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Online Market Resilience to Economic Shocks: Evidence Based on Price Dispersion from the COVID-19 Outbreak in China

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Abstract
We examine the effect of COVID-19 epidemic and the subsequent stay-at-home order on market efficiency in China's online markets. Through a comparison of price dispersion changes across online retail platforms around the lockdown date with the corresponding period in the 2019 lunar year—with the use of a unique and extensive online retail price dataset—we find a counterintuitive decrease in product price dispersion during the epidemic, which is contrary to conventional economic expectations during adverse events. Our study differentiates products by crisis-time demand elasticity—e.g., food versus clothing—and by online search intensity. This reveals that the lockdown and prolonged stay-at-home period facilitated online searches by consumers, which reduced information costs and enhanced market efficiency. The pandemic-induced decrease in price dispersion can be largely attributed to heightened online search activity: after we adjust for the intensity of search, the remaining pandemic effect on price dispersion becomes positive. China's resilient online market acted as a protective buffer during the COVID-19 crisis. The transition from offline to online markets and increased search activities bolstered online market functionality and mitigated the epidemic's repercussions.

Keywords COVID-19 · Pandemic · Price dispersion · Market efficiency · Online market

JEL Classification L16 · D43 · C33

1 Introduction

The COVID-19 pandemic—which stands as the most significant global public health crisis since the 1918 influenza pandemic—has engendered extensive disruptions in global business and economic operations (Duan et al., 2021; Guerrero-Amezaga et al., 2022; Jordà et al., 2022). Despite its relatively modest fatality rate,

Extended author information available on the last page of the article

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the exceptional contagiousness of the COVID-19 virus has triggered pronounced economic contraction in regions with strong economic interconnections (Guo et al., 2022; Stoop et al., 2021).

This study focuses on assessing the effect of the COVID-19 pandemic on the efficiency of China's retail market—with a specific emphasis on the online sector. An adverse economic shock, such as a disaster or pandemic, typically reduces market efficiency by increasing economic uncertainty and information friction, and by prompting the constriction of economic activity (Cochrane, 1996; Kates, 1971; Nelson & Winter, 1964). Existing research on COVID-19 primarily focuses on its effect on financial markets (Ali et al., 2020; Baker et al., 2020; Frezza et al., 2021; Gormsen & Koijen, 2020). While the pandemic's effect on the retail market could have been considerably more severe than on financial markets (Sedov, 2022), empirical evidence on the virus's impact on retail markets is scant.[1]

We use price dispersion—the variation in prices across different online retail platforms for identical products—as a measure of market efficiency and welfare losses (Baye et al., 2006; Burstein & Hellwig, 2008; Nakamura & Steinsson, 2010; Nakamura et al., 2018; Salop & Stiglitz, 1982). Given that the COVID-19 pandemic represents a negative shock to the market, it is expected to increase market friction, which would potentially result in a significant surge in price dispersion across various retail platforms. However, using product fixed-effect models and a difference-in-differences strategy, we find that—surprisingly—the overall level of price dispersion in the Chinese online retail market did not increase after the outbreak of the epidemic but instead decreased significantly. We posit that this unexpected result can be attributed to a distinctive feature of the epidemic: the nationwide lockdown and extended stay-at-home period, which encouraged increased online searching and cross-platform price comparison by consumers.

We offer evidence that uses the Baidu search index as a proxy for consumers' online search intensity. To address potential endogeneity concerns—such as heightened searches could be in response to high online price dispersion—we construct a shift-share instrumental variable for the Baidu search index. The inclusion of the Baidu search index into the model changes the COVID-19's effect on price dispersion and yields primarily positive effects. This indicates that the reduction in price dispersion during the pandemic can be largely attributed to search activity. Moreover, when examining different product categories, we find that broad product categories with low demand elasticities—e.g., food, and to a lesser extent, education and entertainment—exhibited heightened search intensity and, consequently, diminished price dispersion. Conversely, products with high demand elasticities—e.g., clothing—show only marginal increases in search intensity, which results in increased price dispersion.

Our findings indicate that although the epidemic introduced information friction to the market, the transition from offline to online markets along with intensified

[1] An exception is Jiang et al. (2022), who studied the inflation rate in the online retail market during the pandemic and found a very mild increase in aggregated online prices. However, price indices miss the information in price variation: a crucial signal of the market's efficiency.

online search activity mitigated the negative effects of the pandemic. The online market assumes significance as a conduit for demand–supply alignment during the pandemic.

Our study highlights the role of a robust online market in fortifying economic resilience amid pandemics. Given the ongoing global repercussions of COVID-19 and the potential for subsequent waves, evaluating the pandemic's economic repercussions through the lens of the initial outbreak experiences bears substantial relevance for policymaking.

2 Research Design

The COVID-19 outbreak is an unexpected shock that can lead to increased price stickiness, which would typically result in greater price dispersion in the market. We define January 20, 2020—the day when human-to-human transmission of COVID-19 was officially confirmed—as the onset of the outbreak in China. This date was chosen because there was little precautionary action from the public and from the government prior to it. As such, the pandemic's economic impact remained primarily localized and negligible before this date.

To identify the effect of the COVID-19 shock on price dispersion, we need to account for several factors that may confound the analysis: For example, there could be a general decline in price dispersion over time as the online market gradually reaches the equilibrium state of the "law of one price." More problematically, the outbreak of the epidemic is very close in time to the Chinese New Year, which is the most important and longest public holiday in China. This may introduce a shift in market price dispersion due to changes in consumer behavior during this period. Given the synchronous impact of the COVID-19 shock on all online platforms, we employ a cohort difference-in-differences (cohort DID) approach. This involves establishing the control group by analyzing the preceding year during the corresponding lunar calendar period.

Since the outbreak date of COVID-19 is January 20, 2020—five days before 2020 Chinese New Year—we account for the Chinese New Year effect by matching the treatment date of the control group to the date of January 31, 2019: five days before the 2019 Chinese New Year. We focus on an 8-week period before and a 5-week period after the treatment date in both 2020 and 2019 to construct our treated and control samples. By restricting the analysis to a short period before and after the treatment date, we can isolate the effect that can be attributed to changes in consumers' shopping behaviors after the COVID-19 outbreak.

A schematic diagram of the timelines for the research design is shown in Fig. 1.

Last, given the substantial heterogeneity in product characteristics, it is important to consider that different products may inherently exhibit varying levels of price dispersion. For instance, products with inelastic demand often have smaller price dispersion due to limited substitutability, while durable goods tend to exhibit higher price dispersion owing to infrequent search and purchase behavior.

To address this issue, we utilize a regression framework with a product fixed-effects model. This allows us to focus on the changes in price dispersion within each

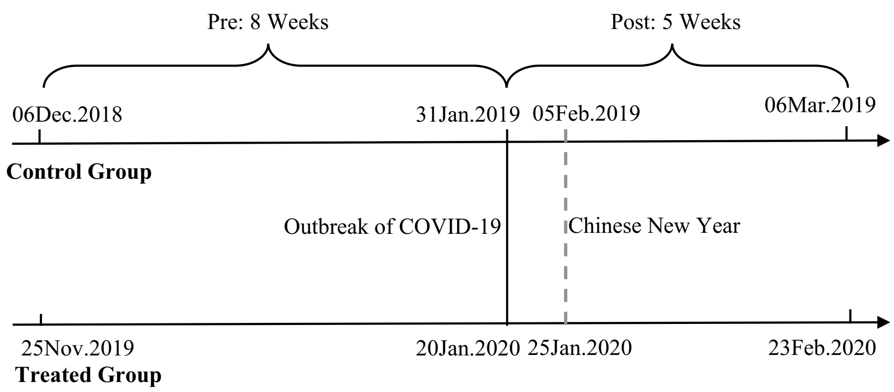


Fig. 1 The cohort DID research design

specific product i before and after the onset of the epidemic. Therefore, we employ the following model:

$$dispersion_{it} = c_i + \beta_1 covid_{it} + \beta_2 treat_i + \beta_3 post_t + \beta_4 week_t + \beta_5 dow_t + \delta x_{it} + \varepsilon_{it}, \tag{1}$$

where $treat_i$ denotes the treated group and $post_t$ equals 1 for every day after Jan. 31, 2019, if $treat_i = 0$ and for every day after Jan. 20, 2020, if $treat_i = 1$. The variable $covid_{it}$ is the interaction of $treat_i$ and $post_t$. The fixed effect c_i controls for the product-specific characteristics that affect a product's price dispersion. Additionally, we include the $week_t$ dummy variable to capture weekly fixed effects, starting from the outbreak of the COVID-19 pandemic, as well as the dow_t dummy variable to account for the day of the week. Furthermore, we incorporate product-level time-varying characteristics, denoted as x_{it}, which may be associated with cross-platform price dispersion. These characteristics include the logarithm of the mean listed price of the product and the number of platforms on which the product is sold.[2]

3 Baseline Results

3.1 The Price Data

After the outbreak of COVID-19, governments globally implemented an array of measures, including: travel restrictions; stay-at-home directives; social distancing protocols; and other preventive policies. These actions culminated in the substantial cessation of in-person markets. In contrast, online markets, propelled by the expansion of the digital economy, have gained heightened importance.

[2] Although the number of platforms might be endogenously influenced by product characteristics, this is not a concern for us. The key variable $covid_{it}$, being an interaction term between $treat_i$ and $post_t$, is unlikely to be related to the number of platforms.

Big data technology allows us to track the dynamics of the high-volume, high-frequency data in the online market (Cavallo, 2013; Cavallo et al., 2017; Liu et al., 2019). The price data that are used in this study are from the iCPI project, which is maintained by Tsinghua University. The iCPI project aims to construct daily consumer price indices for various product categories. These categories are broadly grouped into eight sectors, which align with the framework that is prescribed by the National Statistics Bureau. The sectors encompass: household goods and services; food, tobacco, and liquor; clothing; education and entertainment; housing; healthcare; transportation and communication; and other goods and services.

For this purpose, the project collects daily price information for over 20,000 products that are accessible through more than 300 online platforms within China, and focuses on items that are concurrently offered on multiple platforms. A single "representative store" is chosen for each platform to record the listed daily price. This approach acknowledges that price disparities within a platform might inadequately represent the genuine price variations. Comparing prices and selecting stores within a platform imposes negligible costs on consumers; hence stores with higher prices may not yield much sales volume (Baye et al., 2004). The iCPI project provides valuable data for studying price dispersion across platforms and for assessing the effect of the COVID-19 pandemic on the Chinese online retail market.[3]

The most commonly used measure of price dispersion is the coefficient of variation: the ratio of the standard deviation to the mean (Sorensen, 2000). Specifically, the price dispersion—which is denoted as $dispersion_{it}$—is calculated as the coefficient of variation for the price of product i across different platforms on day t:

$$dispersion_{it} = \frac{standard\ deviation_{it}}{mean_{it}}, \tag{2}$$

where $standard\ deviation_{it}$ and $mean_{it}$ are the standard deviation and mean, respectively, of the price for product i across all platforms on day t. Naturally, calculation of the price dispersion is limited to products that are available across multiple platforms.

Figure 2 displays the density plot of the product-day dispersion data. Merely 12% of products share uniform prices across platforms. A significant portion of products demonstrate discernible degrees of price dispersion.

Table 1 lists the summary statistics of price dispersion for the CPI categories that are defined by the National Statistics Bureau, as well as the other key variables that are used in Eq. (1). All categories display a substantial level of price dispersion, averaging around 17%. Notably, four categories—food, tobacco, and liquor; household goods and services; clothing; and education and entertainment—account for almost 95% of the total observations. Thus, in the subsequent category-level analysis, we focus only on these four categories.

Figure 3 illustrates the dynamics of the daily average price dispersion across all products. The vertical dashed line corresponds to January 20, 2020: the onset

[3] These data can be found on the website of the iCPI project, http://www.bdecon.com/chartsEnglishIndex. More details about the project can be found in Liu et al. (2019).

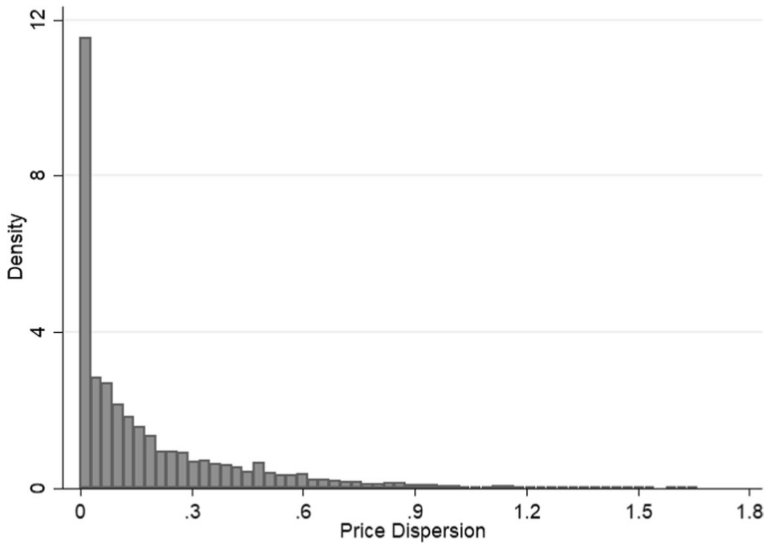


Fig. 2 Histogram of price dispersion

Table 1 Summary statistics

Variable	N	Mean	S.D	Min	Max
Dispersion	594,339	0.1773	0.2289	0.0000	1.6641
By category					
Household goods and services	220,450	0.1696	0.2188	0.0000	1.6641
Food, tobacco, and liquor	151,696	0.1635	0.2043	0.0000	1.4136
Clothing	124,968	0.2203	0.2730	0.0000	1.4142
Education and entertainment	64,942	0.1503	0.1904	0.0000	1.3974
Other goods and services	16,370	0.1807	0.2662	0.0000	1.5770
Transportation and communication	12,341	0.1731	0.2524	0.0000	1.4064
Healthcare	2350	0.1981	0.3015	0.0000	1.2755
Housing	1222	0.2580	0.2750	0.0000	1.3354
Log(price)	594,339	4.9088	1.6553	– 0.0050	15.4391
No. of platforms	594,339	2.2639	0.4643	2.0000	5.0000

of the COVID-19 outbreak. A preliminary assessment indicates that—contrary to an anticipated rise in price dispersion following the outbreak—there appears to be a slightly downward trend.

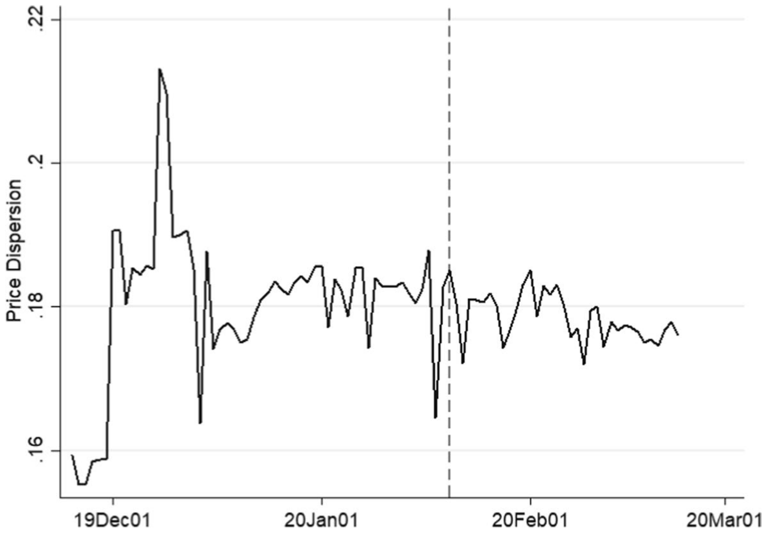


Fig. 3 Daily price dispersion (the dashed line indicates the onset of COVID-19)

3.2 Baseline Empirical Results

We estimate the effect of the COVID-19 on price dispersion using Eq. (1). The results are reported in Table 2. Since we have a relatively large dataset, statistical significance is reported at a higher than conventional level: at 5%, 1%, and 0.1%.

Column (1) presents the canonical fixed effect DID model, in which we include only the cohort variable "treat," the time variable "post," and their interactions "covid." The estimated coefficients of the "covid" variable indicate the impact of the COVID-19 on price dispersion. The results of the DID comparison suggest that there is a significant decrease in the level of price dispersion after the onset of the outbreak.

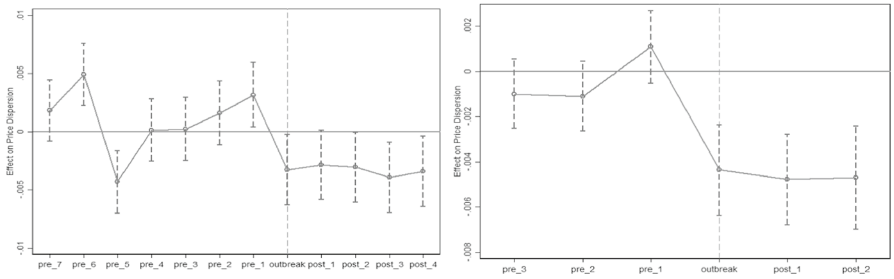
In Column (2), additional temporal control variables—such as day-of-week dummy variables and weekly dummy variables, along with product time-varying controls that include the mean logarithm of price and the number of platforms where the product is available—are included. The estimations remain robust and even increase in magnitude, which further supports the finding that the COVID-19 outbreak led to a decline in price dispersion. Based on the estimated coefficients, and accounting for the average dispersion level of approximately 17.7%, the effect that is associated with the COVID-19 outbreak corresponds to an approximate reduction of 3.3% in price dispersion.

To support the validity of the comparison that is presented in Table 2, it is essential to evaluate the existence of shared trends in price dispersion between the 2019 and 2020 cohorts before the pandemic's outbreak. To investigate this, we introduce an interaction between the weekly fixed effects and the "covid" variable. The estimates for these interactions are displayed in Fig. 4. The trends appear reasonably parallel prior to the pandemic's onset—especially when the data are aggregated into

Table 2 The effects of the COVID-19 epidemic on price dispersion

	(1) Full sample	(2) Full sample	(3) Food, tobacco, and liquor	(4) Education and entertainment	(5) Clothing	(6) Household goods and services
Covid	− 0.00430***	− 0.00588***	− 0.00386**	− 0.00426*	0.000967	− 0.00991***
	(− 5.72)	(− 7.87)	(− 3.10)	(− 2.30)	(0.48)	(− 8.09)
Treat	− 0.000151	0.00486***	− 0.0106***	0.0126***	0.0778***	− 0.00836***
	(− 0.24)	(7.55)	(− 8.51)	(9.69)	(32.72)	(− 8.78)
Post	0.00461***	− 0.00713***	− 0.0111***	0.00257	0.0244***	− 0.0154***
	(7.64)	(− 7.13)	(− 7.23)	(1.11)	(9.03)	(− 9.29)
Log(price)		0.0759***	0.229***	− 0.136***	0.189***	− 0.0700***
		(61.22)	(98.67)	(− 31.87)	(83.33)	(− 30.16)
No. of platforms		0.0498***	0.0520***	0.0241***	0.0714***	0.0679***
		(68.66)	(59.29)	(14.77)	(32.53)	(54.97)
Constant	0.177***	− 0.286***	− 0.829***	0.741***	− 1.006***	0.417***
	(408.42)	(− 45.40)	(− 90.43)	(36.57)	(− 73.03)	(34.15)
Dow	No	Yes	Yes	Yes	Yes	Yes
week	No	Yes	Yes	Yes	Yes	Yes
N	594,339	594,339	151,696	64,942	124,968	220,450

t statistics in parentheses. $^{*}p<0.05$, $^{**}p<0.01$, and $^{***}p<0.001$



(a) Weekly estimates of the effect of COVID-19 (b) Biweekly estimates of the effect of COVID-19

Fig. 4 Dynamic effect of COVID-19

biweekly cohorts. Following the pandemic's emergence, we observe a substantial reduction in overall price dispersion.

It is important to acknowledge that the full sample estimates are aggregated across different product categories, some of which underwent minimal shifts in shopping behavior from offline to online, and thus were not affected by online market developments. Consumer shopping behaviors can vary significantly across different categories or respond differently to the pandemic. For instance, products with high demand elasticity, such as clothing, where consumers might defer purchases until offline stores reopen, could display distinct price dispersion dynamics as compared to products with inelastic demand, such as food. We expect the effect of the online market on price dispersion during this crisis period to be more pronounced for categories that experienced a greater shift in shopping activities toward the online market. In Columns (3) to (6) of Table 2, we report estimates for the four principal categories: Notably, the price dispersion for the clothing category increased slightly following the COVID-19 outbreak, which suggests that the pandemic may have led to greater market friction within the clothing sector. If we use the clothing category to approximate the scenario without an effective online market amid the COVID-19 shock, cross-category comparisons—e.g., Column (3) versus Column (5), which is akin to a triple-difference comparison—indicate that the price dispersion for the relevant online categories decreased by approximately 3%[4]: a significant enhancement in market efficiency.

These results prompt us to offer a rationale for the observed decrease in price dispersion during the epidemic period: To control the transmission of the virus, the Chinese government mandated nationwide stay-at-home directives, which resulted in the closure of most offline stores. Consequently, a significant portion of the daily shopping moved to online platforms, which provided consumers with more time for online searches during their shopping routines. This intensified search activity

[4] To take the food category as an example: The decrease in price dispersion during the outbreak compared to the clothing category is $0.00386+0.000967=0.004827$, and the average price dispersion for this category is 0.1635 (see Table 1); thus the reduction in percentage is 3%.

could contribute to a reduction in disparities among prices that were listed by online retailers.

4 Online Search During the Pandemic and Its Effect on Price Dispersion

Because of the stay-at-home orders that were implemented as a measure to control the transmission of the virus, consumers had more time to search online, and the increased level of searching could have contributed to a decrease in the differences in the prices. To investigate this channel through which COVID-19 outbreak led to decreased price dispersion across platforms, we need to consider the relationship between online search intensity and price dispersion. We collect data from the Baidu search index[5] to construct indices of the daily search intensity for various products and incorporate the index variable into the regression model.

4.1 Construction of the Baidu Search Index

The Baidu search index is a powerful tool for measuring internet search intensity based on click data analysis: similar to Google Trends. There is a challenge in constructing the index, however, because individuals usually search with the use of general terms rather than specific product names and items. For instance, people may search for "coke" instead of "330 ml Coca-Cola."

To address this issue and better reflect real search behaviors, we construct search intensity indices at the subcategory level within the broader eight categories. This encompassed 189 subcategories within our analyzed sample. For each subcategory, we collect Baidu search indices for selected keywords that represent primary or prevalent items in our dataset.

As an illustration, within the subcategory "bicycles" under the category "transportation and communication," we compile Baidu search indices for three specific keywords: "road bicycle"; "mountain bike"; and "bicycle." The volume of keyword searches in each subcategory maintains a proportional relationship with the corresponding subcategory's sample size.

In totality, we collected Baidu search indices for a comprehensive set of 481 keywords, and aggregated them at the subcategory level before matching them with the price data. A detailed outline of the category-keyword structure is available in the supplementary materials.

We gather daily Baidu search indices for each keyword that span the timeframe from January 1, 2018, to December 31, 2020. Outliers are detected and subsequently substituted with minimum and maximum values using the Boxplot method. To eliminate seasonal patterns, time-series decomposition is employed.

[5] www.baidu.com is the largest search engine website in China—especially for searching for information in the Chinese language. A detailed description of how the Baidu search index works can be found on its official website: http://index.baidu.com/v2/main/index.html#/help.

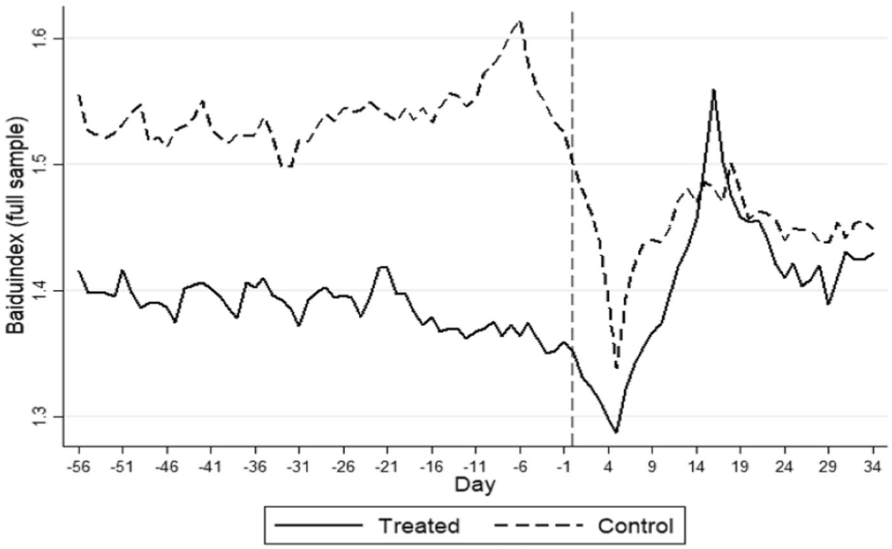


Fig. 5 Daily Baidu search indices

To standardize the indices across keywords, we apply the min–max normalization, to which we then add a constant of 1 so as to avoid zero values. The resulting Baidu search indices fall between 1 and 2. Finally, we choose the Baidu search index within the same timeframe as the period of price dispersion.

Each keyword's Baidu search index is represented as BSI_{kt}, where k represents keywords and t represents days. As the exact matches between keywords and product items are not feasible, we opt to match at the subcategory level. We use Eq. (3) to aggregate the keyword index within each subcategory:

$$BSI_{st} = \left(\prod_{k \in I_s} BSI_{kt}\right)^{\frac{1}{|I_s|}}, \tag{3}$$

where I_s represents the set of keywords for subcategory s, $s \in \{1,2, \ldots, 189\}$.

Figure 5 displays the daily Baidu search index for the full sample, calculated as the arithmetic average of all BSI_{st} values. The vertical dotted line in the figure indicates the day of the COVID-19 outbreak. Clearly, the overall search intensity for consumption rose sharply after the outbreak of the epidemic.

We first quantify the changes in search intensity during the period of the epidemic by running the following difference-in-differences model:

$$BSI_{kt} = \gamma_k + \gamma_1 covid_{kt} + \gamma_2 treat_k + \gamma_3 post_t + \gamma_4 dow_t + \gamma_5 week_t + \varepsilon_{kt}. \tag{4}$$

We use the same DID framework as in Eq. (1), with the Baidu search keyword as the unit of analysis. We are mainly interested in the estimates of γ_1. Additionally, we also report the estimations for each of the four major categories. The outcomes are presented in Table 3.

Table 3 The effects of the COVID-19 epidemic on Baidu search index

	(1) Full sample	(2) Food, tobacco, and liquor	(3) Education and entertainment	(4) Clothing	(5) Household goods and services
Covid	0.0918***	0.186***	0.107***	0.0265***	0.0648***
	(43.89)	(52.06)	(16.54)	(7.27)	(14.87)
Treat	− 0.137***	− 0.137***	− 0.0904***	− 0.0965***	− 0.202***
	(− 105.47)	(− 61.84)	(− 22.46)	(− 42.62)	(− 74.61)
Post	− 0.0776***	− 0.108***	− 0.0660***	− 0.0480***	− 0.0938***
	(− 27.73)	(− 22.71)	(− 7.60)	(− 9.83)	(− 16.10)
Constant	1.532***	1.567***	1.512***	1.488***	1.553***
	(662.76)	(397.79)	(210.95)	(369.02)	(322.70)
Dow	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes
N	51,870	17,836	5642	12,740	10,010

t statistics in parentheses. *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$

The difference-in-differences comparison reveals a significant surge in online search activity during the epidemic. Furthermore, the change in search patterns differ depending on products' different crisis-time demand elasticities. For instance, food remains an imperative necessity in challenging times—as compared to clothing, the purchase of which can be postponed. As is indicated by the estimates in Columns (2)–(5), there was a significant increase in searches for food during the epidemic, whereas clothing-related searches exhibit only marginal growth. Similarly, due to school closures and the shift to online learning, searches for products within the "education and entertainment" category experienced a substantial increase during this period. The upturn in search intensity for the "household goods and services" category falls somewhere in between.

4.2 Price Dispersion During the Outbreak after Incorporating the Effect of Heightened Online Searching

To assess the residual impact of the "covid" variable after accounting for the influence of search intensity, we introduce the one-day lagged Baidu search index as a control. In essence, we employ the following product fixed-effects model:

$$dispersion_{it} = c_i + \beta_1 covid_{it} + \beta_2 treat_i + \beta_3 post_t + \beta_4 week_t + \beta_5 dow_t + \beta_6 BSI_{s,(t-1)} + \delta x_{it} + \varepsilon_{it}. \quad (5)$$

When employing the Baidu search index to accommodate search behavior, there is an important concern with regard to potential reverse-causality between search patterns and price dispersion: For instance, if consumers anticipate that there will be little variation in prices, they may well do less searching, and vice versa. This dynamic could yield apparent counter-intuitive results, such as increased price dispersion that correlates with intensified searching, thereby potentially confounding the residual influence of the COVID-19 outbreak on price dispersion.

To address the potential endogeneity that is associated with the Baidu search index, we instrument it with a shift-share instrumental variable: We exploit the fact that the Baidu search indices can be traced to provinces. For every BSI_{st}—the Baidu search index at the subcategory-by-day level—we construct a shift-share instrument variable $BSI_{SSIV_{st}}$ that corresponds to it. The variable $BSI_{SSIV_{st}}$ is constructed by multiplying an exogenous "shift" variable BT_{pt}—which measures the overall Baidu search pattern at the province level—with a historical "share" variable that represents the proportion of historical Baidu search indices w_{sp} for each province:

$$BSI_{SSIV_{st}} = \sum_{p=1}^{34} w_{sp} BT_{pt}, \tag{6}$$

where $p \in \{1,2,\cdots,34\}$ represents the set of provinces in China.

The shift variable BT_{pt} is constructed based on the daily Baidu search index in each province for the names of the top 10 shopping platforms: *Tmail*; *Taobao*; *JD*; *1688; DangDang*; *Suning*; *PDD*; *Vipshop*; *Amazon*; and *YHD*. We use this variable to measure the temporal "shock" of online shopping in China. It is constructed as the geometric mean of the 10 Baidu search indices:

$$BT_{pt} = \left(\prod_{j=1}^{10} BSI_{jpt}\right)^{\frac{1}{10}}. \tag{7}$$

For the "share" variable w_{sp}, we calculate the proportion of historical Baidu search indices in province p for each subcategory s, where the Baidu search indices are taken as the geometric means for Baidu search indices between January 1, 2018, to December 5, 2018 (a total of 338 days), which represents the period that precedes the study.

$$d_{sp} = \left(\prod_{t_1=-338}^{-1} BSI_{spt_1}\right)^{\frac{1}{338}}, \tag{8}$$

$$w_{sp} = \frac{d_{sp}}{\sum_{p=1}^{34} d_{sp}}. \tag{9}$$

The subcategory at the province-level Baidu search index is calculated similarly as Eq. (3), except now we use the Baidu search index for each keyword k at province p:

$$BSI_{spt} = \left(\prod_{k \in I_{sp}} BSI_{kpt}\right)^{\frac{1}{\lceil I_{sp} \rceil}}. \tag{10}$$

We employ the constructed shift-share instrument as an instrumental variable for the Baidu search index. This is executed within a two-stage framework, wherein the predicted Baidu search index from the first stage is substituted into Eq. (5).

The findings are reported in Table 4: Column (1) presents estimates that are based on the full sample, while Column (2) provides the first-stage estimates,

Table 4 Category-level analysis of price dispersion with Baidu search index

	(1) Full sample	(2) First stage	(3) Food, tobacco, and liquor	(4) Education and entertainment	(5) Clothing	(6) Household goods and services
Covid	0.0108***	0.0636***	0.00376	0.000101	0.0492***	− 0.000826
	(9.71)	(159.33)	(1.37)	(0.04)	(15.55)	(− 0.51)
Treat	− 0.0257***	− 0.0714***	− 0.0213***	0.00868***	− 0.0210***	− 0.0313***
	(− 16.54)	(− 148.33)	(− 6.48)	(4.32)	(− 3.71)	(− 11.90)
Post	− 0.0335***	− 0.0321***	− 0.0235***	− 0.00339	− 0.0358***	− 0.0396***
	(− 26.83)	(− 56.49)	(− 10.97)	(− 1.33)	(− 9.76)	(− 18.33)
Log(price)	0.0813***	0.00354***	0.237***	− 0.130***	0.186***	− 0.0553***
	(63.20)	(5.39)	(98.52)	(− 29.81)	(75.51)	(− 23.24)
No. of platforms	0.0480***	− 0.0120***	0.0524***	0.0229***	0.0742***	0.0686***
	(64.68)	(− 31.95)	(58.93)	(13.47)	(31.65)	(55.36)
L.BSI	− 0.222***		− 0.0583***	− 0.0491**	− 0.973***	− 0.132***
	(− 21.47)		(− 3.40)	(− 2.60)	(− 20.43)	(− 9.21)
L.BSI_SSIV		0.497***				
		(189.41)				
Constant	0.0432*	0.769***	− 0.760***	0.793***	0.444***	0.555***
	(2.54)	(148.93)	(− 26.10)	(22.35)	(6.20)	(22.46)
Dow	Yes	Yes	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes	Yes	Yes
N	557,438	557,438	142,460	61,720	113,948	209,160

t statistics in parentheses. $^{*}p<0.05$, $^{**}p<0.01$, and $^{***}p<0.001$

where we regress the Baidu search index on the shift-share instrument (BSI_SSV) and other control variables. Notably, the instrumental variable positively and significantly predicts the Baidu search index. Column (3)–(6) reports the estimates at the category level.

After adjusting for online search intensity, the effect of the pandemic outbreak on price dispersion shifts toward a positive direction. The coefficient changes from a significantly negative value of -0.00588 before accounting for the effect of heightened online searching, to a significantly positive value of 0.0108 after incorporating search intensity: The market friction effect of the pandemic outbreak becomes prominent after the increased level of searching is taken into account. We observe similar changes in estimates across all four major categories.

The estimates on the Baidu search index corroborate that search intensity is significantly and negatively correlated with price dispersion, in line with the predictions of the search cost theory. Hence, the initial findings that indicated a reduction in price dispersion during the COVID-19 epidemic can be largely ascribed to the increased level of online searching, which was facilitated by stay-at-home directives amid the outbreak.

5 Conclusion and Implications

Price dispersion—a commonly used measure of market efficiency and welfare loss—provides practical insights into market frictions that result from external shocks. Our difference-in-differences analysis reveals that price dispersion in the Chinese online retail market did not increase but instead significantly decreased during the COVID-19 outbreak. This suggests that the online retail market in China demonstrated relatively efficient functioning during the initial wave of the pandemic. We attribute this outcome to the extended holiday period and to the widespread closure of businesses, which led to increased online shopping demand and reduced opportunity costs for searching.

The heightened search activity contributed to smaller price dispersion during the epidemic. Our analysis—which focuses on four product categories with varying crisis-time demand elasticity—supports this explanation: The decreases in price dispersion were mainly for products with relatively low demand elasticity—such as food, tobacco, and liquor—due to their higher online search intensity during the pandemic outbreak. Products with high demand elasticity—such as clothing—were not searched as intensively during the pandemic outbreak as consumers can postpone their consumption. Consequently, these products exhibited increased price dispersion during this period. Moreover, after accounting for the increased search intensity, the negative effect on price dispersion that is associated with the epidemic period disappears and mostly becomes positive.

Therefore, we conclude that China's well-developed online market served as a buffer and offsetting force during the COVID-19 crisis. The shift from offline to online markets, along with increased search activity, bolstered the online market's performance and mitigated the negative effects of the pandemic. The digital infrastructure in China enabled the online market to maintain functional efficiency even during the most challenging period of the COVID-19 outbreak.

These findings illuminate an unexplored channel through which the digital economy can ameliorate the effect of adverse economic shocks. As COVID-19 is expected to persist as an endemic disease, these findings offer promising implications for an era that is characterized by a digital and contactless economy.

Our findings suggest that nurturing a resilient online market can alleviate disruptions and serve as an effective instrument for coordinated epidemic control and economic progress. However, it's important to acknowledge that the study's findings and implications pertain specifically to China's online retail market, where an efficient logistics system and widespread adoption of mobile payment methods likely contributed to market efficiency. To extend these insights to other contexts, comparable price dispersion data from other economies would be essential. Further research is warranted to address this gap.

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