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Online prices and inflation during the nationwide COVID-19 quarantine period: Evidence from 107 Chinese websites

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ABSTRACT

Given the lack of activity in China's offline economy during the COVID-19 quarantine period, online prices provide new insights for analyzing the impacts of the pandemic on the economy. Using online prices from 107 websites in China and the DiD method to remove the Spring Festival effect, we show that the pandemic leads to a 0.4% surge in the overall inflation rate, a 20% decrease in the price change probability, and a 1% decline in the size of absolute price changes. Moreover, the pandemic had heterogeneous impacts on different sectors, leading to significant structural changes in inflation. Specifically, the pandemic hindered the price correction behavior after Spring Festival, and whether products could be consumed while customers stayed at home was an important factor affecting price adjustment and inflation dynamics.

1. Introduction

The outbreak of the COVID-19 pandemic has had tremendous consequences for the global economy (e.g., McKibbin & Fernando, 2020). For example, global stock markets significantly react to COVID-19 (Jin et al., 2022), daily offline consumption has declined considerably (Chen et al., 2021), and the US CPI has underestimated the COVID inflation rate (Cavallo, 2020). In China, the outbreak arrived close to the *Chinese New Year* (abbreviated *CNY* and also called the *Spring Festival*), which is the largest human migration activity in the world (approximately 400 million people during the 2019 *CNY*). Diverse restrictive policies have been enforced to prevent the epidemic from spreading, including the unprecedented lockdown of Wuhan for 76 days and a nationwide quarantine for approximately 20 days.

It is crucial to evaluate the economic impacts of the outbreak of the COVID-19 pandemic and nationwide quarantine. During the quarantine period, the offline economy was seriously affected and almost frozen, which entailed considerable inconvenience for traditional offline price collection. However, the stay-at-home economy has been developing rapidly, including online shopping and online education, and daily high-frequency online prices provide new possibilities for analyzing the impacts of the pandemic on the economy.

In recent years, online prices have received increasing attention. It is found that online and offline price changes are not synchronized but have similar frequencies and average sizes (Cavallo, 2017). In addition, online markets have lower search costs and nominal price adjustment costs (Gorodnichenko et al., 2018). However, to the best of our knowledge, existing studies seldom apply daily online prices to investigate the effects of COVID-19 on the economy during the nationwide quarantine period, and our research

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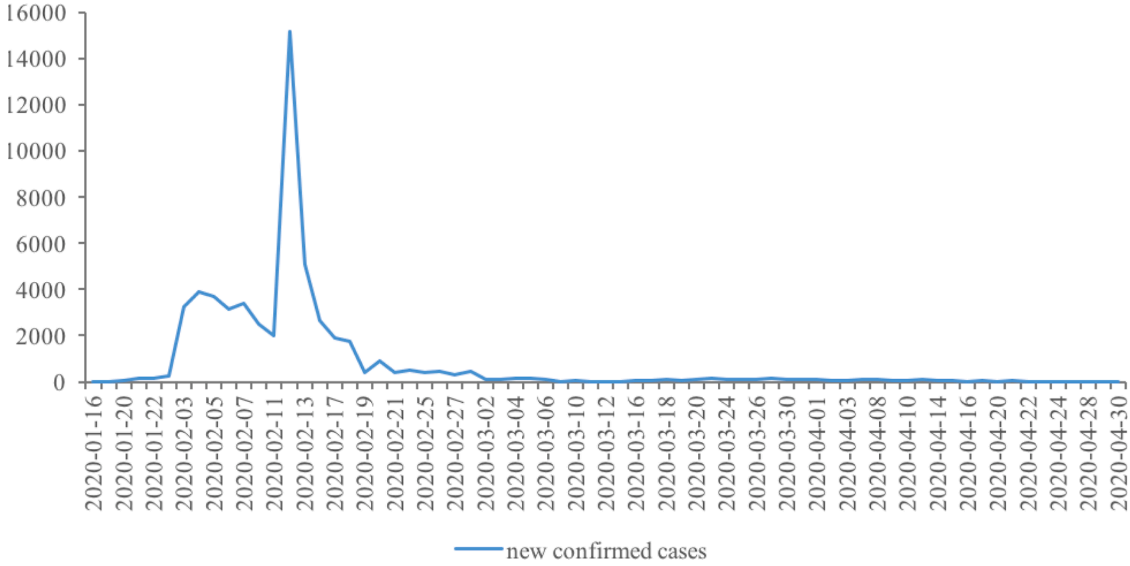


Fig. 1. New confirmed cases of COVID-19 in China

contributes to filling this gap.

In this paper, we adopt online prices from 107 websites in China and the difference-in-differences (DiD) method to analyze the impacts of the pandemic on inflation and price stickiness. We find that the pandemic led to a 0.4% surge in the overall inflation rate but a 20% decrease in price change probability and a 1% decline in the absolute size of price changes during the nationwide quarantine period. In particular, the outbreak of the pandemic and ensuing quarantine policy have had heterogeneous impacts on different industries, which makes price change behavior and price trends diverge across various types of goods and services, thus bringing about structural changes in inflation.

This study offers three main contributions to the field. First, we combine unique daily price data from 107 Chinese websites and DiD method to investigate the economic impacts of the unprecedented nationwide quarantine due to the COVID-19 pandemic. In particular, the official CPI is published monthly, which cannot fully capture the impacts of such high-frequency and extreme shocks due to limited monthly data, especially when a pandemic coincides with an important holiday. Second, we compare the impacts of the nationwide quarantine on the prices of different sectors, providing evidence for the structural changes in inflation and different policies to alleviate the damage. Third, we examine the impacts of COVID-19 on the online prices and stay-at-home economy, a stabilizer of economy during the quarantine, contributing to the studies that have examined the impacts of COVID-19 on economy and enriching the existing research on the inflation and price stickiness.

The remainder of this paper is arranged as follows. Section 2 introduces the data and methodology. Section 3 presents the empirical results. Section 4 concludes.

2. Data and methodology

2.1. Data

The online price data, obtained from the iCPI (Internet-based Consumer Price Index) project at Tsinghua University, contain daily prices from 107 websites[1] covering the entire basket used to compute the official Chinese CPI, including 8 divisions, 27 groups, and 262 classes.[2] The COVID-19 data are from the Wind database (See Fig. 1). The pandemic outbreak began in China on January 20, 2020, and the lockdown of Wuhan began on January 23, 2020, after which many provinces enforced rigorous quarantine policies. Many cities even postponed the resumption of work until February 9 and the reopening of school until February 17. In addition, the number of newly confirmed cases reached a peak of over 15,000 on February 12, 2020 and then gradually declined below 1000 until February 20, showing that the epidemic spread was initially controlled and that public panic was effectively eased. Therefore, the period from

[1] The websites mainly include integrated and vertical e-commerce platforms, including Tmall, JD et al., where the consumers and delivery addresses are in China. Specifically, we do not collect price data from cross-border e-commerce platforms, for example, AliExpress, Amazon, Lazada, Shopee et al. Therefore, the data is unique to China and isolated from the effects of purchases from other countries.

[2] The iCPI includes daily, weekly, ten-day and monthly indices, and they are generated via automatic computation procedures, including data collection, data cleaning, and final processing for online publishing, which avoids human intervention and improves validity. Besides, the iCPI has been published on the website (http://www.bdecon.com) since January 1, 2016, which can be downloaded in databases, including Bloomberg, Wind and CEIC. The steps of designing iCPI are shown in the Appendix A, and more details are available in the paper of Liu et al. (2019).

Table 1
Descriptive statistics of variables.

Variables	Obs	Mean	Min	Max	S.D.
Dependent variables					
Price change	3104546	0.02	0	1	0.14
Price increase	3104546	0.01	0	1	0.10
Price decrease	3104546	0.01	0	1	0.10
Price change size	61957	3.17	-50	100	24.25
(Observations with non-zero changes)					
Absolute price change size	61957	16.51	0	100	18.04
Price increase size	31548	19.32	0	100	21.91
Price decrease size	30409	13.58	0	50	12.18
Independent variables					
year(in 2019=0, in 2020=1)	3104546	0.60	0	1	0.49
ncov(before outbreak=0, after outbreak=1)	3104546	0.62	0	1	0.49
year* ncov	3104546	0.37	0	1	0.48
Control variables					
Ln(Price) (goods price of the previous day)	3104546	4.81	-4.61	17.73	1.83
Food, tobacco and liquor	3104546	0.33	0	1	
Clothing	3104546	0.18	0	1	
Residence	3104546	0.04	0	1	
Household articles and service	3104546	0.24	0	1	
Transportation and communication	3104546	0.06	0	1	
Education, culture and recreation	3104546	0.08			
Health care	3104546	0.05	0	1	
Other articles and services	3104546	0.02	0	1	
Monday	3104546	0.14	0	1	
Tuesday	3104546	0.14	0	1	
Wednesday	3104546	0.15	0	1	
Thursday	3104546	0.15	0	1	
Friday	3104546	0.14	0	1	
Saturday	3104546	0.15	0	1	
Sunday	3104546	0.14	0	1	

Notes: There are seven dummy variables for divisions, and six dummy variables for weekdays.
Sources: Tsinghua University iCPI.

January 20, 2020, to February 20, 2020, can be regarded as the most severe pandemic stage and nationwide quarantine period, and this paper mainly focuses on the impacts of COVID-19 on prices during this period.

2.2. Methodology

Considering that the COVID-19 outbreak was close to the *Chinese New Year* (abbreviated *CNY*) on January 25, 2020, which is the most important holiday for Chinese people and has nonnegligible impacts on the economy, we use the DiD model to evaluate the impact of COVID-19 on prices. To capture the counterfactual price change pattern, we adopt the price data of the same goods basket from a similar period of 2019 as the control group (benchmark), aiming to remove the impact of the *CNY*.[3] Specifically, the sample period of the treatment group is from January 1, 2020, to February 20, 2020, with January 20, 2020 (5 days before the 2020 *CNY*) as the COVID-19 outbreak point; the sample period of the control group is from January 12, 2019, to March 3, 2019, with January 31, 2019 (5 days before the 2019 *CNY*) as the presumptive "outbreak" point.

1. For the price change (increase/decrease) probability analysis, we adopt the panel logit DiD model with product-level panel data, which is shown in eq. (1):

$$ln\left(\frac{Pr_{it}}{1-Pr_{it}}\right) = \alpha + \beta_{did} year_t \times ncov_t + \beta_1 ncov_t + \beta_2 year_t + Z_{it}'\delta + u_{it} \tag{1}$$

Where Pr_{it} is the price change probability of goods i at day t, and Z_{it} is the control variables vector, and

$$year_t = \begin{cases} 1, & t\ is \text{ from January 1, 2020 to February 20, 2020;} \quad the\ treatment\ group \\ 0, & t\ is \text{ from January 12, 2019 to March 3, 2019;} \quad the\ control\ group \end{cases};$$

[3] Since both the COVID-19 pandemic and *Chinese New Year* have nationwide impacts on the whole economy in China, we couldn't take some sectors or regions as the control group. Therefore, we adopt the DiD model with the same goods basket of 2019 as the control group. Some scholars use the similar methods to evaluate the impacts of COVID-19 pandemic. For example, Fang et al. (2020) use DiD to evaluate the lockdown effects on human mobility during the COVID-19 pandemic in China; Chen et al., (2021) employ DiD to study the impacts of the COVID-19 pandemic on consumption in China.

Table 2
Impacts of COVID-19 on the overall price change probability.

Indep Var\ Dep Var	Price Change	Price Increase	Price Decrease
year × ncov	-0.226***	-0.276***	-0.227***
	(0.017)	(0.023)	(0.025)
exp(year × ncov)	0.798	0.759	0.797
ncov	-0.040***	-0.144***	0.092***
	(0.013)	(0.017)	(0.020)
year	0.073***	-0.144***	0.333***
	(0.013)	(0.017)	(0.020)
Control Variables	Yes	Yes	Yes
Number of Obs	3,104,546	3,104,546	3,104,546
Number of Events	61957	31548	30409
Log Likelihood	-299,178	-171,668	-168,517
Akaike Inf. Crit.	598,392	343,373	337,070

Notes: (1) Standard errors are shown in parentheses;(2)*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$; (3) Exp(year × ncov) is reported in this table to better show the impacts of COVID-19 on odds ratios; (4) For brevity, the coefficients of control variables are omitted from the above table, and are available from the authors on request.

Table 3
Impacts of COVID-19 on price change probability for different divisions.

Divisions \ Variables	Year × ncov	exp(year × ncov)	ncov	year	Obs	Log Likelihood
Health Care	-0.543***	0.581	-0.180***	0.557***	151,439	-11,461
	(0.087)		(0.067)	(0.064)		
Clothing	-0.449***	0.638	-0.081**	0.030	560,738	-46,340
	(0.044)		(0.034)	(0.033)		
Transportation and Communication	-0.383***	0.682	-0.143***	0.053	173,087	-16,976
	(0.070)		(0.045)	(0.051)		
Food, Tobacco and Liquor	-0.305***	0.737	0.040*	-0.016	1,035,091	-96,002
	(0.030)		(0.024)	(0.024)		
Education, Culture and Recreation	-0.243***	0.784	0.050	0.187***	254,082	-28,342
	(0.054)		(0.041)	(0.042)		
Residence	-0.185	0.831	0.032	0.348***	112,352	-4,748
	(0.146)		(0.110)	(0.114)		
Household Articles and Service	-0.022	0.978	-0.124***	0.127***	740,757	-79,722
	(0.033)		(0.026)	(0.025)		
Other Articles and Services	0.187**	1.206	0.092*	-0.362***	77,000	-13,710
	(0.074)		(0.053)	(0.060)		

Notes: refer to the notes of Table 2.

$$ncov_t = \begin{cases} 1, & t \text{ is after the outbreak point } (January\ 20,\ 2020\ or\ January\ 31,\ 2019) \\ 0, & t \text{ is before the outbreak point } (January\ 20,\ 2020\ or\ January\ 31,\ 2019) \end{cases};$$

Where β_1(thecoefficientof$ncov_t$)reflects the effect *of Chinese New Year* (with $year_t = 0$, $ncov_t = 1$); β_{did} is the DiD coefficient, indicating the impact of the COVID-19 on the probability of price adjustment after excluding the effect of *CNY*.

2. For the price change size analysis, we adopt the fixed-effect panel DiD model with product-level panel data, which is shown in eq. (2):

$$pcsize_{it} = \alpha + \beta_{did} year_t \times ncov_t + \beta_1 ncov_t + \beta_2 year_t + Z_{it}^{'} \delta + u_{it}, \tag{2}$$

Where $pcsize_{it}$ is the price change (increase/decrease) size of goods *i* at day *t,* and

$$pcsize_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} * 100\%,$$

Where P_{it} is the price of goods *i* at day *t*. Similarly, the absolute price change size $abspcsize_{it}$ is:

$$abspcsize_{it} = \left| \frac{P_{it} - P_{it-1}}{P_{it-1}} \right| * 100\%.$$

3. For the inflation rate change analysis, we adopt the OLS DiD model with daily online inflation rate (iCPI), which is shown in eq. (3):

$$iCPI_t = \alpha + \beta_{did} year_t \times ncov_t + \beta_1 ncov_t + \beta_2 year_t + u_t, \tag{3}$$

Where $iCPI_t$ is the internet-based consumer price index at day *t* with different levels, including the whole basket and eight divisions.

Table 4
Impacts of COVID-19 on the overall price change size.

Indep Var\ Dep Var	price change size(%)	absolute price change size(%)	price increase size(%)	price decrease size(%)
year × ncov	-0.116	-1.009***	0.006	-1.120***
	(0.403)	(0.297)	(0.498)	(0.294)
ncov	-0.234	2.454***	3.603***	1.356***
	(0.013)	(0.017)	(0.020)	(0.236)
year	-3.978***	-3.869***	-4.021***	-2.450***
	(0.308)	(0.226)	(0.369)	(0.231)
Control Variables	Yes	Yes	Yes	Yes
Number of Obs	61,957	61,957	31,548	30,409
Adjusted R^2	0.025	0.046	0.050	0.072
F Statistic	95	179	98	140
P value	0.000	0.000	0.000	0.000

Notes: refer to the notes of Table 2.

Table 5
Impacts of COVID-19 on the absolute price change size for different divisions.

Divisions\Variables	*Year × ncov*	*ncov*	*year*	Obs	Adjusted R^2
Health Care	-4.897***	1.081	-1.108	2,273	0.064
	(1.645)	(1.236)	(1.210)		
Food, Tobacco and Liquor	-1.234***	3.127***	-4.449***	19,506	0.036
	(0.518)	(0.402)	(0.397)		
Education, Culture and Recreation	-1.427	2.151***	1.103	6,025	0.048
	(0.881)	(0.662)	(0.686)		
Clothing	-1.075	4.210***	-4.963***	9,365	0.063
	(0.858)	(0.671)	(0.641)		
Other Articles and Services	-0.928	1.237*	-1.881**	3,440	0.073
	(0.995)	(0.709)	(0.822)		
Household Articles and Service	-0.463	1.834***	-4.207***	17,000	0.046
	(0.550)	(0.432)	(0.421)		
Transportation and Communication	-0.672	3.400***	-3.972***	3,532	0.055
	(1.223)	(0.783)	(0.878)		
Residence	9.368**	-0.351	-8.472***	816	0.040
	(3.675)	(2.746)	(2.817)		

Notes: refer to the notes of Table 2.

3. Empirical results

3.1. *Impacts of the COVID-19 pandemic on price stickiness*

We employ the product-level price data to study the impacts of the COVID-19 pandemic on price changes. The Table 1 shows descriptive statistics of variables. We have over three million observations in total, and the eight divisions of iCPI have different percentages. Besides, the mean daily price change, increase and decrease frequency (equal to the number of price changes/increases/decreases divided by the total observations) are 2%, 1% and 1%, respectively. The mean absolute price change, increase and decrease size are 16.51%, 19.32% and 13.58%, respectively.

Tables 2 and 3 show the impacts of COVID-19 on price change probability. Specifically, to better explain the results of logit model, we obtain the odds ratio equation (See eq. (4)) according to the eq. (1):

$$\Omega_{it} = \frac{Pr_{it}}{1 - Pr_{it}} = \exp\left(\alpha + \beta_{did} year_t \times ncov_t + \beta_1 ncov_t + \beta_2 year_t + Z_{it}^{'}\delta + u_{it} \right) \tag{4}$$

Where Ω_{it} is the odds ratio, equal to the price change probability divided by the probability of no price change. Suppose *Pr* (or Ω) and $Pr^{'}$ (or $\Omega^{'}$) are the price change probability (or odds ratio) before and after the COVID-19, respectively, then we could infer the impact of COVID-19 on the odds ratio after excluding the effect of *CNY* as shown in eq. (5) and eq. (6):

$$\frac{\Omega^{'}}{\Omega} = \frac{\Pr^{'}/(1 - \Pr^{'})}{\Pr/(1 - \Pr)} = \exp(\beta_{did}) \tag{5}$$

$$\frac{\Pr^{'}}{\Pr} = \frac{\exp(\beta_{did})}{1 - (1 - \exp(\beta_{did}))\Pr} \tag{6}$$

Besides, according to Table 1, the mean daily price change frequency is 2%, which could be taken as the mean price change probability *Pr* and substituted into the eq. (6), and thus we could conclude the impacts of COVID-19 on price change probability.

Table 6
Comparison of the COVID-19 Impacts on price change probability among divisions.

Divisions \ Variables	Year × ncov × divison	exp(year × ncov × divison)	Number of Obs	Number of Events	Log Likelihood
Health Care	-0.376*** (0.089)	0.687	3,104,546	151,439	-300,710
Clothing	-0.236*** (0.047)	0.790	3,104,546	560,738	-300,497
Transportation and Communication	-0.163** (0.072)	0.850	3,104,546	173,087	-300,800
Food, Tobacco and Liquor	-0.135*** (0.036)	0.874	3,104,546	1,035,091	-300,687
Residence	0.005 (0.146)	1.005	3,104,546	112,352	-300,182
Education, Culture and Recreation	0.033 (0.057)	1.034	3,104,546	254,082	-300,798
Household Articles and Service	0.281*** (0.038)	1.324	3,104,546	740,757	-300,689
Other Articles and Services	0.422*** (0.076)	1.525	3,104,546	77,000	-300,076

Notes: refer to the notes of Table 2.

The DiD coefficients for the overall price change/increase/decrease probability are -0.226, -0.276 and -0.227, respectively, and the corresponding odds ratios decrease by 20.2%, 24.1% and 20.3%, respectively. Substituting these into the eq. (6), we find that the COVID-19 led the price change/increase/decrease probability to decline by approximately 20%, 24% and 20%.[4]

Except for *Other Articles and Services*, the DiD coefficients for most divisions are significantly negative, and the price change probability (odds ratios) of *Health Care, Transportation and Communication,* and *Food, Tobacco and Liquor* decrease by approximately 42%, 32% and 26%, respectively. In particular, for *Food, Tobacco and Liquor*, the COVID-19 impact (negative) is opposite to the *CNY* effect (positive). These results show that the pandemic led to a significant decrease in the overall price change probability, but the impacts are heterogeneous across different divisions.

Tables 4 and 5 show the impacts of COVID-19 on the size of price changes. The DiD coefficients of the overall absolute size of price changes and price decreases are significantly negative (approximately -1%), but the results for the size of price increases are not significant. Except for *Residence*, the DiD coefficients for most divisions are negative, and *Health Care* and *Food, Tobacco and Liquor* have the most significant declines, which are -5% and -1%, respectively. Specifically, for *Health Care*, the COVID-19 impact is stronger than the *CNY* effect, but it is contrary for *Food, Tobacco and Liquor.* These results show that the pandemic led to a decrease in the overall absolute size of price changes, and the impacts are also heterogeneous across different divisions.

In short, during the quarantine period, the COVID-19 pandemic significantly increased the price stickiness and reduced the absolute size of price changes, and these impacts are heterogeneous across different divisions.

Besides, there are two possible reasons leading to these effects of COVID-19. To elaborate on these reasons, we further adopt the Difference-in-Difference-in-Difference (DDD) model, and compare the heterogeneous impacts of COVID-19 among different divisions. The DDD model is shown in eq. (7):

$$ln\left(\frac{Pr_{it}}{1-Pr_{it}}\right) = \alpha + \beta_{ddd} divison_{i,j} \times year_t \times ncov_t \ + \beta_1 year_t + \beta_2 ncov_t + \beta_3 year_t \times ncov_t + \beta_4 ncov_t \times divison_{i,j} + \beta_5 year_t * divison_{i,j} + Z_{it}^{'}\delta + u_{it} \tag{7}$$

Where $divison_{i,j} = \begin{cases} 1, & when\ goods\ i\ belongs\ to\ division\ j \\ 0, & others \end{cases}$, and β_{ddd} is the DDD coefficient, which indicates the impact of COVID-19 on the price change probability of division *j* comparing with other divisions, after excluding the effect of *CNY*. The results are shown in Table 6.

Firstly, during the nationwide quarantine period, many economic activities were "frozen", and whether products could be consumed while customers stayed at home was an important factor affecting price adjustments. Fang et al. (2020) use the Baidu migration data, and find that the lockdown of Wuhan reduced inflows to Wuhan by 76.98%, outflows from Wuhan by 56.31%. Yang et al. (2021) adopt the data of China Postal Express & Logistics, and show that both inter-provincial and intra-provincial express logistics flows significantly declined during the COVID-19 pandemic stage. Therefore, the lockdown directly reduces demand for travelling, going out or meeting (belonging to pure offline consumption), which led *Transportation and Communication* and *Clothing* to significantly reduce price change probability comparing with other divisions. However, staying at home increased the demand for online entertainment, including online games, videos and learning (belonging to pure online products), and household articles (belonging to online-to-offline products), which led *Education, Culture and Recreation* and *Household Articles and Service* to increase

[4] In fact, in Eq. 6, $(1-\exp(\beta_{did}))P$ is a very small term, which can be omitted. Therefore, both $\frac{P'}{P}$ and $\frac{\Omega'}{\Omega}$ are approximately equal, and we also employ this conclusion for the division analysis.

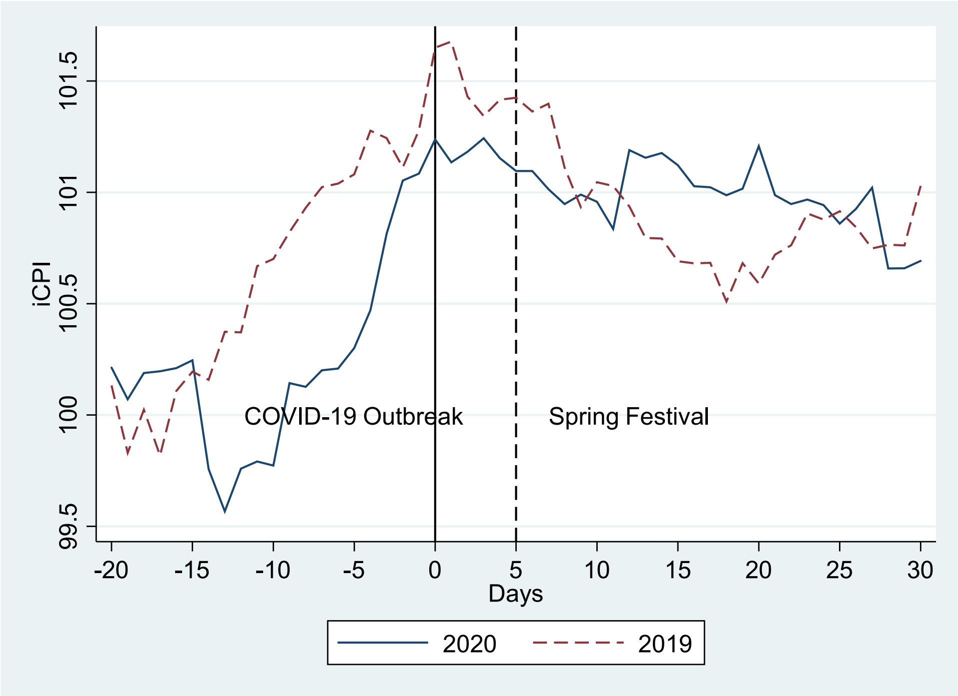


Fig. 2. Impacts of COVID-19 on daily overall online inflation

Table 7
Impacts of COVID-19 on the online inflation rate.

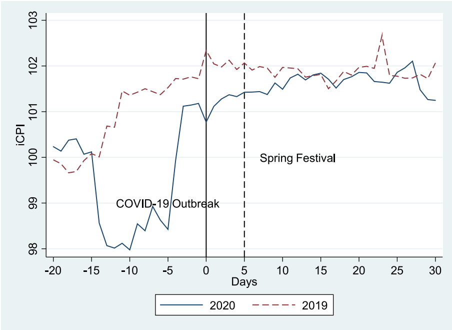
Divisions\Variables	year × ncov	ncov	year	Obs	Adjusted R^2
The Whole Basket	0.431***	0.375***	-0.401***	102	0.461
	(0.141)	(0.0996)	(0.110)		
Health Care	1.116***	1.039***	-1.457***	102	0.674
	(0.263)	(0.186)	(0.205)		
Food, Tobacco and Liquor	0.184	1.371***	-0.741***	102	0.763
	(0.180)	(0.128)	(0.141)		
Education, Culture and Recreation	1.168***	-0.953***	-0.197	102	0.481
	(0.182)	(0.129)	(0.142)		
Transportation and Communication	0.993**	-1.055***	0.758**	102	0.309
	(0.478)	(0.338)	(0.372)		
Other Articles and Services	1.237***	0.0543	0.325	102	0.459
	(0.314)	(0.222)	(0.245)		
Clothing	0.0665	0.917***	-0.720**	102	0.254
	(0.408)	(0.289)	(0.318)		
Residence	-0.0058	0.0979***	0.0378***	102	0.611
	(0.0163)	(0.0115)	(0.0127)		
Household Articles and Service	-0.193	0.662***	-1.813***	102	0.783
	(0.219)	(0.155)	(0.171)		

Notes: refer to the notes of Table 2.

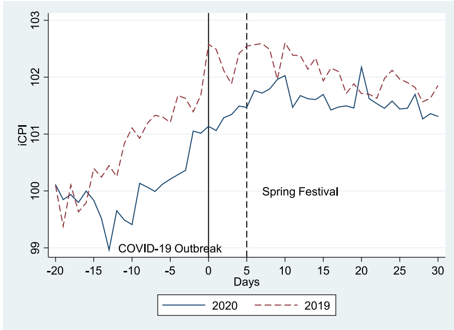
price change probability comparing with other divisions.

Secondly, during the COVID-19 pandemic stage, the government implemented "strict price controls" on some essential products, and failure to comply could be regarded as "price-gouging" and penalized.[5] Specifically, either out of need or out of fear, the demands for masks, alcohol, protective clothing, and medicine related to COVID-19 prevention increased rapidly, and people also stock up on food, and the prices of medical goods and food are subject to stricter controls. Therefore, comparing with other divisions, *Health Care* has the largest drop in price change probability during the quarantine period, while *Food, Tobacco and Liquor* also has obvious declines

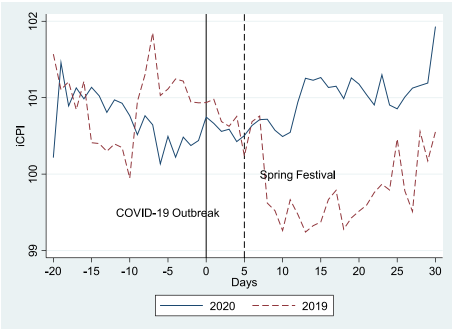
[5] On February 1, 2020, the State Administration for Market Regulation in China issued guidance on the investigation and handling of illegal acts of price gouging during the prevention and control of the COVID-19 epidemic. For more details, please refer to: http://www.gov.cn/zhengce/zhengceku/2020/02/02/content_5473889.htm.



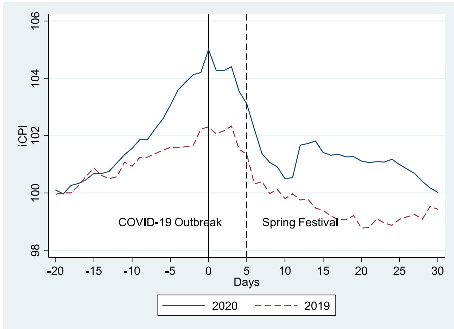
(a) Price Index of Health Care



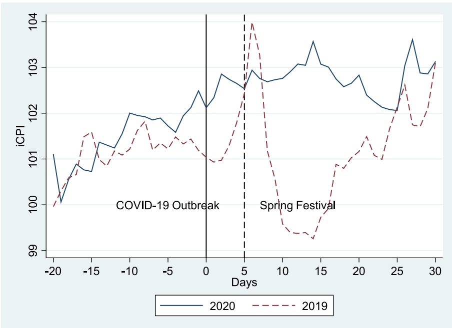
(b) Price Index of Food, Tobacco and Liquor



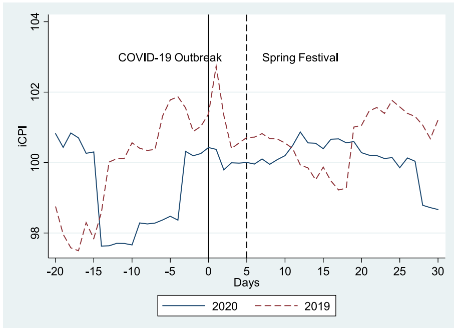
(c) Price Index of Education, Culture, and Recreation



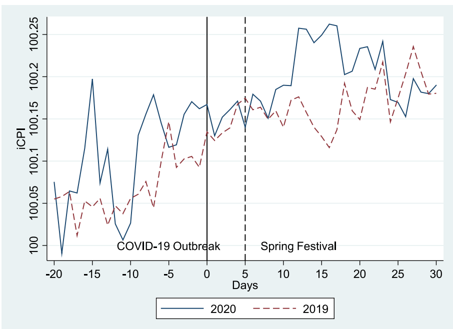
(d) Price Index of Transportation and Communication



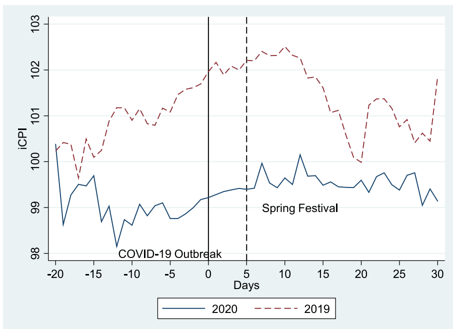
(e) Price Index of Other Articles and Services



(f) Price Index of Clothing



(g) Price Index of Residence



(h) Price Index of Household Articles and Service

Fig. 3. Impacts of COVID-19 on daily online inflation of eight divisions

Table A1
Parallel trend test for the impacts of COVID-19 on inflation.

Divisions\Variables	year × ncov	ncov	year	Obs	Adjusted R^2
The Whole Basket	0.148	0.227**	0.861***	102	0.629
	(0.159)	(0.112)	(0.124)		
Health Care	-0.122	1.161***	1.787***	102	0.694
	(0.278)	(0.197)	(0.217)		
Food, Tobacco and Liquor	2.396***	-1.025***	1.834***	102	0.880
	(0.267)	(0.189)	(0.208)		
Education, Culture and Recreation	-2.865***	1.912***	-0.167	102	0.778
	(0.266)	(0.188)	(0.208)		
Transportation and Communication	-2.897***	1.842***	-0.173	102	0.630
	(0.385)	(0.272)	(0.300)		
Other Articles and Services	-0.952***	1.006***	1.118***	102	0.260
	(0.307)	(0.217)	(0.240)		
Clothing	-0.147	1.064***	0.360	102	0.236
	(0.375)	(0.265)	(0.292)		
Residence	0.635***	-0.537***	0.337***	102	0.918
	(0.0504)	(0.0356)	(0.0393)		
Household Articles and Service	0.0636	0.599***	0.985***	102	0.548
	(0.224)	(0.159)	(0.175)		

Notes:(1)$year_t$ is a dummy variable, which is equal to 1 if the year is 2019 and equal to 0 if the year is 2018. $ncov_t$ is a dummy variable, which equals to 1 if the day is after the presumptive COVID-19 "outbreak" point. (2) standard errors are shown in parentheses;(3) *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$; (4) For brevity, the coefficients of control variables are omitted from the above table, and are available from the authors on request.

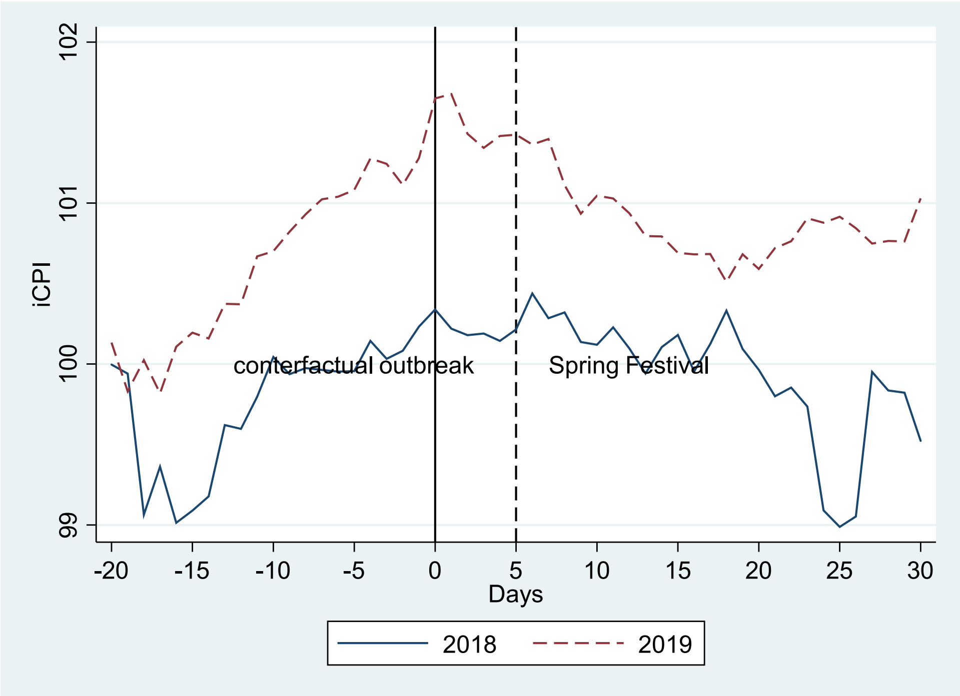


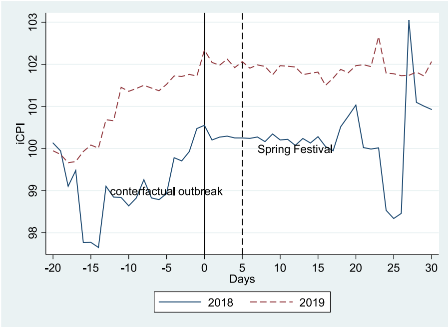
Fig. A1. Comparison of 2018 and 2019 daily overall online inflation

in price changes.

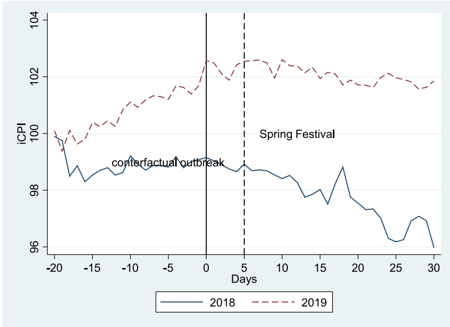
3.2. Impacts of the COVID-19 pandemic on inflation

According to the New Keynesian Phillips Curve (NKPC), the micro price stickiness will affect the macro inflation dynamics. Based on the previous product-level impacts of COVID-19 pandemic on price stickiness, we further investigate the impacts of COVID-19 on inflation.

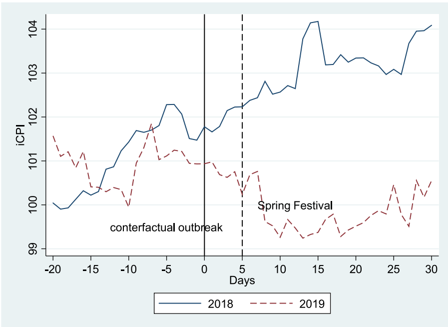
Fig. 2 and Table 7 show the impacts of COVID-19 on overall inflation. We find that in 2020, after the COVID-19 outbreak, there is an obvious increase in the inflation, which remains at a relatively high level after the *Chinese New Year,* quite different from the price



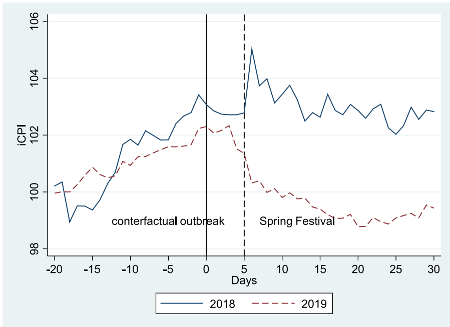
(a) Price Index of Health Care



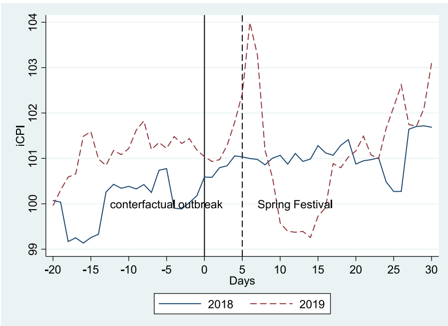
(b) Price Index of Food, Tobacco and Liquor



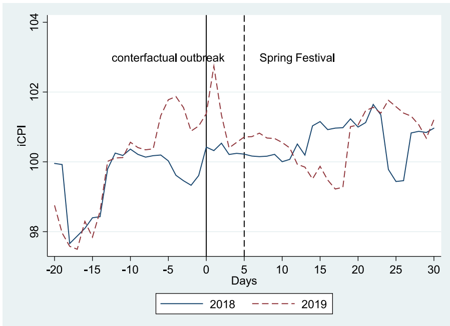
(c) Price Index of Education, Culture, and Recreation



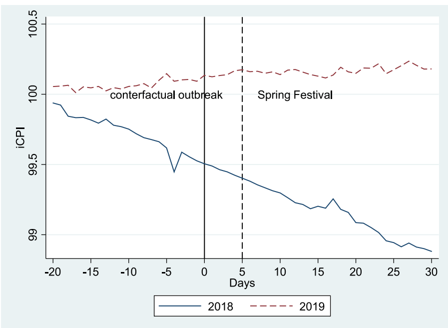
(d) Price Index of Transportation and Communication



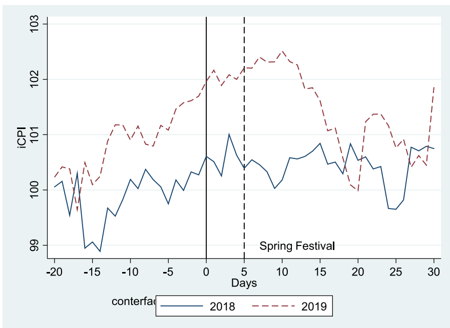
(e) Price Index of Other Articles and Services



(f) Price Index of Clothing



(g) Price Index of Residence



(h) Price Index of Household Articles and Service

Fig. A2. Comparison of 2018 and 2019 daily online inflation for eight divisions correction behavior after the *CNY* in 2019. However, there is a dramatic decline in the overall inflation volatility after the COVID-19 outbreak, which is consistent with the previous findings of the decline in price changes. Specifically, the pandemic led to a 0.4% surge in the overall inflation at a 1% significance level during the nationwide quarantine period.

Fig. 3 and Table 7 show the impacts of COVID-19 on the inflation of different divisions. We find that except for *Residence* and *Household Articles and Service*, the pandemic led to an increase in the inflation rates for most divisions, but the sizes of the increases are different. In particular, *Health Care* was obviously affected by the pandemic, with a large increase of 1.12%, approximating the impact of the *CNY (1.04%)*. Fig. 3.(a) shows that the prices of *Health Care* increased a lot within the first week of COVID-19 outbreak because of the severe shortage of medical goods, and then gradually went up probably due to the price controls of government.

However, for *Food, Tobacco and Liquor,* the impact of *CNY* (1.37%) is obviously larger than that of the pandemic (0.18%). Food prices usually increase significantly during the *CNY*, and then go down after the festival, but the COVID-19 hindered the price correction behavior, and led food prices to stay at a high level due to strong demand and supply disruptions (See Fig. 3.(b)).

In a word, the COVID-19 outbreak and the relevant prevention and control policies could affect the supply and demand of different sectors to varying degrees, including the production cost, consumption habits (shift to online consumption), speed of resumption of work and production et al., thus leading to significant structural changes in inflation.

In addition, we adopt the price data of 2018 and 2019 to do the parallel trend test with the similar methodology in section 2.2. The sample period of the treatment group is from January 12, 2019, to March 3, 2019, with January 31, 2019 (5 days before the 2019 *CNY*) as the presumptive "outbreak" point. The sample period of the control group is from January 23, 2018, to March 14, 2018, with February 11, 2018 (5 days before the 2018 *CNY*) as the presumptive "outbreak" point. If the DiD coefficient is not significant at 1% or 5% significance level, then the main results satisfy the parallel trend hypothesis.

The parallel trend test results are shown in the Table A1 and Fig. A1,2. We find that the DiD coefficients of the whole basket and some of divisions (e.g., Health Care) are not significant, showing that the overall price dynamics in 2019 are the same as that in 2018. Therefore, we can use the DiD to analyze the impacts of COVID-19 shock, and the main DiD results are robust.

4. Conclusions

In this paper, we combine online prices from 107 websites in China and the DiD method to investigate the impacts of the COVID-19 pandemic and nationwide quarantine on price stickiness and inflation. First, we show that the pandemic led to a 0.4% surge in the overall price index but a 20% decrease in the price change probability and a 1% decline in the absolute size of price changes. Second, the COVID-19 pandemic had heterogeneous impacts on different sectors, leading to significant structural changes in inflation. In particular, the COVID-19 pandemic hindered the price correction behavior after Spring Festival, and whether products could be consumed while customers stayed at home was an important factor affecting price adjustment and inflation dynamics.

This paper provides two important implications. First, the heterogeneous impacts and structural inflation features call for differentiated policies to alleviate the damage of the COVID-19 pandemic, which can be divided into three types, namely, anti-inflation, anti-deflation and flexible handling policies. For *Food, Tobacco and Liquor*, attention should be given to preventing inflation, and support for corresponding enterprises to resume work should be increased. For *Health Care*, the situation is special, and it needs to be handled flexibly in accordance with the development of the global epidemic. For the offline service industry, the deflation risk should be considered because people's consumption habits are changing, and the impacts of the pandemic on personal psychology are lasting. Second, in the future, more importance should be attached to the development of the stay-at-home economy and high-frequency inflation indicators based on online prices.

CRediT authorship contribution statement

Tingfeng Jiang: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Funding acquisition. **Taoxiong Liu:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition. **Ke Tang:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Funding acquisition. **Jiaqing Zeng:** Conceptualization, Methodology, Software, Data curation, Validation.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

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Appendix

Appendix A: Design of iCPI

Step 1: Goods Basket Selection

The goods basket of iCPI follows the CPI basket of the National Bureau of Statistics of the People's Republic of China, which consists of the main index, 8 divisions, 27 groups and 262 classes.

Step 2: Data Collection and Cleansing

(1) We collect daily price data of different categories from China's main E-commerce platforms. These e-commerce platforms can be divided into integrated and vertical e-commerce platforms. Specifically, integrated e-commerce platforms refer to platforms involving a wide range of business, including *Tmall, JD* et al., while vertical e-commerce platforms mainly focus on specific categories, such as *Jiuxian* for the liquor category.

(2) Computers automatically collect the required data at the specified time, website (url), and IP. Prices are collected once a day and stored in a dedicated database after collection. Specifically, The IP addresses used for web crawler haven't logged into any shopping account and have no shopping behavior with only browsing behavior, and the physical locations of IP have not changed. Therefore, there are no big data discriminatory pricing problems for the web crawler, and the prices of the same product(url) on different days are comparable.

(3) Data Preprocessing. For the high-frequency daily prices, missing values could be caused by products going out of stock, failures of web scraping or by network instability. Combining the characteristics of daily online prices in China and the methods commonly used in literature (e.g., Cavallo, 2017; Gorodnichenko et al., 2018), we replace the missing values for the first 30 days with the previous price available until the new price information appears for each product. Besides, for the products with large price changes, we take daily price changes that are higher than 100% or lower than -50% as abnormal values and exclude them from price change analysis.

Step 3: Index Calculation

(1) The methods of determining iCPI weights are consistent with the official CPI, that is, the weights at all levels should be determined according to the consumption expenditure structure of households. We obtain the weights of different levels by synthesizing a variety of literature and data.

(2) The calculation methods of iCPI are also consistent with the official CPI. We calculate the daily, weekly, ten-day, and monthly price indices at all levels, including the main index, 8 divisions, 27 groups and 262 classes.

Step 4: Online Publishing

(1) iCPI published through our website is updated every day including daily, weekly, ten-day and monthly indices.

(2) iCPI can also be downloaded in famous databases, including Bloomberg, Wind and CEIC.

Appendix B: Parallel trend test

Appendix Table 1

Figs. A1 and 2

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