. Percentage change in daily offline consumption is the regression coefficients estimated from the difference-in-differences regression on twelve dummy variables, *post0*, *post1*, …, *post11*, interacting with *treat* dummy variable, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *post0* is defined for the sample period [0, 6], whereas *post1*, …, *post11* are defined for the subsequent eleven weeks. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020, whereas the event date for 2019 is defined as February 3, 2019. The blue line displays the percentage changes of daily offline consumption, with shaded area indicating 95% confidence intervals.

Panel A: Goods and services





Panel B: Subcategory

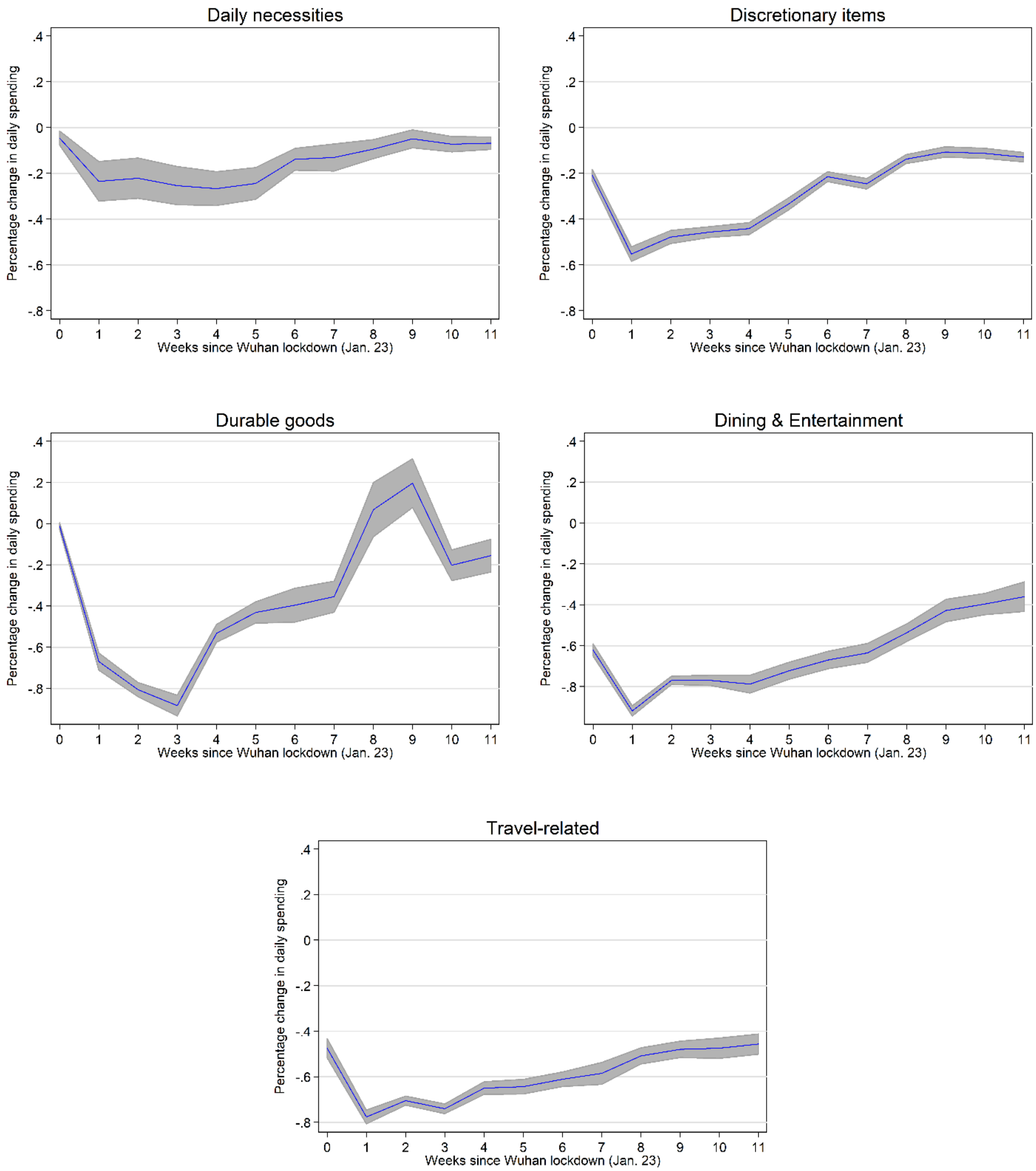
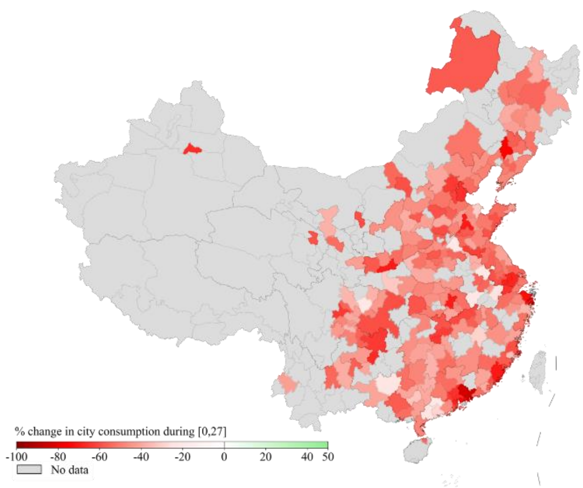


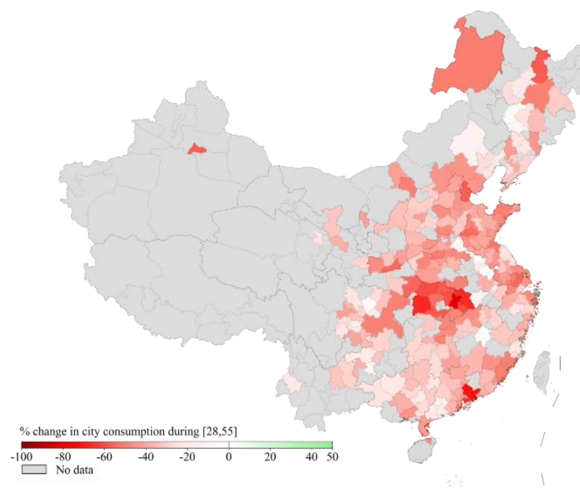
Figure 5: The Impact on Offline Consumption across Cities and over Time

Note: These figures present the effect heterogeneity on offline consumption across cities and over three post-periods: [0,27], [28,55] and [56,82]. Percentage change in daily offline consumption is regression coefficients estimated from the difference-in-differences regression on three sub-period dummy variables described above, interacting with the *treat* dummy variable and 214 city dummies, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019.

Event period [0,27]



Event period [28,55]



Event period [56,82]

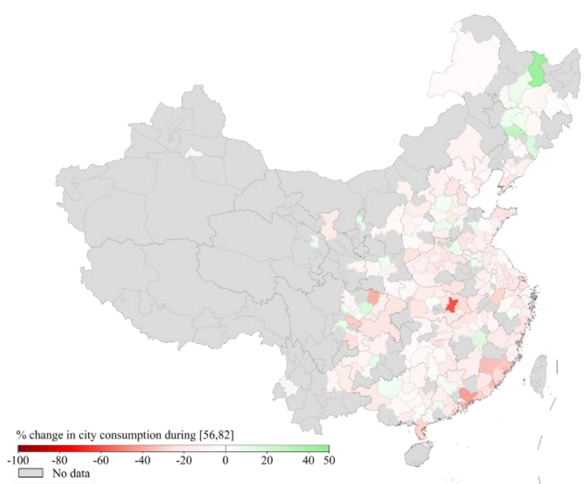


Figure 6: Offline Consumption Changes over Time: By Region Heterogeneity

Note: These figures present the estimated dynamic offline consumption changes for regions with different exposure to service industry (Panel A) and export (Panel B). Percentage change in daily offline consumption is the regression coefficients estimated from the difference-in-differences regression on twelve dummy variables, *post0*, *post1*, …, *post11*, interacting with *treat* dummy variable and three tercile dummies, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *post0* is defined for the sample period [0, 6], whereas *post1*, …, *post11* are defined for the subsequent eleven weeks. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020, whereas the event date for 2019 is defined as February 3, 2019. We classify cities into three groups based on terciles of service industry concentration and export dependence, whereas service industry concentration is defined as the share of city's tertiary industry GDP among its total GDP in 2017, export dependence is defined as the share of city's total export among its total GDP in 2017. GDP, tertiary industry GDP and export trade data are obtained from CEIC database. The blue line displays the percentage changes of daily offline consumption, with shaded area indicating 95% confidence intervals.

Panel A: by service industry concentration

Panel B: by export dependence

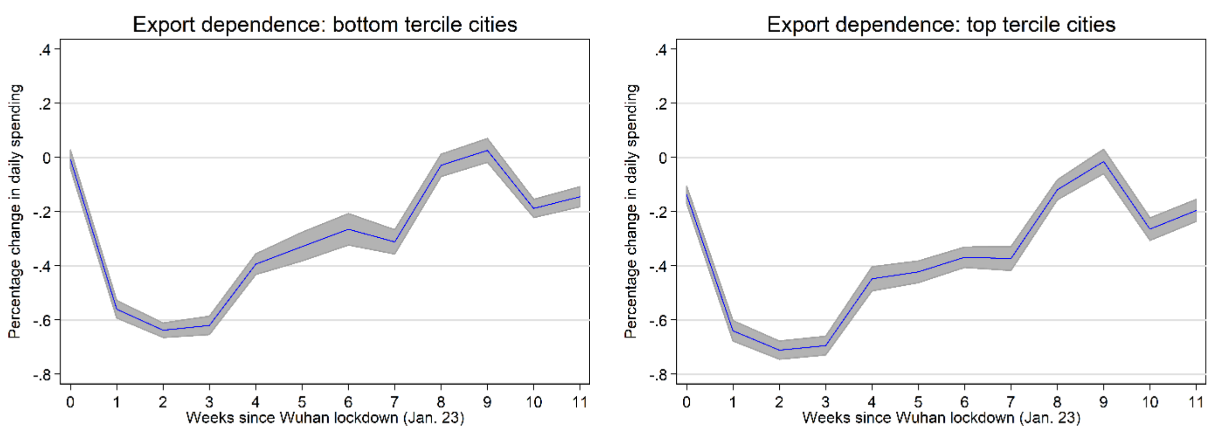


Table 1: Summary Statistics of Daily Offline Consumption

Note: The summary statistics are calculated for daily offline consumption of all cities in the sample (RMB, in millions). The event date 0 is defined as January 23, 2020 (the date when Wuhan lockdown was implemented), whereas the event date 0 for 2019 is defined as February 3, 2019. The pre-period is defined as [-22, -1], whereas the post-period is defined as [0, 82], according to the event date 0. Please refer to Table A1 for detailed classification of consumption types and categories. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: *2019 Sample*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Obs.	Mean	p10	p25	p50	p75	p90
All	22,470	75.23	8.41	16.30	32.62	74.53	281.00
pre: [-22, -1]	4,708	89.89	11.95	21.58	42.28	95.63	320.91
post: [0,82]	17,762	71.35	7.72	15.18	30.44	69.56	270.47

Panel B: *2020 Sample*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Obs.	Mean	p10	p25	p50	p75	p90
All	22,470	33.64	2.41	5.27	12.89	31.20	130.85
pre: [-22, -1]	4,708	63.41	7.75	14.55	27.63	66.06	241.80
post: [0,82]	17,762	25.74	2.05	4.34	10.19	24.11	96.80

Panel C: *Mean difference of city-level offline consumption*

	2019			2020		
	(1)	(2)	(3)	(1)	(2)	(3)
	pre	post	post-pre	pre	post	post-pre
All	89.89	71.35	-18.55***	63.41	25.74	-37.67***
Type:						
Goods	60.67	49.62	-11.05***	41.20	17.47	-23.73***
Services	29.23	21.73	-7.50***	22.21	8.27	-13.94***
Category:						
Daily necessities	5.91	3.67	-2.24***	5.64	2.23	-3.41***
Discretionary items	11.96	7.51	-4.45***	9.62	2.76	-6.86***
Durable goods	42.79	38.44	-4.36**	25.94	12.48	-13.46***
Dining & Entertain.	2.54	2.24	-0.30***	2.61	0.56	-2.04***
Travel-related	2.36	2.21	-0.15***	2.78	0.83	-1.95***
Others	24.33	17.28	-7.05***	16.82	6.88	-9.94***

Table 2: The Impact of COVID-19 on Offline Consumption

Note: This table reports the regression results for the average impact of COVID-19 on offline consumption for all cities in the sample. The dependent variable is the spending amount (spending amt in millions RMB) or spending amount divided by pre-period average spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *treat* is defined as 1 for observations in 2020, and 0 otherwise. *post* is defined as 1 for the post periods [0, 82], and otherwise 0. The event date 0 is defined as January 23, 2020, whereas the event date 0 for 2019 is defined as February 3, 2019. Panel A includes the fixed effects for city, distance to Chinese New Year (CNY) and day of week. In Panel B, the treat-year fixed effect is additionally controlled. Please refer to Table A1 for detailed classification of consumption types and categories. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: *dependent variable is* Spending amt

	(1)	(2)	(3)
	All	Goods	Services
*treat*post*	-18.57***	-12.47***	-6.16***
	(3.23)	(2.27)	(1.20)
treat	-26.63***	-19.37***	-7.15***
	(3.58)	(3.25)	(1.17)
Constant	74.94***	51.66***	23.18***
	(2.89)	(2.39)	(0.69)
Observations	44,940	44,940	44,940
R-squared	0.72	0.71	0.67

Panel B: *dependent variable is* Spending amt/pre-period average

	(1)	(2)	(3)
	All	Goods	Services
*treat*post*	-0.32***	-0.33***	-0.34***
	(0.01)	(0.02)	(0.01)
Constant	0.81***	0.82***	0.81***
	(0.00)	(0.01)	(0.00)
Observations	44,940	44,940	44,940
R-squared	0.57	0.48	0.50

Table 3: The Impact on Offline Consumption: By Detailed Categories

Note: This table reports the regression results for the average impact of COVID-19 on offline consumption for all cities in the sample. The dependent variable is the spending amount by category divided by pre-period average category spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *treat* is defined as 1 for observations in 2020, and 0 otherwise. *post* is defined as 1 for the post-periods [0,82], and 0 otherwise. The event date 0 is defined as January 23, 2020 (the date when Wuhan lockdown was implemented), whereas the event date 0 for 2019 is defined as February 3, 2019. Fixed effects for city, treat-year, distance to Chinese New Year (CNY), and day of week are included. Please refer to Table A1 for detailed classification of consumption types and categories. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

	Spending amt by category /pre-period average category spending average					
	(1)	(2)	(3)	(4)	(5)	(6)
	Daily necessities	Discretionary items	Durable goods	Dining & Entertain.	Travel-related	Others
*treat***post*	-0.15***	-0.29***	-0.35***	-0.64***	-0.59***	-0.25***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	0.69***	0.69***	0.90***	0.88***	0.94***	0.79***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	44,940	44,940	44,940	44,940	44,940	44,940
R-squared	0.44	0.66	0.34	0.63	0.65	0.43

Table 4: The Impact on Offline Consumption: Cross-City Variation in Exposure

Note: This table reports the regression results for the average impact of COVID-19 on offline consumption for all cities in the sample. The dependent variable is the spending amount divided by pre-period average spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. For regression results reported in columns (1) and (3), we include all cites in the sample, whereas for column (2), Wuhan city is excluded. The dummy variable *treat* is defined as 1 for observations in 2020, and 0 otherwise. *post* is defined as 1 for post-periods [0,82], and 0 otherwise, with the event date 0 defined as January 23, 2020 (the date when Wuhan lockdown was implemented), and the event date 0 for 2019 defined as February 3, 2019. *Wuhan city* is defined as 1 for Wuhan. *Top20 Wuhan inflow cities* is defined as 1 for the top 20 cities receiving migrants from Wuhan between January 10 and January 24 of 2020 according to the Baidu migration index (including Beijing, Changsha, Chongqing, Ezhou, Guangzhou, Huanggang, Huangshi, Jingmen, Jingzhou, Nanyang, Shanghai, Shenzhen, Shiyan, Suizhou, Xianning, Xiangyang, Xiaogang, Xinyang, Yichang, Zhengzhou). *City with 0 COVID-19 cases* is defined as 1 for cities without confirmed COVID-19 cases (excluding asymptomatic cases) as of April 13, 2020. *COVID-19 cases per capita* is defined as the total COVID-19 cases (excluding asymptomatic cases) per 10,000 urban population as April 13, 2020. *SICtop* is defined as 1 for cities whose service industry concentration ranked as the upper third, *EDtop* is defined as 1 for cities whose export dependence ranked as the upper third. Service industry concentration is defined as the share of city's tertiary industry GDP among its total GDP in 2017, export dependence is defined as the share of city's total export among its total GDP in 2017. GDP, tertiary industry GDP and export trade data are obtained from CEIC database. Fixed effects for city, treat-year, distance to Chinese New Year (CNY), and day of week are included. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

	Spending amt/pre-period average			
	(1)	(2)	(3)	(4)
*treat***post*	-0.32***	-0.31***	-0.32***	-0.34***
	(0.01)	(0.01)	(0.01)	(0.02)
*treat***post***Wuhan city*	-0.38***			
	(0.01)			
*treat***post***Top20 Wuhan inflow cities*		-0.11***		
		(0.02)		
*treat***post***City with 0 COVID-19 cases*			0.12***	
			(0.04)	
*treat***post***log*(*1+COVID-19 cases per capita*)				-0.03***
				(0.00)
*treat***post***SICtop*				-0.03**
				(0.01)
*treat***post***EDtop*				-0.06***
				(0.02)
Constant	0.81***	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	44,940	44,730	44,940	43,260
R-squared	0.58	0.58	0.57	0.58

Table 5: The Impact on Offline Consumption: Within-City Intensity

Note: This table reports the regression results for the average impact of COVID-19 on offline consumption for all cities in the sample. The dependent variable is the spending amount divided by pre-period average spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *treat* is defined as 1 for observations in 2020, and 0 otherwise. *post* is defined as 1 for post-periods [0,82], and 0 otherwise, with the event date 0 defined as January 23, 2020 (the date when the Wuhan lockdown was implemented). *newcase* is the one-day lagged number of newly confirmed cases (excluding asymptomatic cases). *PTBtop* is defined as 1 if the city's *PTB* is among the top 30 on this date, and 0 otherwise. *deaths* is the one-day lagged number of deaths. Fixed effects for city, treat-year, distance to Chinese New Year (CNY), and day of week are included. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

	Spending amt/pre-period average		
	(1)	(2)	(3)
*treat***post*	-0.30***	-0.31***	-0.31***
	(0.01)	(0.01)	(0.01)
*treat***post***log*(*1+newcase*)	-0.07***		
	(0.01)		
*treat***post***PTBtop*		-0.05***	
		(0.02)	
*treat***post***log*(*1+deaths*)			-0.12***
			(0.01)
Constant	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)
Observations	44,921	44,940	44,940
R-squared	0.58	0.58	0.58

INTERNET APPENDIX

NOT FOR PUBLICATION

Figure A1: Heatmap: City Exposure to COVID-19

Note: This figure presents geographic distributions of three measures of city exposure to COVID-19: percentage of Wuhan migrant inflow from January 10 to January 24 (data source: Baidu), the average number of active cases per 100 hospital beds in the post period of 2020, and the total COVID-19 death as of April 13, 2014. The active cases are defined as confirmed cases minus recovered cases and deaths. In the legend, *No data* indicates the cities without the corresponding data coverage.

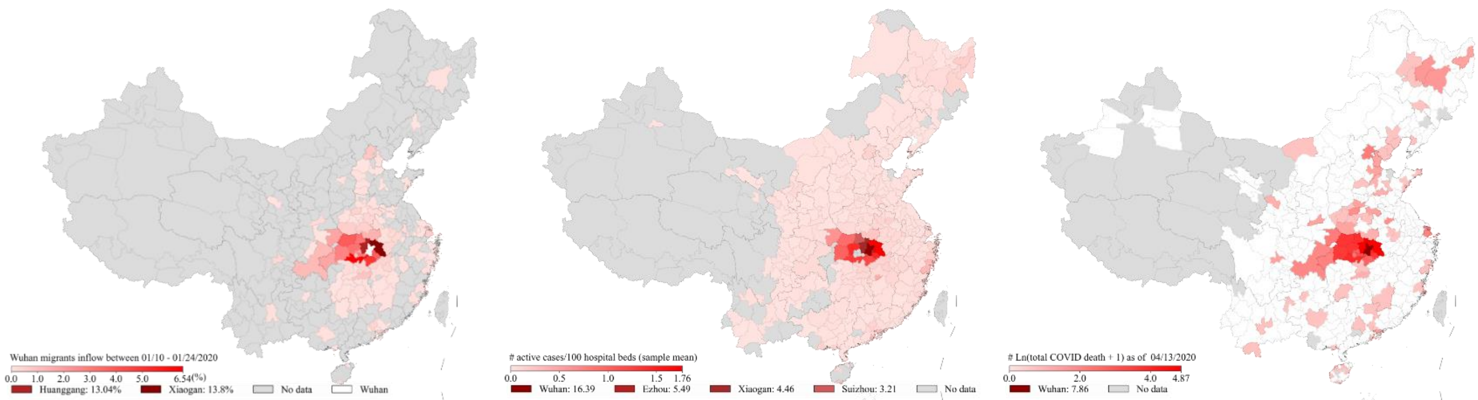


Figure A2: The Dynamic Offline Consumption Response: Excluding Days after Downgrade of Public Health Emergency Level

Note: This figure repeats the dynamic offline consumption response in Figure 3 by restricting to the sample period before cities downgraded from the highest level of public health emergency alerts and responses in China public health management system. The shaded area indicates 95% confidence intervals. *Total # of COVID-19 cases* is the total COVID-19 cases (excluding asymptomatic cases) at the end of the event week.

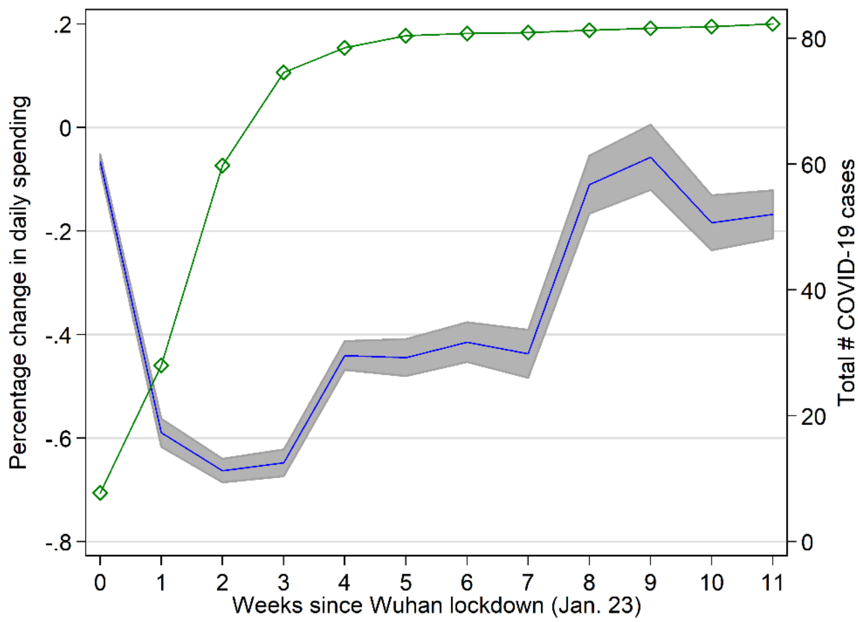


Figure A3: The Daily Dynamic Offline Consumption Response in April 2020

Note: This figure presents the daily dynamic offline consumption response in April. Percentage changes in daily offline consumption are the regression coefficients estimated from the difference-in-differences regression on twenty four dummy variables, *post0*, *post1*, …, *post23*, interacting with the *treat* dummy variable, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *post0* is defined for the sample period [0, 6], whereas *post1*, …, *post9* are defined for the subsequent nine weeks, and *post10*, *post11*, …, *post23* are defined for days during the last two weeks. The figure shows the daily coefficients for April. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020, whereas the event date for 2019 is defined as February 3, 2019. The blue line displays the percentage changes of daily offline consumption, with shaded area indicating 95% confidence intervals. The green line shows the evolution of one-day lagged number of new cases (including asymptomatic cases).

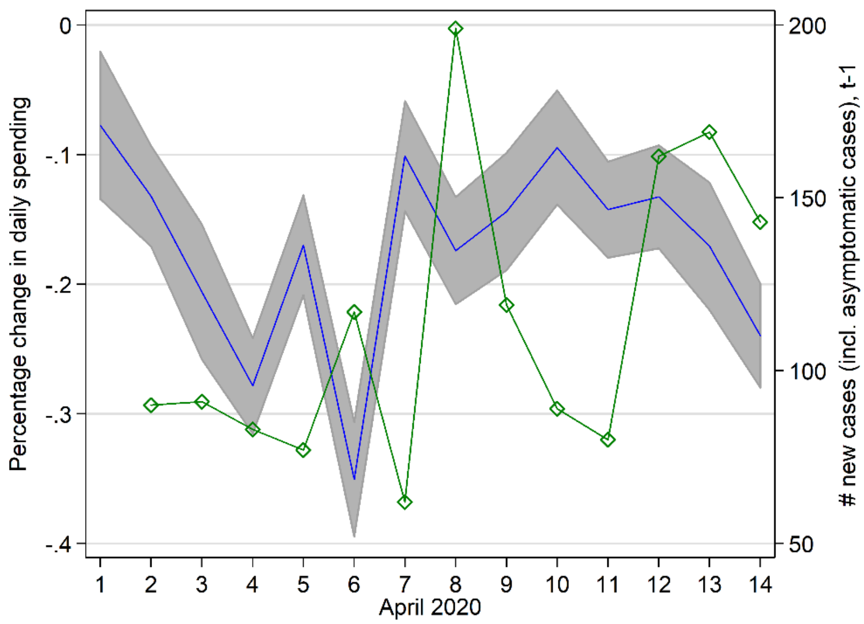
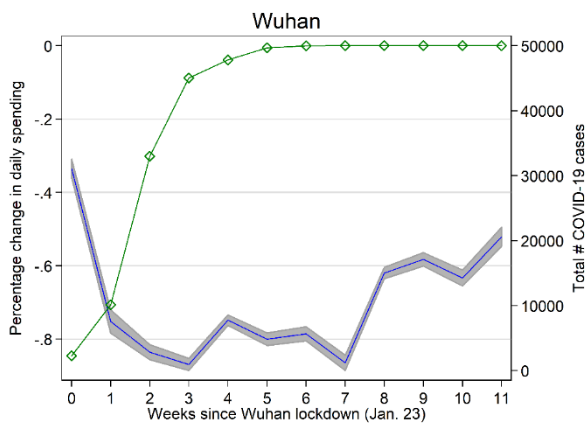


Figure A4: Offline Consumption Changes over Time: Select Cities

Note: This figure displays the estimated dynamic offline consumption changes for five cities: Wuhan, Beijing, Shanghai, Shenzhen, and Guangzhou. Percentage change in daily offline consumption is regression coefficients estimated from the difference-in-differences regression on twelve dummy variables, *post0*, *post1*, …, *post11*, interacting with the *treat* dummy variable and 214 city dummies, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *post0* is defined for the sample period [0, 6] after the event date, whereas *post1*, …, *post11* are defined for the subsequent eleven weeks after the event date. *Treat* is equal to 1 for observations in 2020, and 0 for observations in 2019. The event date is defined as January 23, 2020, whereas the event date for 2019 is defined as February 3, 2019, one day before the 2019 Chinese New Year's Eve. The blue line displays the percentage changes of daily offline consumption, with shaded area indicating 95% confidence intervals. *Total # of COVID-19 cases* is the city's total COVID-19 cases (excluding asymptomatic cases) at the end of each event week.

Panel A: Wuhan



Panel B: Select municipalities

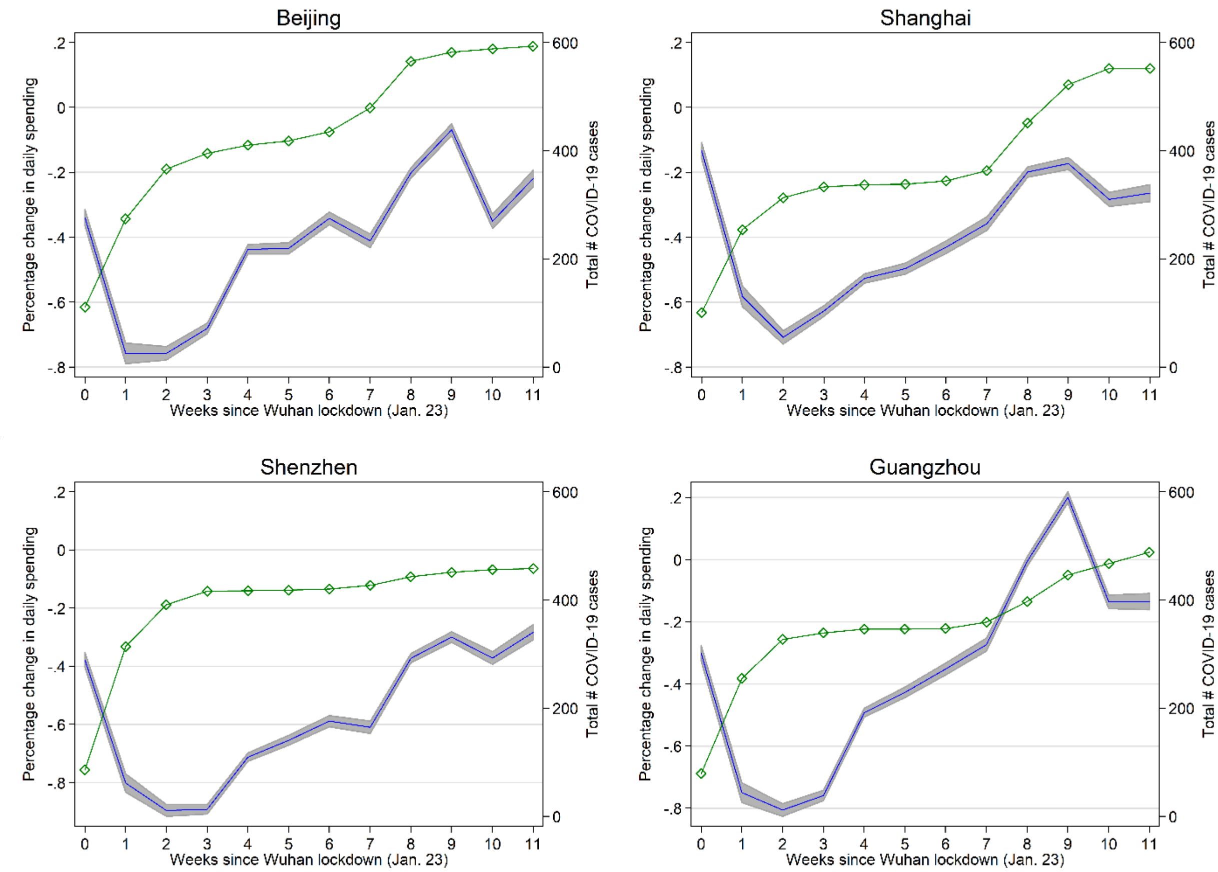


Table A1: Classification of Consumption Categories

Type	Categories	MCC Category
Goods	Durable goods	Furniture & home furnishing
		Home appliance
		Electronics
		Car-related goods
		Housing-related goods
	Daily necessities	Grocery
		Household items
	Discretionary items	Apparel
		Shoes
		Beauty
		Accessories
		Other goods
Services	Dining & Entertainment	Dinner
		Entertainment
	Travel-related	Travel
		Transportation
		Other transportation service
	Others	Other service

Table A2: Summary Statistics of City's Characteristics

Note: This table reports the summary statistics of city's characteristic variables. The dummy variable *Top20 Wuhan inflow cities* is defined as 1 for the top 20 cities receiving migrants from Wuhan between January 10 and January 24 of 2020 according to the Baidu migration index (including Beijing, Changsha, Chongqing, Ezhou, Guangzhou, Huanggang, Huangshi, Jingmen, Jingzhou, Nanyang, Shanghai, Shenzhen, Shiyan, Suizhou, Xianning, Xiangyang, Xiaogang, Xinyang, Yichang, Zhengzhou). The dummy variable *City with 0 COVID-19 cases* is defined as 1 for cities without confirmed COVID-19 cases (excluding asymptomatic cases) for the whole post period. *Total # of COVID-19 cases* is the number of total cases (excluding asymptomatic cases) as of April 13, 2020. *Average PTB* is defined as the average lagged number of active cases per 100 hospital beds over the post-period, where the active cases are defined as confirmed cases after subtracting recovered cases and deaths. *Total # of COVID-19 deaths* is total COVID-19 death toll as of April 13, 2020. All summary statistics are calculated using the observations of 214 cities in the post-period of 2020 only.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Obs.	Mean	p10	p25	p50	p75	p90
Top20 Wuhan inflow cities	213	0.09	0.00	0.00	0.00	0.00	1.00
City with 0 COVID-19 cases	214	0.02	0.00	0.00	0.00	0.00	0.00
Total # of COVID-19 cases	214	367.53	6.00	12.00	32.00	76.00	836.00
Average PTB	214	0.22	0.01	0.01	0.03	0.05	0.92
Total # of COVID-19 deaths	214	15.29	0.00	0.00	0.00	1.00	15.00

Table A3: Online vs. Offline Response: Evidence from 30 Cities

Note: This table reports the difference-in-differences regression result comparing the impact on online consumption relative to offline consumption in 2020, for the sample of the top 30 cities ranked by the 2018 GDP (including Beijing, Changchun, Changsha, Changzhou, Chengdu, Chongqing, Dalian, Dongguan, Foshan, Fuzhou, Guangzhou, Hangzhou, Hefei, Jinan, Nanjing, Nantong, Ningbo, Qingdao, Quanzhou, Shanghai, Shenzhen, Suzhou, Tangshan, Tianjin, Wuxi, Wuhan, Xi'an, Xuzhou, Yantai, Zhengzhou) in the sample. (Note that the diff-in-diff estimate of equation (1) for these 30 cities is -0.44.) The dependent variable is the spending amount (Spending amt) divided by the 2020 pre-period average spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *treat* is defined as 1 for online consumption in 2020, and 0 for offline consumption. *post* is defined as 1 for post-periods [0,82], and 0 otherwise. The event date 0 is defined as January 23, 2020 (the date when Wuhan lockdown was implemented). Fixed effects for city fixed effect, treat, distance to Chinese New Year (CNY), and day of week are included. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

	(1) Spending amt/pre-period average
treat*post	0.31***
	(0.07)
Constant	0.53***
	(0.03)
Observations	6,300
R-squared	0.55

Table A4: Within-City Intensity: Additional Robustness

Note: This table reports additional robustness checks on the within-city intensity heterogeneity results. Panel A reports the results by excluding Wuhan from the sample, and Panel B presents the results by further controlling for stricter mobility-restriction measures that were implemented in other cities in the sample period. The dependent variable is the spending amount divided by pre-period average spending of each city, and all daily consumption data are winsorized at the 1st and 99th percentile to remove the effect of outliers. The dummy variable *treat* is defined as 1 for observations in 2020, and 0 otherwise. *post* is defined as 1 for post-periods [0,82], and 0 otherwise. The event date 0 is defined as January 23, 2020 (the date when Wuhan lockdown was implemented), whereas the event date 0 for 2019 is defined as February 3, 2019. *newcase* is the lagged number of newly confirmed cases (excluding asymptomatic cases). *PTBtop* is defined as 1 if the city's *PTB* is among the top 30 on this date, and 0 otherwise. *deaths* is the one-day lagged number of deaths. *Strict* is defined as 1 since the city begins to implement stricter mobility-restriction measures. Fixed effects for city, treat-year, distance to Chinese New Year (CNY), and day of week are included. Standard errors reported in parentheses are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: *exclude Wuhan city*			
	Spending amt/pre-period average		
	(1)	(2)	(3)
*treat*post*	-0.29***	-0.31***	-0.31***
	(0.01)	(0.01)	(0.01)
*treat*post*log(1+newcase)*	-0.07***		
	(0.01)		
*treat*post*PTBtop*		-0.05**	
		(0.02)	
*treat*post*log(1+deaths)*			-0.16***
			(0.01)
Constant	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)
Observations	44,711	44,730	44,730
R-squared	0.58	0.57	0.57

Panel B: *Controlling for stricter mobility-restriction measures*

	Spending amt/pre-period average			
	(1)	(2)	(3)	(4)
*treat*post*	-0.30***	-0.28***	-0.30***	-0.30***
	(0.01)	(0.01)	(0.01)	(0.01)
*treat*post*log*(*1+newcase*)		-0.07***		
		(0.01)		
*treat*post*PTBtop*			-0.03*	
			(0.02)	
*treat*post*log*(*1+deaths*)				-0.10***
				(0.01)
*treat*post*strict*	-0.08***	-0.06***	-0.07***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.81***	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	44,940	44,921	44,940	44,940
R-squared	0.58	0.58	0.58	0.58