Online Appendix

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

Haiqiang Chen[1], Wenlan Qian[2*], and Qiang Wen[3]

1. Wang Yanan Institute for studies in Economics, Department of Finance, School of Economics, Xiamen University, Xiamen 361005, P.R. China
2. Department of Finance, NUS Business School, National University of Singapore, 15 Kent Ridge Drive, Singapore, 119245
3. Business School, Sichuan University, Chendu 610064, P.R. China

[*]Corresponding author: email: wenlan.qian@nus.edu.sg).

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I. Methods

A. 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 scanner for each city during our sample period, which record spending transactions through POS machines and mobile QR codes (i.e., spending linked to e-wallets of Alipay or WeChat pay accounts). 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. According to the recent statistics provided by China UMS, by the end of 2019, China UMS served close to 8 million offline merchants and 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: National Bureau of Statistics of China).

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 January12, 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. Table A1 shows the classification of offline consumption categories, and Table A2 reports summary statistics.

B. Data on China's COVID-19 outbreak

We download the dataset on China's COVID-19 from China Stock Market & Accounting Research (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. The information is readily accessible from official and social media with active discussion by the general public. In addition, we collect city characteristics, such as population, GDP, and number of hospital beds from China City Statistical Yearbook and China Urban Construction Statistical Yearbook. Table A3 reports summary statistics of city's characteristics.

C. Empirical Methodology

Using the implementation of the Wuhan lockdown (Jan.23, 2020) as the start of the COVID-19 outbreak, we perform the following difference-in-differences regression analysis:

$$Y_{i,t} = \alpha_i + \delta_t + \beta_{post} Treat \times post + \acute{U}_{i,t} \quad (1)$$

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. [1] 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 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:

$$Y_{i,t} = \alpha_i + \delta_t + \sum_{j=0}^{K} \beta_j Treat \times post_j + \acute{U}_{i,t} \quad (2)$$

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

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

interaction terms into equation (1) as follows:

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

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.

II. Main Results

A. The average effect on consumption

We begin by plotting the time-series pattern of daily total offline consumption (Figure A1). 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 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 solid line) stayed persistently low for an extended period, which to a large extent captures the consumption impact of COVID-19.

We use equation (1) and estimate the average effect on daily offline consumption. Table 1 and Table A4 present the average effect of COVID-19 on offline consumption. Table A4 presents the estimated results with the offline spending amount (in millions RMB) as the dependent variable, and the results suggest that offline consumption decreased by 18.57 million RMB per day. Particularly, the offline goods consumption decreased by 12.47 million RMB, almost twice of the decrease of offline services consumption (6.16 million RMB). Table 1 reports the estimated results with the spending amount divided by the pre-period average as the dependent variable. 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%

[2] An 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 of China 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 to the change in 2019.

decrease in offline consumption on average during the post period in 2020, relative to the counterfactual path in 2019. Columns 2 and 3 of Table 1 show offline goods and services consumption decreased by a comparable amount in percentage terms (33% vs. 34%).

For all spending categories, the difference-in-differences coefficients are significantly negative, implying the COVID-19 outbreak hurts all consumption categories (Table A5). Dining & entertainment fell the most, by 64%, followed by travel-related items 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. On the other hand, spending on daily necessities at offline retailers still experienced a decrease likely because consumers largely switched to online retailers for grocery shopping during the epidemic outbreak. Overall, the large impact on entertainment & dining as well as travel spending is in part the outcome of non-essential business closure caused by the strict travel and distancing measures adopted in many cities.

B. 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 findings thus suggest 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 (=14.72 billion*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 concern over spreading germs).

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 of China), 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. 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 A6 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.

C. 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% (Figure A2). The cross-city differences in the consumption impact is strongly associated with the city's exposure to COVID-19. For example, the epicenter city, Wuhan, experienced a 70% decrease in consumption during the twelve weeks after the outbreak, with an additional 38% decrease relative to other cities. The top 20 cities receiving migrants from Wuhan according to Baidu migration index, had an additional 11% decrease relative to other cities (excluding Wuhan). The cities with 0 cases during the sample period enjoyed a 12% less decrease relative to infected cities (Table A7).

We further demonstrate the negative relationship between the impacts on offline consumption and city exposure to COVID-19 in Figure A3. We plot a simple scatterplot between the city-level percentage change in offline consumption and the number of COVID-19 cases as of April 13, 2020. 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.

D. The role of the exposure intensity: within-city

The cross-sectional finding is likely attributable to the consequences of the distancing and mobility-restriction measures as well as a direct effect of the epidemic that reduces consumers' demand. 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 responded to the day-to-day changes in the epidemic severity in the same city while controlling for city and time fixed effects. Mobility-restriction measures as well as the macroeconomic conditions (e.g., unemployment) varied at a much lower frequency in the sample period.

We examine this hypothesis by estimating equation (3) using three proxies of COVID-19 intensity and find evidence of a much stronger decrease in offline consumption in response to the increase in new cases, stress on the hospital system, and the COVID-19 death toll in the city. Column 1 of Table 2 shows doubling the infected cases in a city leads to a 4.9% greater reduction in offline consumption. Column 2 reports the city incurred an additional 5% decrease in offline consumption when it was among the 30 cities with the highest hospital-capacity constraints. Finally, doubling the COVID-19 death toll in a city led to an additional 8.3% decrease of offline consumption (column 3).

We repeat the above regression analysis by excluding Wuhan city and controlling for mobility restriction polices that were implemented during the sample period. 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 A8).[3] 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 changes.

E. The dynamics of the consumption response

To study the dynamics of the consumption response, Figure 1 presents the estimated effect of the week-by-week percentage change in daily total offline consumption during the twelve-week post

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[3] 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.

period. We observed a pattern with an accelerated decline in the first four weeks and a gradual recovery starting from the second month. For the first four weeks, the percentage changes in daily offline consumption are -6.6%, -59%, -66%, and -65%, with all p-values smaller than 0.001. In the fifth week after the COVID-19 outbreak, or late February 2020, the offline consumption started to recover. [4] The recovery peaked 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 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 (Figure A4).

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 A5 indeed demonstrated a strong negative relationship between daily spending and the one-day lagged number of new cases, after including the asymptomatic cases that the government started to report since the beginning of April (we also confirm the visual correlation using a regression analysis). Since most cities had relaxed their mobility restrictions measures by April, this evidence highlights the importance of epidemic containment in driving economic recovery.

Figure A6 shows the dynamic offline consumption responses by consumption type and category. In general, consumption changes show a similar pattern for goods consumption and services. 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. 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.

Figure A7 plots 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 in

[4] 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.

the first month, then becomes much lighter for most areas in the second month, with some cities even showing positive changes in the third month. Several cities such as Beijing, Shanghai, and Guangzhou saw a visible resurgence of COVID-19 cases near the end of the sample period and a large consumption decline subsequently

More specifically, at the epicenter, Wuhan's consumption decrease started immediately and remained persistently large—down by 75%-87% until the eighth week (late March 2020)—before starting a slow recovery (Figure A8). Mega municipalities, such as Beijing, Shanghai, Shenzhen, and Guangzhou, have moderate levels of exposure and show a very significant consumption decrease in the first month and a strong consumption recovery during the second month. Notably, 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.

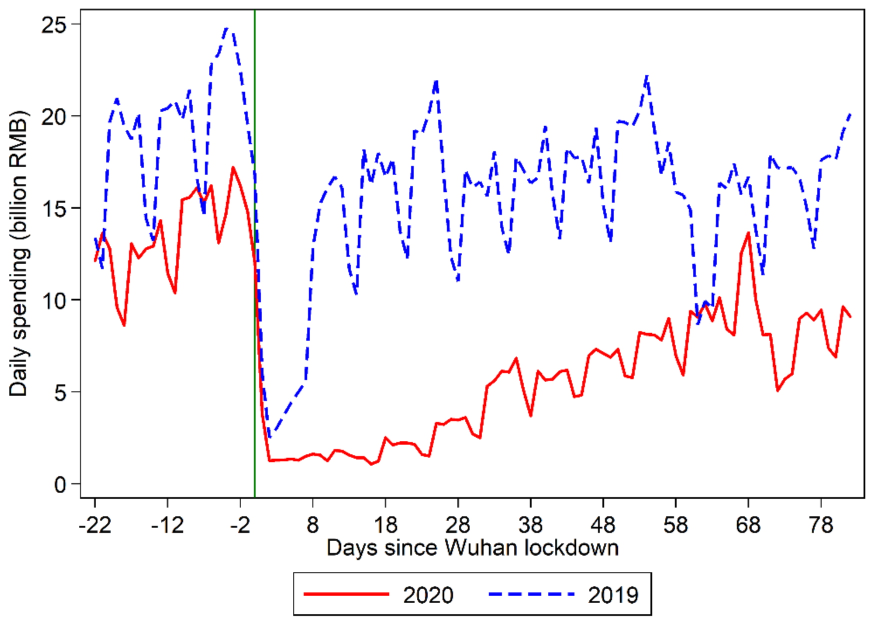
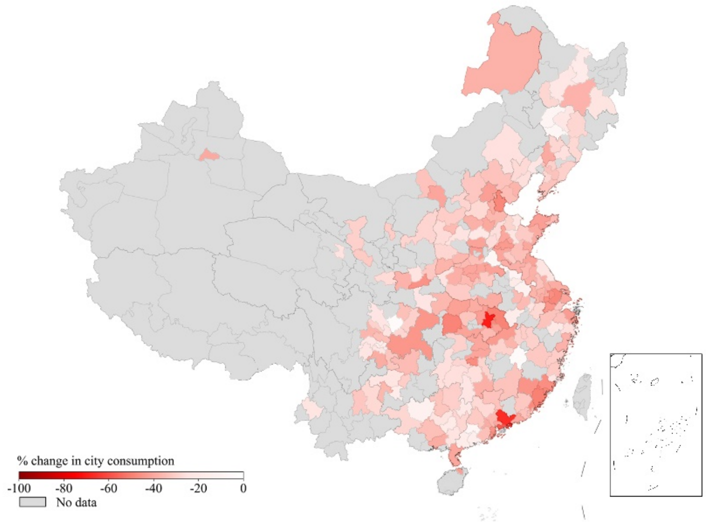


FIGURE A1: DAILY OFFLINE CONSUMPTION: RAW DATA

Note: This figure presents the daily total offline consumption, which is calculated as the sum of all spending through Union-pay Merchant Service (UMS) POS machines and QR scanners for each city-day. 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.



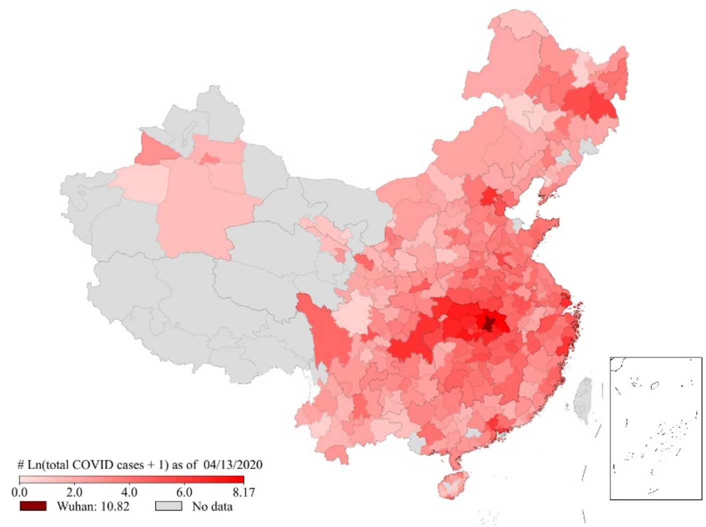


FIGURE A2: THE OFFLINE CONSUMPTION RESPONSE ACROSS CITIES

Note: The figures present 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. Percentage changes in daily offline consumption are 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.

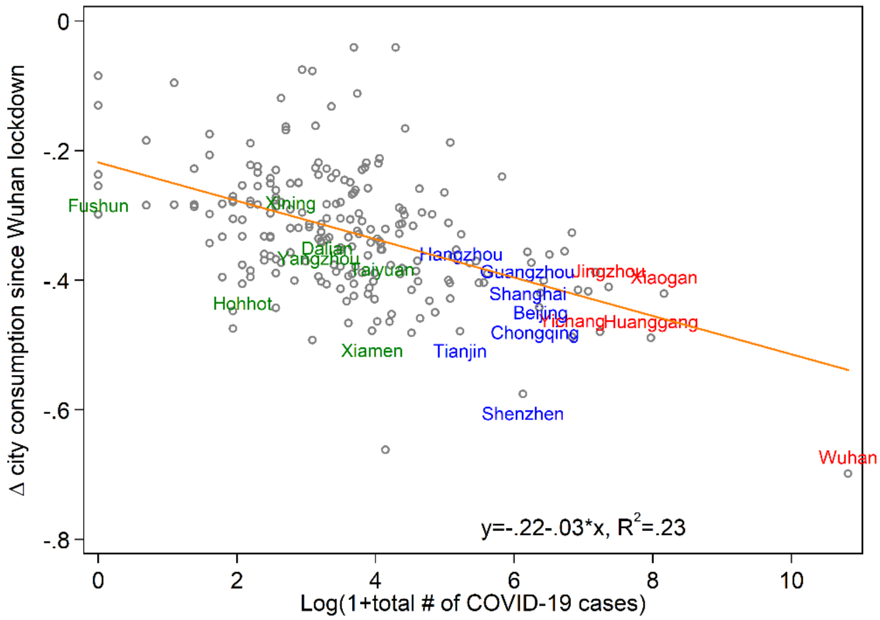


FIGURE A3: PERCENTAGE CHANGE OF CITY CONSUMPTION AND TOTAL # COVID-19 CASES

Note: This figure 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. Percentage changes in daily offline consumption are 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. We also include the fitted line in the scatterplot.

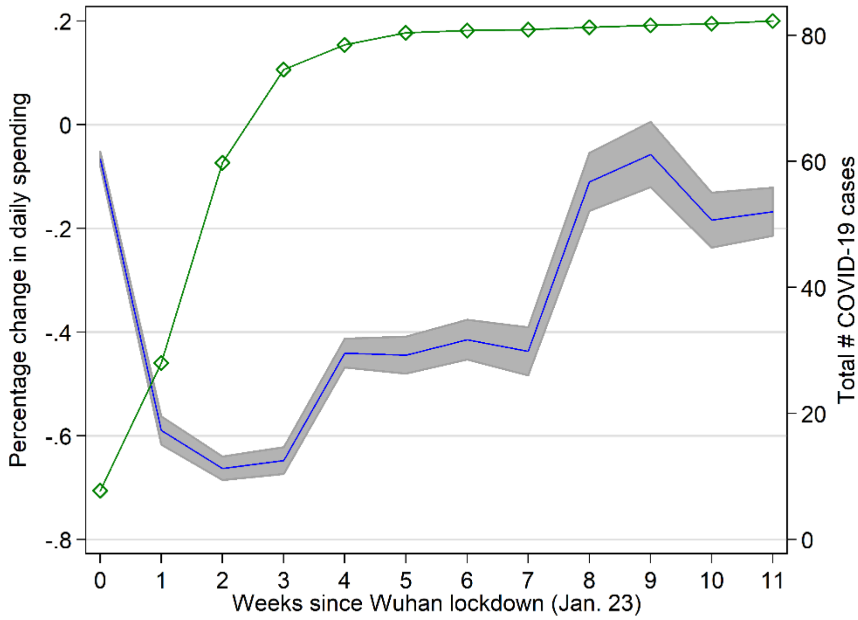


FIGURE A4: THE DYNAMIC OFFLINE CONSUMPTION RESPONSE: EXCLUDING DAYS AFTER DOWNGRADE OF PUBLIC HEALTH EMERGENCY LEVEL

Note: This figure repeats the dynamic offline consumption response of Figure 1 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.

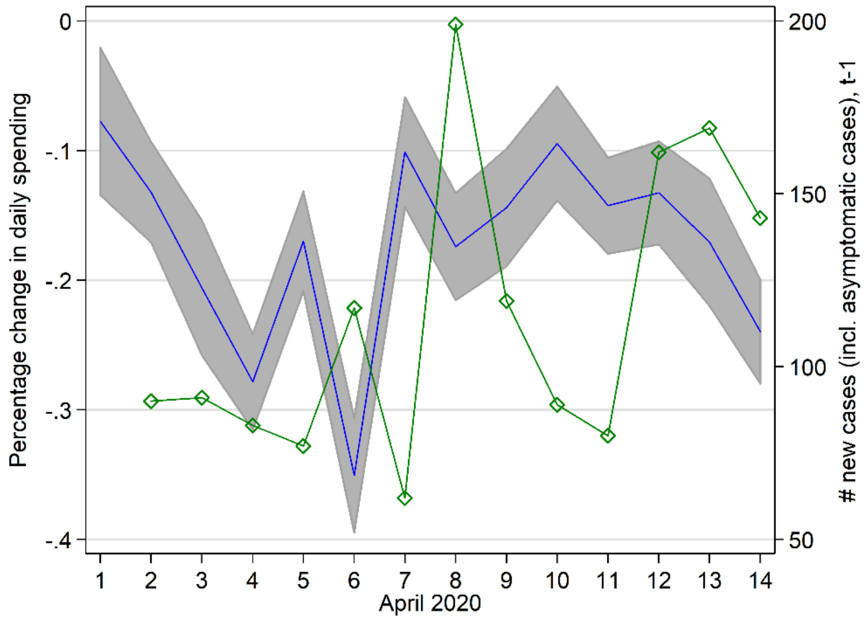
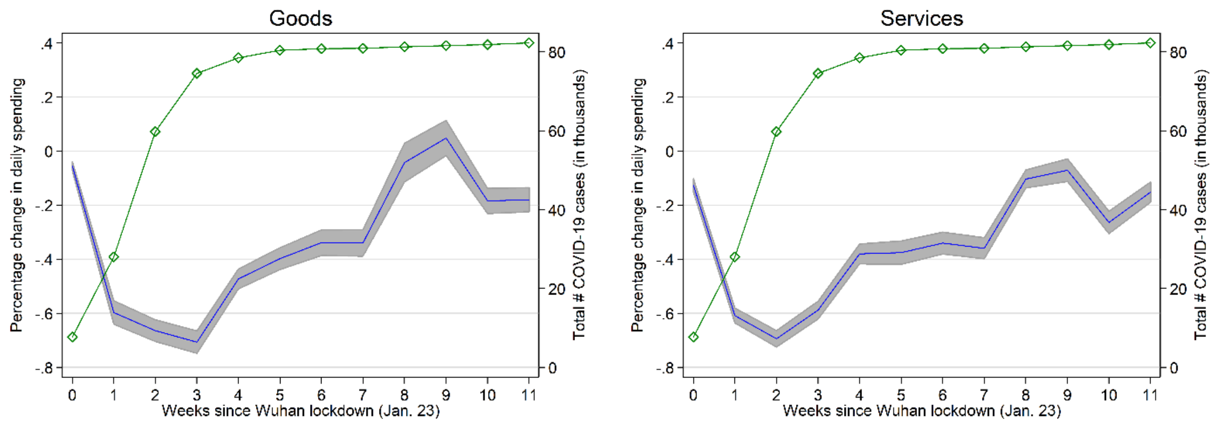


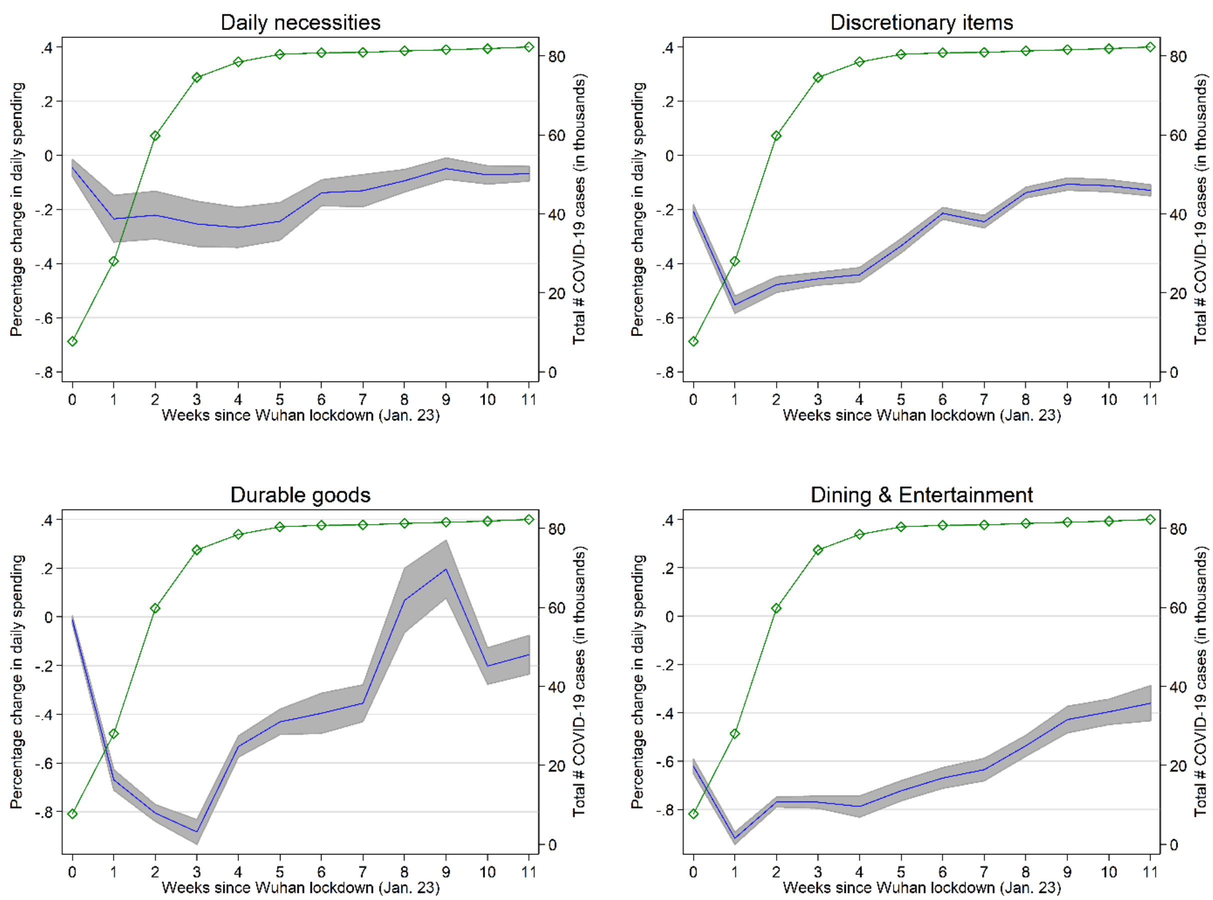
FIGURE A5: THE DAILY DYNAMIC OFFLINE CONSUMPTION RESPONSE IN APRIL

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. This 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).

Panel A: Goods and services



Panel B: Subcategory



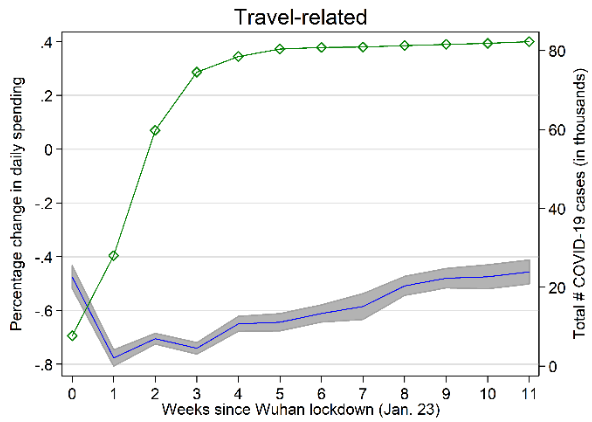
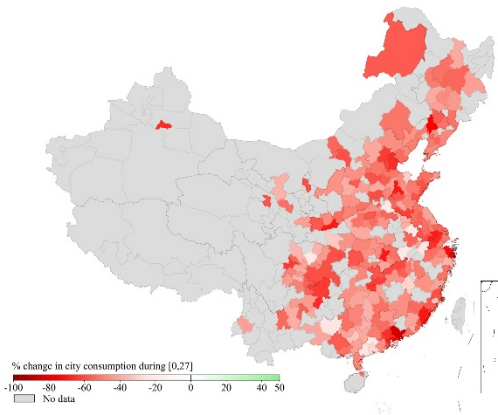


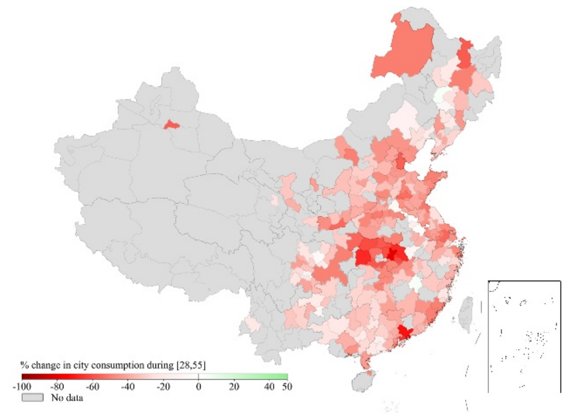
FIGURE A6: OFFLINE CONSUMPTION CHANGES OVER TIME: BY CATEGORY

Note: These figures present the dynamic offline consumption response by categories. Percentage changes in daily offline consumption are 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. The green line shows the total number of COVID-19 cases (in thousands, excluding asymptomatic cases) at the end of the event week. Please refer to Table A1 for detailed classification of consumption types and categories.

Event period [0,27]



Event period [28,55]



Event period [56,82]

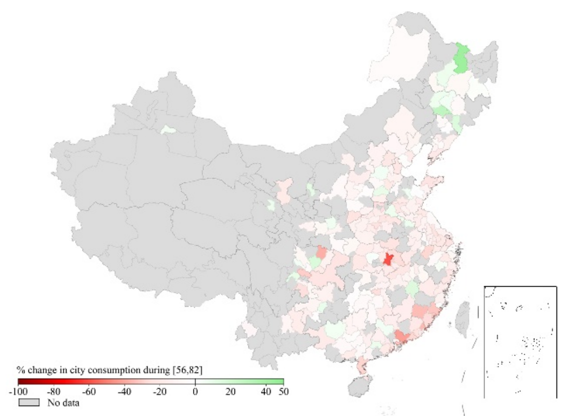
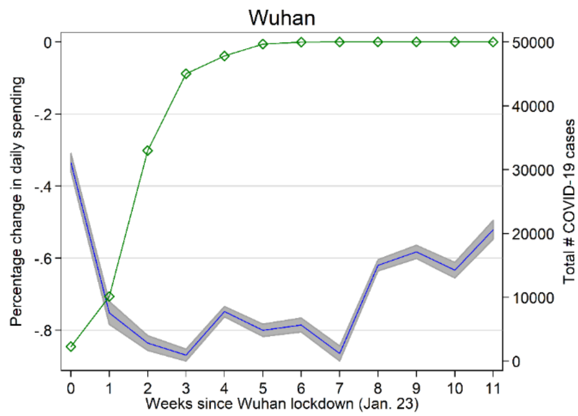


FIGURE A7: THE IMPACT ON OFFLINE CONSUMPTION ACROSS CITIES AND OVER TIME

Note: The figures present the effect heterogeneity on offline consumption across cities and over three post-periods: [0,27], [28,55] and [56,82]. Percentage changes in daily offline consumption are 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.

Panel A: Wuhan



Panel B: Select municipalities

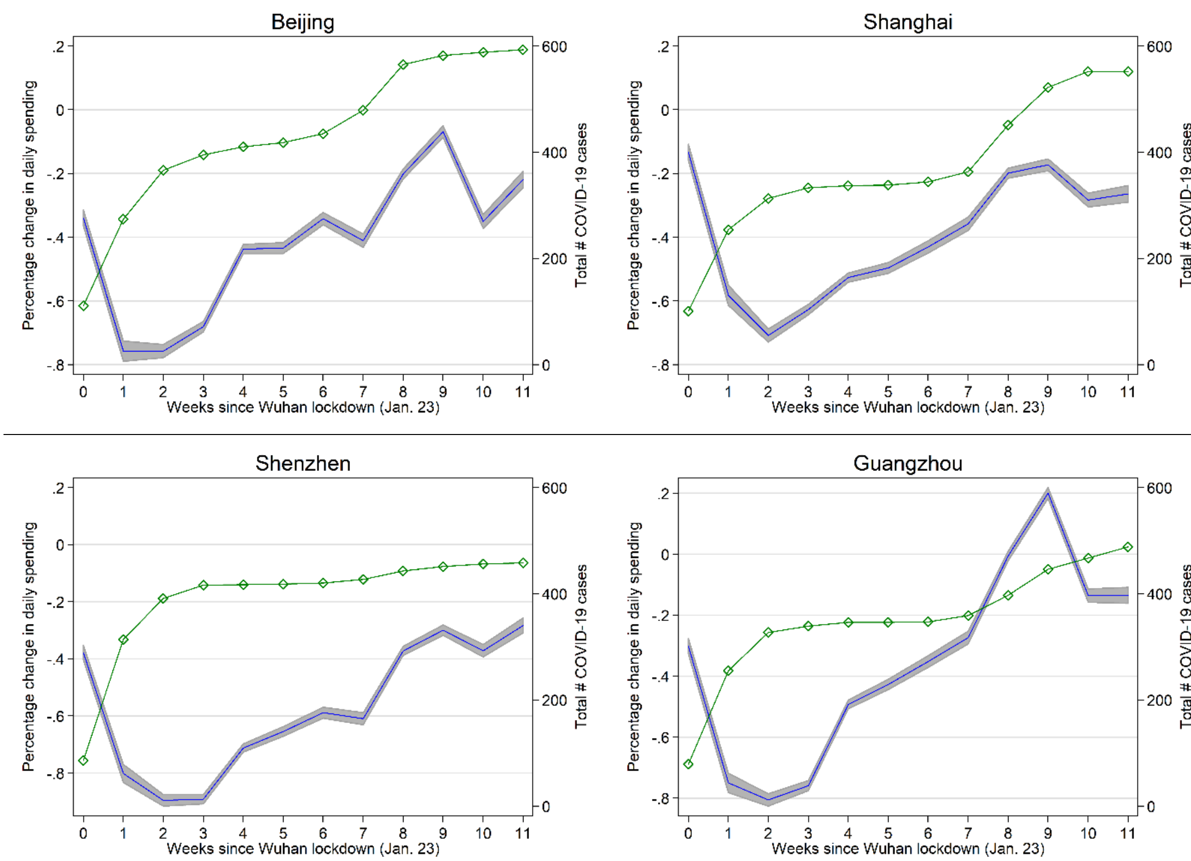


FIGURE A8. OFFLINE CONSUMPTION CHANGES OVER TIME: SELECT CITIES

Note: The figures display the estimated dynamic offline consumption changes for five cities: Wuhan, Beijing, Shanghai, Shenzhen, and Guangzhou.

Percentage changes in daily offline consumption are 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 shaded area indicates 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.

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 DAILY OFFLINE CONSUMPTION

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: [-23, -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: [-23, -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***

Notes: 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 [-23, -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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A3 — SUMMARY STATISTICS OF CITY'S CHARACTERISTICS

	(1) Obs.	(2) Mean	(3) p10	(4) p25	(5) p50	(6) p75	(7) 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

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.

TABLE A4 — THE IMPACT OF COVID-19 ON OFFLINE CONSUMPTION

	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

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) 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. All regressions include the fixed effects for city, distance to Chinese New Year (CNY) and day of week. Please refer to Table A1 for detailed classification of consumption types and categories. Standard errors reported in parentheses are clustered at the city level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A5 — THE IMPACT ON OFFLINE CONSUMPTION: BY DETAILED CATEGORIES

	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

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, 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A6 — ONLINE VS. OFFLINE RESPONSE: EVIDENCE FROM 30 CITIES

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

Note: This table reports the difference-in-differences regression results 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. 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A7 — THE IMPACT ON OFFLINE CONSUMPTION: CROSS-CITY VARIATION IN EXPOSURE

	Spending amt/pre-period average		
	(1)	(2)	(3)
*treat*post*	-0.32***	-0.31***	-0.32***
	(0.01)	(0.01)	(0.01)
*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)
Constant	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)
Observations	44,940	44,730	44,940
R-squared	0.58	0.58	0.57

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, 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. 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE A8 — WITHIN-CITY INTENSITY: ADDITIONAL ROBUSTNESS

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

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, 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.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.