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# Has COVID-19 accelerated the E-commerce of agricultural products? Evidence from sales data of E-stores in China

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## ABSTRACT

We investigated the operation of e-stores specializing in food and agricultural products before and after the occurrence of COVID-19. A difference-in-difference (DID) method was employed to estimate the relationship between COVID-19 and the online sales of agricultural products using data from 164,002 food and agricultural product e-commerce stores (in short, e-stores) of two major Chinese e-commerce platforms in 120 prefectural-level or above cities. The results demonstrated that while COVID-19 and its control measures were associated with a substantial growth in the monthly sales of food and agricultural product e-stores, the growth varies considerably across store scales and with the type of food and agricultural product in which an e-store is specialized. Micro stores experienced much larger growth and played a more important role in maintaining the resilience of the supply chain of food and agricultural products than larger-scale stores; stores selling more essential food items experienced larger growth than those selling leisure food items. A mechanism analysis further revealed that the growth of online sales of agricultural products was mainly driven by changes in consumers' food purchase behaviors from offline channels to online channels (i.e., an increase in the number of online customer orders and price per online order) starting with the onset of COVID-19. The results of this paper underscore the importance of e-commerce in maintaining the resilience of the agri-food supply chain and call for public support of the development of micro- and small-scale e-stores to meet consumers' increasing demand for food supply from those types of stores during the pandemic period.

## 1. Introduction

The COVID-19 pandemic and the many associated control measures posed great challenges to food security around the world (FAO, 2020; Gruere and Brooks, 2021; Zhan and Chen, 2021; Rudin-Rush et al., 2022; Maredia et al., 2022). Lockdown policies compromised residents' ability to access food through physical food stores (Reardon et al., 2021), and panic buying or hoarding caused prices to spike for some food categories (Chenarides et al., 2021; Wang and Na, 2020; Yu et al., 2020). Governments around the world have struggled to balance mitigating the impending food security crisis and containing the spread of the virus. Because e-commerce can improve market performance and avoid direct person-to-person contact, it is regarded as an effective substitute for the offline food market channel during a public health

crisis (Boyaciota-Gunduz et al., 2021; Priambodo et al., 2021; Hong, 2020). However, have COVID-19 and its control measures accelerated the e-commerce of food and agricultural products and, if so, by how much? How does the acceleration vary by the operational scale and other characteristics of e-stores? While these questions have attracted much attention from policy-makers and scholars, rigorous empirical evidence based on large datasets is scarce.

Anecdotal case reports based on macro statistical data from different countries point toward a rapid emergence of e-commerce of agricultural products since the outbreak of the pandemic. Statistical data from China show that China's online retail sales of agricultural products in 2020 reached CNY 414.89 billion (equivalent to US\$ 64.84 billion), with a year-on-year increase of 26.2 %; the annual volume of express mail received and delivered in rural areas exceeded 30 billion, with a year-

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on-year increase of 20 % (DECI, 2020). An OECD document indicates that the share of e-commerce in total retail sales rose from 11.8 % to 16.1 % between the first and second quarters in 2020 in the U.S. and that retail sales via mail order or the internet in April 2020 increased by 30 % compared to the same period in 2019 in the EU (OECD, 2020). A similar growing trend of e-commerce in the agri-food supply chain was also witnessed in India, Africa, Latin America (Reardon et al., 2019), Korea (Park and Lee 2021) and Indonesia (Priambodo, et al., 2021).

In addition to these anecdotal case reports, there are also a growing (yet limited) number of studies using microlevel survey data to investigate the dynamics and heterogeneities of consumers' buying behaviors (Ellison et al., 2020; Gao et al. 2020; Moon et al., 2021; Wang and Na, 2020) and of enterprises' reaction behaviors (Rybczewska et al., 2021; Dannenberg et al., 2020; Mahajan and Tomar, 2020; Priambodo et al., 2021; Shafi et al., 2020). Studies about consumers' purchasing behaviors based on internet survey data from a few hundred consumers have generally found that the occurrence of COVID-19 and its subsequent control measures have encouraged the shift of consumers' purchasing behaviors of food from offline to online channels worldwide (e.g., Chenarides et al., 2021; Ellison et al. 2020 on U.S., Wang and Na, 2020; Gao et al., 2020 on China; Mehrolia et al., 2021 on India, Moon et al., 2021 on Korea). While the findings of this emerging literature on consumer purchase behaviors during the pandemic period using online survey data are generally consistent with the abovementioned anecdotal evidence based on macro statistical data, the key concern with this strand of literature is that online surveys are notorious for issues related to sample selection bias and the poor quality of respondents' answers (Abay, 2020; Anderson et al., 2021; Godlonton et al., 2017).

Regarding the studies on enterprises' reaction behaviors using data from online retailers or e-commerce platforms, the conclusion is more varied and less consistent with anecdotal case reports. Using data from online food delivery platforms in Brazil, Horta et al. (2021) found that the use of online food delivery platforms increased 9–10 % during the lockdown period. In India, the product availability of vegetables, fruits, and edible oils in one of the largest online grocery retailers dropped by 10 % due to difficulties related to the long-distance delivery of goods posed by lockdowns (Mahajan and Tomar, 2020). Using online and telephone interview data from e-groceries in Germany, Dannenberg et al. (2020) argued that while the pandemic and the related 'stay at home' policies opened a window of opportunity for grocery e-commerce to disseminate, the control measures limited the spatial diffusion of online food groceries. Descriptive analysis evidence based on transaction data from 2,921 offline convenience stores in the UK shows that convenient stores have been relatively resistant to the COVID-19 pandemic, with few changes in business occurring during the pandemic period. Therefore, while this strand of literature recognizes the opportunity for digital services in the agri-food supply chain, it also points toward many challenges constraining the utilization of e-commerce of food and agricultural products.

While the literature provides insights into the challenges and opportunities brought about by COVID-19 to the digitization of agricultural supply chains, most of them are based on aggregate statistical data, phone or online survey data or consumer behavior data of small sample sizes. While there are few studies that use data from e-commerce platforms or e-grocery stores, these studies provide mixed conclusions about the evolution of e-commerce in agricultural and food supply chains during the pandemic period. There is also no mention of the heterogeneity in the evolution of e-commerce of agricultural and food supply chains with respect to the scale and type of e-stores. The supply chain system for agricultural products has evolved for decades from local retail stalls to large-scale chain supermarkets to online e-commerce worldwide (Reardon, et al., 2019). During such an evolution, traditional small and medium-sized operators or dealers are often faced with the hazard of being eliminated by the market in a disadvantaged position (Reardon and Timmer, 2012). The COVID-19 shock could potentially make the challenges faced by micro/small operators even worse; however,

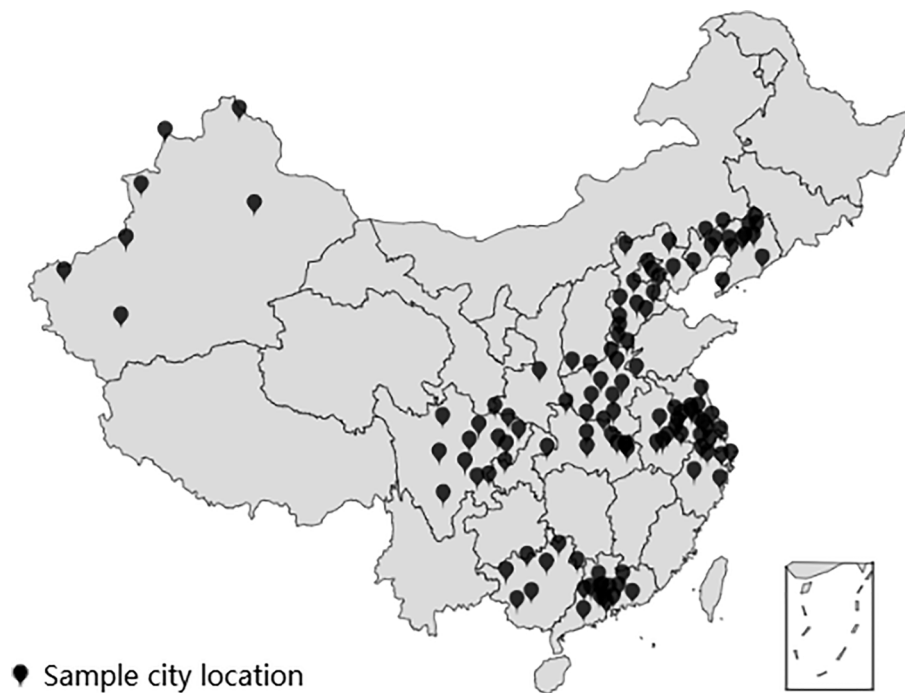
whether this is the case is unclear without rigorous empirical evidence based on panel data from large and representative e-stores.

Utilizing the monthly sales data of 164,002 e-stores of food and agricultural products from January 2017 to June 2020, as well as the detailed information of their registered locations, operational scales and main categories of agricultural products, we are able to address some of the data and methodological challenges mentioned above. More specifically, we use a difference-in-difference (DID) strategy to estimate and quantify the change in online sales of e-stores specializing in food and agricultural products during the COVID-19 period. The DID estimation essentially compares the change in monthly sales of e-stores before and after the COVID-19 outbreak in 2020 with the change between the same periods of the normal years (2017–2018 and 2018–2019). While implementing different control policies and adaptation strategies along with the onset of COVID-19 makes it difficult to estimate the causal effects of COVID-19 and other concurrent control measures and adaptation changes on online sales of agricultural products, we can estimate the association between the combination of the virus and all other things that changed along with the onset of COVID-19 in China and elsewhere and the online sales of agricultural products using DID method. In this paper, the term 'COVID-19' is loosely used as a proxy for the virus and all the other concurrent policy changes that could potentially have influenced the development of e-commerce of food and agricultural products.

Our DID result shows that COVID-19 and its accompanying control measures are associated with a surge of online sales of agricultural products by 97–105 % in 2020, while the online sales for the same period in the previous two years (2017–2018 and 2018–2019) are largely statistically insignificant. The heterogeneity analysis indicates that the micro stores experienced larger growth in online sales than the small and medium-sized stores (69 % vs 18 %, 21 %) and that those stores that specialized in selling fresh and more essential foods experienced larger growth in sales than did those that specialized in selling leisure foods (105 % vs 53 %). The results from the mechanism and sub-component analyses indicate that sales growth was mainly related to the increase in the number of customer orders and the customer unit order price.

This paper makes three contributions. First, it overcomes the limitations of previous studies using macro statistical data, online survey data, or enterprise data of relatively small sample sizes. The current literature mostly uses the annual sales or consumption data at the provincial level to study the overall or average development of the industry, which offers limited insights into the development differentiation among e-stores. The results of this paper offer a more representative picture of the evolution of the e-commerce of food and agricultural products for the first six months after the onset of COVID-19 using data from a vast number of e-stores of different scales from two major e-commerce platforms in China. Second, we analyze the contribution of small to large-scale stores to improving the supply elasticity of agricultural products during the first half year of the epidemic, reveal the association between the pandemic shock and the digital expansion of the agricultural product supply chain, provide an empirical reference for the theoretical innovation of the digital economy, and optimize the support policy of agricultural product e-commerce in the post-COVID-19 era. Third, the large panel data on online sales from the same e-stores before and after the occurrence of the COVID-19 pandemic for multiple years (the COVID year and two pre-COVID years) offer a unique opportunity to employ DID to estimate the evolution of e-commerce of agricultural products due to COVID-19 and all other policies and measures implemented to contain the virus and increase the adaptability, which increases the reliability and policy relevance of our results.

The rest of the paper is organized as follows. Section 2 provides some background of the study. Section 3 describes the sample data, key outcome variables and store characteristics. Section 4 and Section 5 present the main identification strategy and the empirical results, including robustness checks. Section 6 presents the mechanism analysis. Section 7 concludes with policy implications and future research.



**Fig. 1.** Distribution of the sample e-stores of 120 cities. *Notes:* Black drop dots represent the locations of 120 cities where sample e-stores were registered. The self-operated e-stores of Jingdong are not displayed in the figure but are treated as an independent region and are not incorporated into its headquarters location, Beijing.

## 2. Background

### 2.1. E-commerce in China

China was already the world's leader in online retail, accounting for 45 % of global e-commerce transactions before 2020 (Zhang, et al., 2021). Alibaba and Jindong are the two most popular e-commerce platforms in China. Alibaba's Taobao and Tmall platforms and Jindong's e-commerce platform are the two largest merchandise retail e-commerce platforms with the highest market share in China. The number of active users of the Alibaba e-commerce platform in the 2020 fiscal year (April 2019 to April 2020) reached 726 million, with a total turnover of RMB 6.59 trillion (\$1.02 trillion). The number of active users of Jindong reached 362 million in 2019, with a total turnover of RMB 2.09 trillion (\$324.8 billion). The online retail sales of Alibaba and Jindong account for 50.10 % and 26.51 %, respectively, in China's online B2C market (Jiemian News, 2020; WS-ECRC, 2020).

To enable small farmers and agricultural product circulation professionals to share the development of the digital economy, the Chinese government has continuously issued a series of rural e-commerce support policies since 2014 to expand the logistics system, strengthen facilities for processing and packaging, improve the cold chain and storage of agricultural products and cultivate brands of rural e-commerce products. As a result, the gap between urban and rural food delivery supply chains has been narrowed, and the connection between urban and rural areas has been promoted (Lu, 2018; Tang et al., 2020). From 2014 to 2019, the coverage rate of express delivery network increased from 50 % to 96.6 % in towns across the country, and the proportion of direct delivery to villages exceeded 50 % (DECI, 2020), thus establishing a solid foundation for the development of e-commerce for urban and rural residents. The e-commerce transaction scale of fresh agricultural products reached RMB 255.45 billion in 2019 (WS-ECRC, 2020), and agricultural products have been one of the fastest-growing categories of e-commerce in China in recent years (Guo, et al., 2021).

### 2.2. COVID-19 prevention and control in China

COVID-19 broke out and spread in China in January 2020; Wuhan implemented a city-wide lockdown on January 23. All provinces, autonomous regions and municipalities in China successively implemented first-level emergency responses from January 22–24, 2020 to counter this grave public health crisis (Ruan et al., 2021). With the progress of pandemic prevention and control, the strength of the prevention and control measures were adjusted according to the severity of COVID-19 in each locality. As of June 30, 2020, the entire country has entered a low-risk phase, and control measures have been lowered to their third level.

## 3. Data and sample descriptions

### 3.1. Data and sample

The dataset for this study comes from a monthly city/store-level dataset of online sales of food and agricultural products provided by Moojing, a popular data technology company focused on e-commerce big data mining. Moojing aggregates all transaction records listed on partners' e-commerce platforms to provide users with detailed information of when, how much, what and from which e-stores food and agricultural products are sold. Moojing aggregates the original data into a monthly dataset by e-store ID. We have access to the monthly data of all 164,002 registered e-stores in 15 provinces on the Taobao (Tmall) and Jindong e-commerce platforms from January 1, 2017 to June 30, 2020, under the business category of agricultural products. The data consist of store name, store ID, sales volume, quantity of customer orders, average unit price per customer order, product category, etc. Considering the dataset includes monthly data for several years before the pandemic and six months during and after the outbreak of the pandemic, it is ideal for us to employ the DID method to evaluate the association between COVID-19 and e-store sales and identify underlying mechanisms.

According to their registered cities, our sample of e-stores are sorted

and classified into 120 prefecture- or above-level cities in 15 provincial administrative regions, which account for 35.5 % of the 338 prefecture-level cities in China. Among them, 51 cities are located in the east region, 33 cities are located in the central region, 21 cities are located in the west region and 14 cities are located in the northeastern region. In the regional classification of e-stores by the Jingdong platform, a small number of self-operated e-stores (0.1 % of the total sample stores) are identified separately and are not classified within any city; therefore, Jingdong's self-operated e-stores are treated as an independent region and are not incorporated into any other real cities. The central region includes all prefecture-level cities in Hubei Province. The e-commerce platforms also document where the e-stores' orders are delivered at the city level; they show that most e-stores only operate in their city of registration and that a few large e-stores, approximately 5 % of the sample, have set up branches or warehouses in other cities to save logistics costs. Because the sales in other cities are less than those in their registration city and the management and customer service personnel mainly work in the registration city, these stores remain included in their city of registration. While the cities in the sample cover over one-third of the whole country, the population of permanent residents in these cities accounts for 46.22 % of the whole country (equivalent to a total of 647 million people). The GDP of the sample cities accounts for 55.42 % of the whole, while the GDP of the primary industry accounts for 41.35 % of that for the whole country in 2019. Moreover, as of June 30, 2020, there were 72,634 confirmed cases of COVID-19 in the sample cities, accounting for 87.23 % of the total number of confirmed cases in China. A total of 7,546 cases were confirmed in the sample area outside Hubei, accounting for 49 % of the other confirmed cases. Fig. 1 shows the distribution of the 120 cities where the sample e-stores were registered.

### 3.2. Measures and descriptions of key variables

#### 3.2.1. Explained variables

In addition to the e-store-level data on monthly sales, the monthly quantity of customer orders (QCO) and the average unit price per customer order (UPCO), we also aggregate the store-level data into city-level data to obtain the total monthly sales and total monthly quantity of customer orders for each city. The sales variables are censored by 1 % (elimination of the top and bottom 0.5 %) to avoid the potential bias caused by outliers.<sup>2</sup> Finally, we convert the sales and quantity of customer orders into standard monthly values to address the fact that there are different numbers of days in different months.<sup>3</sup>

We generate three variables, namely, the number of active e-stores, the number of entering e-stores, and the number of exiting e-stores, to characterize agricultural product e-commerce activity at the city level. The number of active e-stores is used to understand how the number of operating entities online was affected by the pandemic and is measured by how many e-stores have nonzero sales records in the current month in a city. Agricultural product e-commerce is dominated by small and micro e-stores. Some agricultural products have a clear supply season, and many stores have no sales records for some months; however, it is difficult to distinguish no sales due to seasonality from no sales due to the performance of stores. We follow the methods of Chu and Manchanda (2016) and Jin et al. (2020) and treat the stores that first appeared in the sample period and have no record of any rating or reputation as having entered the market in the current month; then, we set the last month when the sales record was nonzero as the month of the exiting time for an e-store. This information was used to generate two

other variables, i.e., the number of entering stores and the number of exiting stores in each city. At the same time, we use the method of Xu and Guo (2018) to measure the net entry rate of stores as  $Ent_{j,t}$ , which was calculated as follows:

$$Ent_{i,t} = (Nstore_{i,t} - Nstore_{i,t-1}) / Nstore_{i,t-1} \quad (1)$$

where  $Nstore_{j,t}$  is the number of active stores in month  $t$  of city  $i$ . The calculation of the net exit rate of stores ( $Exit_{j,t}$ ) is similar.

#### 3.2.2. Explanatory variables

Previous studies have found that e-commerce has an aggregation effect, with successful early adopters encouraging latecomers to participate in e-commerce and do business online (Zeng et al., 2019; Zhang et al., 2017). Therefore, the monthly sales and monthly orders of an individual e-store are affected by the level of e-commerce development within the city. The store dataset enables us to obtain two characteristic indicators that reflect the level of e-commerce development within a city. The first indicator is the *Herfindahl-Hirschman index (HHI)* for agricultural product e-commerce in a city. The HHI measures the concentration of agricultural product e-stores in a given city. HHI can be calculated as follows:

$$HHI_{it} = \sum_{j=1}^n (X_{i,j,t} / X_{i,t})^2 = \sum_{j=1}^n s_{i,j,t}^2 \quad (2)$$

where  $X_{i,t}$  is the total sales of agricultural products in month  $t$  by all the e-stores in city  $i$ ,  $X_{i,j,t}$  is the total sales of store  $j$  in month  $t$  and city  $i$ ,  $s_{i,j,t}$  is the market share of agricultural products of store  $j$  in month  $t$  and city  $i$ , and  $n$  is the number of e-stores in city  $i$  during month  $t$ .

The second indicator is the *size of stores in the previous year*. According to the criteria of retail enterprises of the "statistical classification method for large-, medium-, small-, and micro-sized enterprises (2017)" (No. 213) issued by the National Bureau of Statistics, an e-store can be classified into micro, small, medium or large enterprises based on its total sales volume in the previous year. Based on the number of e-stores belonging to one of the four size categories, we can then calculate the proportion of e-stores of each size for each city in each month.

Previous studies have indicated that the consumption demands of different commodities varied greatly during the pandemic, which is related to customers' food safety concerns and the storage resistance of products (Andersen et al., 2020; Ben Hassen et al., 2020; Bracale and Vaccaro, 2020). To investigate the heterogeneity in online sales among different categories of agricultural products before and after the pandemic, commodities sold by e-stores can be reclassified into three main categories according to their characteristics, namely, fresh products, storable products and specialty leisure products. Fresh products include fruits, seafood, meat, cold drinks, frozen food, vegetables and eggs. Storable products include food and beverage packaging, beverage preparation, grain and oil nonstaple food, condiment, tea, North South dry goods and instant food. Specialty leisure products include leisure food, nuts and specialty food products.

The operation and performance of an e-store can also be affected by the social and economic conditions of the province and the city in which the e-store is located, especially the infrastructure such as networks and express delivery coverage. Based on the literature (Zeng et al., 2019; Tang et al., 2020; Ju et al., 2020) and data availability, we include the local resident population and disposable personal income per capita in the evaluation analysis to control for the influence of market demand factors. Variables indicating e-commerce infrastructure and circulation of agricultural products are also included to control for the local infrastructural conditions, which are represented by the number of mobile phone users, express delivery volume above the designated scale, and total toll reduction due to green channel vehicles. Finally, the e-commerce economy has been one of the fastest growing private economies over the last decade in China; thus, relevant indicators of the market

<sup>2</sup> As a sensitivity analysis, we also used the full sample for our analysis, the results, nevertheless, are highly consistent with the main results.

<sup>3</sup> For a given month  $t$  where  $t \in \{1, 2, \dots, 12\}$ , the standardized monthly sales or COQ in city  $i$  is computed as: [Total Sales (or COQ) in city  $i$  of month  $t$  / number of days of month  $t$ ] \* 30,

**Table 1**  
Variable's definition and description.

Category	Name	Code	Description
Outcome variables	Monthly sales	<i>Sales</i>	Monthly sales of agricultural products by an e-store (yuan RMB, logarithm)
	Quantity of customer orders	<i>QCO</i>	Monthly quantity of customer orders for an e-store (number, logarithm)
	Unit price per customer order	<i>UPCO</i>	Monthly Average unit price per customer order for an e-store (RMB, logarithm)
City development variables	Nonstate-owned economic development score	<i>SOB</i>	Nonstate-owned economy development score (province, year)
	Government and market relationship score	<i>GAM</i>	Government and market relationship scores (province, year)
	Resident population	<i>Pop</i>	Resident population (person, year, logarithm)
	Monthly disposable personal income per capita	<i>PerInc</i>	Monthly disposable personal income per capita of local residents (yuan RMB per month, logarithm)
Infrastructure variables	Express delivery volume above the designated scale	<i>Express</i>	The monthly volume of express delivery above the designated scale (10,000 pieces, logarithm)
	Number of mobile phone users	<i>Mobile</i>	Monthly mobile phone users (10000 user, logarithm)
	Toll reduction due to green channel vehicles	<i>Green</i>	Total toll reduction due to green channel vehicles (RMB 100-million, yearly, logarithm)
Industry development variables	Herfindahl-Hirschman index	<i>HHI</i>	Herfindahl-Hirschman index of local agricultural e-stores
	Herfindahl-Hirschman index of top 5 percent	<i>HHI5</i>	Herfindahl-Hirschman index of the top 5 percent local agricultural e-stores
	Store size according to the sales	<i>Size</i>	yearly total sales, =1 if less than RMB 1 million, =2 if equal or above RMB 1 million and less than RMB 5 million, =3 if equal or above RMB 5 million and less than RMB 10 million, =4 if equal or above RMB 10 million.

economy development index are included to control for the business environment, which are represented by the nonstate-owned economic development score and government and market relationship score according to the calculation of Wang et al. (2020). The variables' definitions and explanations are presented in Table 1. Except for the few variables that have data sources specifically indicated, other control variables have been drawn from the national or provincial statistical yearbooks.

### 3.2.3. Summary statistics

Before we present summary statistics, it is important to define the treatment/control group and before/post period. These concepts in this paper are similarly defined as in recent studies using difference-in-difference (DID) to evaluate the relationship between COVID-19 and various outcomes (Chang and Meyerhoefer 2020 on demand for online food shopping services; Fang et al., 2020 on labor mobility; Ruan et al., 2021 on vegetable prices). As in these studies, we define the treatment and control groups (or samples) based on the temporal dimension. More specifically, we define the period from August 2019 to June 2020 as the treatment group ( $treat_t = 1$ ) and the same periods (according to the Chinese calendar month) for the previous two years (i.e., September

2017-July 2018 and August 2018 - June 2019) as the control group ( $treat_t = 0$ ). Since the public announcement of COVID-19 and the subsequent lockdown measures occurred in late January 2020, we define January-June 2020 and the same period in the previous two years by the Chinese calendar (January-June 2019 and February-July 2018) as the post period ( $post_t = 1$ ) and the remaining months (August-December 2019, August-December 2018, September 2017-January 2018) as the 'before' period ( $post_t = 0$ ).<sup>4</sup>

Table 2 reports variable means for the full sample, the before/post period of the treatment group, and before/post period of the control group. Specifically, column (1) presents the mean across all selected observations in 2017–2020. Columns (2) and (3) includes observations from the post period and the before period of the treatment group, respectively, whereas columns (5) and (6) includes observations from the post period and the before period of the control group, respectively. Columns (4) reports the mean difference between column (2) and (3), and column (7) present the mean difference between columns (5) and (6). Finally, column (8) presents the difference between columns (4) and (7), measuring the difference of the before/post differences between the treatment group and the control group.

The descriptive statistics in Table 2 yields several insights about the dynamics of the explained and the explanatory variables during the before and the post periods and between the treatment and control groups. First, the values of the main outcome variables (online sales, quantity of customer orders, and unit price per customer order) are all significantly larger in the post period than in the before period for the treatment group (column (2) vs column (3)), while the same before and post period comparison for the control group (column (5) vs column (6)) shows the opposite dynamics.<sup>5</sup> The combination of a significant growth in sales and customer orders since the onset of the pandemic for the treatment group and the significant decline in sales and customer orders over the same period for the control group (i.e., non-COVID years) suggests a possible shift from offline sales to online sales of food and agricultural products in response to COVID-19 and the associated control measures. Second, the unconditional difference-in-difference (DID) results reported in column 8 show that the pandemic and its control measures is associated with 71 %, 29 %, and 26 % increases in online sales, customer orders and the unit price per customer order, respectively. Finally, while most of the differences in the explanatory variables between before and after periods or between the treatment and control groups are statistically significant, the magnitude of the difference is generally small in most cases. While the descriptive evidence in Table 2 is informative about the potential shift from offline to online sales of agricultural products, we need to perform a rigorous econometrics analysis to verify whether the differences in outcomes between the treatment and control groups are indeed associated with COVID-19 and its associated control measures.

<sup>4</sup> The fact that the cutoff month varies between 2018 and the following two years is because the CLNY happened to be in January 2020 but in February in both 2018 and 2019. Similar to other studies in the literature (Ruan et al. 2021; Fang et al., 2020), our strategy of matching time periods according to Chinese lunar calendar is to control for the influence of CLNY, one of the most important festivals in China.

<sup>5</sup> At the request of one of the reviewers, we also conducted a trend analysis to show whether the trend in online sales of e-stores for the post-COVID months relative to the trend for the pre-COVID period is indeed different. To do so, we assigned values 0, 1, 2, and 3, 4 to each of the five pre-COVID months (from earliest to latest), and 5, 6, 7, 8, 9, 10 and 11 to the six post-COVID months. And we define a post-COVID dummy ( $post_t$ ) which equals 1 for the post-COVID months and zero for the pre-COVID months. The trend analysis regression is  $y_{i,t} = \alpha + \beta post_t + \gamma Mon_t + \delta (post_t \times mon_t) + \varepsilon_{i,t}$ . The results are presented in appendix Table 2. The positive and significant coefficient of the interaction term between the month and the post dummy variable suggest that the slope between the trend is indeed significantly different in the post-treatment period relative to the pre-treatment period.

**Table 2**  
Variables summary.

Variable	(1)	(2)		(3)	(4)	(5)		(6)	(7)	(8)
	All	Treatment Group				Control Group				
	Mean	Post period	Before period	(2)-(3)	Post period	Before period	(5)-(6)	(4)-(7)		
Sales	7.381	8.210	7.805	0.405***	6.927	7.235	-0.308***	0.713***		
COQ	4.124	4.682	4.435	0.248***	3.901	3.941	-0.039***	0.287***		
CUP	3.473	3.701	3.642	0.059***	3.274	3.472	-0.199***	0.258***		
HHI	0.099	0.090	0.107	-0.017***	0.088	0.108	-0.020***	0.003***		
HHI5	0.323	0.306	0.339	-0.033***	0.319	0.325	-0.007***	-0.026***		
SOB	8.607	8.635	8.629	0.006*	8.624	8.57	0.054***	-0.048**		
GAM	7.035	7.085	7.057	0.028***	7.05	6.991	0.059***	-0.031***		
Pop	6.850	6.892	6.889	0.003	6.845	6.818	0.027***	-0.024***		
Express	10.012	10.228	10.152	0.076***	9.998	9.87	0.128***	-0.052***		
Mobile	8.837	8.874	8.885	-0.010***	8.841	8.794	0.047***	-0.057***		
PerInc	8.043	8.124	8.101	0.023***	8.025	7.998	0.027***	-0.004***		
Green	0.691	0.691	0.693	-0.002	0.69	0.691	-0.001	-0.001		
Size	1.158	1.196	1.183	0.013***	1.151	1.136	0.014***	-0.001		
N	1,209,791	178,550	210,222		380,281	440,738				
Number of stores	142,026	58,744	55,726	3018	103,646	90,883	12,763	-9745		
Periods		Jan. -June 2020	August-December 2019		Feb.-July 2018, Jan. - June 2019	Sep. 2017-Jan. 2018, Aug-Dec. 2019				

Notes: To avoid the influence of data skew distribution, all result variables Pop, and PerInc in city development variables and express and mobile in infrastructure variables in the table are converted by natural logarithms. \*\*\*, \*\*, \* denote significance at 1% level, 5% level, and 10% level, respectively.

**Table 3**  
The association between COVID-19 and online sales of agricultural product e-stores.

	(1)	(2)	(3)
<i>Treat</i> × <i>post<sub>t</sub></i>	1.048*** (28.43)	0.971*** (29.67)	0.968*** (29.78)
HHI		-0.796** (-2.40)	-0.758** (-2.30)
HHI5		0.642*** (3.36)	0.614*** (3.28)
SOB		2.120*** (5.03)	2.174*** (5.11)
GAM		0.680** (2.47)	0.661** (2.38)
Pop		0.056 (0.83)	0.113* (1.69)
Express		0.575*** (9.33)	0.572*** (9.22)
mobile		-0.366 (-0.90)	-0.409 (-0.99)
perInc		-0.128 (-1.10)	-0.120 (-1.03)
Green		0.063 (0.06)	0.039 (0.04)
Constant	7.355*** (281.35)	-17.683*** (-6.39)	-18.042*** (-6.46)
R-squared	0.046	0.051	0.052
Month FEs	Yes	Yes	Yes
Store FEs	Yes	Yes	Yes
Province × Time	No	Yes	Yes
City × Time	No	No	Yes
Cluster	City	City	City
N	1,209,791	1,209,163	1,209,163
Number of stores	142,026	141,999	141,999
Control Group	2017 Sept.-2018 Jul.	2017 Sept.-2018 Jul.	2017 Sept.-2018 Jul.
	2018 Aug.-2019 Jun.	2018 Aug.-2019 Jun.	2018 Aug.-2019 Jun.

Notes: This table presents the association between COVID-19 on e-stores' sales of agricultural products based on DID Equation (3). Standard errors are clustered at the city level, and robust t-statistics are in parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

#### 4. Identification strategy

After the outbreak of COVID-19, pandemic prevention control measures were implemented nationwide almost at the same time. To evaluate the association between COVID-19 and the related control measures and the online sales of agricultural products, we must consider the CLNY effect on online retail (Chen, et al., 2020). Similar to Christmas in Western countries, before CLNY Eve, Chinese e-commerce platform companies and e-stores offer various promotions or coupons to attract customers. After CLNY Eve, most people, including e-store staff and couriers, take a holiday trip to return to their hometowns. Therefore, in normal years, the period before CLNY Eve was the peak season for online retail, followed by the off-season after CLNY, with an average 30–50 % drop in orders (Tang and Feng, 2020; Guo et al., 2021), which is also supported by our descriptive evidence in Table 2. January 23, 2020 was the lockdown policy start date and the day before CLNY Eve. To control for the CLNY influence and other seasonality effects on online sales of food and agricultural products, we employ a difference-in-difference (DID) strategy to assess the association between COVID-19 and online sales of food and agricultural product e-stores. The purpose is to compare the change in online sales before and after the COVID-19 outbreak in 2020 with those of the same periods in previous years. More specifically, our DID model can be specified as follows:

$$Y_{i,t} = \alpha + \beta Treat_i \times Post_t + \gamma' X_{i,t} + C_i + \delta_t + \varepsilon_{i,t} \quad (3)$$

where the dependent variable,  $Y_{i,t}$ , is the monthly sales of agricultural products for e-store  $i$  in month  $t$ .  $Treat_i$  is the treatment dummy variable (=1 if in the treatment group, 0 otherwise).  $Post_t$  is the post period dummy variable (=1 if in the post period, 0 otherwise).  $X_{i,t}$  is a vector of time-varying control variables introduced in Section 3.2.2.  $C_i$  is the store fixed effect that captures time-invariance factors at the store level.  $\delta_t$  is the month fixed effect to control for the unobservable month effects on online sales (e.g., the effect of CLNY and other seasonality effects at the month level). The interaction terms of cities and time trends are also included to absorb unobserved temporal heterogeneity.  $\varepsilon_{i,t}$  is the random error term. The coefficient of interest,  $\beta$ , estimates the reduced form association between COVID-19 and the related control measures and online sales of food and agricultural product e-stores.

The DID model compares the outcomes of e-stores' sales from January to June 2020 and September 2019 to December 2019 (COVID-19 sample) relative to the difference in outcomes in the corresponding

lunar calendar months in the previous two years (non-COVID-19 sample as control). Our empirical strategy thus exploits the change in e-stores' sales before and after COVID-19 while differencing out the season effect and other potential factors that vary in the first and second halves of the year. The same strategy was employed by Chang and Meyerhoefer (2020) to evaluate the association between COVID-19 and offline consumption and by Ruan et al. (2021) as one of the identification strategies for evaluating the relationship between COVID-19 and the price of vegetables in wholesale markets in China.

The key assumption underlying the validity of the DID approach is the parallel trend assumption, an alternative to the counterfactual. The parallel trend assumption in our context implies that in the absence of COVID-19, the trend of e-store sales between the treatment and control groups is the same. Following the literature of related studies (Ruan et al., 2021; Fang et al., 2020), we can specify the following event analysis model to check the existence (or lack thereof) of the parallel pretrend:

$$Y_{it} = \alpha + \sum_{j=-5}^5 \gamma_j^* (Treat_i \times Period_j) + \beta' X_{it} + C_j + \delta_t + \varepsilon_{it} \quad (4)$$

where  $Period_j$  is defined as a set of dummy variables for specific periods representing the  $j$ th month before and after the COVID-19 outbreak, with "+" and "-" indicating after and before the event month, respectively. The coefficient  $\gamma_j$  estimates the relationship between COVID-19 and online sales of agricultural products during the corresponding time period  $j$ . The presence of parallel pretrend would mean that  $\gamma_j = 0$  for all the negative "j"s.<sup>6</sup>

## 5. Estimation results

### 5.1. Results of DID estimates

Table 3 reports the DID estimates of Equation (3) for the association between COVID-19 and the sales of agricultural products through e-stores. The DID results show that the COVID-19 pandemic is associated with a large and statistically significant (at 1 % throughout) surge in the monthly sales of agricultural products by an average e-commerce store. The results are also highly consistent across model specifications, with the estimated increase in online sales ranging between 97 % (Columns 2 and 3) and 105 % (Column 1).<sup>7</sup> These results are in line with those of related studies in other countries. In Canada, online digital ordering increased by 142 % in December 2020 compared to December 2019 (Goddard, 2021). Food delivery spending increased approximately 70 % in the first week of February 2020 in the USA (Baker, et al. 2020). Considering the stringency of the Chinese lockdown policies, it is not surprising to see that the increase in online sales of agricultural products in China is comparable to that in the U.S. and Canada.

<sup>6</sup> While it is standard to test for parallel pre-trends as a way to support the untestable assumption of parallel counterfactual trends, it is worth noting that the presence of parallel pre-trends does not necessarily mean that the untestable assumption of parallel counterfactual trends is satisfied.

<sup>7</sup> Due to the missing value of *HHIS* in 10 cities for some months, 628 observations were dropped in columns (2) and (3). To show how sensitive the results are affected by the change in observations, we follow the suggestion by one of the reviewers and set the missing values of *HHIS* to zero and include a dummy variable which equals one for the 628 observations and zero otherwise. The results from the new regressions (appendix table A1) are highly consistent with those in Table 3. For example, the coefficients of  $Treat \bullet Post_t$  only changed very slightly, from 0.971 to 0.970 and from 0.968 to 0.967, respectively.

**Table 4**

The association of COVID-19 and online sales of agricultural product e-stores by month.

	(1) Sales (log)	(2) Sales (log)
5 months before (j = -5)	-0.272*** (-4.615)	-0.168** (-2.017)
4 months before (j = -4)	-0.331*** (-6.004)	-0.237*** (-2.884)
3 months before (j = -3)	-0.017 (-0.374)	0.046 (0.727)
2 months before (j = -2)	-0.101*** (-3.390)	-0.052 (-1.080)
Event month (j = 0)	0.389*** (7.812)	0.308*** (3.624)
1 month after (j = 1)	0.420*** (4.676)	0.353*** (3.211)
2 months after (j = 2)	0.637*** (10.233)	0.509*** (5.393)
3 months after (j = 3)	1.230*** (21.364)	1.139*** (12.647)
4 months after (j = 4)	1.009*** (15.722)	0.901*** (9.317)
5 months after (j = 5)	1.363*** (20.116)	1.227*** (12.597)
Control variables	No	Yes
N	1,209,163	1,209,163

Notes: This table reports the dynamic relationship between COVID-19 and e-stores' sales of agricultural products based on Equation (6). The month before the outbreak of the pandemic (j = -1) was dropped as the base month, so the reported coefficients capture online sales of all other months relative to the dropped month. Control variables and fixed effects included are the same as Table 3. Standard errors are clustered at city level and robust t-statistics in parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

### 5.2. Dynamic relationship between the pandemic and online sales of e-stores

The DID estimates in Table 3 capture the overall association between COVID-19 and the control measures on the monthly online sales of agricultural products over the 5-month period starting after the onset of COVID-19; however, they do not show how the relationship evolves over time. The results of the event analysis (Equation (4)) not only present the month-by-month association between COVID-19 on online sales of agricultural products during the post-COVID months but also allow us to check the existence (or lack thereof) of the parallel pre-trends based on a joint test for the coefficients of the pre-COVID months. The results from the event analysis are shown in Table 4 and Fig. 2.

Three important findings emerge from the analysis. First, the results for the months preceding the outbreak of COVID-19 suggest that there is no strong evidence that the monthly sales for the pre-COVID months of 2020 performed very differently from those in previous years (Column 2), especially for the two months immediately before the pandemic (K = -2 and K = -3). Using K = -1 (December 2019) as the base group, the coefficients for K = -2 (November 2019) and K = -3 (October 2019) are not only statistically insignificant, and the magnitude is extremely small (-0.052 and 0.046, respectively). Second, not only are the results from the post-COVID months statistically significant at 1 % throughout but the magnitudes are much larger and positive, showing that the COVID-19 pandemic is associated with a surge in online sales of agricultural products. Third, although the increase in online sales of agricultural products was immediately apparent after the outbreak of COVID-19, the increase generally accelerated over time. While the pandemic is associated with an increase in online sales of agricultural products by 30 % and 35 % during the first and second months after the outbreak of the pandemic, the surge of online sales peaked in the fourth month (114 %) and again in the sixth month (122 %), suggesting that COVID-19 facilitated the emergence of e-commerce of food and agricultural products.



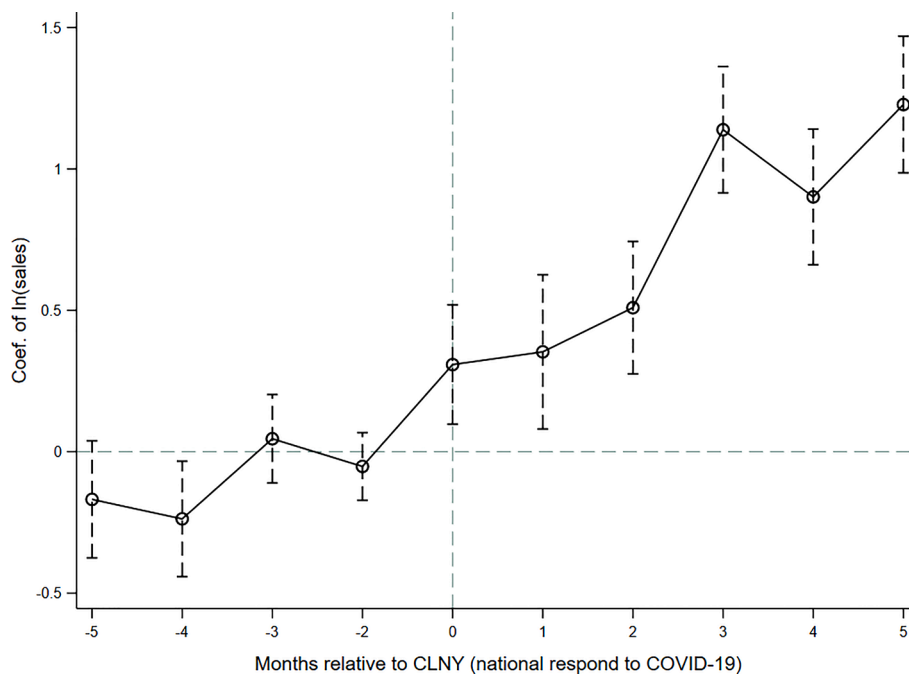


Fig. 2. Event Analysis on the relationship between COVID-19 and monthly sale of e-stores of agricultural products. Notes: The circles are point estimates of DID, and the intervals are the 99 percent confidence intervals. The dependent variable is ln(sales).

Table 5

Heterogeneity in the association between COVID-19 and online sales of agricultural product e-stores.

	(1) Hubei Province	(2) Non-Hubei Province	(3) Fresh foods	(4) Storable foods	(5) Specialty leisure products	(6) Micro stores	(7) Small stores	(8) Medium & large stores
<i>Treat</i> × <i>post</i>	0.007 (0.071)	0.991*** (29.676)	1.054*** (28.598)	0.962*** (18.559)	0.525*** (6.608)	0.688*** (23.545)	0.182*** (6.961)	0.208*** (4.253)
<i>N</i>	66,779	1,142,384	588,091	523,008	98,064	1,064,797	98,064	46,302

Notes: The dependent variable is ln(sales). Each column reports the coefficient of treat from one regression with controls for e-store FE, month FE. Standard errors are clustered at city level. Robust *t*-statistics in parentheses. \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

The results of the event analysis can alternatively be displayed more vividly and clearly as in Fig. 2. The results on the right side (post-COVID months) are in clear contrast to those on the left side (pre-COVID months). While the results on the left show that the online sales of agricultural products for the pre-COVID months in the COVID year (September 2019- June 2020) relative to the same period in the non-COVID years (August 2017-July 2018 and September 2018-June 2020) fluctuated around zero with smaller negative values in general, the results on the right side indicate that the online sales of agricultural products accelerated for most of the first six months after the onset of COVID-19.

### 5.3. Heterogeneity analysis

In addition to the overall association between COVID-19 and online sales of agricultural products estimated above, we also examine the heterogeneity in the association between COVID-19 on online sales of agricultural products across different groups. First, we expect the association to vary with the degree of stringency of lockdown policy. Second, we expect the association to vary with the storability and function characteristics of different product categories. Finally, we are also interested in examining the heterogeneity in the association across the sizes of e-stores. To explore the heterogeneity along these dimensions, the same DID equation is regressed for several subsamples.

The results of the heterogeneity regressions are reported in Table 5. The result of the Hubei Province subsample is insignificant and much smaller than that of the non-Hubei Province sample (0.007 vs 0.991).

There are two possible explanations for these seemingly unexpected results. First, as the worst-affected region and where the virus was first discovered, the government implemented the most stringent lockdown and stay-in-home measures in Wuhan and other cities of Hubei Province. Meanwhile, express logistics between Hubei and other provinces were specially arranged to ensure that the supplies of essential agricultural commodities were unlocked while minimizing human contacts. The unprecedented control measures in Hubei Province posed a huge challenge in the local market to nationwide e-commerce platforms outside of Hubei, which typically involve long-distance transportation of goods. However, more flexible local e-commerce models were developed rapidly through coordination between local governments and third-party enterprises or through local social networking platforms to reduce long-distance transportation. Therefore, it is the local e-commerce models (rather than the nationwide e-commerce platforms) that acted as the primary e-commerce model in Hubei Province before May 2020 (Guo et al., 2021).

The results in Columns (3) - (5) indicate that during the COVID-19 period, the sales of fresh food and agricultural products increased much more than the sales of storable products and specialty leisure products. Chinese families usually purchase fresh foods offline, such as fruit, vegetables and meat, but purchase specialty leisure products from stores both offline or online. With the shift of the consumption channel from offline shopping to online shopping in response to COVID-19 and the lockdown measures, it is anticipated that the food items that were sold through offline markets in usual years (e.g., fresh fruit, vegetables, and meat) would be affected more by COVID-19 and the associated

control measures. On the other hand, as a considerable amount of specialty leisure products was purchased through e-commerce stores before the pandemic, the association is expected to be weaker. Another reason why specialty leisure products are less associated is that they are not conceived as being as essential as fresh foods. It is interesting to note that the relationship between COVID-19 and online sales of storable foods was barely smaller than that of fresh foods (a surge of 96 % vs 105 %). One reasonable explanation is that consumers may have also substituted fresh foods with storable foods (canned foods), which is a possibility that was also raised by Ruan et al. (2021).

In terms of business scale, Columns (6)-(8) indicate that micro e-stores experienced a larger sales growth than small e-stores, as well as the mid and larger e-stores (69 % vs 18.2 % vs 20.8 %). It is worth noting that this result is significantly different from previous studies on the relationship between the pandemic and offline enterprises, which were based on questionnaire surveys. For example, the survey by Zhu et al. (2020), conducted during the early stage of the pandemic, shows that 85 % of small, medium and microenterprises were unable to maintain their cash balance for three months. In a survey by Zhang and Yang (2020) conducted in the middle of March 2020, 70 % of the enterprises with <50 employees had not yet returned to work. There are two reasons to explain the difference. First, previous studies sampled all enterprises, but e-commerce enterprises account for only a small portion of these enterprises. Therefore, their results show overall association on enterprises from all industries. However, how e-commerce enterprises' response to the pandemic is obviously different from that of other industries. Second, the self-employed micro e-stores, which account for nearly 85 % of agricultural product e-stores, are mainly operated by households. They are basically uninfluenced by the disruption of employment. In contrast, the large flagship e-stores will be more affected due to the large scale of the operations team. No one was prepared for the sudden shock of COVID-19; however, maintaining decentralization to a certain level in normal years, which has a disadvantage regarding operational efficiency, would reduce environmental risks and improve supply chain resilience when a situation similar to the COVID-19 pandemic is coming (Aday and Aday, 2020).

## 6. Mechanism analysis

The theory of the platform economy indicates that the market expansion of e-commerce platforms has significant cross-side and same-side network effects, which bring about the improvement of operational efficiency and competitiveness (Armstrong, 2006; Hinz, et al., 2020; Rysman, 2009). However, the outbreak of COVID-19 is the first major public health crisis to occur since the development of the platform economy. The customers and orders on the buyers' side increased sharply, mainly due to the shift of consumption channels rather than the cross-side network effect. If sales growth mainly comes from an increase in customers, then growth is more likely to be sustained. However, if the growth mainly comes from the rise of price or rush purchase, then the growth is bound to fall later. The latter two situations have been confirmed by relevant research (Ruan, et al., 2021; Wang and Na, 2020). The availability of data on orders, unit order prices, the number of new e-stores and the number of stores closed allow us to directly check some of the mechanisms underlying the growth of online sales of agricultural products.

### 6.1. A sub-component analysis: quantity of customer orders vs unit price per customer order

For an e-store, its sale is equal to the product of quantity of customer orders (QCO) and unit price per customer order (UPCO). The growth of sales may come from the joint growth of the latter two or mainly from the growth of one of them. The increase in either the quantity of customer orders or the unit price per customer order implies a potential shift in consumers' purchase behaviors from offline to online channels.

**Table 6**

The associations between Covid-19 and QCO, UPCO and CUPCO of agricultural product e-stores.

	(1) QCO (log)	(2) UPCO (log)	(3) CUPCO (log)
<i>Treat × Post</i>	0.464*** (16.161)	0.452*** (27.555)	0.415*** (26.958)
<i>N</i>	1,209,163	1,209,163	1,209,163

*Notes:* This table reports the association between Covid-19 and e-stores' sales of agricultural products based on DID equation (1). The dependent variables of column 1–3 are monthly QCO, UPCO and Comparable Unit Price per Customer Order (CUPCO), respectively. Control variables and fixed effects included are the same as table 3. Standard errors are clustered at city level and robust *t*-statistics in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

The former implies an increase in the number of customers or an increase in consumers' purchase frequency, while the latter implies (1) an increase in the quantity of goods purchased per order or (2) an increase in food product prices. However, we posit that the rise of food product prices by e-stores during the pandemic period is unlikely. In fact, the Chinese central and local government has implemented many policies to ensure the stability of prices since February 2020 (Ye et al., 2020). Except for the short-term rise in the price of protective articles, i.e., masks, in the early stage of the epidemic, food prices are found to be quite stable (Yu et al., 2020). Moreover, monthly data can absorb the short-term price fluctuations. It is argued that the digitization of the agricultural product supply chain is likely to decrease the prices of products and services rather than raise prices (Dannenberg, et al., 2020; Reardon and Timmer, 2012). A study on the effect of the COVID-19 pandemic on the food prices of a large number of food products sold through the Amazon platform finds that the overall price level of fresh food at Amazon even slightly decreased during the COVID-19 pandemic (Hillen, 2021). A previous study has shown that many consumers purchased more than usual to avoid shopping in stores offline (Chenarides et al., 2021). Therefore, the UPCO increase is mostly likely to reflect an increase in the quantity of food products per order.

To examine which factor plays a more important role, we treat QCO and UPCO as two sub-component variables of the online sales of agricultural product e-stores since the onset of COVID-19 in equation (1). The results are reported in Table 6.

The results of Table 6 show that the COVID-19 outbreak is associated with a significant increase in both QCO and UPCO (both significant at 0.01 level). The magnitudes of increase are also similar in both cases (46.4 % for QCO and 45.2 % for UPCO, respectively). Adjusting for price inflation only slightly reduced the change on UPCO from 45.2 % to 41.5 % (column 3). Therefore, considering the huge base of online shopping users in China, the results tend to suggest that the growth of online sales of agricultural products during the COVID period was largely contributed by the substantial increase in the number of new online customers (and/or more frequent online purchases) and unit package size of agricultural products.

### 6.2. Entry and exit of e-commerce stores

As described in Section 3, the large panel data allow us to generate the number of new entering e-stores, number of exiting e-stores, and number of active e-stores, as well as the entering rate and exiting rate of e-stores, all at the city level. These variables can partially address the supply side of e-commerce for agricultural products during the pandemic period. Table 7 reports the results of the association between the pandemic and the e-store entry and exit by estimating Equation (3) with the city-level new entry and exit variables as the dependent variables and the corresponding city-level control variables on the right side. The regression results for the number of new e-stores, number of e-stores closed, number of active stores, entry rate and exiting rate are reported in Columns 1–5.

**Table 7**  
The association between COVID-19 and e-store entry and exit.

	(1) New entering e-stores (log)	(2) E-stores closed (log)	(3) Existing e-stores (log)	(4) New entering e-stores (rate)	(5) E-stores closed (rate)
<i>Treat × Post</i>	-1.573*** (-27.541)	0.480*** (14.700)	-0.113*** (-8.201)	-0.094*** (-28.844)	0.023*** (8.219)
<i>Control variables</i>	Yes	Yes	Yes	Yes	Yes
<i>Month Fes</i>	Yes	Yes	Yes	Yes	Yes
<i>City Fes</i>	Yes	Yes	Yes	Yes	Yes
<i>Province × Treat</i>	Yes	Yes	Yes	Yes	Yes
<i>City × Time</i>	Yes	Yes	Yes	Yes	Yes
R-squared	0.47	0.19	0.39	0.38	0.19
N	3899	3781	3899	3899	3899

Notes: This table presents the DID estimates of the ATEs of COVID-19 on Chinese agricultural product e-stores' enter and exit at city level. Control variables included are the same as Table 3. Standard errors are clustered at the city level and robust *t*-statistics are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table 8**  
The association between COVID-19 and sales of agricultural product e-stores at the city level.

	(1) Total sales (log)	(2) Mean sales (log)	(3) Median sales (log)	(4) Total QCO (log)	(5) Mean QCO (log)	(6) Mean UPCO (log)
<i>Treat × Post</i>	0.100*** (3.220)	0.213*** (7.673)	0.736*** (21.233)	0.098*** (2.64)	0.211*** (5.794)	0.084*** (10.185)
<i>Control variables</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Month Fes</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>City Fes</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Province×Treat</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>CityTime</i>	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.33	0.43	0.43	0.33	0.41	0.23
Observations	3899	3899	3874	3899	3899	3899

Notes: This table presents the DID estimates of the associations between COVID-19 and agricultural product e-stores with different outcome variables at the city level based on Equation (3). Control variables included are the same as Table 3. Standard errors are clustered at the city level and robust *t*-statistics are in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

As seen from Table 7, COVID-19 poses great difficulties for the entry of new e-stores. Specifically, the results of Column (1) show that the number of newly opened stores decreased by 157 % in the first half of 2020, while Column (2) shows that the epidemic resulted in a significant increase in the number of closed stores (48 %). A decrease in newly opened stores and an increase in the number of stores closed will inevitably reduce the number of existing e-stores, which is also confirmed by the fact that the number of active e-stores was reduced by 11.3 % (Column 3). However, due to the large number of existing e-stores, the contribution of the reduction of new entry and the increase in the exit of e-stores to the overall reduction of e-stores is relatively small, by 9.4 % (Col. 4) and 2.3 % (Col. 5), respectively. We expect that the loss of sales due to the reduction of active e-stores was likely offset by an increase in the number of orders or quantity per unit of order of the active e-stores. Considering that the average monthly sales of an average e-store has almost doubled since the onset of COVID-19, much larger than the 11.3 % (assuming the 11.3 % loss of sales were fully substituted), it can be further suggested that the growth of online sales of agricultural products in the first half of 2020 comes mainly from the behavioral changes in the demand side (increase in the total number of orders and the quantity of products per order).

6.3. Change in overall e-commerce of agricultural products

The results above indicate two competing effects on the e-commerce of agricultural products. The analysis based on store-level data shows a drastic increase in online sales of an average e-store since the onset of COVID-19. In contrast, the analysis based on city-level data indicates that the pandemic reduced new entry while increasing the number of stores closed. These two competing effects make the net relationship between the pandemic and the e-commerce of agricultural products at the

industrial level or city level ambiguous. To understand the overall relationship at the industrial level and explore the growth distribution across e-stores, we estimate the overall association of COVID-19 and the e-commerce of agricultural products using city-level data, as shown in Table 8.

Table 8 shows that the outbreak of COVID-19 is associated with a significant increase in the total monthly online sales of food and agricultural products (Column 1), suggesting that the increase in sales at the store level not only offset the reduction of sales associated with fewer new entries and more exits of e-stores but also outperformed it, which resulted in a net growth of online sales of agricultural products. The magnitudes of the different outcome variables give us more insights. Overall, the pandemic increased the online sales of agricultural products by 10 %. The mean of e-stores' sales in a city increased by 21.3 % (Col. 2), while the median increased by 73.6 % (Col. 3), all of which suggests that the micro and small stores experienced much higher growth in sales than large stores. This finding is consistent with the results of Columns (6)-(8) of Table 5. The significant increases in total QCO, mean QCO and mean UPCO at the city level further confirm that the online sales growth is mainly due to the increase in new customers and the increase in quantity of agricultural products per order.

7. Policy implications

Abundant anecdotal evidence has already suggested that the pandemic might have facilitated the digital transformation of the supply chain of food and agricultural products. However, the literature is largely based on data from phone and online surveys of a relatively small number of consumers or enterprises. Our study is of much more policy relevance because it is based on data from a large sample of e-stores and investigates the overall sale's growth as well as the heterogenous growth

across different e-stores.

First, our findings show that e-commerce provides more online orders (46 % growth) of agricultural products for more customers and plays an important role in unblocking the urban–rural cycle during the pandemic. The results provide strong support for industry policies promoting the digital transformation of the agri-food supply chain to increase its flexibility during the ongoing and future public health crisis. Our results also show the importance of a good relationship between government and market development and the local infrastructure in promoting the e-commerce of agricultural products during the pandemic period. Given the large regional differences in governance and markets as well as the regional difference in infrastructure (Ma and Fang, 2020; Tang et al., 2020), they are critical to the development of e-commerce. According to Ali reports, the regional difference and difference between rural and urban areas in e-commerce development will remain large in 2021 (AMI and AliResearch, 2022). Improving local transportation and logistical infrastructure and enhancing the effectiveness of local governance should be an important condition for the more balanced development of e-commerce to benefit a broader range of people to access food during crisis times.

Second, the results indicate that the pandemic and the associated lockdown measures significantly reduced the entry and encouraged the exit of e-stores, and the existing micro and small e-stores are more resilient and experienced a larger growth in sales. Therefore, while paying attention to the digitalization transformation of traditional industries, it is necessary to support online operating entities (especially those of micro and small operational scales) with tax abatement and brand building so that they can not only gain higher market competitiveness but also improve the resilience of the agricultural product supply chain and stabilize off-farm employment for farmers.

Finally, our research findings also offer some guidance to international communities that are currently struggling with food insecurity problems. We find relatively few studies on this topic using data from Africa, Latin America and Central Asia, except for some anecdotal evidence (Alcedo et al., 2022; Reardon et al., 2021). More rigorous analysis using large and more representative datasets from farmers, consumers or e-service providers are needed to understand the performance and role of e-commerce and ICT technologies in general in addressing food insecurity during the public health crisis. This is especially important because most of the past pandemic started in the developing world, and these countries tend to suffer the most from the crisis.

## 8. Conclusions

The COVID-19 pandemic has undoubtedly been the largest public health crisis in the last century. Countries and industries around the world have implemented measures to reduce the negative effects of the pandemic. Digitalization provides a powerful tool to reduce the shock and even usher in development. Many studies have asserted that the pandemic setting provides a window of opportunity for e-commerce to expand rapidly. Although digitalization during the COVID-19 period is one of the most discussed topics, studies using rigorous methods and microlevel big data are rare. This paper provides direct evidence of the relationship between COVID-19 and the development of the e-commerce of agricultural products using operational data from a large number of e-stores in China. The DID method was employed to identify and quantify the association between COVID-19 and food and agricultural product online sales, and how the association varies with e-store characteristics.

The DID results show that COVID-19 was associated with a substantial growth in the online sales of agricultural products. Fresh agricultural products with high repurchase frequency and a high degree of perishability experienced a larger growth in online sales. Micro- and

small-sized e-stores enjoyed a higher growth rate of sales than large-sized e-stores. Furthermore, mechanism analysis indicated that online sales growth was mainly due to the increase in the number of customers (i.e., number of orders) and customer unit order price. The days of implemented lockdowns, developed intercity transportation and expressed logistics for last miles are associated with the increase of online sales for agricultural products. Meanwhile, COVID-19 was associated with a significant decline in the entry of new e-stores and a significant increase in the number of stores closed. Further analysis using city-level sales data indicates that the COVID-19 pandemic was associated with a net increase in the online sale of agricultural products (by 10 %) and reconfirms that the micro- and small-scale e-stores experienced a larger growth and that the overall number of orders at the city level increased by 12 %.

The operational data from a large number of e-stores make it possible to explore the association between the COVID-19 pandemic and the e-commerce of agricultural products at the e-store and city levels; however, a lack of data on the characteristics of e-store operators limits our ability to investigate how pandemic and industry assistance policies affect the performance of e-stores across the characteristics of e-store operators and the ensuing implications on the production and circulation of agricultural products. Future research using e-commerce platform data combined with agricultural product suppliers' characteristic data will allow us to examine some of these issues. In the future, we also hope to have access to operational data of e-stores for more post-COVID months so that we can also evaluate the longer-term association between COVID-19 and agricultural e-commerce. While we were able to demonstrate that the demand for online food supply from consumers has been the main driver for the surge in online sales of agricultural products during the pandemic period, our data do not allow us to understand the mechanism underlying this finding. This exploration is also left for future research.

## CRedit authorship contribution statement

**Jianxin Guo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Songqing Jin:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Jichun Zhao:** Data curation, Investigation. **Hongbiao Wang:** Data curation, Investigation. **Fang Zhao:** Data curation, Investigation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A

See Tables A1–A2.

**Table A1**  
The association between COVID-19 and Chinese e-stores' online sales of agricultural product e-stores (including dropped observations in Table 3).

	(1)	(2)	(3)
<i>Treat •Post<sub>t</sub></i>	1.048*** (28.43)	0.970*** (29.69)	0.967*** (29.81)
<i>HHI</i>		-0.803** (-2.43)	-0.768** (-2.33)
<i>HHI5</i>		0.646*** (3.40)	0.619*** (3.31)
<i>SOB</i>		2.120*** (5.03)	2.175*** (5.10)
<i>GAM</i>		0.680** (2.48)	0.662** (2.38)
<i>Pop</i>		0.056 (0.83)	0.112* (1.69)
<i>Express</i>		0.575*** (9.34)	0.572*** (9.25)
<i>mobile</i>		-0.368 (-0.90)	-0.410 (-1.00)
<i>perinc</i>		-0.127 (-1.10)	-0.119 (-1.02)
<i>Green</i>		0.068 (0.06)	0.045 (0.04)
<i>Dropped</i>		-0.102 (-0.42)	-0.066 (-0.27)
<i>Constant</i>	7.335*** (281.35)	-17.677*** (-6.40)	-18.045*** (-6.47)
<i>R-squared</i>	0.046	0.051	0.052
<i>Month FEs</i>	Yes	Yes	Yes
<i>E-store FEs</i>	Yes	Yes	Yes
<i>Province × Time</i>	No	Yes	Yes
<i>City × Time</i>	No	No	Yes
<i>Cluster</i>	City	City	City
<i>N</i>	1,209,791	1,209,791	1,209,791
<i>Number of e-stores</i>	142,026	142,026	142,026
<i>Control Group</i>	2017 Sept.-2018 Jul.	2017 Sept.-2018 Jul.	2017 Sept.-2018 Jul.
	2018 Aug.-2019 Jun.	2018 Aug.-2019 Jun.	2018 Aug.-2019 Jun.

Notes: The regressions reported in this table is to address the sample size difference between column 1 of table 3 (full sample) and columns 2 and 3 of table 3 (missing 628 observations due to missing values for HHI5). To address this, we generate a dummy variable that equals one for the missing observations and replace the missing value of HHI5 by zero. We then re-estimate the same regressions as in Table 3 with the addition of the newly created dummy variable and the new HHI5 variable using the full sample. Robust *t*-statistics are in parentheses, \*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1.

**Table A2**  
Trends of online sales of agricultural product e-stores between the pre- and the post-COVID periods.

<i>Post*Month</i>	0.042*** (15.185)
<i>Month</i>	-0.062*** (-19.504)
<i>Post</i>	0.112*** (12.886)
<i>Cons</i>	0.181 (1.622)
<i>R-squared</i>	0.87
<i>N</i>	388,772

Notes: This table reports the trend analysis on online sales of agricultural product e-stores between the pre-COVID and the post-COVID periods. For the month variable, we assign 0, 1, 2, 3, 4, 5 for each of the five pre-treatment months and 6, 7, 8, 9, 10, 11 for each of the six post-treatment months. For the post variable, it equals to 1 for the post-COVID months and 0 for the pre-COVID months. E-store fixed effects are included, and standard errors are clustered at city level. Robust *t*-statistics in parentheses. \*\*\* *p* < 0.01, \*\* *p* < 0.05, \* *p* < 0.1.

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