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Abstract

Vegetable pesticide residues are a pervasive food safety concern. Utilizing over half a million records of vegetable tests from 287 cities, we find that COVID-19 increases the national average pesticide residue by 11% during the peak months of the pandemic in China. The pandemic nearly doubled the pesticide testing failure rate in cities with the highest infection rates. Empirical evidence suggests that the estimated effect stems from pandemic-induced disruptions in vegetable production and transportation, which result in untimely pest control and subsequent overuse of pesticides. Pandemic-related vegetable pesticide residue changes increase health risks by up to 10% in cities with the highest COVID-19 infection rates. Our findings underscore the significant impact of social disruptions on food safety through a channel largely overlooked in the literature.

Keywords: social disruptions, food safety, COVID-19, vegetable pesticide residue, health

1 Introduction

Social disruptions, such as pandemics and natural disasters, can affect food security by disrupting agricultural production and transportation, which may even lead to serious food safety issues (De Haen and Hemrich, 2007; Laborde et al., 2020; Ristaino et al., 2021).[1] During the disruptions, food production and logistic disruptions may prevent farmers from adopting optimal food safety standards. For example, pandemics may prevent the timely use of pesticides and fertilizers, and to compensate for yield losses, farmers may overuse pesticides and fertilizers later, leading to food safety problems. Similarly, the lack of timely transportation may force farmers to apply more food preservatives, which can bring about food safety issues. This study utilizes data from COVID-19 to infer the potential impact of social disruptions on food safety.

Specifically, we examine the impact of the COVID-19 outbreak on vegetable pesticide residues, using data from over 656,000 records of vegetable pesticide residue testing conducted during the pandemic in China. Vegetable pesticide residues are one of the major global food safety concerns (Zilberman et al., 1991; Friedle et al., 2021; Wilson and Tisdell, 2001). Intensive agricultural practices have led to widespread pesticide use to control pests and maximize yields, resulting in the accumulation of pesticide residues in vegetables (Morrison Paul et al., 2002; Li et al., 2021). Vegetable pesticide residues could cause acute and chronic health effects, especially among young children (Pascale and Laborde, 2020; Sunding and Zivin, 2000; Eom, 1994; Hoffmann et al., 2019).

Vegetable production and transportation were significantly affected during the COVID-19 in China, where strict epidemic prevention and control policies were implemented. Once diagnosed as positive in a COVID-19 test, individuals are promptly isolated for treatment. The duration of isolation typically lasts for at least 14 days.

[1] Food security is about ensuring that people have access to enough nutritious food to lead healthy lives, while food safety is about ensuring that the food people consume is free from harmful contaminants and is safe to eat (Shaw, 2007). Both concepts are essential for public health and well-being, but they address different aspects of the food system.

Additionally, people who have been to areas with high or medium risk of the epidemic also face the risk of being quarantined. The COVID-19 pandemic reduced working time flexibility and labor hiring in rural areas. Due to the transportation disruptions caused by the COVID-19 lockdowns, high or medium-risk areas faced severe shortages of vegetable supplies (Ruan et al., 2021). If the pandemic prevents farmers from purchasing or applying pesticides promptly, subsequent pest outbreaks could potentially lead to excessive use of pesticides. In addition, the pandemic might have disrupted the supply chain and delayed the sale of vegetables, which could lead farmers to use additional pesticides to preserve vegetables. Our data support these concerns. A simple summary of statistics shows that cities with a high vegetable pesticide test failure rate are usually those with a high COVID-19 infection rate during the pandemic (Figure 3).

We identify the impact of COVID-19 on vegetable pesticide residue based on the plausibly exogenous rollout of COVID-19 across Chinese cities. An event study shows that cities with early and later COVID-19 outbreaks had no differential trends in vegetable pesticide test failure rates before the pandemic, while the test failure rate significantly increased in cities with COVID-19 outbreaks. Our difference-in-differences estimates suggest that a 1 percentage point increase in the COVID-19 infection rate significantly increases the pesticide residue testing failure rate by 5.5 percentage points. The peak impact of the COVID-19 pandemic raised the national failure rate for vegetable pesticide testing by 11 percent. In the top 1 percent of cities with the highest COVID-19 infection, the pandemic almost doubled the pesticide testing failure rate. These findings are robust to including various control variables, using different sets of fixed effects, and adopting alternative estimation methods.

We also present evidence supporting that the COVID-19 pandemic increases vegetable pesticide residue by impacting vegetable production and transportation. First, we find that COVID-19 had a larger effect on pesticide residue in vegetable-exporting cities than in vegetable-importing cities. Second, we find that the COVID-19 outbreak significantly reduced the vegetable output of a city. Third, we show that COVID-19 had no significant effect on the pesticide testing failure rate of processed vegetables. Fourth, we find a larger effect on the testing failure rate in small and poor cities with weaker vegetable supply chains. Finally, we find no effect on the testing failure rate of pesticides that are unlikely affected by the pandemic-caused disruption in vegetable production and transportation. We also show that the elevated testing failure rate is not caused by more stringent testing standards. The test standard is mandated by the central government and has remained constant throughout the pandemic.

Finally, we evaluate the effect of COVID-19 on health risks through vegetable pesticide residue. We combine the estimated city-level effect of COVID-19 on pesticide residue with the marginal effect of vegetable pesticide intake on health risks derived from the literature. Our database contains information on the exact residue level of each pesticide that is assessed as failed in each test. We find that while the mean effect of the pandemic-caused health risk through vegetable pesticide residue is low (0.16%), the effect could be quite large in cities with high COVID-19 infection rates. For example, COVID-19 increased the health risk by 2.5% in Shanghai, 4.6% in Sanya, and 9.6% in Wuhan during 2020–2022.

By examining the effect of COVID-19 on vegetable pesticide residue, this study contributes to understanding the impact of social disruptions on food safety. Although many studies have examined the effect of social disruptions on food security (e.g., Laborde et al., 2020; Ristaino et al., 2021; Alabi and Ngwenyama, 2023), the impact of social disruptions on food safety has been generally ignored (see Béné (2020) and Munialo and Mellor (2024) for the most recent reviews of the literature). Our study shows that vegetable production and logistic disruptions during the pandemic led to a significant increase in vegetable pesticide residue, creating substantial health risks for all vegetables consumers. We also find that the health risk is much higher in small and poor cities with weaker vegetable supply chains, suggesting that more attention should be paid to food safety issues in disadvantaged small and poor cities during a social disruption.

Our study also contributes to understanding the determinants of vegetable pesticide residue. Vegetable pesticide residuals are a global concern as recent intensive agricultural practices led to widespread pesticide use to control pests and maximize yields (Zilberman et al., 1991; Friedle et al., 2021; Wilson and Tisdell, 2001). Understanding factors that affect pesticide residue has important policy implications as pesticide overuse may create long-term environmental damage, such as groundwater contamination (Lai, 2017) and pesticide resistance (Gagic et al., 2021), and acute and chronic health effects (Pascale and Laborde, 2020; Sunding and Zivin, 2000). Existing studies on the determinants of pesticide residues generally focus on the effect of other factors such as farming technologies (Tambo et al., 2021), related regulations (Möhring et al., 2020), and enforcement stringency (Foster and Babcock, 1991). This study is the first to examine the impact of a social disruption on vegetable pesticide residue and to explore potential channels of this effect.

Finally, this study contributes to understanding the impact of COVID-19. Many studies find that COVID-19 severely disrupted daily lives and adversely impacted physical and mental well-being (Paakkari and Okan, 2020), labor markets (Coibion et al., 2020), productivity (Bloom et al., 2023), and inequality (Adams-Prassl et al., 2020). Our study highlights an unexpected channel of the impact of COVID-19 on health and the environment: vegetable pesticide residue. Based on more than half a million records of vegetable pesticide residue testing during the pandemic, this study finds that the pandemic-caused vegetable production and disruptions substantially increased health risks by increasing vegetable pesticide residue. This finding is consistent with the observation that the lack of access to fresh vegetables is a major issue in pandemic-affected regions (Richards and Rickard, 2020; Çakır et al., 2021; Ruan et al., 2021). In addition, as a high level of pesticide residue corresponds to a high level of pesticide use and environmental pollution (Braga et al., 2020; Tang et al., 2021), our finding also suggests a negative environmental effect of COVID-19.

The paper is organized as follows. Section 2 provides the study background. Section 3 details the data and empirical strategies. Section 4 presents the main empirical results and Section 5 concludes. Additional results are presented in the Appendix.

2 Background

2.1 Impacts of pesticides

Pesticides, including both chemical and biological agents, are indispensable in modern agriculture for controlling pests that threaten food security. Pesticide use is instrumental in increasing agricultural productivity and essential for sustaining the global population (Schneider et al., 2023; Wang et al., 2022). The benefits of pesticide use need to be evaluated against potential adverse impacts as the unregulated and excessive application of pesticides is associated with a plethora of environmental and health risks (Tang et al., 2021), such as environmental pollution, decreased biodiversity, and potential for health hazards arising from the presence of pesticide residues in food (Zou et al., 2023). Moreover, the human consumption of vegetables contaminated with pesticide residues has been implicated in a range of health concerns (Li et al., 2021), such as endocrine disruption and increased carcinogenic risks, highlighting the need for a balanced approach to pesticide use.

2.2 Pesticides regulation in China

The Chinese government has implemented a comprehensive strategy to control and monitor pesticide residues in the food supply chain. First, China has established a robust regulatory framework that includes setting stringent maximum residue limits for pesticides in food, aligning with international standards.[2] Second, China has implemented risk-based monitoring, focusing on crops that are most likely to be contaminated and pesticides that pose the highest risk to human health. Third, a critical component of the monitoring strategy is the systematic sampling and testing of agricultural products at various stages of the supply chain, from the farm to the market. Finally, efforts are made to increase public awareness about pesticide residues and food safety, such as the publication of testing results and the enforcement actions taken against non-compliance. Despite these efforts, monitoring has detected regular instances where pesticide residues surpass the national limits, underscoring the imperative for ongoing enhancement in pesticide regulation and management practices.

2.3 COVID-19 control in China

Individuals diagnosed as positive are promptly isolated for treatment and close contacts are traced and quarantined to curb the spread of the virus during COVID-19. Local communities ensure the reporting and supervision of positive test results through various mechanisms. Electronic Health Code Systems that use mobile apps and other means to record and track individuals' health information and test results in real-time, ensuring proper handling and isolation of positive cases. The duration of isolation typically lasts for at least 14 days following diagnosis. A positive test result significantly impacts individuals' daily lives and work. Positive patients are usually prohibited from going outside, participating in group activities, or visiting public places to reduce the risk of transmission.

[2] Global entities such as the Codex Alimentarius Commission play a pivotal role in establishing guidelines for maximum residue limits of pesticides in foodstuffs to safeguard consumer health (Drogué and DeMaria, 2012).

3 Data and Method

3.1 Data

3.1.1 Vegetable pesticide residue

We construct a comprehensive dataset on vegetable pesticide residue based on the food safety sampling and testing information disclosed by 247 organizations of the Administration for Market Regulation in China. As stipulated by the Food Safety Laws, these organizations are mandated to conduct randomized sampling across all segments of the food supply chain in all prefecture cities in mainland China and to publicly disseminate the test outcomes. We construct the dataset in the following steps. First, we located all official websites hosting food safety test outcomes. Second, we retrieved all relevant documents from each identified website.[3] Third, we employed various algorithms to extract tabular data from the acquired files, ensuring a comprehensive collection of testing records.[4] Finally, we purged files unrelated to vegetable pesticide residue testing, such as the records of non-vegetable items and legal documents pertaining to court cases.

We obtained a dataset containing 656,000 records of vegetable safety sampling and testing from 287 out of the 293 prefecture cities in mainland China from 31 January 2020 to 31 December 2022.[5] Each record contains the name and category of the vegetable tested, the time and location of the test, and the pass/fail assessment of the test. For tests assessed as "failed," the records also contain the name of each exceeded pesticide, the level of each exceeded pesticide, and the standard of the assessment.[6]

[3]The Administration for Market Regulation organizations post their test results in a variety of formats.

[4]We developed a custom mapping schema to align disparate column names across all formats to a unified set of food safety test attributes, facilitating the integration of data into a singular, coherent dataset.

[5]Data before 2020 are only available for a small number of prefecture cities, and data after 2022 are generally not available when we construct the dataset.

[6]For records documenting failed tests, we have employed advanced natural language processing techniques to meticulously extract information regarding detected adulterants from the inspector's

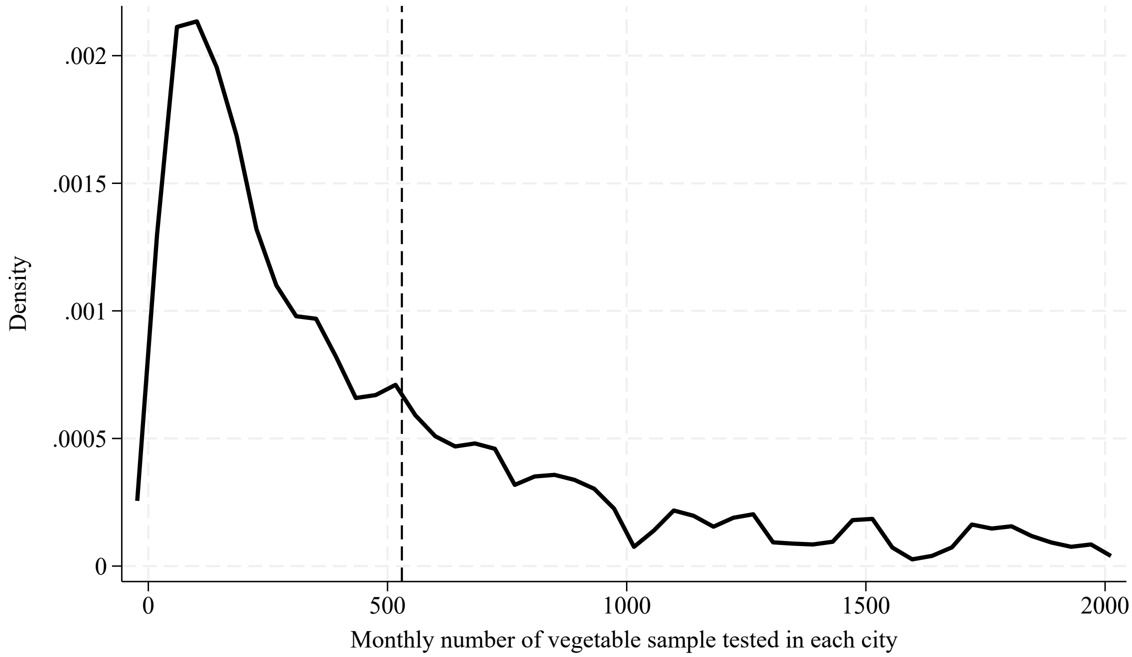

Figure 1: Distribution of the monthly number of vegetable samples tested in each city

Note: We calculate the monthly total number of vegetable samples tested in each city during the sample period and plot the density of distribution in this figure. The dashed vertical line denotes the average number of vegetable samples tested.

Among the 656,000 records, 572,000 are related to fresh vegetables, and the remaining 83,000 are for processed vegetables. Our main analysis uses data for fresh vegetables, and data for processed vegetables are only used for robustness checks. Figure 1 presents the distribution of the monthly number of fresh vegetables tested in each city. The monthly average number of vegetable samples tested is 533, with large variations across cities. Figure 3 presents the percentage of tests recorded as failed in each city (Panel A) and each month (Panel C).

3.1.2 COVID-19 infection rate

Daily data on COVID-19 infection in each city are collected from the official websites of cities in China. We construct the daily data on COVID-19 infection from January 2020

notes.

to December 2022. China began officially disclosing the COVID-19 infection data at the end of December 2019 and stopped reporting the data at the end of December 2022. China gradually lifted COVID-19 epidemic control measures after December 2022. The primary data used in our analysis is the daily number of COVID-19 confirmed cases.

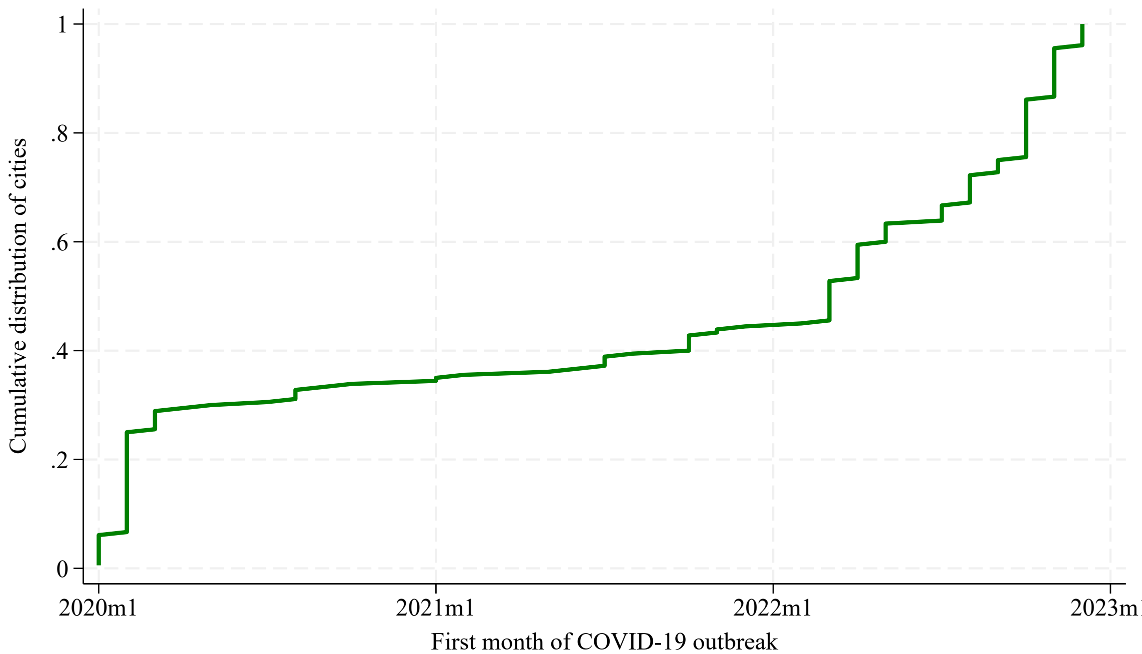

Figure 2: Roll out of COVID-19 across Chinese cities

Note: This figure presents the distribution of the first month of the COVID-19 outbreak across cities. The first month of the COVID-19 outbreak is defined as the first month of local COVID-19 outbreak that had led to the classification of this city as a medium to high-risk area; this definition excludes controllable imported cases of COVID-19.

The key explanatory variable used in the study, the COVID-19 infection rate, is calculated as the number of confirmed cases per hundred population in each day of a city. In event studies, we define the outbreak of COVID-19 as the first month of the local COVID-19 outbreak that had led to the classification of this city as a medium to high-risk area, which also excludes controllable imported cases of COVID-19. Figure 3B reports the cross-city variation in the infection rate. Figure 2 reports the accumulated distribution of the timing of the COVID-19 outbreak across cities.

3.1.3 Auxiliary data

Our analysis utilized the following city-year-level data: population size, GDP per capita, rural income, mechanical power per agricultural land area, and vegetable output, all sourced from the National Bureau of Statistics. Additionally, we utilized climate data, including mean temperature, total precipitation, humidity, and wind speed, derived from the China Meteorological Administration. We also used the search index for pesticide regulations, obtained from Baidu, China's leading search engine akin to Google in the United States. These variables are mainly used as control variables and moderating variables.

3.2 Method

3.2.1 Effect of COVID-19 on pesticide residue

We estimate the effect of COVID-19 on pesticide residue based on the following regression model:

$$y_{ivcd} = \tau_v + \tau_c + \tau_d + \alpha Cov_{cd} + X_{cd}\beta + \epsilon_{ivcd}, \tag{1}$$

where y_{ivcd} is the vegetable pesticide residue test outcome for test i of vegetable v in city c on day d. In each test, the outcome is either pass ($y = 0$) or fail ($y = 1$), where fail indicates the pesticide residue exceeds the regulatory limits. The key explanatory variable, Cov_{cd}, is the COVID-19 infection rate in city c and day d. The infection rate is defined as the number of people recorded as COVID-19-positive per hundred population. COVID-19-positive patients who recovered or deceased by day d are not counted when calculating the infection rate. In robustness checks presented in Appendix Table A.5, we find comparable results when replacing the COVID-19 infection rate with the dummy of COVID-19 outbreak, which is defined as the first month (columns 1–3) or first day (columns 4–6) of local COVID-19 outbreak that had led to the classification of this city as a medium to high-risk area.

The model includes vegetable-type fixed effects (τ_v) and city-fixed effects (τ_c) to account for potential confounding factors that are time-invariant for a given vegetable and city and includes day-fixed effects (τ_d) to account for common shocks in a given day. In robustness checks, we include city-by-year, week-by-year, and week-by-city fixed effects and find comparable results. The model also consists of a vector of time-varying control variables (X_{cd}) to address potential omitted variable concerns. The control variables included in the baseline analysis are four exogenous climatic variables that may affect both pesticide residue and COVID-19 infection: daily mean temperature, total precipitation, humidity, and wind speed. In robustness checks, we also control for per capita GDP, rural income, mechanical power per area, and legal regulations search index.[7] Finally, ϵ_{ivcd} is an error term that will be clustered at the city level, city-year level, or month-year level.

The coefficient α captures the effect of the COVID-19 infection rate on pesticide residue based on the assumption that, conditional on the fixed effects and control variables, the COVID-19 infection rate is not driven by omitted determinants of vegetable pesticide residue. We support this assumption by showing that the estimates of α are robust to controlling for various factors that could affect either COVID-19 infection or pesticide residue. More importantly, we present evidence showing that cities with early and later COVID-19 outbreaks have no preexisting different trends in pesticide residue based on the following event study regression model:

$$y_{vcm} = \tau_v + \tau_c + \tau_m + \sum_{j=\underline{j},j\neq -1}^{\bar{j}} \gamma_j d_{cm}^j + X_{cm}\beta + \epsilon_{vcm}, \tag{2}$$

where y_{vcm} is the average pesticide testing failure rate for vegetable v in city c and

[7]The local income level measured by per capita GDP and rural income has the potential to affect the financial funds available for epidemic control. The mechanization rate measured by mechanical power per area may affect pesticide residue when COVID-19 infection reduces the labor available for agricultural production. The legal regulations search index, which measures the frequency of online searches for vegetate pesticide residue-related information, is used to control for differences in concerns about pesticide residue across cities.

month m, and d^j_{cm} is a dummy variable that equals 1 for city c if month m is j months away from the first month of COVID-19 outbreak in the city and equals 0 otherwise.[8] For example, $d^{-3} = 1$ if the month is 3 months before the COVID-19 outbreak in the city, and $d^4 = 1$ if the month is 4 months after the COVID-19 outbreak in the city. The event study is set at the monthly level to fully capture the effect over the 36 months of the sample period and to reduce the effect of daily and weekly fluctuations. Figure 2 shows that there were substantial differences in the timing of the COVID-19 outbreak across the sample cities.

3.2.2 Effect of COVID-19 on health through pesticide residue

Pesticides could have substantial detrimental effects on health. Health issues linked to pesticide exposure include cancers and tumors, neurological and cognitive damage, congenital anomalies, and reproductive problems such as infertility (Verger and Boobis, 2013; EEA, 2023). We infer the detrimental effect of COVID-19 on health through pesticide residue by combining the estimated impact of COVID-19 on pesticide residue with the effect of pesticide residue on health.

Specifically, we follow the literature (Verger and Boobis, 2013; FAO, 2020; Khan et al., 2020) to estimate the effect of COVID-19 on health in city c through pesticide residue according to:

$$\Delta HI_c = HI_c \times IDR_c \tag{3}$$

where IDR_c is the changes in the average pesticide testing failure rate across all vegetables in city c caused by COVID-19, and HI_c is the cumulative health risk for all pesticides detected in vegetables in city c. The cumulative health risk is calculated

[8] Recall that we define the timing of the COVID-19 outbreak in a city as the first month of the local COVID-19 outbreak that had led to the classification of this city as a medium to high-risk area. Our data shows that the first month when the first case of local COVID-19 infection was reported is generally the first month of the COVID-19 pandemic in a city.

according to the following:

$$HI_c = \sum_k (HQ_{k,c} \times ProbP_{k,c}), \tag{4}$$

where $ProbP_{k,c}$ is the proportion of samples contaminated by pesticide k over all contaminated samples in city c , and $HQ_{k,c}$ is the health risk of pesticide k in city c. The health risk of certain pesticides is determined by comparing the value of the estimated daily intake of certain pesticides (EDI) with the acceptable daily intake (ADI) according to

$$HQ_{k,c} = \frac{EDI_{k,c}}{ADI_k} \times 100\%, \tag{5}$$

where $ADI_k(mg/kg \cdot day)$ is the acceptable daily intake of pesticide k obtained from WHO (2023) and $EDI_{k,c}(mg/kg \cdot day)$ is the daily intake of pesticide k in city c calculated according to

$$EDI_{k,c} = \frac{(R_{k,c} \times FC_p)}{BW}, \tag{6}$$

where $R_{k,c}$ (mg/kg) is the average concentration of pesticide residue k in contaminated vegetable samples in city c (calculated based on our pesticide residue dataset), FC_p (kg/d) is the per capita dietary consumption of vegetables in province p, which is calculated based on data from National Bureau of Statistics of China; the city-level vegetable consumption data is not available. $BW(kg)$ is the average body weight of Chinese adults assumed by the Codex Alimentarius Commission and WHO to estimate EDI.

4 Results

4.1 Correlation between COVID-19 and pesticide residue

We observed a positive association between the pesticide test failure rate and the COVID-19 infection rate. A sample with a pesticide concentration higher than the corresponding legal limit is defined as a test failure (see Appendix Table A.1). Figure 3A shows substantial variation in the pesticide testing failure rate across cities, ranging from 0.19% to 18.1%. Figure 3B shows significant variation in the COVID-19 infection rate across cities, ranging from 0 to 1.1% (i.e., 1.1 infection per 100 population). Comparing Figures 3A and 3B, we find that cities with a high pesticide test failure rate are usually those with a high COVID-19 infection rate.

Figure 3C provides further support by showing a positive association between the pesticide test failure rate and COVID-19 infection rate over time. We classify all sample cities into five equal-sized groups based on their average COVID-19 infection rate and then plot the monthly pesticide testing failure rate for the first and last groups, respectively. We find that the high-infection group of cities has a much higher pesticide test failure rate than the low-infection group of cities over most of the sample months. Although the simple correlation suggests a strong positive effect of COVID-19 infection on local vegetable pesticide residue, this correlation could be driven by other factors. The next subsection examines the effect of COVID-19 infection on local vegetable pesticide residue after controlling for potential confounding factors.

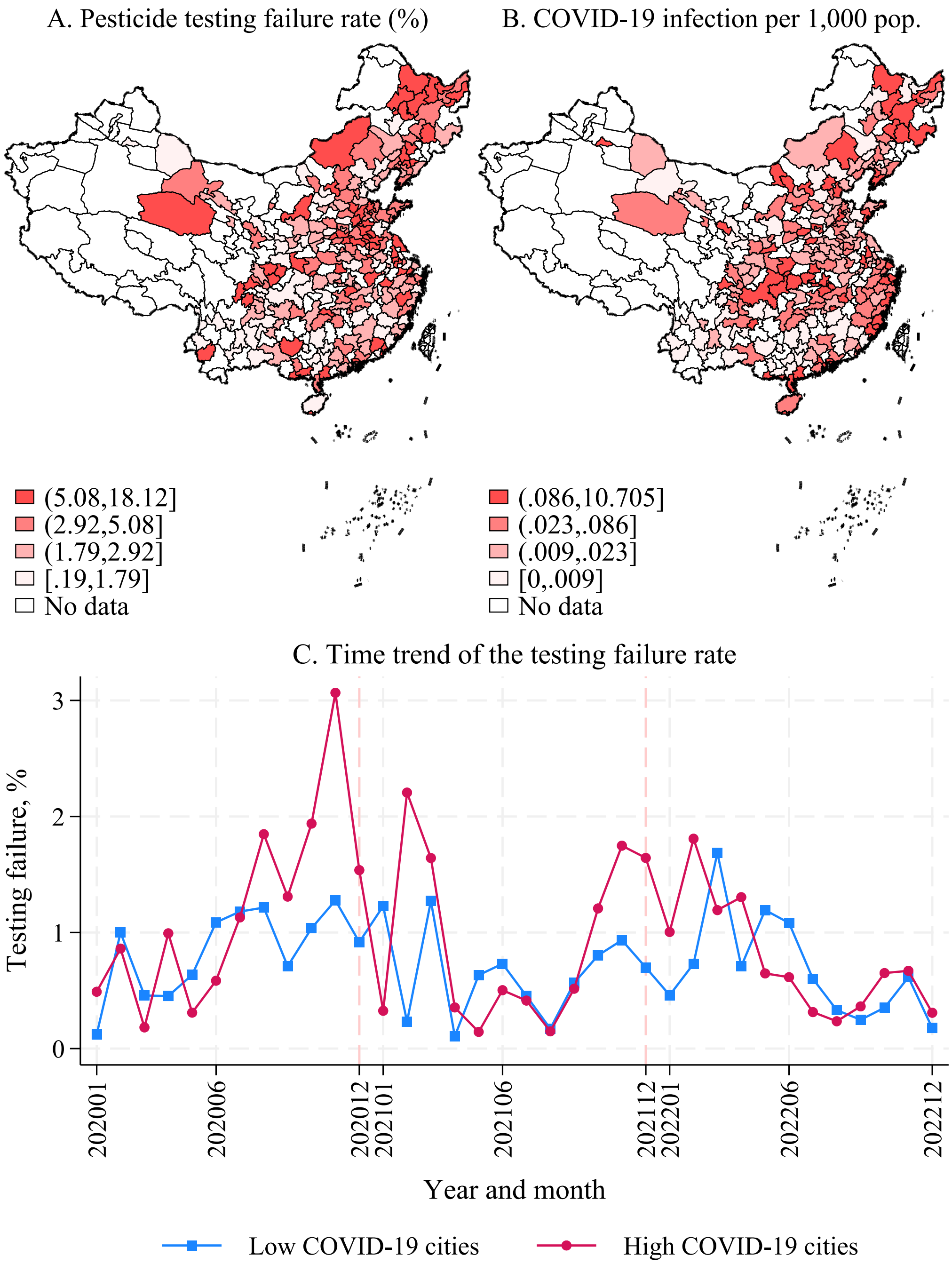

Figure 3: Pesticide testing failure rate and COVID-19 infection rate

Note: Panel A presents the city-level vegetable pesticide testing failure rate, calculated as the city-level average failure rate over the sample period for all vegetables tested. Panel B presents the COVID-19 infection per 1,000 population, calculated as the average number of infections per thousand population over the sample period. Panel C presents the monthly testing failure rates for the high- and low-infection groups of cities. We classify all cities into 5 equal-sized groups according to their average COVID-19 infection rate and define the first group as the low-infection group and the last group as the high-infection group.

4.2 Dynamic effects of COVID-19 outbreak on pesticide residue

Figure 4 presents the dynamic effect of the COVID-19 outbreak on vegetable pesticide residue, estimated based on the event-study model (2). We define the timing of the COVID-19 outbreak in a city as the first month of the local COVID-19 outbreak that had led to the classification of this city as a medium to high-risk area (see Footnote 8 for more details). We estimate the effects of 9-month lags and 24-month leads; estimates beyond these lags and leads are not precisely estimated due to small sample sizes. The event study identifies the dynamic effect of the COVID-19 outbreak on vegetable pesticide residue by comparing cities with different outbreak dates.

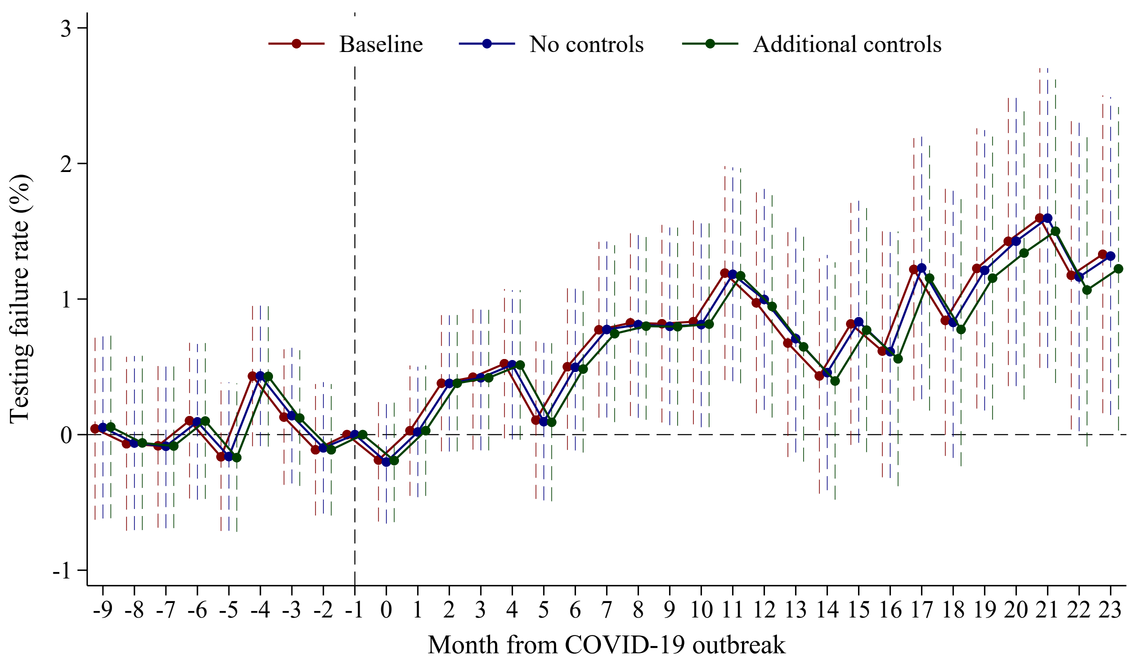

Figure 4: Event study of the effect of COVID-19 outbreak on vegetable pesticide testing failure rate

Note: This figure presents the effect of the COVID-19 outbreak on vegetable pesticide testing failure rate, estimated based on the event-study model (2). We present the estimates with the four baseline control variables (i.e., daily mean temperature, total precipitation, humidity, and wind speed), estimates excluding these control variables, and estimates additionally include four other control variables (Per capita GDP, rural income, legal regulations search index, and mechanical power per area), respectively. The vertical dashed lines denote the 95% confidence intervals.

The identification is based on the parallel trends assumption that the lags of COVID-19 outbreak should have no significant effect on pesticide residue (i.e., estimates of

γ_j is not statistically different from zero for $j < 0$ in the model (2)). Figure 4 shows that the estimated coefficients of the 9-month lags are close to zero and all statistically insignificant at the 5% level. This finding supports the parallel trend assumption that cities with early and later COVID-19 outbreaks are comparable. In other words, conditional on the fixed effects and control variables included in the model, the estimated dynamic effects of the COVID-19 outbreak are unlikely to be primarily driven by omitted confounding factors that could lead to different trends across cities.

The estimates of the 24 lags suggest that the COVID-19 outbreak significantly increased the pesticide residue and the effect growing over time. We also show in the figure that this finding is robust to excluding the four climatic control variables (i.e., daily mean temperature, total precipitation, humidity, and wind speed) from the model. This finding mitigates the concern that the estimated effect could be driven by omitted climatic factors that may simultaneously affect the COVID-19 infection rate and the pesticide residue. We also show that the estimated effects are comparable when controlling for four additional factors that could affect the COVID-19 infection rate or the pesticide residue (see Footnote 7 for details). In addition, Figure A.2 in the Appendix adopts the interaction-weighted estimator proposed by (Sun and Abraham, 2021) to address the potential bias of the event study in the presence of treatment effects heterogeneous across cohorts. The resulting estimates are comparable, although with wider confidence intervals.

In the event study, the size of a specific estimated coefficient needs to be interpreted relative to the omitted reference group of the estimation (Nunn and Qian, 2011). In addition, the event study identifies the effect of the COVID-19 outbreak but not necessarily the effect of COVID-19 intensity (i.e., the infection rate). Cities with early COVID-19 outbreaks may not necessarily have higher COVID-19 infection rates if they were successful in subsequently controlling the virus. To obtain a more direct effect size of the COVID-19 pandemic on vegetable pesticide residue, the next section estimates the effect of the COVID-19 infection rate.

4.3 The Impact of COVID-19 infection rate

Table 1 presents the effect of COVID-19 infection rate on vegetable pesticide testing failure rate, estimated based on the model (1). The baseline estimate in column 1 suggests that a 1 percentage point increase in the COVID-19 infection rate (i.e., 1 additional infection per 100 population) significantly increases the pesticide residue testing failure rate by 5.5 percentage points. Given that the highest monthly average national infection rate during our sample period was 0.06 percent, the estimates suggest that the peak national impact of the COVID-19 pandemic on the vegetable pesticide testing failure rate was 0.33 percentage points, about 11 percent of the national mean testing failure rate of 3.01 percentage points. As the COVID-19 infection rate varied widely across cities, the impact is much larger in some cities. For example, for the top 1 percent city-days with the highest COVID-19 infection, the infection rate was 0.517 percent. Therefore, COVID-19 increased the pesticide testing failure rate in these city days by as much as 2.84 percentage points, close to the mean pesticide residue testing failure rate in the sample.

Table 1: Effect of COVID-19 infection rate on vegetable pesticide testing failure rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	Excluding control variables	Including additional controls	Cluster at month-year level	Cluster at city level	Cluster at city-year level	Including week-by-year fixed effects	Including week-by-city fixed effects	Excluding large cities
COVID-19 infection rate	0.055***	0.058***	0.057***	0.055***	0.055***	0.055***	0.055***	0.054***	0.065***
	(0.005)	(0.005)	(0.005)	(0.021)	(0.017)	(0.017)	(0.005)	(0.007)	(0.007)
Day-fixed effects	Y	Y	Y	Y	Y	Y	N	N	Y
Vegetable-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-fixed effects	Y	Y	Y	Y	Y	Y	Y	N	Y
Four exogenous controls	Y	N	Y	Y	Y	Y	Y	Y	Y
Observations	572,863	572,863	572,863	572,863	572,863	572,863	572,866	572,866	489,693
R-squared	0.104	0.104	0.105	0.104	0.104	0.104	0.091	0.088	0.107

Notes: This table presents the estimates of Model 1. Column 1 presents the baseline estimate, column 2 excludes the four exogenous control variables (daily mean temperature, total precipitation, humidity, and wind speed), column 3 includes addition control variables (Per capita GDP, rural income, legal regulations search index, and mechanical power per area), column 4 clusters the error term at the month-year level, column 5 clusters the error term at the city level, column 6 cluster the error term at the city-year level, column 7 replaces the day-fixed effects by the week-by-year fixed effects, column 8 replaces the day- and city-fixed effects by the week-by-city fixed effects, and column 9 excludes cities with 2018 population more than 10 million. Standard errors are reported in parentheses. Significance levels are *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

We provide various robustness checks to verify the estimated effect of COVID-19 infection rate on vegetable pesticide residue. Columns 2 and 3 show that the estimated effect is robust to omitted variables. Column 2 excludes the four climatic control variables and finds a comparable estimated effect. This finding mitigates the concern that the estimate could be driven by omitted climatic factors that may simultaneously affect the COVID-19 infection rate and the pesticide residue. Column 3 shows that the estimated effect is comparable when controlling for four additional factors that could affect the COVID-19 infection rate or the pesticide residue. Columns 4–6 show that the estimated effect is not significantly affected by clustering the error term at the month-year level, city level, and city-year level, respectively. This finding mitigates the concern that the estimated effect could have been biased by autocorrelation or cross-sectional correlation within cities. Columns 7 and 8 further control for the week-by-year and week-by-city fixed effects, respectively, and find comparable estimates. Column 9 excludes the 17 cities with a population of more than 10 million to address the concern that COVID-19 is more likely to break out in these large cities.[9] The estimate becomes slightly larger compared to the baseline estimate.

Another potential concern is that the higher testing failure rate following the COVID-19 pandemic may reflect stricter testing standards rather than an actual effect on the pesticide residue. This argument is not well supported as we do not find any changes in the standard of pesticide tests before and after the COVID-19 pandemic. The standard is stipulated by the Central government and cannot be changed in the absence of new legislation. Note that as we have observed that the COVID-19 outbreak increased the pesticide testing failure rate, governments can increase the number of vegetable samples tested in response to the higher failing rate. However, our finding should not be biased by a larger number of samples tested because we measure the pesticide testing failure rate as the ratio between the number of failed tests and the total number of

[9]These cities are Chongqing, Shanghai, Beijing, Chengdu, Guangzhou, Shenzhen, Wuhan, Tianjin, Xi'an, Suzhou, Zhengzhou, Hangzhou, Shijiazhuang, Linyi, Dongguan, Changsha, and Qingdao.

tests. There is no reason to believe that a larger number of tests could increase the failure rate. In addition, we find no significant changes in the trend of the number of vegetable samples tested following the COVID-19 pandemic (Appendix Figure A.1).

4.4 Heterogeneity in the impact of COVID-19

Panels A--C of Figure 5 examine the heterogeneity in the impact of COVID-19 infection rate on vegetable pesticide testing failure rate with respect to the population size, GDP per capita, and annual mean temperature (moderating variables) of the sample cities, respectively. The heterogeneity effect is estimated based on the following regression model:

$$y_{ivcd} = \tau_v + \tau_c + \tau_d + \alpha_1 Cov_{cd} + \alpha_2 Cov_{cd} * Dummy_c + X_{cd}\beta + \epsilon_{ivcd}, \tag{7}$$

where $Dummy_c$ is a dummy variable that indicates whether the moderating variable in the city is above the median of all sample cities in 2018, and all other variables are the sample as defined in the baseline model (1). The dummy variable equals 1 for cities with the moderating variable above the median and 0 otherwise. We use the 2018 value of the moderating variables to avoid the potential endogenous effect of COVID-19. The effect for cities with a moderating variable below and above the median is captured by α_1 and $\alpha_1 + \alpha_2$ and denoted as 'Low' and 'High,' respectively, in Figure 5.

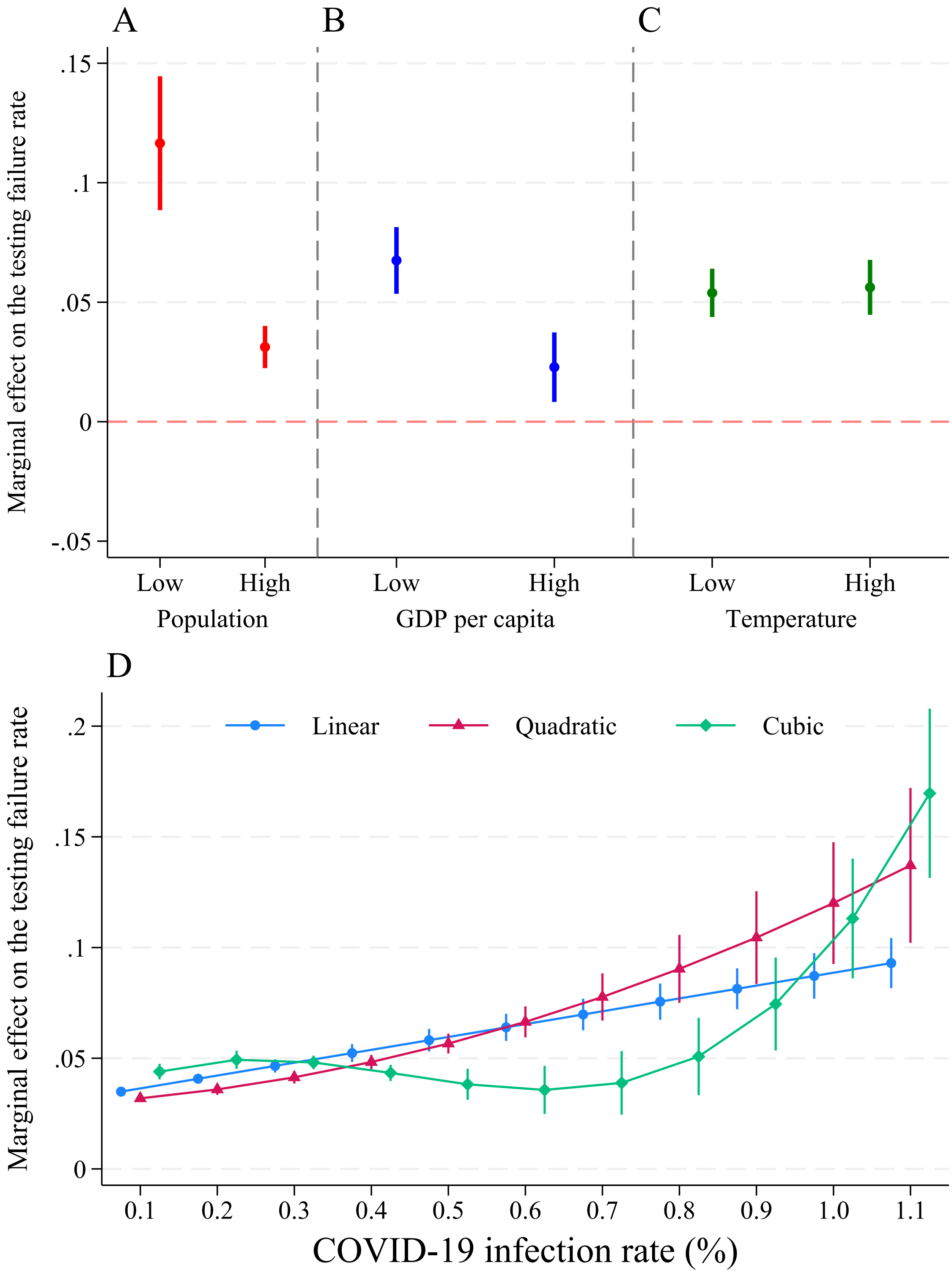

Figure 5: Heterogeneity and nonlinear effects of COVID-19 on vegetable pesticide testing failure rate

Note: Panels A to C present the differences in the effects of COVID-19 between sample cities with population size, GDP per capita, and annual mean temperature above and below the median, respectively. The estimates are based on the model (7). Panel D presents the linear, quadratic, and cubic effects of COVID-19 infection rate on the testing failure rate across the distribution of the COVID-19 infection rate, estimated by additionally including the quadratic and cubic terms in model (1). The vertical line in each figure presents the 95% confidence interval.

Panel A shows that the effect is much lower in cities with a population size above the median than in cities with a population size below the median (0.03 versus 0.12), which is plausible because larger cities have tighter pesticide residue regulation and a more efficient vegetable supply chain even under the pandemic. Similarly, Panel B shows that the effect is much lower in cities with a GDP per capita above the median; cities with a lower GDP per capita are generally those with a smaller population size. These findings suggest that more attention should be paid to pesticide residues in disadvantaged small and poor cities during a pandemic. Panel C finds no significant difference in the effect between cities with high and low annual mean temperatures. This finding further alleviates the concern that the estimated effect of COVID-19 can be driven by the confounding effect of temperature.

Panel D presents the linear, quadratic, and cubic effects of COVID-19 infection rate on the testing failure rate across the distribution of the COVID-19 infection rate, estimated by additionally including the quadratic and cubic terms in model (1). Both the quadratic and cubic estimates suggest that the marginal effect of COVID-19 on pesticide residue increased with the COVID-19 infection rate. This finding is consistent with the fact that the strictness of epidemic control, which could disrupt vegetable production and transportation, increased sharply with the COVID-19 infection rate. This finding suggests that disproportionately, more efforts should be directed towards addressing vegetable pesticide residue issues in cities with high levels of pandemic.

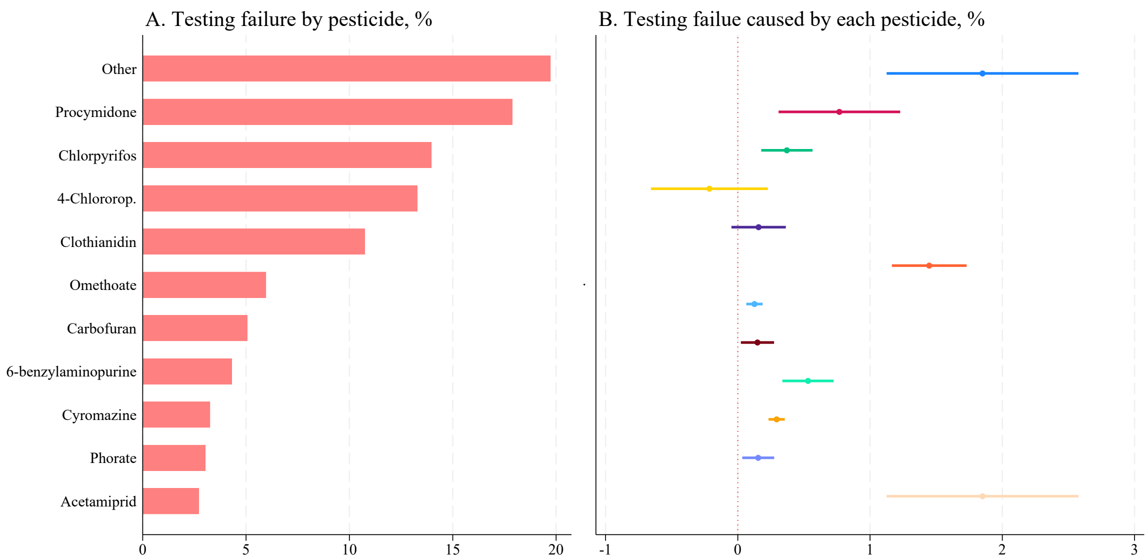

Figure 6: Effect of COVID-19 outbreak on pesticide testing failure rate
Note: Panel A presents the percentage of testing failure caused by each of the top 10 most frequently overused pesticides. Panel B presents the estimated effect of COVID-19 on the testing failure rate caused by each of these pesticides. The corresponding point estimates are reported in Table A.4.

We also find significant differences in the effects of COVID-19 infection on the residue of different pesticides. We estimate the effect on each of the top 10 most frequently detected pesticides based on the model (1). These 10 pesticides account for 80.3% of the total number of failed tests of pesticide residue. Figure 6A presents the share of each pesticide in the failed tests, and Table A.2 describes the function of each of these pesticides in vegetable production. Figure 6B shows that the marginal effects of COVID-19 on testing failure are widely different across pesticides.[10] The figure also shows that the estimated effect on pesticides other than these top 10 pesticides (the group of "other") is much larger, suggesting that the COVID-19 pandemic had a larger effect on the overuse of less frequently detected pesticides.

[10]Among the 10 most frequently overused pesticides, only the two pesticides (ranked in the third and fourth) that are mainly used in early stages of vegetable production are unaffected. As presented in Table A.2, the third pesticide, sodium 4-chlorophenoxyacetate, is usually used to stimulate root formation of vegetables, and the fourth pesticide, clothianidin, is primarily applied as a seed treatment and soil treatments in the initial stages of vegetable production.

4.5 Mechanism analyses

Intuitively, the pandemic disrupts vegetable production and transportation, leading to excessive pesticide usage. Specifically, the COVID-19 pandemic might have led to local control measures that interrupt the supply of agricultural inputs. If farmers cannot obtain pesticides timely, the subsequent outbreak of vegetable diseases and pests may force farmers to use excessive amounts of pesticides and thus increase pesticide residue. In addition, even if the pandemic does not affect the supply of pesticides, it may still impact the timeliness of farmers' pesticide usage. Anecdotal evidence suggests that the COVID-19 pandemic limits working time flexibility and labor hiring in rural areas of China. Finally, the pandemic might have disrupted the supply chain and delayed the sale of vegetables, which could lead farmers to use additional pesticides to preserve vegetables. We find three pieces of evidence supporting that the COVID-19 pandemic increases vegetable pesticide residue by impacting vegetable production and transportation.

First, we show that COVID-19 had a larger effect on the pesticide residue in vegetable exporting (production) cities than in vegetable importing (consumption) cities. If the effect on pesticide residue is caused by the impact on vegetable production and transportation, we should find a larger effect if a COVID-19 pandemic occurred in a vegetable exporting city. We define a city as a vegetable exporting (importing) city if its per capita vegetable output in 2018 is above (below) the median of all cities.[11] As presented in columns 1 and 2 of Table 2, the estimates confirm that the impact of COVID-19 on the pesticide testing failure rate is larger in vegetable exporting cities than in vegetable importing cities.

[11]the real data on city-level vegetable importing and exporting are not available

Table 2: Mechanisms of the effect of COVID-19 on pesticide overuse

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Testing failure rate		Log vegetable output			Testing failure rate of processed vegetables			
	Vegetable exporting cities	Vegetable import-ing cities	All cities	Vegetable exporting cities	Vegetable importing cities	Baseline	Excluding control variables	Including additional control variables	Including week-by-year fixed effects
COVID-19 infection rate	0.074***	0.046***	-0.045***	-0.100***	-0.056***	-0.012	-0.012	-0.010	-0.008
	(0.016)	(0.005)	(0.004)	(0.005)	(0.002)	(0.008)	(0.008)	(0.008)	(0.006)
Day-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	N
Vegetable-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Four exogenous controls	Y	N	Y	Y	Y	Y	N	Y	Y
Observations	285,368	287,483	545,648	270,305	275,332	208,370	208,370	208,370	208,382
R-squared	0.144	0.107	0.992	0.978	0.997	0.149	0.148	0.150	0.095

Notes: This table presents the estimates of different versions of the model (1). Columns 1 and 2 estimate the effect for vegetable exporting and importing cities, respectively. Columns 3–5 report the estimated effects of COVID-19 infection rate on log vegetable output; column 3 uses the data from all sample cities, and columns 4 and 6 focus on vegetable exporting and importing cities, respectively. Columns 6–9 estimate the effect of COVID-19 infection rate on the testing failure rate of processed vegetables; column 6 presents the baseline estimate, column 7 excludes the four exogenous control variables, column 8 includes the four additional control variables, and column 9 replaces the day-fixed effects with the week-by-year fixed effects. Standard errors are reported in the Parentheses. Significance levels are *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Second, we find that the COVID-19 pandemic reduced vegetable output. Columns 3–5 of Table 2 present the estimated effect of COVID-19 infection rate on log vegetable output for all sample cities, vegetable exporting cities, and vegetable importing cities, respectively. The estimations are based on modified versions of the model (1) that use city-year-level log vegetable output as the dependent variable. The vegetable exporting and importing cities follow the same definition as before. We find that a 1% increase in the COVID-19 infection rate would significantly reduce the vegetable output in an average city by 4.5 %. The estimated marginal effect is much larger in vegetable-exporting cities (10.0%) than in vegetable-importing cities (5.6%). The larger impact on vegetable-exporting cities confirms that vegetable transportation has also been affected by the pandemic.

Third, we show that COVID-19 had no significant effect on the pesticide testing failure rate of processed vegetables. If the impact on vegetable pesticide residue is through affecting vegetable production and transportation but not other channels, such as the testing standard and food processing, we should expect no significant effect on the testing failure rate of processed vegetables. We estimate the effect of COVID-19 on the testing failure rate of processed vegetables based on the model (1). The data for the testing failure rate of processed vegetables come from the same sources. As presented in column 6 of Table 2, we find no significant effect of the COVID-19 infection rate on the testing failure rate of processed vegetables. Columns 7–9 show that this finding is robust to control variables and fixed effects.

4.6 Impact on health risk through pesticide residue

We further evaluate the effect of COVID-19 on health risks through the channel of vegetable pesticide residue. This is a challenging task as the connection between pesticide residue and health is complicated. We can only roughly estimate the extent to which COVID-19 could affect the overall health risk through the channel of vegetable pesticide residue. As detailed in the Method section, we combine the estimated city-level average effect of COVID-19 on pesticide residue with the marginal effect of vegetable pesticide intake on health risk (derived from the literature) to evaluate the effect of COVID-19 on health risk through the channel of vegetable pesticide residue. Importantly, our database contains information on the exact residue level of each pesticide that is assessed as failed in each test. This information enables us to infer the effect of the level of pesticide residue. We calculate the effect on health risk by comparing the actual intake of each pesticide with the acceptable daily intake to enable comparison.

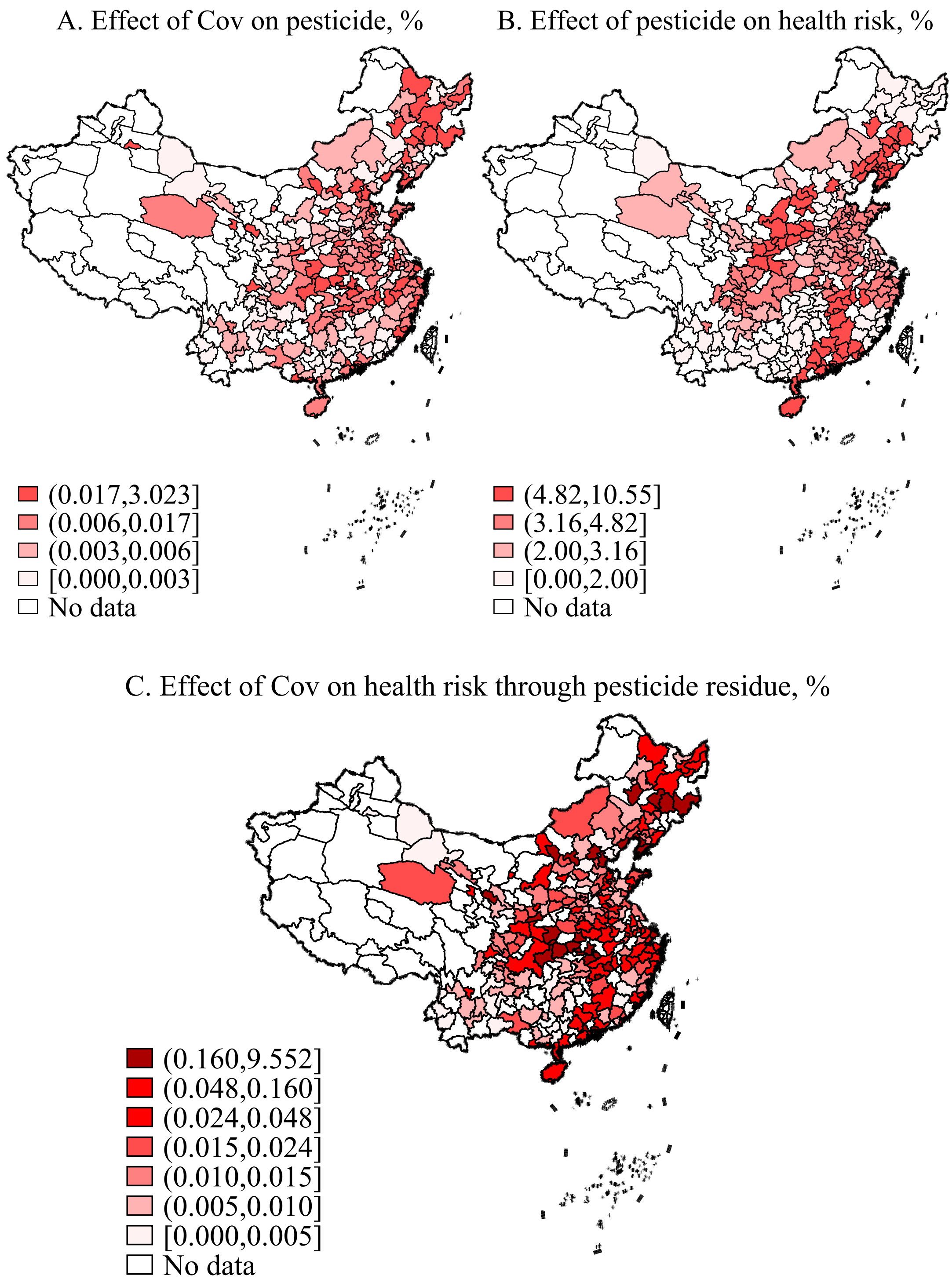

Figure 7: Predicted impact of vegetable pesticide residue caused by COVID-19 on health risk

Note: Panel A presents the estimated effect of COVID-19 on the pesticide testing failure rate. Panel B presents the marginal effect of vegetable pesticide residue on health risk, calculated based on the method described in subsection 3.2.2. Panel C presents the impact of COVID-19 on health risk, calculated by combining the estimates presented in Panels A and B.

Our results show a substantial effect of COVID-19 on health risks in cities with a high COVID-19 infection rate. Figure 7A presents the average effect of COVID-19 on the pesticide residue testing failure rate in each city, and Figure 7B presents the estimated marginal effect of pesticide residue on health risk. The cross-city variation in the marginal effect of pesticide residue on health risk comes from the differences in per capita vegetable consumption and types of pesticides used. Figure 7C presents the average effect of COVID-19 infection rate on health risk through the channel of vegetable pesticide residue. Although the mean effect on health risk is low (0.16%), the effect could be quite large in cities with high COVID-19 infection rates. For example, COVID-19 increased the health risk by 2.5% in Shanghai, 4.6% in Sanya, and 9.6% in Wuhan. Note that the health risk is calculated based on the average pesticide intake caused by COVID-19 during 2020–2022 and should be interpreted accordingly.

5 Concluding Remarks

While it is well known that social disruptions can affect food security by disrupting agricultural production and transportation, the potential impact of social disruptions on food safety has been generally overlooked. Food production and logistic disruptions caused by social disruptions may prevent farmers from adopting optimal food safety standards, thus leading to food safety issues. This study utilizes the data from COVID-19 to infer the potential impact of social disruptions on food safety.

Based on data from over 656,000 records of vegetable pesticide residue tests conducted in China during COVID-19, we find that COVID-19 has increased the national average pesticide residue by 11 percent during the peak months of the pandemic. In cities with the highest infection rates, the pandemic nearly doubled the pesticide testing failure rate. We provide several pieces of evidence suggesting that this effect stems from pandemic-induced disruptions in vegetable production and transportation, which result in untimely pest control and subsequent overuse of pesticides. We also estimate that the pandemic-caused increases in vegetable pesticide residue heightened the health risks by up to 10 percent in cities with the highest COVID-19 infection rates. These findings confirm the significant impact of social disruptions on food safety.

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A Appendix for Online Publication

A.1 Summary statistics appendix

Table A.1: Standard of vegetable pesticide testing failure for the top 20 pesticides

Pesticide name	Number of failed tests in the sample	Standard of test failure
Isofenphos-methyl	184	0.01mg/kg
Carbendazim	227	2mg/kg
Emamectin benzoate	303	0.015mg/kg
Isocarbophos	321	0.05mg/kg
Avermectins	338	0.05mg/kg
Imidacloprid	386	0.5mg/kg
Thiamethoxam	519	0.3mg/kg
Cyhalothrin	523	0.5mg/kg
Fipronil	585	0.02mg/kg
Fenthion	598	0.05mg/kg
Acetamiprid	700	0.2mg/kg
Phorate	783	0.01mg/kg
Cyromazine	840	4mg/kg
6-Benzylaminopurine	1112	0mg/kg
Carbofuran	1305	0.02mg/kg
Omethoate	1537	0.02mg/kg
Clothianidin	2768	0.04mg/kg
4-Chlorophenoxyacetic	3422	0mg/kg
Chlorpyrifos	3599	0.02mg/kg
Procymidone	4606	0.2mg/kg

Notes: This table presents the standard of pesticide testing failure for each of the 20 most frequently overused pesticides. There are more than a hundred pesticides used in vegetable production, and the top 20 pesticides account for 91.2% of the total cases of testing failure.

Table A.2: Functions of the pesticides that are most frequently overused

Name	Number of failed tests	Functions of the pesticide
Procymidone	4606	Procymidone is a fungicide used in agriculture to control fungal diseases. It effectively targets a variety of fungi, such as mold and mildew, protecting crops from infections.
Chlorpyrifos	3599	Chlorpyrifos is a widely used organic phosphorus insecticide with contact killing, gastric toxicity, and fumigation effects. It interferes with the normal nerve conduction of insects by inhibiting the activity of acetylcholinesterase, leading to the death of pests.
4-Chlorophenoxyacetic	3422	4-Chlorophenoxyacetate is a synthetic plant growth regulator commonly used to stimulate root formation in cuttings and to control fruit ripening in certain crops.
Clothianidin	2768	Clothianidin is an insecticide used primarily in agriculture. It effectively controls a wide range of pests, such as aphids, whiteflies, and thrips. It is primarily applied as a seed treatment, sprayed onto plants, or used in soil treatments in the initial stages of vegetable production.
Omethoate	1537	Omethoate is an insecticide and acaricide used in agriculture to control a variety of pests such as aphids, leafhoppers, and mites.
Carbofuran	1305	Carbofuran is a broad-spectrum herbicide widely used in agriculture and landscaping. It effectively controls a wide range of weeds, including annual and perennial grasses and broadleaf weeds.
6-Benzylaminopurine	1112	6-Benzyladenine is a synthetic cytokinin plant hormone. It is widely used in plant tissue culture and horticulture to promote cell division, shoot initiation, and overall plant growth.
Cyromazine	840	Cyromazine is an insecticide used primarily for controlling flies in agricultural and domestic settings, applied in baits, sprays, or as a dust.
Phorate	783	Phorate is an insecticide and acaricide used in agriculture. It effectively controls a wide range of pests, such as aphids, leafhoppers, and mites.
Acetamiprid	700	Acetamiprid is a systemic insecticide widely used in agriculture. It effectively controls a broad spectrum of pests, such as aphids, whiteflies, and thrips.

Notes: This table presents the top 10 pesticides that are most frequently overused.

A.2 Result appendix

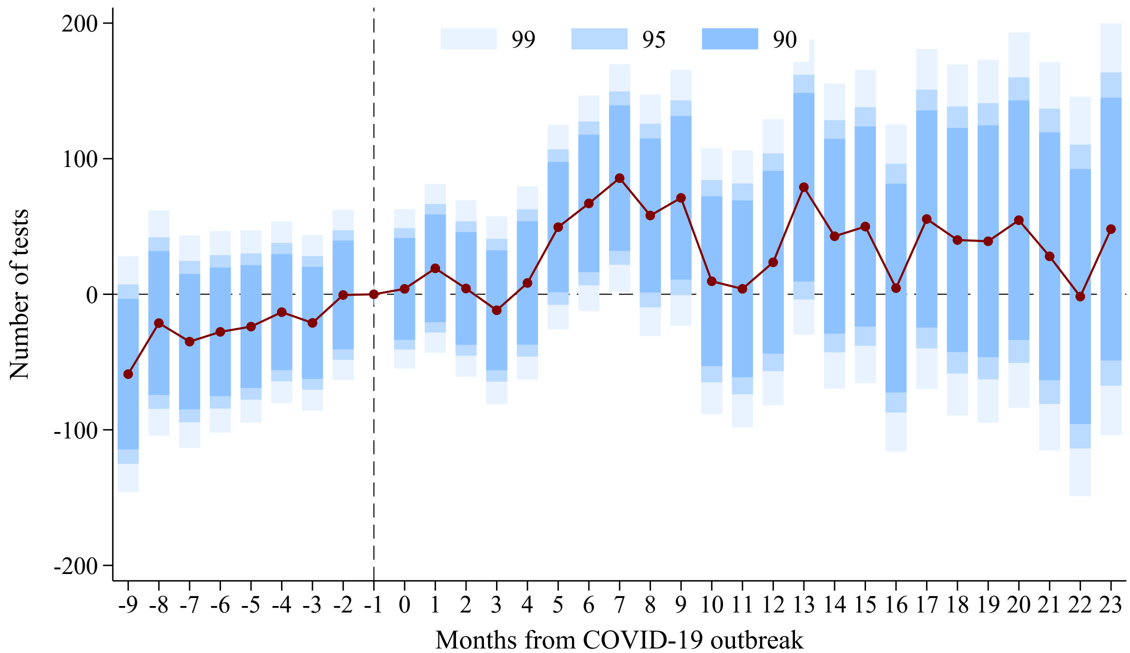

Figure A.1: Effect of COVID-19 outbreak on the number of vegetable samples tested in each month

Note: This figure presents the estimates of a modified version of Model 2 with the dependent variable of the number of vegetable samples tested in each month.

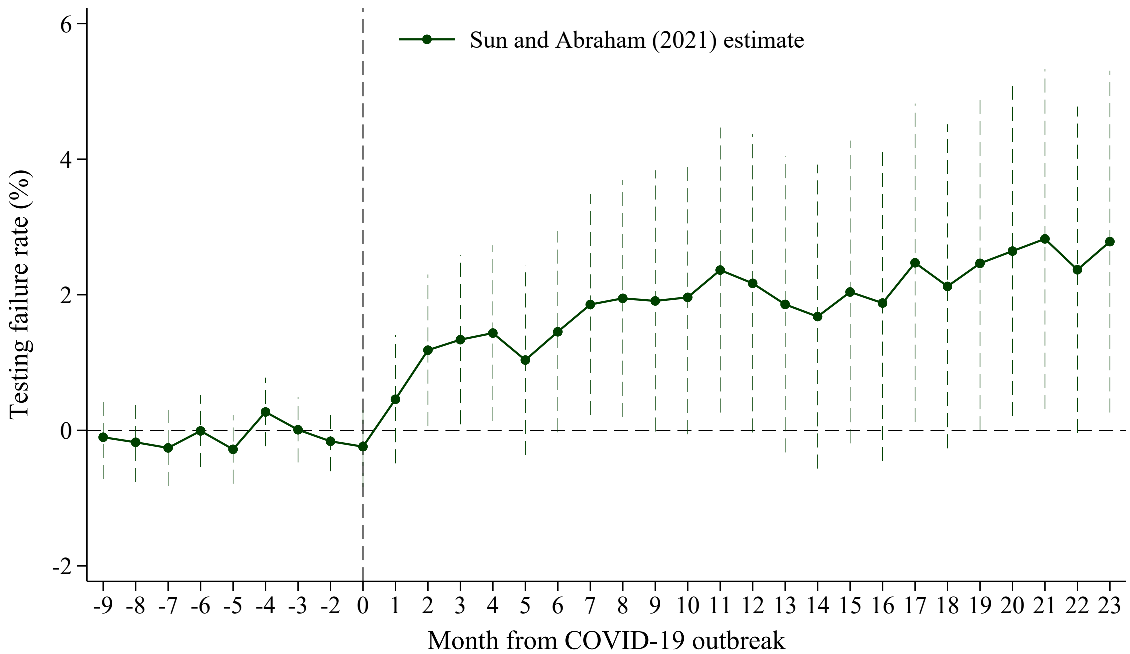

Figure A.2: Event study of the effect of COVID-19 outbreak on vegetable pesticide testing failure rate, Sun and Abraham (2021) estimate

Note: This figure presents the effect of the COVID-19 outbreak on vegetable pesticide testing failure rate, estimated based on the event-study model (2), using the interaction-weighted estimator proposed by (Sun and Abraham, 2021).

Table A.4: Effect of COVID-19 on the testing failure rate of different pesticides

	(1) Top1	(2) Top2	(3) Top3	(4) Top4	(5) Top5	(6) Top6	(7) Top7	(8) Top8	(9) Top9	(10) Top10	(11) Other
COVID-19 infection rate	0.008***	0.004***	-0.002	0.002	0.014***	0.001***	0.001**	0.005***	0.003***	0.002**	0.019***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.004)
Day-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y
Vegetable-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Four exogenous controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	558,395	557,678	557,668	557,667	556,561	556,382	556,470	556,137	556,131	556,124	559,025
R-squared	0.068	0.078	0.081	0.053	0.040	0.083	0.041	0.035	0.034	0.020	0.055
Percentage in the sample	17.9%	14.0%	13.3%	10.7%	6.0%	5.1%	4.3%	3.3%	3.0%	2.7%	19.7%

Notes: This table presents the estimates of model (1) for the testing failure caused by different pesticides. Columns 1 to 10 report the estimated effect of the COVID-19 infection rate on the testing failure rate caused by each of the pesticides listed in the column header. The column header also reports the percentage of testing failures caused by each pesticide. Column 11 reports the estimated effects for all other pesticides ranked beyond the top 10. Hetroskedasticity-robust standard errors are reported in the Parentheses. Significance levels are *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table A.5: Effect of COVID-19 outbreak on vegetable pesticide testing failure rate

	(1)	(2)	(3)	(4)	(5)	(6)
	Define treatment at month level			Define treatment at day level		
	Baseline	Excluding control variables	Including additional controls	Baseline	Excluding control variables	Including additional controls
COVID-19 outbreak	0.002***	0.002***	0.003***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Day-fixed effects	Y	Y	Y	Y	Y	Y
Vegetable-fixed effects	Y	Y	Y	Y	Y	Y
City-fixed effects	Y	Y	Y	Y	Y	Y
Four exogenous controls	Y	N	Y	Y	Y	Y
Observations	572,863	572,863	572,863	572,863	572,863	572,863
R-squared	0.104	0.103	0.105	0.104	0.103	0.105

Notes: This table presents the estimates of a modified version of the model (1) that uses the dummy of COVID-19 outbreak instead of COVID-19 infection rate as the key explanatory variable. Columns 1–3 define the COVID-19 outbreak as the first month in which COVID-19 infection was observed in the city, and columns 4–6 define the COVID-19 outbreak as the first day in which COVID-19 infection was observed in the city. Columns 1 and 4 include the four baseline control variables, columns 2 and 5 exclude all control variables, and columns 3 and 6 include the four additional control variables. Standard errors are reported in the Parentheses. Significance levels are *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.