Online Supplement. Additional Tables and Figures for Paper "COVID-19 and E-commerce Operations: Evidence from Alibaba"

A. Summary Statistics from Section 3

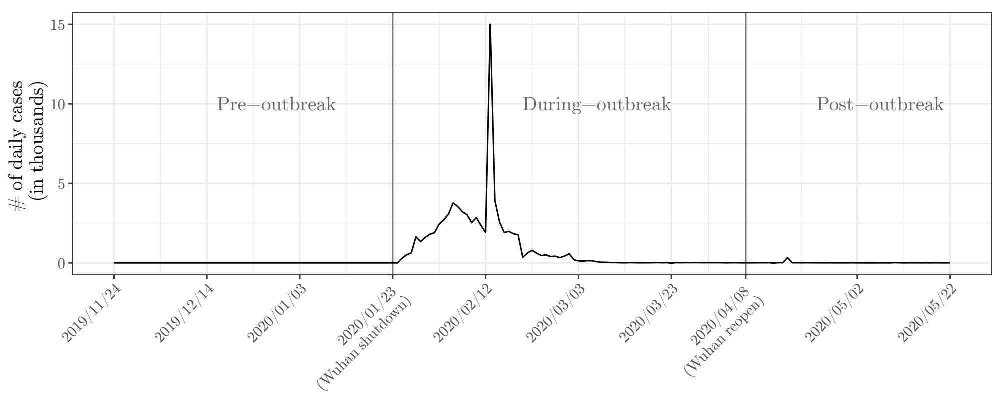

Figure 1 Daily Confirmed COVID-19 Cases in China

Notes: There is a spike of daily cases on February 13. It is mainly due to the change of reporting method, which adds clinically diagnosed cases to the existing laboratory-confirmed cases.

Mainland China consists of 4 direct-administered municipalities (Shanghai, Beijing, Chongqing, and Tianjin), 293 prefecture-level cities (e.g., Hangzhou, Wuhan), and 388 county-level cities. Prefecture-level cities govern county-level cities, mostly rural areas with a smaller population. Our panel data includes 4 municipalities, 283 prefecture-level cities, and 52 county-level cities. There are only 10 prefecture-level cities (Danzhou, Bijie, Tongren, Shigatse, Changdu, Linzhi, Shannan, Haidong, Turpan, and Hami) missing in our data. According to National Bureau of Statistics of China (2019), the covered cities in our panel data comprises 92.5% of the total population in China in 2019.

In Table 1, we summarize a list of variables we have collected from Alibaba, Cainiao, and China CDC. Note that some of the (time series) variables are collected only at the national level due to restricted data access at the Alibaba group. For the same reason, we provide summary statistics in Table 2 for our key outcome variables with anonymized scales.

B. Robustness Checks from Section 4.2

We change the threshold of 10 cases to 5 and 20 cases and rerun our model (Equation (3) from Section 4.2) in Table 4. As we can see, the estimates are consistent across Columns (1)–(3).

In Figure 2, we breakdown $DuringWuhanShutdown_t$ and $AfterWuhanReopen_t$ from Equation (3) into a set of week-specific dummy variables and estimate the impact of COVID-19 intensity by week relative to Wuhan shutdown. As we can see, the weekly effect becomes insignificant two weeks after Wuhan reopens.

Table 1 List of Variables

Variable	Description	Unit of Obs.	Period	Source
		Sales related		
Sales	Total sales of Alibaba's e-commerce platforms	City-day	2019/11/24 – 2020/05/27 & 2018/12/05 – 2019/06/08 & 2017/12/16 – 2018/06/19	Alibaba
		Logistics related		
TotalOrder	Total number of logistics orders	City-day	2019/11/24 – 2020/05/27 & 2018/12/05 – 2019/06/08	Alibaba-Cainiao
AvgDeliveryTime	Average package delivery time	City-day	2019/11/24 – 2020/05/27 & 2018/12/05 – 2019/06/08	Alibaba-Cainiao
		Customer ordering process		
Cart Add-on/Item-view	Number of cart add-ons divided by number of item-views	Day	2019/11/24 – 2020/04/12 & 2018/12/05 – 2019/04/24	Alibaba
Order/Cart Add-on	Number of orders divided by number of cart add-ons	Day	2019/11/24 – 2020/04/12 & 2018/12/05 – 2019/04/24	Alibaba
		COVID-19 case data		
DailyCases	Number of confirmed COVID-19 cases	City-day	2019/01/20 – 2020/05/27	China CDC

Table 2 Summary Statistics of Key Variables for the 2019 and 2020 Periods (City-day Panel Data Normalized to Mean 0 Standard Deviation 1 for Anonymity)

		Before Wuhan shutdown	During Wuhan shutdown	After Wuhan reopen
2020 data	Calendar date	2019/11/24 – 2020/01/22	2020/01/23 – 2020/04/07	2020/04/08 – 2020/05/27
($N = 63,054$)	Number of days	60	76	50
	Sales mean (std.)	0.137 (1.510)	−0.046 (0.787)	0.120 (0.991)
	TotalOrder mean (std.)	0.100 (1.150)	−0.126 (0.852)	0.182 (1.150)
	AvgDeliveryTime mean (std.)	−0.154 (0.787)	0.681 (1.360)	-0.278 (0.718)
2019 data	Calendar date	2018/12/05 – 2019/02/02	2019/02/03 – 2019/04/19	2019/04/20 – 2019/06/08
($N = 63,054$)	Number of days	60	76	50
	Sales mean (std.)	−0.053 (1.030)	−0.090 (0.704)	−0.014 (0.847)
	TotalOrder mean (std.)	−0.035 (0.959)	−0.074 (0.903)	0.044 (1.000)
	AvgDeliveryTime mean (std.)	−0.123 (0.782)	−0.079 (0.899)	−0.305 (0.700)
2020 − 2019	Mean difference in *Sales*	0.190***	0.046***	0.134***
	Mean difference in *TotalOrder*	0.135***	−0.052***	0.138***
	Mean difference in *AvgDeliveryTime*	−0.031***	0.760***	0.027***

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

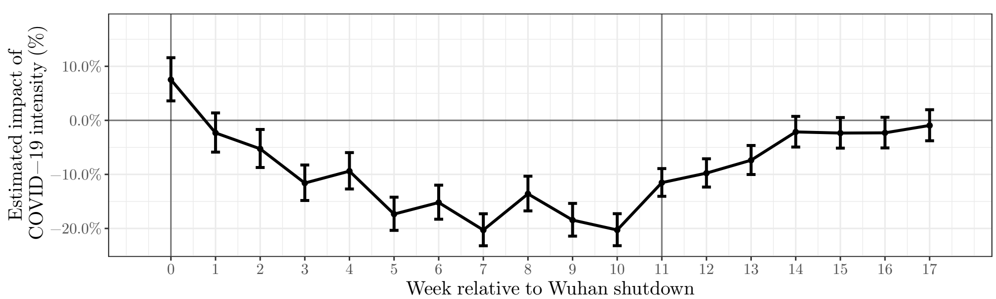

Figure 2 Impact of COVID-19 Intensity on E-commerce Sales by Week

C. Matching Estimators from Section 4.2

This section seeks to obtain a cleaner causal estimate for the impact of COVID-19 intensity on e-commerce sales. We collect additional data on city-level characteristics (by year-end of 2019) from the National Bureau of Statistics of China. The city-level characteristics include administrative land area, GDP per capita, average

Table 3 Timing of Containment Policies Across Cities

City	Province	Start date	End date	Cases[1]	City	Province	Start date	End date	Cases
Panel A. Shutdown					**Panel C. Checkpoint**				
Wuhan	Hubei	2020/01/23	2020/04/08	49,122	Shijiazhuang	Hebei	2020/02/05	2020/03/24	29
Huanggang	Hubei	2020/01/23	2020/03/25	2,905	Sanya	Hainan	2020/02/05	2020/02/23	54
Ezhou	Hubei	2020/01/23	2020/03/25	1,391	Yangzhou	Jiangsu	2020/02/05	2020/02/23	23
Jingmen	Hubei	2020/01/24	2020/03/25	925	Jinan	Shandong	2020/02/05	2020/02/21	47
Xiantao	Hubei	2020/01/24	2020/03/25	0	Maanshan	Anhui	2020/02/06	2020/02/23	38
Qianjiang	Hubei	2020/01/24	2020/03/25	0	Suzhou	Jiangsu	2020/02/06	2020/02/23	87
Enshi	Hubei	2020/01/24	2020/03/25	4	Zhuhai	Sichuan	2020/02/06	2020/02/24	98
Shiyan	Hubei	2020/01/24	2020/03/25	672	Yaan	Sichuan	2020/02/06	2020/02/24	7
Xianning	Hubei	2020/01/24	2020/03/25	836	Shenzhen	Guangdong	2020/02/07	2020/02/22	417
Suizhou	Hubei	2020/01/24	2020/03/25	1,307	Hefei	Anhui	2020/02/07	2020/02/23	174
Yichang	Hubei	2020/01/24	2020/03/25	931	Lanzhou	Gansu	2020/02/07	2020/02/14	35
Huangshi	Hubei	2020/01/24	2020/03/25	1,014	Tangshan	Hebei	2020/02/07	2020/03/24	58
Xiaogan	Hubei	2020/01/24	2020/03/25	3,518	Guangyuan	Sichuan	2020/02/07	2020/02/24	6
Enshitujiazumiaozu	Hubei	2020/01/24	2020/03/25	252	Chengdu	Sichuan	2020/02/07	2020/02/24	143
Jingzhou	Hubei	2020/01/24	2020/03/25	1,579	Guiyang	Guizhou	2020/02/07	2020/02/15	36
Tianmen	Hubei	2020/01/24	2020/03/25	0	Lianyungang	Jiangsu	2020/02/07	2020/02/23	48
Xiangyang	Hubei	2020/01/28	2020/03/25	0	Tianjin	Tianjin	2020/02/07	2020/03/15	136
Panel B. Partial shutdown					Guangzhou	Guangdong	2020/02/07	2020/02/22	346
Wenzhou	Zhejiang	2020/02/02	2020/02/19	504	Suining	Sichuan	2020/02/07	2020/02/24	17
Zhengzhou	Henan	2020/02/04	2020/02/25	157	Ziyan	Sichuan	2020/02/08	2020/02/24	4
Hangzhou	Zhejiang	2020/02/04	2020/02/19	169	Foshan	Guangdong	2020/02/08	2020/02/22	84
Zhumadian	Henan	2020/02/04	2020/02/25	139	Huizhou	Guangdong	2020/02/09	2020/02/22	62
Ningbo	Zhejiang	2020/02/04	2020/02/19	157	Mianyang	Sichuan	2020/02/09	2020/02/24	22
Haerbin	Heilongjiang	2020/02/04	2020/02/24	198	Deyang	Sichuan	2020/02/09	2020/02/24	18
Fuzhou	Fujian	2020/02/04	2020/02/23	72	Hanzhong	Sanxi	2020/02/09	2020/02/23	26
Panel C. Checkpoint					Dongguan	Guangdong	2020/02/09	2020/02/22	99
Huaian	Jiangsu	2020/02/03	2020/02/23	0	Wuxi	Jiangsu	2020/02/09	2020/02/23	55
Nantong	Jiangsu	2020/02/04	2020/02/23	40	Shanghai	Shanghai	2020/02/10	2020/03/22	337
Xuzhou	Jiangsu	2020/02/04	2020/02/23	79	Beijing	Beijing	2020/02/10	2020/03/25	413
Nanjing	Jiangsu	2020/02/04	2020/02/23	93	Eerduosi	Inner Mongolia	2020/02/12	2020/02/24	0
Zhenjiang	Jiangsu	2020/02/04	2020/02/23	12	Wulanchabu	Inner Mongolia	2020/02/12	2020/02/24	3
Linyi	Shandong	2020/02/04	2020/02/21	49	Tongliao	Inner Mongolia	2020/02/12	2020/02/24	7
Jingdezhen	Jiangxi	2020/02/04	2020/02/13	6	Bayannaoer	Inner Mongolia	2020/02/12	2020/02/24	8
Haikou	Hainan	2020/02/05	2020/02/23	39	Alashan	Inner Mongolia	2020/02/12	2020/02/24	0
Nanchang	Jiangxi	2020/02/05	2020/02/13	230	Wuhai	Inner Mongolia	2020/02/12	2020/02/24	2
Nanning	Guangxi	2020/02/05	2020/02/24	55	Hulunbeier	Inner Mongolia	2020/02/12	2020/02/24	6
Suqian	Jiangsu	2020/02/05	2020/02/23	13	Xingan	Inner Mongolia	2020/02/12	2020/02/24	1
Qingdao	Shandong	2020/02/05	2020/02/21	60	Chifeng	Inner Mongolia	2020/02/12	2020/02/24	8
Kunming	Yunnan	2020/02/05	2020/02/13	53	Baotou	Inner Mongolia	2020/02/12	2020/02/24	11
Taian	Shandong	2020/02/05	2020/02/21	35	Xilinguole	Inner Mongolia	2020/02/12	2020/02/24	9
Taizhou	Jiangsu	2020/02/05	2020/02/23	37	Huhehaote	Inner Mongolia	2020/02/12	2020/02/24	7

Notes: This is a duplicate table from Table A1 in Fang et al. (2020). We collected additional data for the end date of containment policies. [1] "Cases" refers to the total number of confirmed cases by the time of start date in each city.

income, total population, population density per km^2, number of employed, total retail sales, and number of hospitals. Among the 339 cities invested in this study, 145 (40%) cities have less than 10 confirmed cases during the COVID-19 outbreak. We consider these cities as the control benchmark. The other 194 cities with high COVID-19 intensity are the treatment group. We then use matching to construct a subsample that achieves a better balance. We use propensity score matching (PSM) to improve the balance regarding propensity scores. The second coarsened exact matching (CEM) improves the covariate balance in particular.

C.1. Propensity Score Matching (PSM)

For the PSM, we estimate a logistic regression based on the city-level characteristics and obtain the predicted probability (i.e., propensity score) of each city having more than 10 cases. We find a one-to-one match in the control group with the closest value of propensity score (caliper is set at 0.2 standard deviations). The matched sample has 107 cities in the treatment group and control group, respectively. (The matching rate is 63%.) To assess the balance across two groups, we plot the distributions of propensity scores by group in Figure 3. It shows that the two distribution significantly overlaps with each other.

Table 4 Impact of COVID-19 Intensity on E-commerce Sales (with Different Thresholds)

	Log($Sales$)		
	(1)	(2)	(3)
$TotalCases > 10 \cdot DuringWuhanShutdown$	-0.126^{***}		
	(0.003)		
$TotalCases > 10 \cdot AfterWuhanReopen$	-0.060^{***}		
	(0.004)		
$TotalCases > 5 \cdot DuringWuhanShutdown$		-0.115^{***}	
		(0.003)	
$TotalCases > 5 \cdot AfterWuhanReopen$		-0.069^{***}	
		(0.004)	
$TotalCases > 20 \cdot DuringWuhanShutdown$			-0.138^{***}
			(0.003)
$TotalCases > 20 \cdot AfterWuhanReopen$			-0.052^{***}
			(0.004)
Date FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Observations	63,054	63,054	63,054
R^2	0.986	0.986	0.986

Robust standard errors clustered by city in parentheses

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

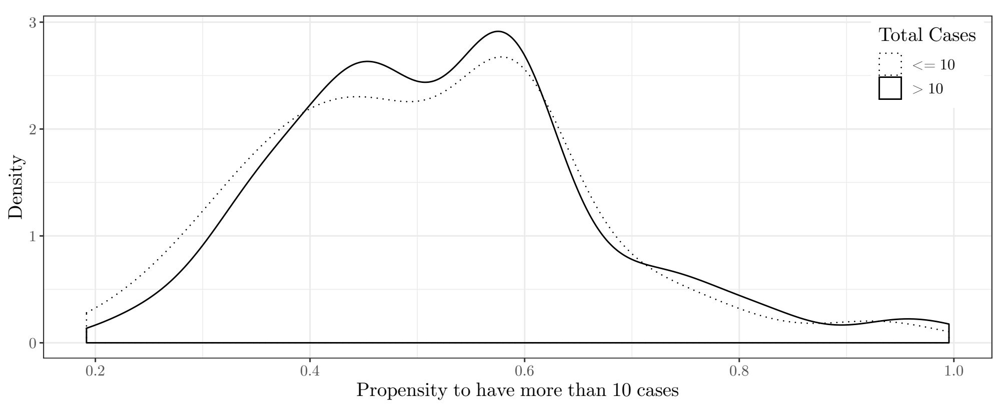

Figure 3 Distribution of Propensity Score After Matching

C.2. Coarsened Exact Matching (CEM)

We also conduct a CEM on the city-level covariates, which effectively improves the covariate balance. We summarize each covariate before and after matching in Table 5. After matching, we find no significant mean difference across the two groups.

Table 5 Covariate Balance Before and After CEM

	Before Matching			**After Matching**		
	Total Cases			Total Cases		
	≤ 10	> 10	p-Value	≤ 10	> 10	p-Value
Administrative land area (sq. km)	20,860	13,713	0.00	15,053	13,953	0.33
GDP per capita (RMB)	57,265	66,692	0.01	52,195	53,239	0.70
Average wages of employees (RMB)	72,461	74,197	0.67	69,256	68,810	0.67
Total population (10,000 persons)	371	530	0.00	351	350	0.95
Population density (persons per km^2)	326	529	0.00	328	350	0.46
Employed persons in units (10,000 persons)	48.79	70.31	0.02	38.90	35.31	0.29
Total retail sales of consumer goods (10,000 yuan)	10,071,163	15,614,983	0.00	8,410,182	7,758,285	0.40
Number of hospitals and health centers (unit)	81.90	80.24	0.00	87.06	78.53	0.20
Observations	145	194		103	49	

D. Robustness Check from Section 4.3

The fixed-effect DID model (Equation (4)) in Section 4.3 leverages containment policy changes for identification. We can examine the robustness of our estimates by examining whether the effect appears before the implementation. In Table 6 Column (2), we added a set of dummy variables, which equals 1 only during the one month before the start date of each containment measure. None of the coefficients are statistically significant. It suggests that the containment effect does not appear spuriously before it happens. As such, it serves as a falsification test, which further strengthens the validity of our estimates.

E. Heterogeneous Impact of COVID-19 Across Buyers and Sellers: Suggestive Evidence on "Digital Expansion"

This section provides some suggestive evidence on how the demand and supply side of e-commerce reacts to the pandemic. We collect additional subsampled data for the 2019 and 2020 data and estimate the overall impact of COVID-19 on e-commerce sales for particular buyer/seller segments.

First, we partition all consumers based on their total number of orders in 2019 and estimate Equation (1) in Columns (1) and (2) of Table 7 for each subgroup. We find that the sales for both customers at the top 25% and the bottom 75% percentile decrease significantly during the outbreak. After Wuhan shutdown, the

Table 6 Impact of Containment Policies on E-commerce Sales: Robustness Check

	Log($Sales$)	
	Main	Falsification test
	(1)	(2)
$Checkpoint\_Before1Month$		0.016
		(0.015)
$PartialShutdown\_Before1Month$		0.027
		(0.014)
$Shutdown\_Before1Month$		0.021
		(0.011)
$Checkpoint$	-0.050^{***}	-0.044^{***}
	(0.004)	(0.004)
$PartialShutdown$	-0.113^{***}	-0.102^{***}
	(0.010)	(0.012)
$Shutdown$	-0.811^{***}	-0.801^{***}
	(0.008)	(0.009)
$AfterCheckpoint$	-0.053^{***}	-0.048^{***}
	(0.004)	(0.005)
$AfterPartialShutdown$	-0.011	-0.001
	(0.011)	(0.012)
$AfterShutdown$	-0.064^{***}	-0.055^{***}
	(0.008)	(0.010)
Day of week FE	Yes	Yes
Lunar date FE	Yes	Yes
Observations	63,054	63,054
R^2	0.988	0.988

Robust standard errors clustered by city in parentheses
$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

bottom 75% of customers significantly increase their sales on the platform by 11% ($p < 0.001$), while the impact on the top 25% of customers remains negative. (Note that the bottom 75% of customers also include a small proportion of new customers, around 0.9% who have never shopped on Alibaba.) The results on the top 25% of frequent buyers echo the anecdotal evidence from the USA (Badger and Parlapiano 2020), showing that the rich have significantly cut their spending since the outbreak. Moreover, to distinguish individual and corporate sellers, we quantify the impact of COVID-19 on the sellers for the C-to-C (taobao.com) and B-to-C (tmall.com) platforms, respectively. We partition all individual sellers on the C-to-C platform based on their annual sales in 2019 and carry out a similar subgroup analysis in Columns (3) and (4). We find that on the C-to-C platform, only large sellers are negatively affected by COVID-19, while small- and medium-sized sellers have gained significantly from the pandemic. Specifically, we estimate 35% ($p < 0.001$) and 24% ($p < 0.001$) decrease in sales for the top 25% of sellers during Wuhan shutdown and after Wuhan reopen, respectively. In contrast, there is a significant increase in sales (by 50% and 26%, respectively) for the bottom 75% of sellers. We further present the results for corporate sellers on the B-to-C platform in Columns (5) and (6). It shows that large corporate sellers at the top 25% percentile take a larger hit during COVID-19 than the bottom 75%. After Wuhan reopen, there is a sharp increase for small and medium sellers, while the negative impact on the large sellers persists. For example, we estimate an 18% ($p < 0.001$) increase in sales for the small- to medium-sized corporate seller but a 9% ($p < 0.001$) decreases for large sellers.

Table 7 Heterogeneous Impact of COVID-19 on E-commerce Sales Across Buyers and Sellers

	Log($Sales$)					
	By customer order frequency in 2019		By seller annual sales in 2019 (C-to-C)		By firm annual sales in 2019 (B-to-C)	
	Bottom 75%	Top 25%	Bottom 75%	Top 25%	Bottom 75%	Top 25%
	(1)	(2)	(3)	(4)	(5)	(6)
$Year2020$	0.404^{***}	0.415^{***}	1.383^{***}	0.541^{***}	0.665^{***}	0.231^{***}
	(0.013)	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)
$Year2020 \cdot DuringWuhanShutdown$	-0.145^{***}	-0.341^{***}	0.399^{***}	-0.430^{***}	-0.051^{**}	-0.188^{***}
	(0.017)	(0.020)	(0.021)	(0.019)	(0.019)	(0.019)
$Year2020 \cdot DuringWuhanShutdown$	0.102^{***}	-0.251^{***}	0.233^{***}	-0.272^{***}	0.166^{***}	-0.090^{***}
	(0.019)	(0.022)	(0.024)	(0.021)	(0.021)	(0.021)
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Lunar date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,108	126,108	126,108	126,108	126,108	126,108
R^2	0.104	0.074	0.245	0.095	0.140	0.075

Robust standard errors clustered by city in parentheses
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

References

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