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Assessing and addressing the coronavirus-induced economic crisis: Evidence from 1.5 billion sales invoices

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ABSTRACT

We probe the effects of the COVID-19 pandemic and the subsequent containment policies on business activities in China by exploiting 1.5 billion sales invoices. Using a difference-in-differences approach, we estimate that the average drop in sales is between 23% and 35%, depending on firm size, for the 12-week period after Wuhan's lockdown. Firms in industries requiring more intensive face-to-face interactions suffer more. Also, cities relying on investment-driven economic growth are more resilient. Lastly, governments' economic stimulus policies are more effective for medium-sized and large firms. Our findings shed new light on the policy debates on supporting business during the pandemic.

1. Introduction

The COVID-19 crisis, a once-in-a-century pandemic, has caused a mounting number of deaths and created a perfect storm for the global economy. To contain and prevent the spread of the coronavirus, almost all countries imposed stringent public health measures, that came with the side effect of significantly slowing economic activities. The COVID-19 pandemic has fundamentally reshaped production methods and lifestyles, leading to profound and lasting impacts on the global economy. Following COVID-19, other infectious diseases such as the resurgence of Ebola in parts of Africa, and the spread of the Monkeypox virus have emerged, posing new challenges. These developments underscore the critical importance of evaluating the impact of COVID-19. Consequently, exploring the most effective policy responses is paramount. This exploration is marked by ongoing debates among policymakers and experts over the optimal measures to manage the pandemic. These debates often revolve around finding the right balance between strict public health protocols, such as lockdowns and social distancing, and strategies aimed at fostering economic recovery, like reopening businesses and easing travel restrictions. Such discussions are crucial for formulating policies that effectively balance public health priorities with the need to revive and sustain economic growth.

While the COVID-19 pandemic has subsided, the challenges it presented to policymakers and academics offer valuable insights for addressing future health crises. Policy makers and academics addressing the dilemma face several challenges. First, fast-evolving health situations, like the one experienced during COVID-19, necessitate timely economic response measures, which traditional survey-based macroeconomic indicators at low frequency may not provide. Second, containment strategies and reopening stages vary significantly across cities for the same country, nationwide or state/province-wide official economic measures cannot be used to evaluate the policy effectiveness even after the data are released. Third, official macroeconomic data are often revised and smoothed

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(Bell & Wilcox, 1993; Borup & Schütte, 2022; Wilcox, 1992), so they may filter out information essential for policy making. As a result, raw data directly collected from business sectors provide a more accurate gauge of the devastating effects of COVID-19 on the economy.

In this paper, we use a proprietary data set on firm sales in China to assess the economic impacts of the pandemic and subsequent containment policies and the speed of recovery after the country reopened. As one of the first countries stunned by the COVID-19 outbreak, China implemented probably the strictest measures to control and prevent the spread of the virus. Although lockdown restrictions have proven to be effective in managing viral outbreaks, questions have arisen about the economic costs paid by society, especially after China recorded its first negative quarterly gross domestic product (GDP) growth of −6.8% for 2020Q1. Additionally, it is crucial to understand the heterogeneity in economic recovery over time and across regions. These insights are essential not only for comprehending the full economic impact of the COVID-19 pandemic but also for preparing more resilient economic strategies in the face of potential future global health crises. Finally, a comprehensive evaluation of the effectiveness of various government interventions and public policies provides policy makers with the insights needed to choose the most appropriate stimulus measures when facing future public health emergency shocks.

To achieve these goals, we require access to alternative high-frequency and granular data. Thanks to the fast development of big data technology in China's financial markets, we obtain such data from Daokou Fintech, a leading big data company, which collects various sources of non-structural data and creates risk profiles for individual firms using artificial intelligence (AI) algorithms. Here, we explore transaction invoices for value-added tax (VAT) claims. Following the Business Tax-to-VAT reform in May 2016, domestic registered businesses are now subject to an internationally adopted tax structure with a simpler, clearer, and more scientific VAT system. VAT invoices are thus issued for firms' tax purposes and contain information about the issuer, the issuer's geographic location and industry, the RMB amount sold, and the date of issuance. The data set contains more than 1.5 billion invoices issued between January 1, 2019, and April 16, 2020, and accounts for 11% of total firm sales in China. The comparison between the invoice-based sales data and the official numbers reported in the Fourth National Economic Census indicates that the transaction-aggregated data have a similar coverage across industries and geographic areas. Overall, firm sales extracted from VAT invoices allow us to measure the economic activities in China, at both granular and real-time levels.

Our main objective is to evaluate the impact of the COVID-19 crisis on business activities in China. Specifically, we implement a difference-in-differences (DID) approach to compare the post-lockdown sales across firm size groups with the 2019 values, which act as the benchmark. Our empirical results reveal several patterns.

First, over the 12-week period after Wuhan's lockdown, the average firm sales drop by 29%, 23%, 33%, and 35% for micro, small, medium-sized, and large firms, respectively, suggesting that larger firms may be better equipped to adapt to public health measures. The most severe impacts happened during the second four-week subperiod, when businesses (unable to foresee the COVID-19 pandemic) had expected to be back to business after the Chinese New Year's holiday. Industries that require more intensive face-to-face interactions, such as the catering and hotel industry, witness larger and longer decreases in sales, and around one-third of sales disappear when the provincial governments announce public health measures.

Second, local governments responded quickly to the crisis by issuing hundreds of public policies to stimulate the economy. We classify these policies into three groups: financial assistance, fee reductions, and tax exemptions. We find that, except for the tax exemption policies that benefit small firms, all three policies positively affect the sales of medium-sized and large firms. None of these policies has any significant effect on micro firms' activities. Therefore, while local governments intended to alleviate the COVID-19 shock to micro and small businesses, which are essential for labor market, the policies have not achieved this goal.

Third, the effects of the COVID-19 pandemic on business activities vary across cities. Large cities with higher population are more resilient to the shock. In addition, cities in which economic growth is driven by investment are less affected by the pandemic, implying that service-industry-driven economies may experience steeper growth slowdown. Parachuted officials, often less familiar with local contexts, appear to have a weaker response capability to sudden pandemic shocks, with this negative impact being particularly pronounced in micro, small and medium-sized enterprises. On the other hand, local economic development measured by income per capita does not have a clear relationship with the severity of the sales drop.

Our contributions to the literature are twofold. First, we construct a high-frequency data set to measure the business activities of firms with different sizes across all cities in China. The invoice-based sales data represent 11% of the total sales in China and exhibit similar coverage patterns across industries and regions. Compared with the traditional macroeconomic data provided by the government, our big data are at a daily frequency and are available to users with a time lag of only two weeks. Moreover, our invoice-based data include information about geography, industries, and the underlying products/services sold allowing researchers to investigate economic activities in a more detailed manner. Second, relying on the comprehensive sales data, we are able to illustrate the direct and immediate impact of the COVID-19 crisis on business activities in China. Our paper is the first to document how real economic activities react to the COVID-19 crisis and the follow-up stimulus policies for different-sized firms over time. Chen, Qian, and Wen (2021) also provides direct evidence of the immediate economic impact of COVID-19. Chen et al. (2021) primarily focuses on consumer-side consumption, shedding light on how pandemic-related changes affected consumer behavior and retail patterns. In contrast, our study delves into business-to-business (B2B) activities, providing a comprehensive view of the pandemic's impact on the broader business ecosystem. This approach includes examining not just direct consumer-facing businesses but also the interconnections and dependencies along the supply chain.

Literature review. Our paper is firstly related to the research on the economic impact of COVID in China. Firms, being the mainstay of economic activities, have been significantly impacted by COVID in China. The effects of government policies, including non-pharmacological interventions (NPIs) and economic and financial support measures, on firms form a critical and widely-discussed topic. For instance, studies by Dai et al. (2021), Chen, Cheng, Gong, and Li (2022), and Guo, Huang, Wang, and Wang (2022) illuminate the diverse impacts of the pandemic on small businesses. Dai et al. (2021) highlight the immediate and substantial effect of lockdowns on SMEs, followed by a slow recovery trajectory. Chen, Cheng, et al. (2022) examines the differential effectiveness of government relief policies on SMEs, indicating a disparity between policy intentions and actual outcomes. However, these studies often rely on survey data with considerable time lags, limiting the exploration of businesses' real-time responses from impact to recovery. Guo et al. (2022), using transaction data from a leading Fintech firm in China focuses on the informal economy, revealing the intense disruptions faced by offline micro businesses, especially in urban areas and among vulnerable groups like female merchants. While offering valuable policy insights, their focus on very small merchants does not comprehensively capture the broader economic picture. Ai, Zhong, and Zhou (2022) estimates the impact of the COVID-19 pandemic on the economy through firm-level electricity consumption data from Hunan province, China, and the data is somewhat limited in scope. A wider data scope is utilized by Chen, Chen, Liu, Luo, and Song (2022), who estimate the economic cost of China's lockdowns through city-to-city truck flow data, finding a 54% reduction in truck flows during a one-month full lockdown, and subsequently estimating its impact on GDP. However, their study primarily focuses on the economic costs of government NPI policies, without a heterogeneous analysis by firm size.

By exploiting big data on firm transactions, we are able to quantify the impact of the COVID-19 crisis on countrywide business activities in China, including the responses of various-sized businesses to government financial support policies. China introduced one of the strictest containment strategies in the world to eradicate COVID-19 within two months; however, the accurate economic cost of these measures is less clear. Our research complements these studies by using granular invoice data to capture the heterogeneous responses of a wide range of firms of different sizes and providing a more nuanced understanding of the recovery process. To the best of our knowledge, this paper is the first to evaluate the direct economic cost for a disease eradication strategy and thus provides evidence for policy makers who must design policies that trade off between supporting the economy and supporting public health.

The most closely related paper to ours is Chetty et al. (2020), who construct a high- frequency data set from private sector data to track U.S. economic activities during the pandemic. While their data include more categories than ours, such as consumption, earnings, unemployment, and job postings, their firm revenue data cover small businesses only, whereas our cover the entire scope. Our paper complements theirs, but our focus is on the second- largest economy in the world. Both papers add to an emerging thread of studies that exploit alternative and non-structural data for academic research.[1]

Our study also contributes to the debate among policy makers and researchers about the trade-offs between keeping the economy going and protecting public health during the COVID-19 crisis. Mulligan (2021) estimates the annualized shutdown cost to be $7 trillion for the U.S. economy. Barrot, Grassi, and Sauvagnat (2020) estimate that while business closures due to COVID-19 could cost up to $700 billion, shuttering businesses saves 36,000 lives. Lin and Meissner (2020) find that social distancing measures have spillover effects on both public health and the economy, suggesting that the trade-off between the two comes with externality.[2]

This paper is related to the fast-growing literature investigating the various aspects of the economic impact of the COVID-19 pandemic globally. Bartik et al. (2020) zero in on the response of small businesses using a survey-based approach and find that financially fragile small businesses are hit hardest. Different from their approach, our approach uses real-time sales data from different-sized to examine the negative impact of disease containment measures on business activities and to analyze how firms recover after Wuhan's lockdown restrictions are lifted. Several other papers concentrate on the consumption responses in different countries, including the United States (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020), the United Kingdom (Hacioglu Hoke, Känzig, & Surico, 2020), China (Chen et al., 2021; Duan, Wang, & Yang, 2020), Denmark (Andersen, Hansen, Johannesen, & Sheridan, 2020), and Spain (Carvalho et al., 2021). A couple of papers, including Lewis, Mertens, and Stock (2020) and Bick and Blandin (2020), construct weekly measures from U.S. economic and labor market indices that track the pandemic-induced response over time.[3] Our paper draws a comprehensive picture of both the drop and the recovery in business activities by firm size using real-time transaction-level sales data.

Broadly speaking, our study adds to the literature that incorporates public health into economics, including the role of government in public health emergencies (Fetzer et al., 2020; Huang, Wang, Chen, & Zhiwei, 2020; Pathak, Tayfun Sönmez, Unver, Bumin, & Yenmez., 2020; Schmitt-Grohé, Teoh, & Uribe, 2020), optimal lockdown measures (Acemoglu, Chernozhukov, Werning, & Whinston,

[1] Kim, Parker, and Schoar (2020) uses detailed transaction-level data from checking and credit-card accounts of small business and households to document the impact of local infections and policies during the COVID-19 pandemic in the U.S. Other studies on the impact of COVID-19 exploit alternative high-frequency data on branch-week bank deposit rates (Levine et al., 2020), scanner data (Jaravel & O'Connell, 2020), medical claims and cellphone data (Cantor, Sood, Bravata, Pera, & Whaley, 2022), Facebook surveys (Alekseev et al., 2023), Google search data (Brodeur, Clark, Fleche, & Powdthavee, 2021; Kong & Prinz, 2020), income and poverty (Han, Meyer, & Sullivan, 2020), unemployment claims (Casado et al., 2020), health care system (Chatterji & Li, 2020; Ziedan, Simon, & Wing, 2020), e-commerce platform (Chang & Meyerhoefer, 2021), and so forth.

[2] Additional empirical work on the trade-off between supporting the economy and supporting public health includes Adda (2016), Adams-Prassl, Boneva, Golin, and Rauh (2020), Fisman, Lin, Sun, Wang, and Zhao (2021), and Li et al. (2020), whereas theoretical studies include Aum, Lee, and Shin (2021), Favero, Ichino, and Rustichini (2020), and Hong et al. (2020).

[3] Many papers examine the effects of COVID-19 along different dimensions of the economy, including the stock markets (Alfaro, Chari, Greenland, & Schott, 2020; Baker et al., 2020a; Croce, Farroni, & Wolfskeil, 2020; Davis et al., 2020; Ding et al., 2021; Fahlenbrach, Rageth, & Stulz, 2021; Gormsen & Koijen, 2020; Hassan, Hollander, van Lent, & Tahoun, 2020; Ru et al., 2020; Schoenfeld, 2020), bond market (Bordo and Duca, 2020; Elenev, Landvoigt, & Van Nieuwerburgh, 2022; Gilchrist, Wei, Yue, & Zakrajšek, 2020; He, Nagel, & Song, 2022; He & Krishnamurthy, 2020; Ma, Xiao, & Zeng, 2022; O'Hara & Zhou, 2021), mutual fund market (Pástor and Vorsatz, 2020), labor market (Adams-Prassl et al., 2020), pandemic-induced economic uncertainty (Altig et al., 2020; Baker et al., 2020b), and social distancing measures (Allcott et al., 2020; Barrios, Benmelech, Hochberg, Sapienza, & Zingales, 2021; Briscese, Lacetera, Macis, & Tonin, 2020; Cornelson & Miloucheva, 2020; Dingel & Neiman, 2020; Durante, Guiso, & Gulino, 2021; Greenstone & Nigam, 2020; Gupta et al., 2021; Koren and Petö, 2020; Wright, Sonin, Driscoll, & Wilson, 2020).

2020; Alvarez, Argente, & Lippi, 2021; Jones, Philippon, & Venkateswaran, 2021; Wang, Tang, Feng, & Lv, 2020), and the impacts of the 1918 Spanish flu (Almond, Chen, Greenstone, & Li, 2009; Barro, Ursúa, & Weng, 2020; Brainerd & Siegler, 2003; Correia, Luck, & Verner, 2022; Dahl, Hansen, & Jense, 2020; Karlsson, Nilsson, & Pichler, 2012; Velde, 2022) and the HIV epidemic on developing countries (Canning, 2006; Fortson, 2011; Oster, 2005, 2012; Young, 2005). By quantifying the impact of the COVID-19 pandemic and subsequent containment policies on business activities and evaluating firms' recovery in China, our paper shows how disease containment measures dramatically slowed the world's second-largest economy, which managed to bounce back once local governments relaxed stay-at-home restrictions.

2. Data

In this section, we describe the construction and sources of data used in this paper, including individual firms' sales data; local governments' announcements of a public health emergency; post-pandemic economic stimulus policies; and city-level pandemic, macroeconomic, and community mobility data.

2.1. Sales data

Our data set on individual firms' business transactions is the de-identified data that we obtain from Daokou Fintech, a leading FinTech platform in China.[4] Specifically, the company collects information about transactions based on the invoice issued for claiming the value-added tax (VAT).[5] The raw VAT data are from State Taxation Administration in China and Daokou Fintech has data access to one of the country's largest invoice management companies. In addition, the company collects characteristics of all registered firms in mainland China from the State Administration for Industry and Commerce (SAIC).[6] From the invoices uploaded by corporations and self-employed business entities, we can extract information from the de-identified transactions, including the RMB amount of sales, the date of transaction, and the industry and registered location of the invoice issuer (seller).

We have access to all the invoice data at the transaction level from January 1, 2019, to April 16, 2020. The total number of invoices for this sample period is around 1.53 billion with an RMB value of 39.82 trillion. These invoices have been issued by 3.9 million unique firms and 1.7 million self-employed entities.[7] China's official annual statistics do not reflect data on firm sales, but every five years, the National Bureau of Statistics of China (NBS) conducts a nationwide economic census, the latest of which was conducted during the calendar year 2018. By comparing our 2019 sales data to the 2018 aggregate sales reported by the Fourth National Economic Census, we can gauge the coverage of our data set. The total sales extracted from our invoice data set for 2019 was RMB 33.4 trillion, whereas that number was 294.6 trillion in the nationwide economic census for 2018, implying a coverage of 11.3% (=33.4/294.6) with our data set. Meanwhile, the coverage ratios for the number of corporations and self-employed entities are 17.7% and 2.7%, respectively, suggesting that self-employed businesses are less likely to pay VAT and thus less covered by our sample.[8]

Our data also cover firms and self-employed business entities in all 343 prefectures/directly controlled cities and 19 industries classified by NBS. One concern for our invoice-based sales data is that they might be biased toward some region or industry. This, however, is not the case. Sales are similarly distributed across provinces and industries in our sample and in the full sample reported by the 2018 economic census (Fig. A1 in the appendix). The same is true if we compare the distributions of the number of firms across industries, provinces, and sizes measured by the registered equity capital (Fig. A2 in the appendix). Therefore, we are confident that our sales samples based on VAT invoices provide representative coverage for all regions and industries.

A couple of papers rely on survey data (Bartik et al., 2020; Crossley, Fisher, & Low, 2021) or aggregate economic variables (Lewis et al., 2020) to measure business activities after the COVID-19 outbreak in the United States. Compared to these approaches, our VAT-based sales data offer several advantages. First, our data have the most comprehensive and unbiased coverage of China's business activities across firm size, location, and industry, a feature that allows us to quantify the heterogeneous impacts due to COVID-19 pandemic on Chinese economy. Second, that our data are at a daily frequency allows us to accurately measure how China's business activities respond to the pandemic-induced restrictions that are imposed and later lifted. Third, this paper complements papers

[4] The company collects and processes data on firms' transactions, business registrations, litigation, online job postings, and other information from both proprietary and public data sources. The company then applies various pieces of information on risk management, marketing, and firm credit evaluation using big data techniques and artificial intelligence algorithms. The data we have access are firms' sales extracted from transaction-level invoices. The company's website is http://www.daokoujinke.com.

[5] All firms selling products and services in China are obligated to pay value-added taxes. The tax amount payable is the output tax minus the input tax for a given period. If the output tax is insufficient to offset the input tax, the excess credit can be carried forward for the following periods.

[6] Firm characteristics include registration status, registered equity capital, industry, location of registration, and the ownership type.

[7] In this paper, we follow the National Bureau of Statistics of China (NBS) and State Administration for Industry and Commerce's (SAIC) classification of corporations and self-employed entities. Corporations are registered enterprises with a business license. Self-employed entities are the individual labor-based entities, including self-employed individuals who work in industries of industrial, service, construction, catering, etc.; non-enterprise private entities; and individuals without a business license but who have fixed places of business and have engaged in business activities for at least three months.

[8] Because the NBS census does not include firms in the primary industry (agriculture) or public administration, in this comparison, we also exclude invoices issued by firms in the primary and public administration industries. Note that the total sales in the primary and public administration industries in our 2019 sample are only RMB 0.376 and RMB 0.002 trillion, respectively, which are much smaller than the sales of 33.4 trillion in other industries.

using real-time household debit/credit card transaction data to gauge consumption responses to disease containment measures (Alexander & Karger, 2020; Carvalho et al., 2021; Chen et al., 2021; Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2023). Chetty et al. (2020), whose data comprehensively cover household consumption, job postings, unemployment, and small business revenue at a daily frequency, offers the most similar counterpart study to ours, while their study is from a U.S. perspective.

Our VAT invoice sample ranges from January 1, 2019, to April 16, 2020. A firm is included in our sample only if it has at least one invoice for 2019.[9] We sort firms into four size categories based on their 2019 annual sales and the industry they belong to. For each industry, the NBS demarcates sales cutoffs to classify firms into four categories: micro, small, medium-sized, and large. For example, the cutoff for large firms in the construction industry is RMB 800 million, whereas it is RMB 100 million for firms in the catering industry (for details, see Table A1 in the appendix). Fig. 1 charts the total sales and the number of firms by size category. While 41.8% and 42.9% of sales in RMB value come from large and medium-sized firms, the number of these relatively large firms account for only 0.3% and 7.2% of the number of all firms. On the other hand, small and micro firms account for 23.2% and 69.2%, respectively, in the number of firms, while the total sales of these two groups represent only around 15%.

Fig. 2 graphs weekly RMB sales and the relative sales w.r.t. the four-week average before the Wuhan's lockdown. Week 0 refers to the week ending on January 23, 2020, when Wuhan's lockdown was announced. A few observations are worth discussing. First, after Wuhan's lockdown, business activities, as measured by firm sales, dramatically plunged to almost zero and slowly recovered to around 50% of the pre-lockdown level after 12 weeks. Second, even though the lockdown is coincident with the 2020 Chinese New Year's holiday, the impact of COVID-19 is prominent as it took less than four weeks for business activities to fully resume after the 2019 holiday. Third, there is clear end-of-month seasonality for sales, probably because firms tend to clear transactions at a pre-determined monthly frequency. Fourth, sales across all four size categories experienced a dramatic drop in the first eight weeks after the announcement of Wuhan's lockdown but recovered later at a similar speed. In Section 3, we will provide detailed analyses of how firms with different sizes are adversely affected by the pandemic and then recover afterward.

2.2. Other data

We collect the dates associated with provinces' public health emergency announcements from provincial-level government news releases. In China, the central government delegates public health emergency announcements to provincial-level governments. Public health emergencies are categorized into four levels with level one being the highest risk and level four the lowest risk. Each level corresponds to different mobility restrictions that local governments can impose.[10] Fig. 3 plots the proportion of public health response by emergency level from January 23, 2020, to April 16, 2020.[11]

To examine how business activities react to the post-pandemic local government stimulus policies, we also collect detailed information about those stimulus measures. Since the first policy issued by Wenzhou, Zhejiang on January 30, 2020, local governments have issued 912 policies as of April 16, 2020, with the aim of cushioning the heavy economic shock. We classify these local stimulus policies into three groups based on their contents, including 596 measures related to provisions of financial assistance, 544 measures on fee deferrals and reductions, and 357 measures on tax exemptions and reductions.[12] Fig. 4 plots the total number of economic support policies by day as well as by group. First, local stimulus measures were issued over time, with around 60% issued in February 2020. Second, policies with financial assistance measures were more commonly issued than the other two groups of policies. Third, a local government may have issued multiple policies that support economic stimulus in different ways.

The number of confirmed cases and deaths related to COVID-19 has been downloaded from CSMAR. Macroeconomic variables at the city level, including income per capita, population, and fixed-asset investment over GDP, come from the City Statistical Yearbook. We fill in missing values using the City Statistical Communique on Economic and Social Development. Daily within-city movement intensity, inflow from Wuhan, and inflow from other Hubei cities have been obtained from Baidu. Temperature and humidity data have been obtained from National Meteorological Information Center, and the air quality index comes from the Ministry of Ecology and Environmental.

[9] We exclude firms that only have invoices for 2020 to rule out the possibility of bias due to data expansion; that is, some firms started using the invoice management service of our data vendor in 2020. This filter excludes 3.02 million invoices, or 0.2% of our entire sample. On the other hand, we keep those firms that only issued invoices in 2019, as issuing no invoices in 2020 could represent the extreme scenario that a firm has been affected by the pandemic-induced containment measures.

[10] According to the National General Emergency Plan for Public Emergencies issued by the State Council, the announcements of public health emergency are classified and based on severity, controllability, and the consequences of the emergency: level I (extraordinarily serious), level II (serious), level III (large), and level IV (ordinary).

[11] Since the number of level IV observations in our sample is very small and the difference between mobility restrictions in level III and level IV is negligible, we merge level IV with level III in our analysis.

[12] We classify all policies into three non-exclusive categories in accordance with three sets of key words. One policy could be classified into two or even three groups simultaneously if it contains keywords from both or all three sets. The keywords related to financial assistant include "financial support," "interest reduction," "rollover," "special-purpose loan," "exemption for penalty due to late interest payment," "not withdrawing loans," "repayment deferral," "COVID-19 loan," "increasing credit lines," etc. The keywords related to fee deferral and reduction include "fee reduction," "fee deferral," "social security exemption/deferral/extension," "unemployment insurance remission," "rental reduction," "employment subsidy," etc. The keywords related to tax exemptions and reductions include "value-added-tax reduction," "other taxes reduction," "tax subsidies," "tax reporting extension," etc.

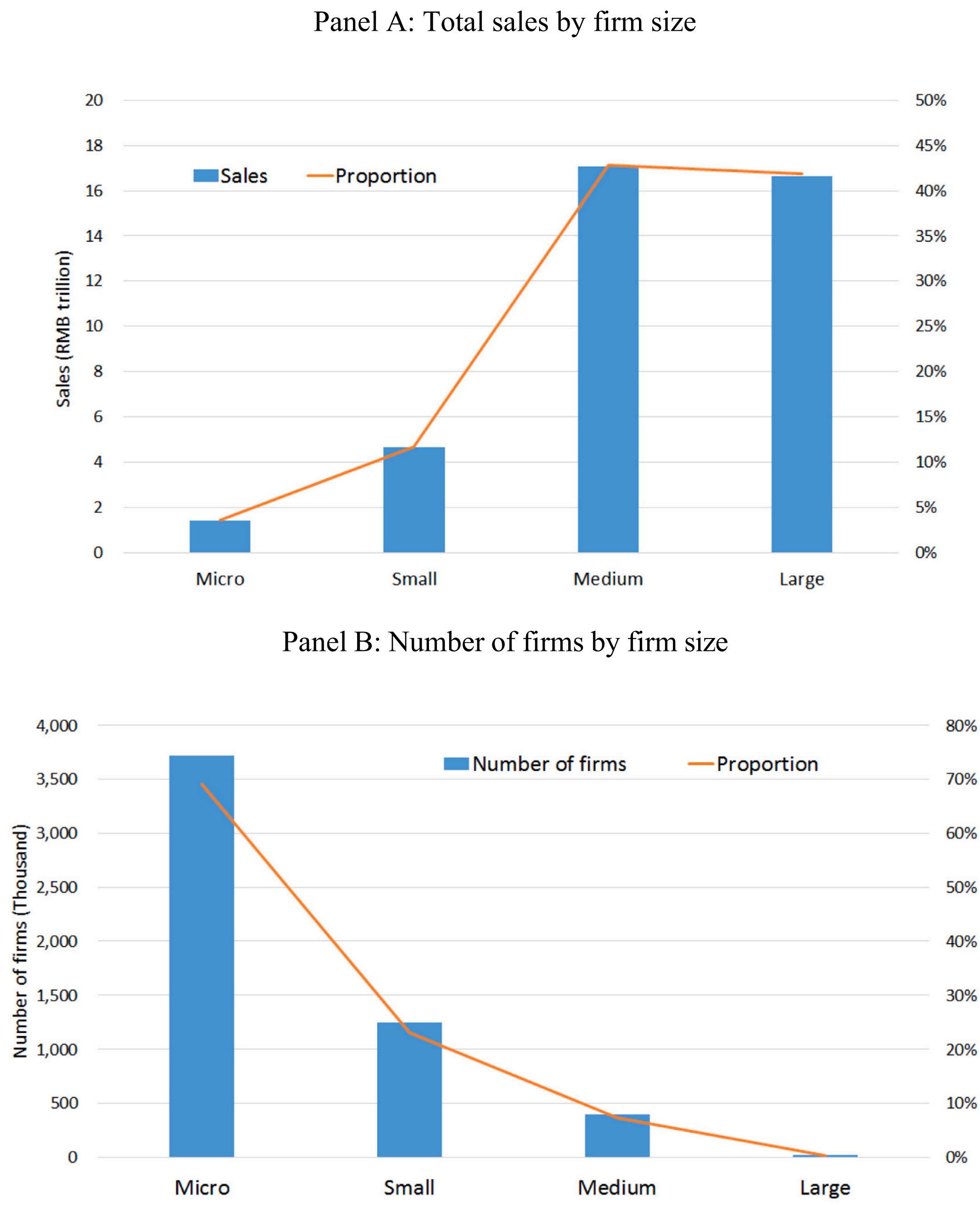


Fig. 1. Sales and the number of firms by size.
This figure plots the aggregate sales and the number of firms by size during our sample period of January 1, 2019, to April 16, 2020. Firms are sorted into one of four size categories based on their 2019 sales, in accordance with the NBS industry cutoffs. Panel A plots the aggregate sales in RMB trillion for large, medium-sized, small, and micro firms during the sample period. Panel B plots the number of firms by size.

2.3. Summary statistics

We aggregate firm sales to four industry-dependent size groups at the city and daily levels, that is, a size-city-day panel. The panel data have been winsorized at the 1% and 99% levels. Our raw data cover January 1, 2019, to April 16, 2020. To ensure the data availability of the counterfactual business activities in 2019 and minimize the impact of the end-of-month seasonality, we select the 2020 sample period to be December 27, 2019, to April 16, 2020, which is 4 weeks before and 12 weeks after the January 23, 2020, Wuhan lockdown. We define week 0 as the week ending on January 23, 2020. Following Chen et al. (2021), we match the lunar

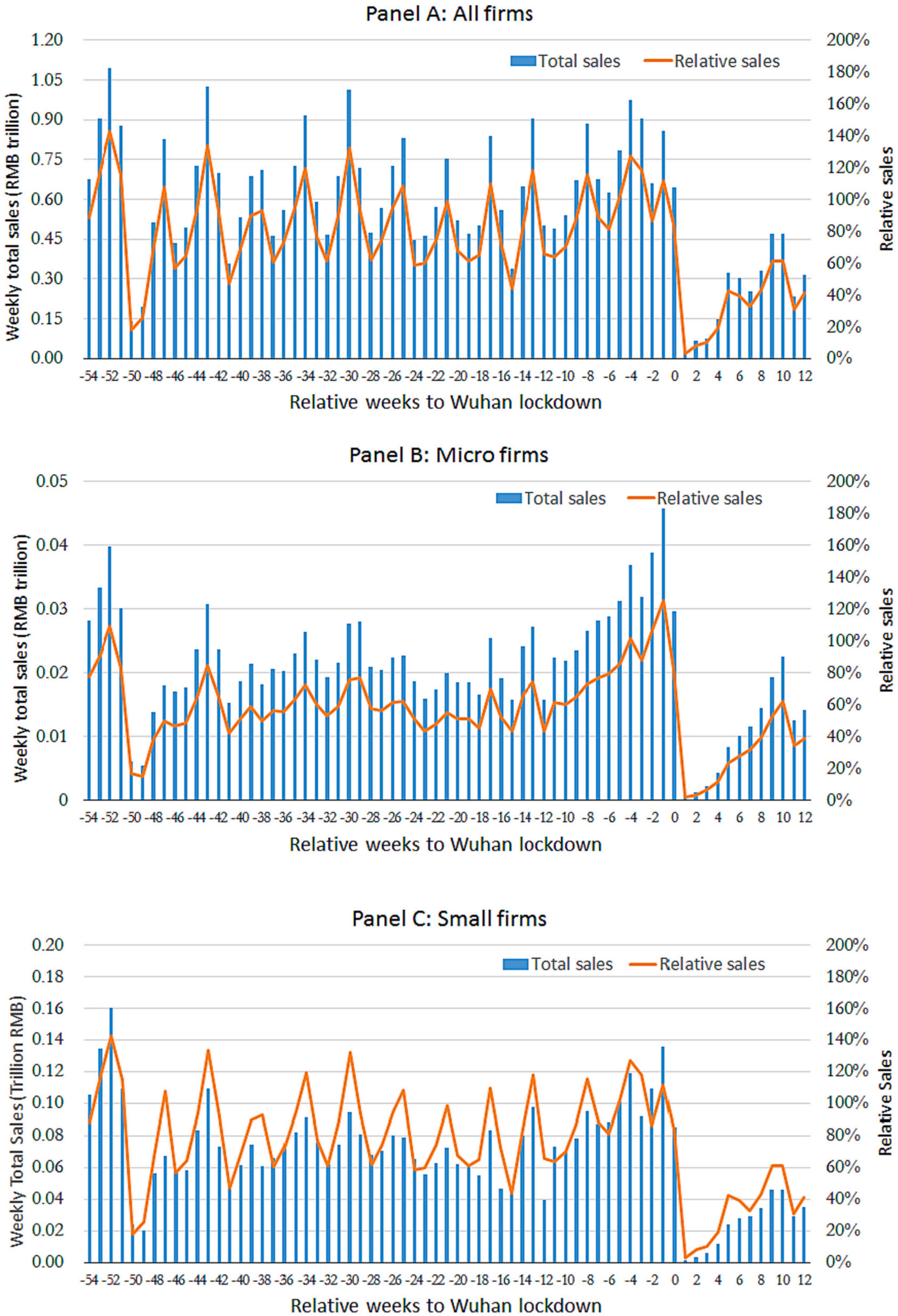


Fig. 2. Weekly aggregate sales.
This figure plots the weekly aggregate sales and relative sales during our sample period of January 1, 2019, to April 16, 2020. Week 0 is the week ending on January 23, 2020, when Wuhan was under complete lockdown. Relative sales (y-axis) have been calculated as weekly sales over the

average sales from week −3 to week 0. Panel A plots the weekly aggregate sales and relative sales for all firms. Panels B to E plot the weekly sales and relative sales by firm size, where firms are sorted into one of four size categories based on their 2019 sales, in accordance with the NBS industry cutoffs.

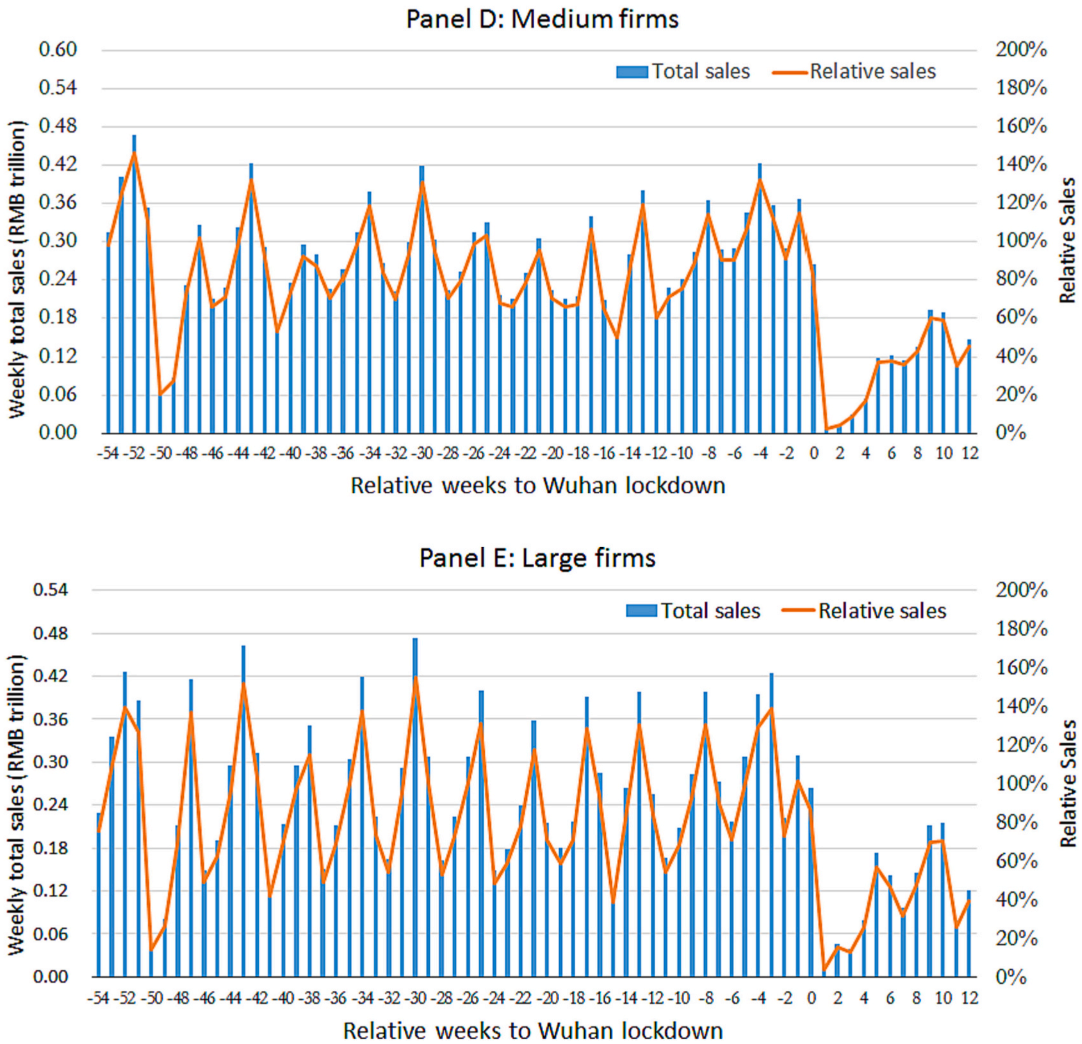


Fig. 2. (*continued*).

calendar in 2020 and 2019 to control for the seasonality due to the Chinese New Year's holiday. Specifically, as January 23, 2020, is one day before the Chinese New Year's Eve, February 3, 2019, is defined as a counterpart "day 0" for 2019. Therefore, we use January 7, 2019, to April 28, 2019, as the benchmark sample period. Our final sample includes two subperiods of December 27, 2019–April 16, 2020, and January 7, 2019–April 28, 2019, aggregated at size-city-day level. Following Chetty et al. (2020), we normalize daily sales w.r.t. the daily average over the four-week window before the starting date of Wuhan's lockdown, so all our daily observations are comparable across time and city. Specifically, relative sales are defined as daily sales for firms within a size group divided by the daily average of December 27, 2019–January 23, 2020, for 2020 and January 7, 2019–February 3, 2019, for 2019. Therefore, all our estimates reflect the change in sales (expressed as a percentage) due to the COVID-19 crisis compared to the pre-holiday level.[13]

Table 1 presents summary statistics for relative firm sales for the 2020 affected sample and the 2019 benchmark sample. Panel A shows that after Wuhan's lockdown, the average relative sales are only 45% compared to the pre-lockdown four-week daily average for firms belonging to a size group in one city. The much lower post-event sales reflect both the holiday effect and the COVID-19 crisis. To

[13] We eschew the use of the sales level as our dependent variable for two reasons. First, as previously mentioned, our data do not contain all invoices issued by firms in China; therefore, the point estimates using the sales level lack an economic interpretation even though the data coverage is unbiased. Second, the time-series variations across large and small cities for the sales level are vast, resulting in less meaningful economic estimation. With this in mind, our results, which are available on request, still hold when using the sales level as the dependent variable.

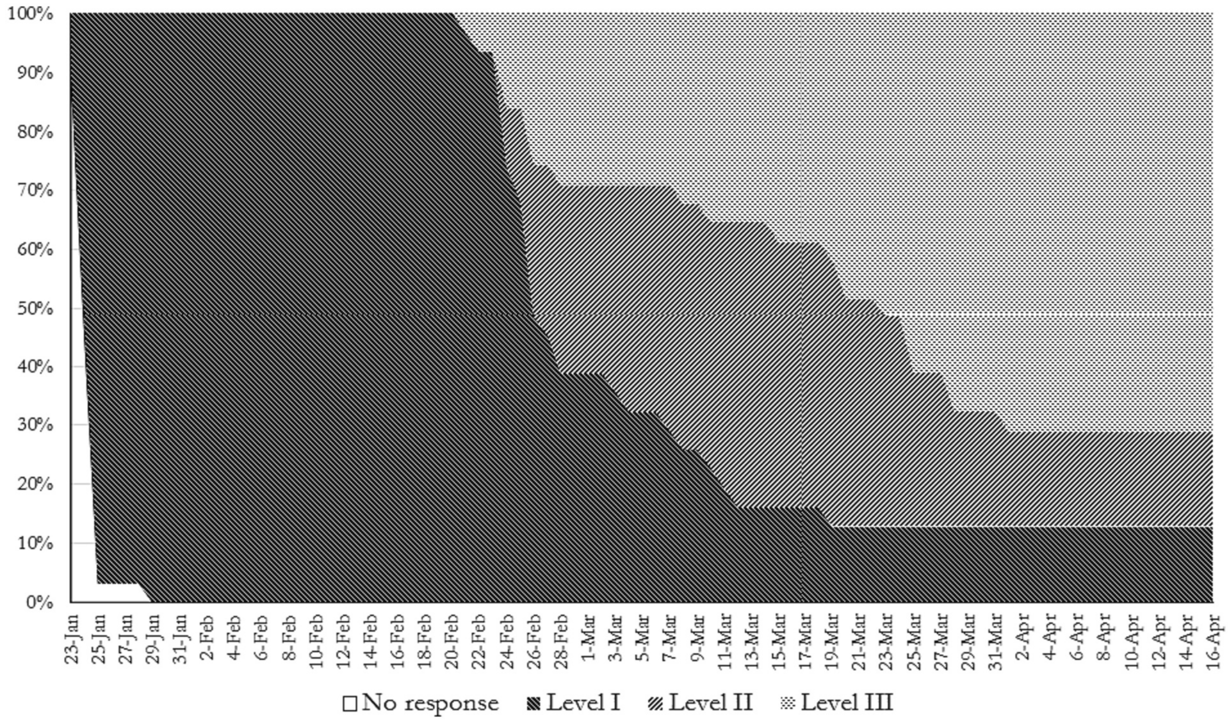


Fig. 3. Public health response by emergency level.
This figure plots the proportion of public health response by emergency level for the sample period of January 23, 2020, to April 16, 2020. The dates of announcements were hand-collected from news releases.

show this more clearly, we report the average relative sales for four different size groups in 2019 and 2020 in Panels B and C. In 2019, during the 12 weeks after the event date, which covers the Chinese New Year's holiday, the average sales are 57% and 47% of the pre-holiday sales for micro and small firms, and the numbers are 65% and 71% for medium-sized and large firms. The smaller relative sales for small firms suggest that the holiday has a stronger effect on small firms, which rely more heavily on labor for their operations.[14] In 2020 after the COVID-19 pandemic hit, average relative sales ring in at only 29%, 24%, 32%, and 37% for micro to large firms compared to the pre-lockdown four-week daily average. These values are much smaller than the 2019 numbers. Note that the pre-lockdown sales are similar in 2019 and 2020, validating our choice of 2019 as a benchmark. In the formal analysis, we will implement DID regressions to measure the COVID-19 impacts on sales in 2020 using 2019 as the control year.

3. Empirical results

In this section, we first present our formal empirical design, which aims to measure the impact of the COVID-19 pandemic on China's business activities by firm size. Next, we report three sets of results: first, the time-varying and firm-size-dependent impacts of COVID-19, as well as heterogeneous impacts across various industries; second, the effectiveness of local government economic stimulus measures; and third, the city characteristics that affect the magnitude of the impact and the speed of recovery due to the COVID-19 pandemic.

3.1. Research design

In this paper, we probe how the COVID-19 outbreak affected China's business activities while strict containment measures were in place. An ideal setting would include randomness for introducing strict containment measures across locations and firms. However, what's best for an economic study is not necessarily what's ideal for containing a viral outbreak. In reality, China effectively shut down the whole country for four weeks after Wuhan's January 23 lockdown and then gradually lifted the public health measures.

What also complicates the identification is that the period of strict containment measures overlaps with the Chinese New Year's

[14] Our 2019 sample ends on April 28, 2019, which does not cover the month-end days that usually see larger sales. In addition, the March 2019 sales are also larger than the April 2019 sales because of the quarter-end effect. As a result, the average daily relative sales for the post-event period in 2019 are only 50% to 70% of those for the pre-holiday period. In our formal analysis, we include a time fixed effect to control for seasonality in our sales data.

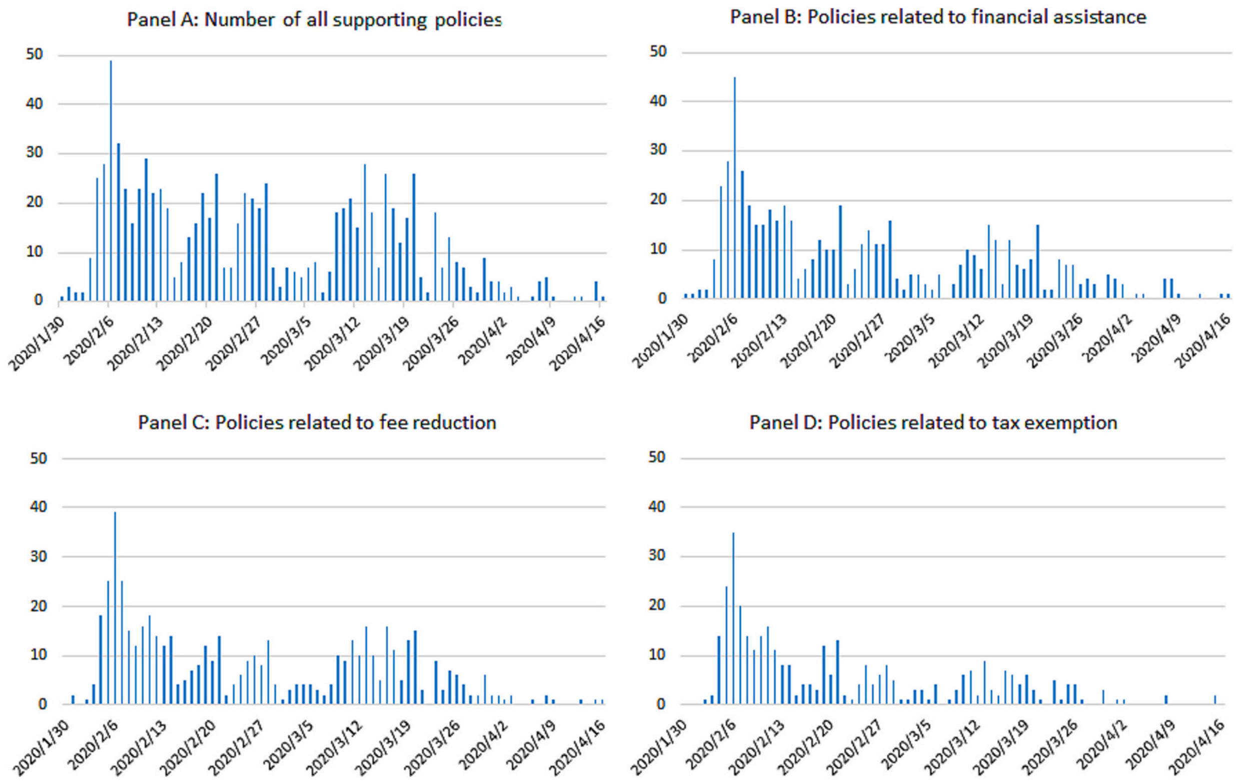


Fig. 4. Government interventions and stimulus policies.
This figure plots the number of local government economic stimulus policies for the sample period of January 30, 2020, to April 16, 2020. Panel A plots the daily number of local stimulus policies. Panels B to D plot the daily number of policies related to financial assistance, fee deferrals and reductions, and tax exemptions and reductions. One policy could be related to two or three of these categories and thus be included in multiple groups. The stimulus policies were collected through news and provided by Daokou FinTech.

holiday, a period when business activities, especially for small businesses, significantly decrease for two to four weeks compared to other months of the year. As a result, we need to tease out the effect of the COVID-19 crisis from the effect of the holiday. Lastly, firm sales in China exhibit strong seasonality: sales are much smaller on weekends and holidays, and larger at the ends of the month and quarters. Therefore, we control for seasonality when evaluating the effect of the COVID-19 pandemic.

We tackle these challenges following a DID strategy similar to the one proposed by Chen et al. (2021) and Fang, Wang, and Yang (2020). First, we use the 2019 daily sales 4 weeks before and 12 weeks after the event day matched by the lunar calendar as the benchmark. The event days are February 3rd for 2019 and January 23rd for 2020.[15] The identification assumption here is that, without the pandemic, sales patterns would be the same across the two years, except for the time trend that can be absorbed by time fixed effects. Second, we include two sets of time fixed effects. The first set of time fixed effects includes the number of days from the event day that captures the holiday effect. The second set includes the day of week that absorbs the within-week seasonality.[16] Third, we add city fixed effects to control for time-invariant heterogeneous shocks across cities, as well as size fixed effects that absorb size-dependent

[15] We also use the exact timing of announcements of different cities for robustness check in Table A2, Panel A. But our decision to select January 23rd, 2020, the date of Wuhan's lockdown, as the event day in our main regressions is informed by the precedent in the literature and the unique characteristics of our data. First, this approach aligns with the methodologies employed in studies like Fang et al. (2020), Chen et al. (2021), and Ai et al. (2022), which disentangle the effect of lockdown on mobility, consumption expenditure and electricity consumption, respectively, by comparing the lockdown and pre-lockdown periods in 2019 and 2020. Second, our data mainly covers the first wave of the pandemic until April 2020, capturing the nationwide impact and resulting panic. For instance, as shown in Fig. A3, the Baidu Migration Index indicates that even cities not under lockdown by January 23rd, 2020, such as Beijing, Shanghai, Guangzhou, and Shenzhen experienced significant disruptions in population movement. Therefore, designating the lockdown of Wuhan as the event date is reasonable, as after this, regardless of whether the city officially announced a lockdown or not, people's willingness to travel voluntarily significantly decreased, and economic activities were greatly affected. Third, following the insights from Chen et al. (2022a), the effects of policy interventions, even when localized, can have spillover effects into other economically linked areas. This perspective is supported by the findings of Bonadio et al. (2021), Baqaee and Farhi (2022).

[16] In the robustness tests, we also include day-of-the-month fixed effects, and the results are similar (Panel B, Table A2).

Table 1
Summary statistics.

Panel A: Size-city-day panel								
	Obs.	Mean	SD	P5	P25	Median	P75	P95
All	296,212	0.58	0.63	0.01	0.11	0.39	0.84	1.79
Pre-lockdown	74,777	0.97	0.71	0.08	0.38	0.89	1.38	2.26
Post-lockdown	221,435	0.45	0.54	0.00	0.08	0.29	0.64	1.43
Post-pre		−0.52		−0.26	−3.45	−11.39	−35.76	−156.36
t-stat		(−206.94)						

Panel B: Average relative sales by size group, 2019				
	Micro	Small	Medium	Large
Pre-lockdown	0.99	0.99	0.99	0.92
Post-lockdown	0.57	0.47	0.65	0.71
Post-pre	−0.42	−0.52	−0.33	−0.21
t-stat	(−71.83)	(−85.38)	(−46.35)	(−20.83)

Panel C: Average relative sales by size group, 2020				
	Micro	Small	Medium	Large
Pre-lockdown	0.98	0.99	0.98	0.90
Post-lockdown	0.29	0.24	0.32	0.37
Post-pre	−0.70	−0.74	−0.66	−0.53
t-stat	(−132.58)	(−136.51)	(−112.17)	(−65.20)

This table presents summary statistics for relative sales at the city-day-size level. Relative sales are defined as the daily sales over the average daily sales of December 27, 2019–January 23, 2020, for the 2020 observations and January 7, 2019–February 3, 2019, for the 2019 observations. The pre-lockdown periods are January 7, 2019–February 3, 2019, and December 27, 2019–January 23, 2020, the post-event periods are February 4, 2019–April 28, 2019, and January 24, 2020–April 16, 2020. Panel A presents summary statistics for the full sample. Panels B to C present average daily city sales by size group for the 2019 and 2020 subsamples.

shocks to business sales.[17] Lastly, following Chetty et al. (2020), we use relative sales as our main dependent variable, that is, daily sales divided by average daily sales over the pre-event four weeks,[18] which measure the relative drop in business activities without worrying about any potential structure change of the sales data across these two years.[19]

Specifically, we use the following DID regression in a city-day-size panel:

$$Sales^{relative}_{c,t,s} = \alpha_c + \tau_t + D_s + D_s \times Post_t + \sum_{s=1}^{4} B_s D_s \cdot Y_{2020} \cdot Post_t + \varepsilon_{c,t,s}, \tag{1}$$

where α_c and τ_t are city fixed effects and the two sets of time fixed effects absorb city and time invariant shocks; D_s correspond to the four size groups, where D_1 indicates micro firms and D_4 indicates large firms; Y_{2020} is a dummy variable that equals one for 2020 observations; $Post_t$ equals one for the post-event periods, that is, after January 23rd for 2020 and after February 3rd for 2019; and $D_s \times Post_t$ denotes fixed effects that capture size-dependent common shocks post the event day. Note that we do not need the interactive fixed effects $D_s \times Y_{2020}$, because all 2019 and 2020 observations are normalized by their pre-event averages, respectively. The point estimates B_s (s = 1, 2, 3, 4) measure the average daily percentage drop in sales by firm size for a typical city.

One leading concern with our empirical strategy is that sales in 2019, i.e., our benchmark year, may exhibit different patterns compared to the 2020 sales before the event day. Fig. 5 shows that it is not the case. The relative sales for four size categories are almost the same in the four-week pre-lockdown window in two years. Therefore, the parallel trend assumption is satisfied for our DID analysis. On the other hand, the relative sales are substantially smaller in 2020 than those in 2019 after the event day, suggesting clear treatment effect due to Wuhan's lockdown.

One concern regarding our research specification is that small firms are more likely to evade tax and hence the VAT-invoice may not reflect the true sales for smaller firms. We believe our main results are still valid for the following three reasons. First, we use the relative firm sales for each size group as our dependent variable and our short sample period of 16 weeks ensures the time-varying

[17] Table A2, Panel C, presents the results after including city×time fixed effects to control for the city-time dependent shocks. The results are similar to our baseline results.
[18] Alternatively, we measure relative sales as daily sales divided by average same-day-of-week sales during the pre-event four weeks. All results are similar and available on request.
[19] Another reason that we do not use the sales level as our dependent variable is that our sales data cover around 11% of total sales, which makes the economic interpretation of estimated coefficients less meaningful.

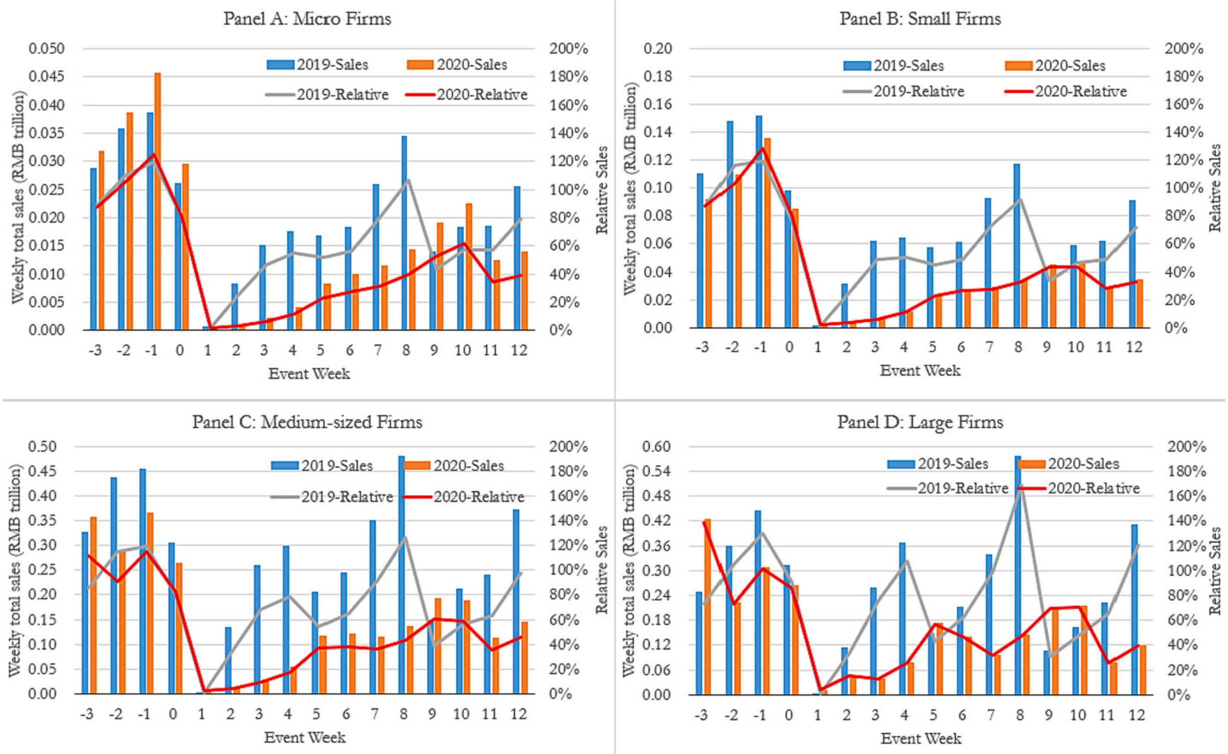


Fig. 5. Weekly sales around the event day.
This figure plots the weekly aggregate sales and relative sales from 4 weeks before to 12 weeks after the event day. The event days are February 3 for 2019 and January 23 for 2020. Week 0 refers to the week ending on the event day. Relative sales (right y-axis) have been calculated as weekly sales over the average sales from week −3 to week 0. Panels A to D plot the weekly sales and relative sales by firm size, where firms are sorted into one of four size categories based on their 2019 sales, in accordance with the NBS industry cutoffs.

Table 2
Impacts of COVID-19 on sales.

	Full	Subsamples		
	[1, 12]	[1, 4]	[5, 8]	[9, 12]
	(1)	(2)	(3)	(4)
Micro firms β_1	−0.29***	−0.27***	−0.43***	−0.17***
	(−12.08)	(−5.75)	(−13.89)	(−4.46)
Small firms β_2	−0.23***	−0.23***	−0.33***	−0.13***
	(−10.48)	(−4.99)	(−10.23)	(−3.63)
Medium firms β_3	−0.33***	−0.38***	−0.46***	−0.17***
	(−11.82)	(−7.57)	(−11.45)	(−3.51)
Large firms β_4	−0.35***	−0.42***	−0.46***	−0.17**
	(−8.23)	(−5.90)	(−6.56)	(−2.54)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Size * $Post_t$	Yes	Yes	Yes	Yes
Obs.	296,212	147,187	149,063	149,516
Within R^2	0.0752	0.0637	0.0840	0.0147

This table reports regression results for the average impacts due to the COVID-19 lockdown on relative sales by firm size. Relative sales are defined as daily sales divided by the pre-lockdown 28-day average of each corresponding year. The event day is set to January 23, 2020, when Wuhan was under lockdown and a lunar calendar matched event day for 2019 is set to February 3, 2019. β_1/β_4 measures the average impact at the city-day level for micro/large firms. The full sample period includes 4 weeks before ([−3,0]) and 12 weeks after ([1,12]) the event day. Three subsamples include daily observations in [−3,0] and [1,4], [5,8], and [9,12] weeks, respectively. The sample periods are January 7, 2019, to April 28, 2019, and December 27, 2019, to April 16, 2020. Heteroscedasticity consistent *t-statistics* clustered by city and day are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

change in tax evasion activities to be small. Second, the VAT was first piloted in 2012 and completed throughout the country in 2016. Under VAT, both economic and legal costs of tax evasion are much higher compared to the old business tax system. Third, we exclude firms with only 2020 invoices to rule out the possibility that small firms in 2019 are more likely to evade tax.

In addition to the above benchmark specifications, we delve into other subsample analyses, evaluations for state of emergency announcements, and stimulus policy responses. We will discuss these specifications in their respective sections. We employ ordinary least squares (OLS) regressions, and standard errors are clustered by city and day.

3.2. Main results

Table 2 reports the size-dependent effects on Chinese business activities due to the COVID-19 pandemic. Column (1) presents the estimated impacts for the four firm size groups over the 12-week window after Wuhan's lockdown. On average, large firms experience the most substantial drop in sales by 35%, followed by a 33% for medium-sized firms, a 29% for micro firms, and a 23% for small firms.[20] While the impacts are not strictly monotonic across different sized firms, large and medium-sized firms experience steeper drops in sales compared with small and micro firms, suggesting that larger firms may be able to better comply with the government's containment measures and thus can reduce their business activities. On the other hand, small businesses, which are usually privately owned and have been historically less resistant to health epidemics, have to keep business going, at least to some extent, to survive.

In Columns (2) to (4), we further examine the effect of the COVID-19 crisis on sales over three different subperiods: [1,4], [5,8], and [9,12] weeks post-lockdown. The same pattern of larger firms experiencing a larger drop in sales is also evident in the first two subperiods (Columns 2 and 3), whereas all firms resume to around 85% of their normal sales level eight weeks after Wuhan's lockdown (Column 4).

We acknowledge that fully exploring and explaining the underlying reasons for the heterogeneity across firm size is a complex endeavor, potentially extending beyond the scope of our current study. Nevertheless, we can provide some preliminary explanations. While we cannot directly ascertain the supply chain network relationships between firms from our data, we can offer an explanation from a supply chain perspective based on publicly available data. Specifically, we utilized data from CSMAR to determine the geographic proximity of public companies to their upstream and downstream supply chain entities. Our findings in Fig. A4 reveal a negative relationship between a company's revenue and the geographic distance of its supply chain partners, indicating that larger firms tend to have more geographically concentrated supply chains.

Even though the public companies are typically large firms, this finding provides some insights into why larger businesses might be more significantly impacted during the outbreak of a pandemic like COVID-19. This agglomeration effect, while beneficial under normal circumstances, suggests a higher vulnerability to region-specific disruptions, such as lockdowns or local outbreaks. In such scenarios, the interconnected nature of these geographically concentrated supply chains can lead to a cascading effect, where a disruption in one part of the chain can quickly ripple through the entire network, significantly impacting larger companies at the center of these clusters.

One observation worthy of note is that sales decrease by a greater amount during the second four-week period than the first one, and such an effect is more obvious for small and micro firms. This finding suggests that firms could not have their employees back to work even after the holiday month. In other words, whereas 2019 sales quickly resumed after the Chinese New Year's holiday month, 2020 sales remained low because of the COVID-19 mobility restrictions, leading to a larger DID effect for the second four-week period post- Wuhan lockdown.[21] For the four-week period that is eight weeks after Wuhan's lockdown, business activities quickly resume to around 85% of the usual level. The message from Table 2 is that COVID-19 containment measures reduced China's business activities across different-sized firms by around 20%–45% for the first eight weeks after Wuhan's lockdown, but the economy bounced back quickly afterward.

We have also obtained data from He, Pan, and Tanaka (2020) to identify the accurate timing when the firms were affected by the pandemic prevention measures. Specifically, He et al. (2020) collected the local government's lockdown policies city by city from news media and government announcements and defined a city as locked down when all three of the following preventive measures were enforced: ban on non-essential commercial activities in everyday life, prohibition of all forms of resident gatherings, or limitations on both private and public transportation. We use these exact timing of lockdowns in various cities as event dates and replicate the results in Table 2. Results shown in Table A2, Panel A reveal that the main results are robust and the average firm sales drop by 30%, 26%, 36%, and 40% for micro, small, medium-sized, and large firms, respectively, suggesting that larger firms may be better equipped to adapt to public health measures.

Our invoice-based sales data also contain information on the industry that an invoice issuer belongs to, a fact allowing us to examine the heterogeneous impacts of COVID-19 pandemic by industry. We consider 18 industries and drop the Public Administration

[20] For comparison, we report the sales of publicly listed firms in the first quarter of 2019 and 2020 as well as the Q1-Q1 growth in Appendix Table A3. The 3676 public firms experienced an average drop in sales by 8.1% in the first quarter of 2020.

[21] Employees working for small businesses in China usually do not take off the two-day weekend. Instead, they work for six or sometimes even seven days a week during most weeks of a year. But during the Chinese New Year's period, small business employees take a two- to four-week vacation, resulting in significantly low business activities for the first four weeks after the Chinese New Year's Eve. This is also true for 2019, as relative sales during the four-week holiday period are 32.3%, 31.3%, 45.8%, and 54.4% for micro, small, medium-sized, and large firms. Because relative sales for the four-week holiday period in 2019 are already quite low for small businesses, their DID estimates are smaller than those of large firms in the subperiod of weeks [1,4].

Table 3
Impacts of COVID-19 on sales: Heterogeneous industry effects.

	Weeks [1, 4]				Weeks [5, 8]				Weeks [9, 12]			
	Micro	Small	Medium	Large	Micro	Small	Medium	Large	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Agriculture	−0.23***	−0.22***	−0.22**	0.09	−0.21***	−0.22***	−0.24***	−0.16	−0.16***	−0.12***	−0.08	0.02
	(−6.23)	(−5.95)	(−2.61)	(0.55)	(−5.90)	(−6.33)	(−2.94)	(−0.92)	(−3.87)	(−2.73)	(−1.04)	(0.18)
Mining	−0.27**	−0.31***	−0.15	0.11	0.01	−0.24***	−0.27***	−0.23	0.14	−0.10	−0.12	−0.01
	(−1.98)	(−3.20)	(−1.11)	(0.38)	(0.13)	(−2.96)	(−2.77)	(−1.18)	(1.63)	(−1.24)	(−1.33)	(−0.06)
Manufacturing	−0.30***	−0.40***	−0.48***	−0.44***	−0.52***	−0.57***	−0.61***	−0.57***	−0.14***	−0.14**	−0.13	−0.12
	(−7.17)	(−7.99)	(−6.46)	(−3.32)	(−9.69)	(−7.51)	(−6.43)	(−4.50)	(−3.07)	(−2.06)	(−1.50)	(−0.92)
Utilities	−0.26***	−0.17***	−0.21**	−0.10	−0.18***	−0.09	−0.16**	−0.12	−0.25***	−0.18***	−0.17**	−0.13
	(−5.71)	(−2.71)	(−2.51)	(−0.81)	(−3.68)	(−1.56)	(−2.36)	(−1.07)	(−4.73)	(−2.95)	(−2.45)	(−0.93)
Construction	−0.15***	−0.15***	−0.18***	−0.14*	−0.18***	−0.18***	−0.25***	−0.20***	−0.09**	−0.11***	−0.19***	−0.13**
	(−3.17)	(−3.19)	(−3.56)	(−1.74)	(−5.31)	(−5.16)	(−6.63)	(−2.98)	(−2.43)	(−3.32)	(−4.82)	(−2.28)
Wholesales & retail	−0.36***	−0.31***	−0.43***	−0.53***	−0.53***	−0.45***	−0.49***	−0.47***	−0.22***	−0.10**	−0.10**	−0.10
	(−7.45)	(−6.97)	(−8.52)	(−7.88)	(−15.36)	(−12.50)	(−11.03)	(−7.17)	(−5.14)	(−2.58)	(−2.07)	(−1.21)
Trans. & logistics	−0.42***	−0.46***	−0.54***	−0.27***	−0.43***	−0.42***	−0.49***	−0.27***	−0.20***	−0.14**	−0.14**	−0.03
	(−9.50)	(−6.81)	(−8.68)	(−2.82)	(−9.32)	(−7.43)	(−6.32)	(−2.72)	(−3.71)	(−2.61)	(−2.09)	(−0.27)
Hotels & catering	−0.56***	−0.53***	−0.58***	−0.52***	−0.71***	−0.63***	−0.64***	−0.54***	−0.34***	−0.42***	−0.48***	−0.47***
	(−9.91)	(−9.07)	(−7.44)	(−5.83)	(−17.34)	(−17.06)	(−9.96)	(−4.84)	(−8.97)	(−11.73)	(−7.36)	(−4.49)
IT & comm Tech	−0.40***	−0.31***	−0.38***	−0.44***	−0.46***	−0.33***	−0.32***	−0.39***	−0.21***	−0.21***	−0.13**	−0.20*
	(−9.87)	(−6.98)	(−7.92)	(−6.50)	(−14.69)	(−10.21)	(−6.25)	(−4.14)	(−4.63)	(−5.56)	(−2.31)	(−1.88)
Financial Services	−0.12	−0.46***	−0.44***	−0.65***	−0.12	−0.22***	−0.31***	−0.63***	0.04	−0.04	−0.11	−0.23***
	(−1.08)	(−9.23)	(−8.60)	(−6.82)	(−1.61)	(−4.13)	(−5.86)	(−8.47)	(0.51)	(−0.83)	(−1.64)	(−3.08)

	Weeks [1, 4]				Weeks [5, 8]				Weeks [9, 12]			
	Micro	Small	Medium	Large	Micro	Small	Medium	Large	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Real Estate	−0.42***	−0.44***	−0.67***	−0.41	−0.34***	−0.36***	−0.54***	−0.50**	−0.14**	−0.18***	−0.30***	−0.51***
	(−10.08)	(−9.13)	(−11.03)	(−1.21)	(−8.01)	(−7.77)	(−10.51)	(−2.61)	(−2.52)	(−3.17)	(−4.51)	(−2.67)
Leasing & services	−0.35***	−0.29***	−0.33***	−0.37***	−0.45***	−0.35***	−0.27***	−0.36***	−0.26***	−0.26***	−0.26***	−0.21***
	(−8.32)	(−6.96)	(−7.22)	(−5.97)	(−15.00)	(−14.36)	(−7.45)	(−5.79)	(−6.15)	(−6.62)	(−6.06)	(−3.13)
Sci & tech	−0.29***	−0.26***	−0.31***	−0.45***	−0.36***	−0.29***	−0.38***	−0.46***	−0.11***	−0.12***	−0.11**	−0.17*

(*continued on next page*)

Table 3 (*continued*)

	Weeks [1, 4]				Weeks [5, 8]				Weeks [9, 12]			
	Micro	Small	Medium	Large	Micro	Small	Medium	Large	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	(−7.85)	(−6.92)	(−6.70)	(−5.88)	(−10.82)	(−12.02)	(−7.21)	(−5.34)	(−2.64)	(−3.27)	(−2.09)	(−1.94)
Environmental	−0.19***	−0.15***	−0.02	0.03	−0.21***	−0.09*	−0.07	−0.17**	−0.08	−0.08*	−0.12***	−0.14*
	(−3.11)	(−2.93)	(−0.34)	(0.15)	(−3.89)	(−1.98)	(−1.31)	(−2.43)	(−1.66)	(−1.97)	(−2.72)	(−1.80)
Resid. services	−0.45***	−0.36***	−0.35***	−0.29***	−0.43***	−0.36***	−0.31***	−0.24***	−0.27***	−0.25***	−0.22***	−0.00
	(−10.51)	(−9.94)	(−8.10)	(−3.53)	(−15.81)	(−12.14)	(−7.57)	(−4.19)	(−6.75)	(−6.33)	(−4.59)	(−0.04)
Education	−0.26*	−0.69***	−1.00***	−1.01***	−0.64***	−0.78***	−0.71***	−1.28***	−0.31***	−0.29***	−0.22	−0.65***
	(−1.82)	(−4.61)	(−6.21)	(−2.98)	(−7.55)	(−10.66)	(−5.64)	(−6.85)	(−3.66)	(−3.37)	(−1.62)	(−4.30)
Health Services	−0.35***	−0.50***	−0.41***	−0.50***	−0.31***	−0.57***	−0.47***	−0.37*	−0.21***	−0.32***	−0.33***	−0.18
	(−5.00)	(−7.72)	(−6.17)	(−4.24)	(−4.40)	(−8.02)	(−7.74)	(−1.88)	(−3.35)	(−4.72)	(−5.13)	(−1.11)
Entertainment	−0.13*	−0.24***	−0.24**	−0.26	−0.30***	−0.30***	−0.27***	−0.25	−0.30***	−0.29***	−0.27***	−0.15
	(−1.84)	(−2.80)	(−2.51)	(−0.70)	(−6.28)	(−5.84)	(−3.89)	(−0.83)	(−6.58)	(−5.78)	(−3.19)	(−0.59)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE*$Post_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	403,214	409,090	329,968	126,810	466,685	474,408	384,790	150,317	476,421	483,745	389,844	150,365
Within R^2	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.02	0.01	0.01	0.01	0.01

This table reports the impacts of the COVID-19 lockdown on sales for 18 NBS-classified industries. The dependent variable is relative sales divided by the pre-lockdown 28-day average. For each four-week post-lockdown subsample and each firm size group, we conduct a regression at the city-day level, whereby we interact industry dummies with $Y_{2020} \cdot Post_t$ as the variables of interest. The sample periods are January 7, 2019, to April 28, 2019, and December 27, 2019, to April 16, 2020. Heteroscedasticity-consistent *t-statistics* clustered by city and day are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

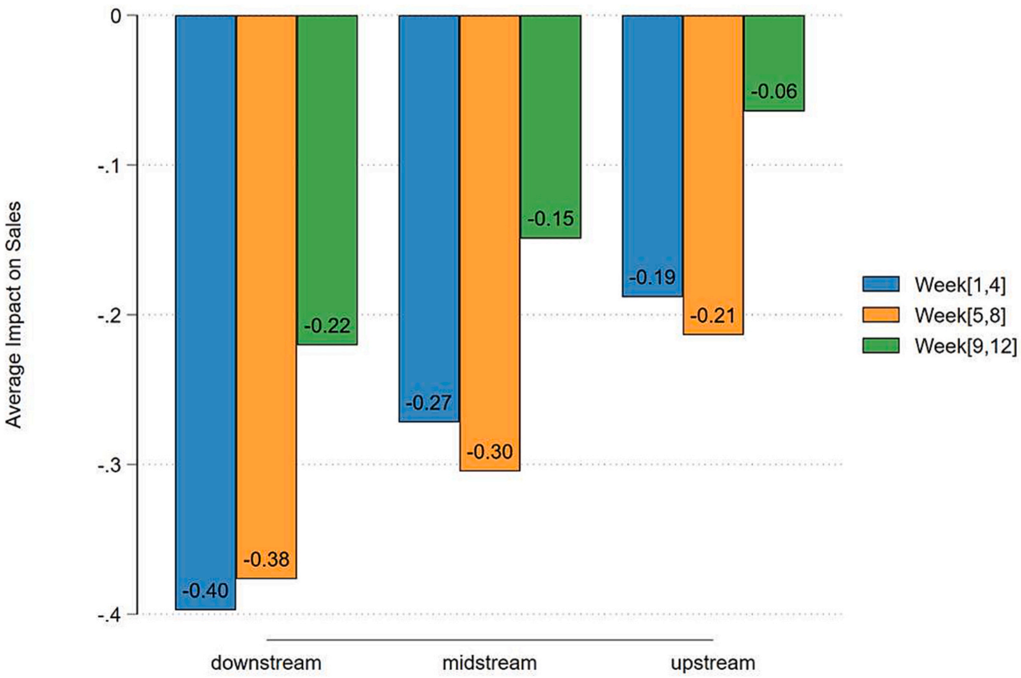


Fig. 6. Impact of COVID-19 on B-to-B sales across supply chain segments over time.
This figure is a visualization of coefficients in Table 3. We categorize 18 industries into upstream, midstream, and downstream sectors according to their position in the supply chain. The upstream sector consists of raw material suppliers and producers, specifically industries within Agriculture and Mining. The midstream sector encompasses processors and manufacturers, which include Manufacturing, Utilities, and Construction industries. The downstream sector refers to businesses that engage directly with consumers, notably those in retail and service industries. This figure depicts the average impact of the COVID-19 pandemic on B-to-B sales within three supply chain segments over three time intervals. The blue bars represent the first interval (Weeks 1 to 4 after COVID outbreak), the orange bars indicate the second interval (Weeks 5 to 8), and the green bars show the third interval (Weeks 9 to 12). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Impacts of COVID-19 on sales under various emergency response levels.

	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
Level 1 • Y_{2020}	−0.319***	−0.294***	−0.242***	−0.372***	−0.369***
	(−10.00)	(−10.22)	(−8.76)	(−10.67)	(−7.93)
Level 2 • Y_{2020}	−0.316***	−0.339***	−0.279***	−0.331***	−0.317***
	(−8.70)	(−10.88)	(−9.84)	(−8.18)	(−5.50)
Level 3 • Y_{2020}	−0.270***	−0.262***	−0.195***	−0.291***	−0.345***
	(−7.93)	(−8.89)	(−7.65)	(−7.48)	(−6.28)
Level 1	0.174**	0.172***	0.101	0.188**	0.229**
	(2.39)	(2.70)	(1.63)	(1.99)	(2.14)
Level 2	0.196***	0.243***	0.158**	0.184*	0.191*
	(2.66)	(3.65)	(2.47)	(1.91)	(1.75)
Level 3	0.196***	0.222***	0.142**	0.201**	0.218**
	(2.65)	(3.43)	(2.21)	(2.07)	(1.97)
City FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	No	No	No	No
Obs.	296,212	76,247	75,873	74,437	69,654
Within R^2	0.07	0.12	0.07	0.10	0.05

This table reports the impacts of COVID-19 public health emergency responses on sales. The dependent variable is relative sales divided by the pre-lockdown 28-day average. Response-level indicators equal one for cities within a province on a day when a specific level of emergency response is in place, and a lunar-calendar-matched indicator of hypothetical emergency response is used for 2019. For sales of all firms as well as for each of the four size groups, we conduct a regression at the city-day level with response-level indicators interacted with Y_{2020} as the main explanatory variable. The sample periods are January 7, 2019, to April 28, 2019, and December 27, 2019, to April 16, 2020. Heteroscedasticity-consistent *t-statistics*, which are clustered by city and day, are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

industry because most observations from this industry are missing at the city-day level for micro and small firms.[22] Conditional on each combination of the first four-week subperiod and size group, we run the following regression at the city-day-industry level:

$$Sales^{relative}_{c,t,k,\bar{s}} = \alpha_c + \tau_t + Ind_k + Ind_k \times Post_t + \sum_{k=1}^{18} \beta_k^{\bar{s}} Ind_k \cdot Y_{2020} \cdot Post_t + \epsilon_{c,t,k,\bar{s}} \tag{2}$$

where Ind_k denotes industry dummies with k referring to an NBS classified industry, and $\beta_k^{\bar{s}}$ captures the drop in relative sales across various industries for a given size group $\bar{s}$.

Table 3 presents the results. A few observations are worth discussing. First, the impacts of COVID-19 vary significantly across industries; for example, industries that heavily rely on face-to-face interactions suffer most, including wholesales & retail, hotel & catering, and education,[23] while primary and secondary industries, such as agriculture, mining, and utilities, experience much smaller decreases in sales, especially large firms, indicating that necessary productions and services are still in stable operation. Second, while all industries suffer from the pandemic for the first eight weeks, only a few industries, such as hotels & catering, experience a continued drop in sales for more than eight weeks, because of the nature of these business activities. Third, the size-sales sensitivity, that is, whether large firms face a larger or smaller COVID-19-induced drop in sales, is industry dependent, and thus, no general pattern is observed. We find similar patterns for publicly listed firms: the sales of listed firms in hotel & catering, residual services, entertainment industries drop the most while the sales of listed firms in agriculture, financial services, and leasing & services industries drop the least (Appendix Table A3). But the magnitude of sales drop is smaller for listed firms, suggesting that these largest and most efficient firms in China suffer less during the pandemic.

Drawing upon the coefficients presented in Table 3, our study categorizes 18 industries into three distinct sectors of the supply chain: upstream, midstream, and downstream. The upstream sector comprises raw material suppliers and producers (Agriculture and Mining). The midstream includes processors and manufacturers (Manufacturing, Utilities, and Construction), while the downstream sector typically refers to businesses that directly interact with consumers, such as retail and services. Our analytical findings are visually represented in Fig. 6, which reveals that the impact on downstream sales diminished over time, while for midstream and upstream sectors, there was an initial increase followed by a recovery. This pattern suggests that demand shocks from the pandemic propagated upstream along the supply chain, potentially highlighting one of the key variables that drove the downturn in B-to-B activities. These observations are consistent with spillover effects of COVID and align with the insights from Bonadio, Huo, Levchenko, and Pandalai-Nayar (2021), Baqaee and Farhi (2022), and Chen, Chen, et al. (2022) which underline the interconnectedness of industries and the wide-reaching consequences of disruptions within a supply chain.

Wuhan's lockdown can be seen as a countrywide movement to implement public health strategies. Additionally, provinces can declare states of emergencies in their own jurisdictions, scenario that results in varying levels of public health measures at different magnitudes throughout China. Therefore, we also investigate how local business activities responded to a province's announcement of emergency responses. The declaration of a state of emergency at the three levels is province dependent and time varying, and both details allow us to measure the impacts of public health measures along varying magnitudes. Specifically, we use the following specification for the city-day-size panel:

$$Sales^{relative}_{c,t,s} = \alpha_c + \tau_t + D_s + \sum_{l=1}^{3} \delta_l Level^l_{c,t} + \sum_{l=1}^{3} \beta_l Level^l_{c,t} \cdot Y_{2020} + \epsilon_{c,t,s}, \tag{3}$$

where $Level^l_{c,t}$ ($l = 1, 2, 3$) equals one if a city c at day t belongs to a province where a level l emergency response is declared and zero otherwise. We assign 2019 observations a hypothetical response indicator after the lunar calendar is matched. β_l denotes the average drop in sales when a province announces a level l emergency.

Table 4 reports the results. Column 1 presents the estimated average impacts of a declaration of a state of emergency on firms for all four size groups. Compared to 2019 sales, 2020 sales drop by 31.9% and 31.6% for level 1 and level 2 responses, respectively, which are around 5% larger than the effect of a level 3 response. Next, we fix each size group and run regressions at the city-day level. Columns 2 to 5 report the impacts on micro, small, medium-sized, and large firms' sales, respectively. For micro and small firms, the patterns are similar to that observed for the full sample; that is, sales drop more for the first two levels of emergency response but less for the third-level response. Under the third-level emergency response, on average, small firms' sales resume to 80% of level from the same period in the previous year, the highest among all four groups. For medium-sized and especially large firms, sales continue to be low even when a province relaxes its emergency response to level 3, with sales decreasing by 29.1% and 34.5%, which are close to the values under level 1 and level 2 responses. All estimates are statistically significant at the 1% significance level.

Evidence provided in this section indicates that the COVID-19 outbreak and subsequent containment measures significantly affected China's business activities, ranging from micro/small businesses to large entities. The impact is larger for firms in industries requiring more face-to-face interactions. They, thus, suffer from stay-at-home and social distancing measures. After the first two months of strict public health measures, the economy started to resume with firm sales quickly bouncing back once restrictions were lifted.

[22] The 2019 total sales in Public Administration in our sample is only RMB 2 billion, the smallest amount among all 19 industries, whereas the total 2019 sales of our sample is RMB 33.4 trillion.

[23] The percentage change in the education industry is greater than 100% for medium-sized and large firms in the first four to eight weeks. The 2019 post-event increase in education sales is large because education drops significantly before the Chinese New Year when the school semester ends.

Table 5
The effect of local stimulus policies.

Panel A: Financial assistance policies

	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
$\ln(1 + N^{financial})$	0.02**	0.00	0.01	0.04***	0.03*
	(2.30)	(0.50)	(1.19)	(3.10)	(1.69)
Control	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	No	No	No	No
Obs.	106,515	27,249	27,147	26,679	25,440
Within R^2	0.01	0.02	0.02	0.02	0.00

Panel B: Fee reduction policies

	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
$\ln(1 + N^{fee})$	0.02**	0.01	0.02	0.04***	0.03*
	(2.37)	(0.77)	(1.48)	(2.79)	(1.80)
Control	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	No	No	No	No
Obs.	106,515	27,249	27,147	26,679	25,440
Within R^2	0.01	0.02	0.02	0.02	0.00

Panel C: Tax exemption policies

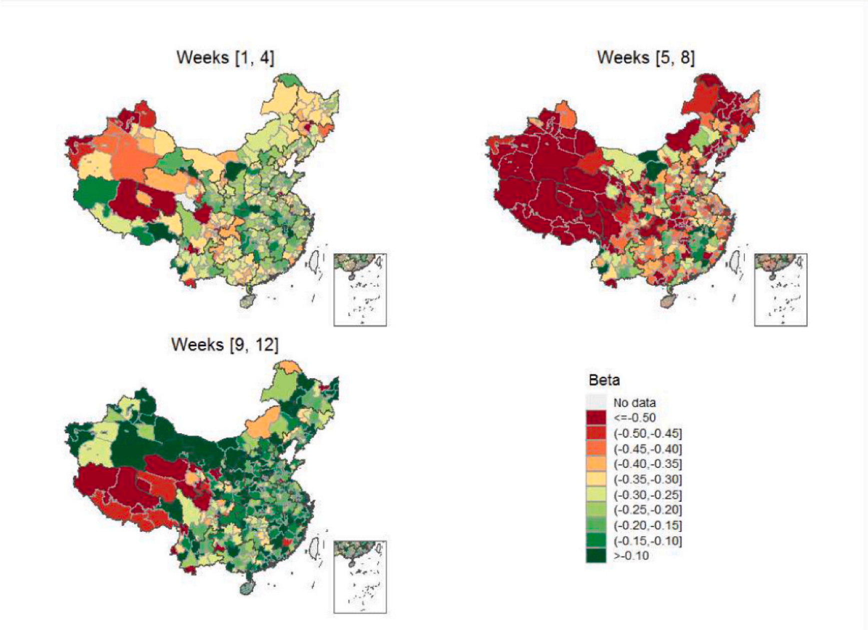
	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
$\ln(1 + N^{tax})$	0.03***	0.02	0.03**	0.04***	0.04**
	(2.96)	(1.47)	(2.35)	(2.87)	(2.16)
Control	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Size FE	Yes	No	No	No	No
Obs.	106,515	27,249	27,147	26,679	25,440
Within R^2	0.01	0.02	0.02	0.02	0.01

This table reports the effect of local stimulus policies on economic recovery. The dependent variable is relative sales divided by the pre-lockdown 28-day average. The explanatory variables are the number of policies that belong to the three types of stimulus policies: financial assistance (Panel A), fee reductions (Panel B), and tax exemptions (Panel C). Control variables include the number of confirmed COVID-19 cases, within-city movement intensity, and three indicators for emergency response levels: inflow of residents from Wuhan; inflow of residents from other Hubei cities; and the temperature, humidity, and air quality index. The sample period is December 27, 2019, to April 16, 2020. Heteroscedasticity-consistent *t-statistics*, which are clustered by city and day, are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

3.3. Effects of local stimulus policies

Facing the most severe economic challenge since the 1978 reforms and opening-up, the Chinese government, like other governments around the world, took fast action to mitigate the economic impacts caused by the COVID-19 pandemic. Since mobility restrictions were gradually removed starting from mid-February, both central and local governments have introduced various stimulus policies to stabilize the economy and employment. A couple of recent studies examine the effectiveness of technology-based policies, including health QR codes (Xiao, 2020), in resuming economic activities as well as digital coupon programs (Liu, Shen, Li, & Chen, 2021), in stimulating household consumption. In this section, we focus on local governments' economic stimulus measures. Specifically, all local policies are classified into three non-exclusive groups, that is, one policy could belong to more than one group, based on its contents, including financial assistance, fee reductions, and tax exemptions (for details, see Section 2.2).

Panel A: Impacts on micro firms' sales



Panel B: Impacts on small firms' sales

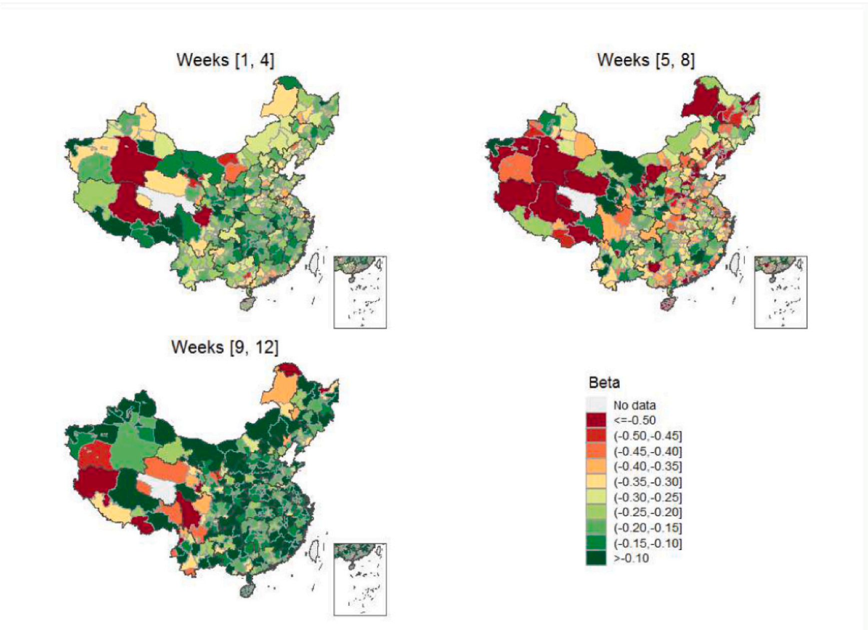
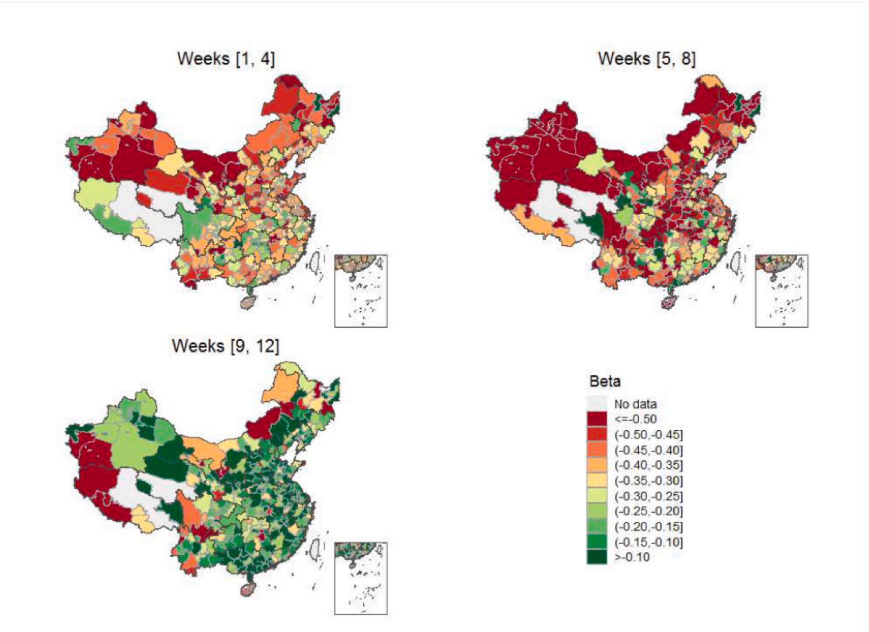


Fig. 7. COVID-19's effect on sales by city.
This figure plots a heatmap of the estimated coefficients for the effects of COVID-19 on sales by city. Panels A to D plot regression coefficients for micro, small, medium-sized, and large firms, respectively.

Panel C: Impacts on medium-sized firms’ sales



Panel D: Impacts on large firms’ sales

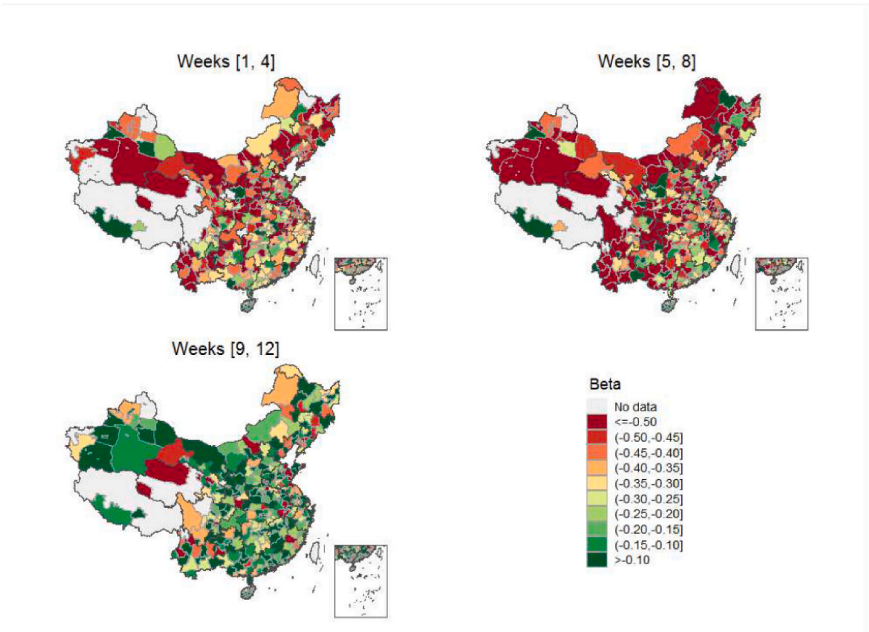


Fig. 7. (*continued*).

Our objective is to evaluate whether any type of local government stimulus policy helps firms recover. Because some cities issued policies within these three categories multiple times, we use the number of policies belonging to one of the three categories for city c as of day t as our explanatory variable. We run the following regression in the sample period of December 27, 2019 to April 16, 2020, for all four size groups and each size group $\overline{s}$:

$$Sales^{relative}_{c,t,s} = Day_t + D_s + b_j ln\left(1 + N^j_{c,t}\right) + X'_{c,t}e + \epsilon_{c,t,s}, \tag{4}$$

where $j \in$ {financial assistance, fee reduction, tax exemption} and $N^j_{c,t}$ measure policy intensity; Day_t denotes the daily fixed effects; $X_{c,t}$ denotes a vector of control variables, including the number of confirmed COVID-19 cases, within-city movement intensity, and three indicators of emergency response levels (inflow of residents from Wuhan, inflow of residents from other Hubei cities, temperature, humidity, and air quality index); and b_j is of our interest and expected to be positive if local policies are effective.[24]

Table 5 reports the results. The first column of Panel A shows that sales across all size groups increase by 2% more, on average, for cities that introduced financial assistance policies compared to those that did not. If we look into the subsamples of four size groups, financial assistance policies have a positive economically and statistically significant impact on medium-sized and large firms, with magnitudes of 4% (t-statistic = 3.10) and 3% (t-statistic = 1.69), respectively. The finding suggests that, even though many policies target small and micro firms to assist them in mitigating the unprecedented liquidity shock, only medium-sized and large firms seemingly benefit from these stimulus measures.

Similar findings, shown in Panel B of Table 5, are observed for the effectiveness of fee reduction policies. The positive policy impacts are 4% and 3% for medium-sized and large firms' sales, and both numbers are statistically significant. On the other hand, the tax exemption policies have positive and statistically significant effects on business activities for all firms, except for micro firms (Panel C). Overall, our results suggest that local government stimulus measures in general are most efficient at reviving large firms to normal levels, whereas micro firms, which have been most vulnerable during the COVID-19 crisis, only receive negligible benefits from stimulus measures.[25]

Our findings that larger firms have benefited more significantly from government measures compared to their smaller counterparts have profound implications for market dynamics and welfare analysis. This favoritism could lead to increased market consolidation. It also raises concerns for long-term economic resilience, as a diverse mix of businesses, including smaller ones, is vital for innovation and adaptability. We recommend balanced economic recovery policies, offering targeted support for smaller enterprises and ensuring fair competition. In summary, while large firms benefit in the short term, a holistic approach considering all business sizes is essential for a sustainable, inclusive post-COVID economic recovery.

It is a valid concern that more severely affected cities may likely adopt more aggressive stimulus policies, resulting in endogeneity and bias in the estimated policy effect. We acknowledge the existence of such endogeneity and include the number of COVID-19 cases as control to partially address the concern. Meanwhile, our main objective is to evaluate the heterogeneous effects of local stimulus policies on firms with different sizes, and thus the endogenous cross-city variation in stimulus policy caused by severity of the pandemic may be less a serious concern. The issue of endogeneity remains unresolved in our analysis. However, our focus is not on establishing strict causality to explore the causal impact of government policies. Instead, like studies such as Chen, Cheng, et al. (2022), we aim to provide suggestive evidence on how government policies affect firms.

3.4. Cross-city determinants of the impact of COVID-19 and recovery

Because of different exposures to the COVID-19 pandemic, cities have implemented different public health measures. As a result, one expects that business activities across cities also should be differently affected. More importantly, after mobility restrictions were lifted and local governments enacted stimulus measures, we expect that firms in some regions may have recovered faster than others because of regional characteristics. In this section, we explore the cross-city variations in the effects of COVID-19 on later recovery. We start by estimating the city-level impacts of COVID-19 using the following model specification:

$$Sales^{relative}_{\bar{c},t,s} = \tau_t + D_s + D_s \times Post_t + \sum_{s=1}^{4} \beta^{\bar{c}}_s D_s \cdot Y_{2020} \cdot Post_t + \epsilon_{\bar{c},t,s}, \tag{5}$$

where $\bar{c}$ indicates that we fix a city in the DID regression with size-day panel. Fig. 7 visualizes estimated $\beta^{\bar{c}}_s$ for three four-week subsamples after Wuhan's lockdown as heatmaps. Panel A plots the geographic distribution of the effect of COVID-19 on micro firms' sales. Note that compared to 2019 sales, 2020 sales suffer more over the second four-week period after Wuhan's lockdown, compared with the first four-week period. The reason is that most micro firms may have suspended operations during the four-week Chinese New Year's holiday in 2019, that is, the relative (to pre-holiday) sales in 2019, leading to smaller DID estimates for the pandemic-hit 2020 compared to the benchmark year 2019. On the other hand, in weeks 5 to 8, the decrease in sales (43% on average) is

[24] In this exercise, because our objective is to evaluate the effectiveness of stimulus policies in 2020 and our dependent variable is already scaled by the pre-lockdown four-week daily average, we do not need the 2019 sample as our benchmark. Meanwhile, daily fixed effects absorb all countrywide shocks, including the effect of the COVID-19 crisis on sales. Lastly, we select those control variables as other studies find that they are related to COVID-19 severity and thus restriction intensity.

[25] The findings that local government economic stimulus policies were more effective for medium-sized and large firms can be attributed to these firms' better ability to leverage such support. Larger firms often have more experience and resources to navigate bureaucratic processes and meet the requirements for government aid. Additionally, the scale of operations in larger firms means that the same amount of stimulus can have a more substantial relative impact, allowing them to utilize the resources more efficiently (e.g., Song, Storesletten, & Zilibotti, 2011; Brown and Earle, 2017; Chen et al., 2022b). Chen et al. (2022b) also finds that financial support policies seem ineffective in easing cash constraints for SMEs or promoting the reopening of small businesses, which may stem from challenges in accessing policy-oriented loans and the misallocation of credit.

Table 6
Determinants of cross-city COVID-19 impacts.

		Micro			Small			Medium			Large	
	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Macro characteristics												
ln(GDP per capita)	−0.013	0.021	−0.043	−0.006	0.053*	−0.017	0.016	0.044	−0.039	0.022	0.033	−0.047
	(−0.63)	(0.62)	(−1.25)	(−0.34)	(1.89)	(−0.66)	(0.69)	(1.24)	(−0.86)	(0.42)	(0.50)	(−0.73)
ln(Population)	0.039*	0.184***	−0.037	0.023	0.109***	−0.012	0.087**	0.103*	0.030	0.076	0.098	−0.021
	(1.90)	(5.00)	(−0.99)	(1.06)	(2.93)	(−0.35)	(2.57)	(1.80)	(0.49)	(1.24)	(1.35)	(−0.32)
FAI/GDP	0.033**	0.088***	0.006	0.044***	0.124***	0.036*	0.030	−0.001	0.013	−0.003	−0.026	0.016
	(2.12)	(3.13)	(0.25)	(3.32)	(5.74)	(1.69)	(1.39)	(−0.02)	(0.39)	(−0.07)	(−0.50)	(0.35)
Industrial structure												
Share of GDP-Agriculture sector	−0.161*	−0.111	0.015	−0.217**	−0.053	0.025	0.050	0.113	−0.042	0.023	−0.335	−0.011
	(−1.81)	(−0.68)	(0.09)	(−2.52)	(−0.34)	(0.15)	(0.31)	(0.48)	(−0.15)	(0.08)	(−0.81)	(−0.04)
Share of GDP-Service sector	0.063	0.178	−0.220	0.058	0.219	−0.158	0.216**	0.191	−0.153	0.519*	0.684**	0.115
	(0.76)	(1.27)	(−1.63)	(0.70)	(1.58)	(−1.37)	(2.04)	(0.93)	(−0.75)	(1.89)	(2.29)	(0.44)
Share of Labor-Construction	−0.031	−0.063	−0.146	0.122**	0.215**	0.032	0.417***	0.572***	0.134	0.202	0.346*	−0.047
	(−0.44)	(−0.64)	(−1.48)	(2.44)	(2.55)	(0.49)	(5.29)	(4.41)	(1.13)	(1.44)	(1.93)	(−0.30)
Share of Labor-Manufacturing	0.072	−0.033	−0.055	−0.039	0.016	0.071	0.194***	0.348***	0.131	0.163	0.204	0.046
	(1.10)	(−0.33)	(−0.60)	(−0.80)	(0.17)	(0.96)	(2.82)	(3.36)	(0.96)	(1.12)	(1.15)	(0.31)
Share of Labor-Hotels & catering	−0.039	0.271	0.061	0.165	0.721	−0.189	1.973***	4.230***	2.418***	−2.329**	−2.109**	−2.671***
	(−0.15)	(0.68)	(0.16)	(0.48)	(1.03)	(−0.74)	(5.63)	(7.80)	(2.67)	(−2.11)	(−2.48)	(−3.89)
		Micro			Small			Medium			Large	
	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Medical condition												
ln(#Doctors)	−0.003	−0.077	0.015	−0.020	−0.049	0.042	0.031	0.024	0.053	−0.062	−0.082	−0.027
	(−0.10)	(−1.60)	(0.29)	(−0.73)	(−1.12)	(1.04)	(0.83)	(0.43)	(0.78)	(−1.01)	(−0.91)	(−0.38)
ln(Hospital beds)	−0.028	−0.078*	−0.042	0.046**	0.030	−0.011	−0.038	0.014	−0.020	−0.040	0.022	0.027
	(−1.01)	(−1.93)	(−1.03)	(2.01)	(0.74)	(−0.26)	(−1.28)	(0.25)	(−0.39)	(−0.60)	(0.27)	(0.43)

(*continued on next page*)

Table 6 (*continued*)

	Micro			Small			Medium			Large		
	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Local officer background												
Economic Background	−0.002	−0.020	0.002	−0.002	−0.020	−0.001	−0.017	0.000	0.015	0.001	−0.024	−0.005
	(−0.19)	(−1.16)	(0.10)	(−0.16)	(−1.16)	(−0.07)	(−1.17)	(0.00)	(0.63)	(0.05)	(−0.65)	(−0.15)
Parachute appointment	−0.020*	−0.021	−0.016	−0.015*	−0.018	−0.018	−0.033**	−0.055**	−0.021	0.031	0.047	0.006
	(−1.83)	(−1.14)	(−0.93)	(−1.72)	(−1.14)	(−1.33)	(−2.16)	(−2.19)	(−0.86)	(1.10)	(1.28)	(0.20)
ln(Sale)	−0.005	0.014	0.060***	−0.041***	−0.056***	0.003	−0.036**	−0.077***	0.007	−0.008	−0.042	0.044
	(−0.56)	(0.90)	(3.76)	(−5.34)	(−3.90)	(0.21)	(−2.58)	(−3.25)	(0.29)	(−0.43)	(−1.60)	(1.56)
ln($N_{covid19}$)	0.002	−0.025***	0.013**	0.001	−0.028***	−0.003	−0.022***	−0.055***	−0.018*	0.024	−0.004	0.009
	(0.45)	(−3.30)	(2.00)	(0.27)	(−4.57)	(−0.61)	(−3.06)	(−4.80)	(−1.68)	(1.35)	(−0.23)	(0.73)
Constant	−0.073	−0.336	0.677*	−0.460**	−1.331***	−0.108	−0.988***	−1.680***	−0.157	−0.492	−1.048	0.214
	(−0.33)	(−0.89)	(1.81)	(−2.31)	(−4.05)	(−0.34)	(−3.52)	(−3.53)	(−0.29)	(−0.81)	(−1.43)	(0.29)
Obs.	278	278	278	278	278	278	278	278	277	275	277	277
Adj. R^2	0.05	0.17	0.05	0.26	0.27	0.00	0.23	0.20	0.04	0.02	0.02	0.00

This table reports the results for the cross-city determinants of the impacts of COVID-19 on firms' sales. The dependent variables are the beta estimates of the impacts of the COVID-19 lockdown on sales for four firm size groups and three four-week subperiods. The explanatory variables are the macro characteristics including log values of GDP per capita, the log values of population, and fixed-asset investment over GDP; industrial structure variables including share of GDP of agriculture sector, share of GDP of service sector, share of workforce in construction industry, share of workforce in manufacturing industry, share of workforce in hotels catering industry; medical condition variables including number of doctors, number of hospital beds; local officer background variables including their educational qualifications in economics or management, and whether they were promoted locally or appointed from outside the city. Control variables include 2019 sales and the number of a city's confirmed COVID-19 cases. We conduct a cross-sectional regression at the city level. Heteroscedasticity-consistent t-statistics are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

more evident for many cities compared with the first four weeks (27% on average), suggesting that mobility restrictions in 2020 prevented employees from returning to work at micro firms, to a great extent. But eight weeks later, when most public health measures were lifted, the drop in average sales is 17% across all 343 cities in our sample.

Panel B plots the geographic distribution of the drop in sales for small firms. Note that relative sales are less severely affected by the pandemic for small firms than for micro firms. The average drops are 23% and 33% for the first and second four-week periods. On the other hand, Panels C and D demonstrate that medium-sized and large firms sustained the most severe drops in sales, with the average decreases being 38% and 40% for the first four-week period and 45% and 46% for the second four-week period. But most sales recover eight weeks later for firms across various size groups. Overall, the city-level estimates are consistent with our main findings in Table 2 that public health restrictions have dramatically disrupted day-to-day economic activities, especially for medium-sized and large firms. Whereas micro firms' activities froze during strict containment measures, small firms seem to be more resilient.

From Fig. 7, we also see that differences in the effects of COVID-19 exist across regions. The differential impacts of COVID-19 on eastern, central, and western cities indeed reflect the underlying variations in city characteristics, such as macroeconomic characteristics, industrial structures, medical conditions, and local officer background. Next, we explore the cross-city determinants for such heterogeneity by running regressions of beta estimates on city characteristics. Our objective is to understand why some cities experienced deeper decreases in sales than others. Our study incorporates various dimensions of city level characteristics, including macro characteristics, industrial structure features, medical conditions, and local officer characteristics. Specifically, the macro characteristics encompass ln(GDP per capita), indicating economic development; ln(population), reflecting city size; and the ratio of fixed- asset investment over GDP. Industrial structure variables include the agriculture sector's GDP share, the service sector's GDP share, and the workforce shares in construction, manufacturing, and hotels & catering industries. Medical condition variables cover the number of doctors and hospital beds. Additionally, we manually collected the educational and professional backgrounds of mayors and party secretaries across various cities, defining two new variables: *Economic background*, assessing officials' expertise in economics and management, and *Parachute appointment*, examining if officials were externally appointed, impacting their familiarity with local issues and crisis management effectiveness.

Table 6 presents the results for regressing beta coefficients estimated from Eq. (5) on those city characteristics. We control for the number of confirmed COVID-19 cases and 2019 total sales. We first examine the regression coefficients of the macro characteristic variables. Columns 1 to 3 report the results for micro firms. Larger cities see less of a drop in sales for the first eight weeks, and cities relying on fixed-asset investment experience less of a drop in sales. Columns 4 to 6 and Columns 7 to 9 report the results for small and medium-sized firms. Note that for the first eight weeks, small and medium-sized firms in richer, larger, and investment-driven cities experience less of a drop in sales. The results suggest that cities of which the economies depend less on face-to-face interactions, that is, they are driven by investment, have relatively higher business activities. This finding echoes economic forecasts that developed economies, which are mainly driven by consumption- and service-related industries, would experience more severe economic slowdowns due to the pandemic.

The regression coefficients of the industrial structure variables indicate that cities with a dominant construction industry, experienced a lesser initial impact from COVID-19. This result appears to be due to the inherent nature of such industries, which typically involve less direct, face-to-face interaction. As shown in Fig. A5, we also find that there is a significant positive correlation between a city's level of fixed asset investment and the proportion of its workforce employed in the construction industry. Thus, this observation indicates that the mitigating impact of fixed asset investment might mirror the cross-industry results.

Additionally, there is differential impact of local versus parachuted officials in managing the pandemic. Parachuted officials, often less familiar with local contexts, appear to have a weaker response capability to sudden pandemic shocks, with this negative impact being particularly pronounced in micro, small and medium-sized enterprises.

Overall, our findings in this section indicate that characteristics related to regions' economic development are related to the severity of COVID-19 impacts during the first eight weeks, but the effect is not clear for large firms, which are usually better able to comply with containment measures.

4. Conclusion

The COVID-19 pandemic has had devastating effects on the global economy. China is one of the countries that enacted the most stringent public health measures in response to COVID-19 and has successfully managed the viral outbreak, yet it has experienced its most severe economic slowdown over the past 40 years. By exploiting transaction-level data on firms' sales from 1.5 billion invoices, we estimate the impact of the COVID-19 pandemic on business activities and analyze how firms recovered once public health restrictions were lifted. On average, sales drop by 23% to 35% for the 12-week period after Wuhan's lockdown, depending on firm size. Larger firms endure a prolonged decrease in sales, and micro firms sustain harsher decreases compared with small firms. Eight weeks after the Wuhan lockdown, business activities gradually resume to around 85% of the normal level. We find differences in the effects of COVID-19 across industries, with stronger effects observable in industries requiring more face-to-face interactions. In addition, local business activities react to provincial governments' announcements of a public health emergency.

After documenting the unprecedented economic challenges prompted by the COVID-19 outbreak, we investigate the effectiveness of local governments' stimulus policies and relief programs intended to boost the economy. We find that all three types of policy measures, namely, financial assistance, fee reductions, and tax exemptions, alleviate the pandemic- induced shock of medium-sized and large firms, whereas micro and small firms do not enjoy clear benefits from these policy responses. Lastly, regional, heterogeneous impacts exist, and firms located in smaller and service-industry-dependent cities have suffered more after the Wuhan lockdown. Parachuted officials appear to have a weaker response capability to sudden pandemic shocks.

While exploring the long-term effects of the pandemic are indeed valuable, our study intentionally focuses on the immediate and direct impact of the first wave in early 2020 (e.g., Ai et al., 2022; Chen et al., 2021; Fang et al., 2020; He et al., 2020; Pei, de Vries, & Zhang, 2022). This approach provides unique insights into the acute phase of the crisis, which is critical for understanding the magnitude and source of the problem due to the unprecedented nature of the crisis in the past century (e.g., Chen et al., 2021). We believe our contribution lies in the precise quantification of these impacts. Using a comprehensive dataset allows us to measure the pandemic's effects with greater accuracy than previous studies, providing valuable information about the scale of disruptions across different industries and firm sizes. Additionally, our study extends beyond the usual focus on public firms (e.g., Ding, Levine, Lin, & Xie, 2021), or SMEs (e.g., Chen, Cheng, et al., 2022; Dai et al., 2021; Guo et al., 2022). By examining firms of varying sizes, we offer a more nuanced understanding of how the pandemic affected different segments of the economy, which is essential for tailored policy interventions. Another key aspect of our research is the examination of government support policies. By analyzing these measures, we contribute to the understanding of how such interventions can mitigate the adverse effects of unprecedented crises like the COVID-19 pandemic. Unfortunately, due to the limited sample periods of the data, we are unable to further explore the long-term impacts of the pandemic.

It should be noted that this paper utilized aggregated data for each city-week-size cell, which may overlook the extensive part. we recognize that our study did not explicitly address the role of the destructive innovation process during the pandemic. This aspect, marked by the rapid entry and exit of firms and the potential reshaping of market dynamics, is indeed a crucial element.

In addition to illuminating COVID-19's direct impacts on business activities and later recovery, our transaction-level invoice data could be applied to other facets of COVID-19 economics research. For example, after matching the data with shareholder information from individual firms, researchers could examine whether the behavior differs between state-owned and private firms, as well as how firms benefit from stimulus measures designed to target private firms only, such as rental relief programs. Researchers could also investigate whether firms absorb losses themselves or share this risk with employees, that is, by cutting jobs or even filing for bankruptcy. Moreover, the data allow researchers to quantify the spillover effects from upstream to downstream. We leave these topics for future research.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Appendix

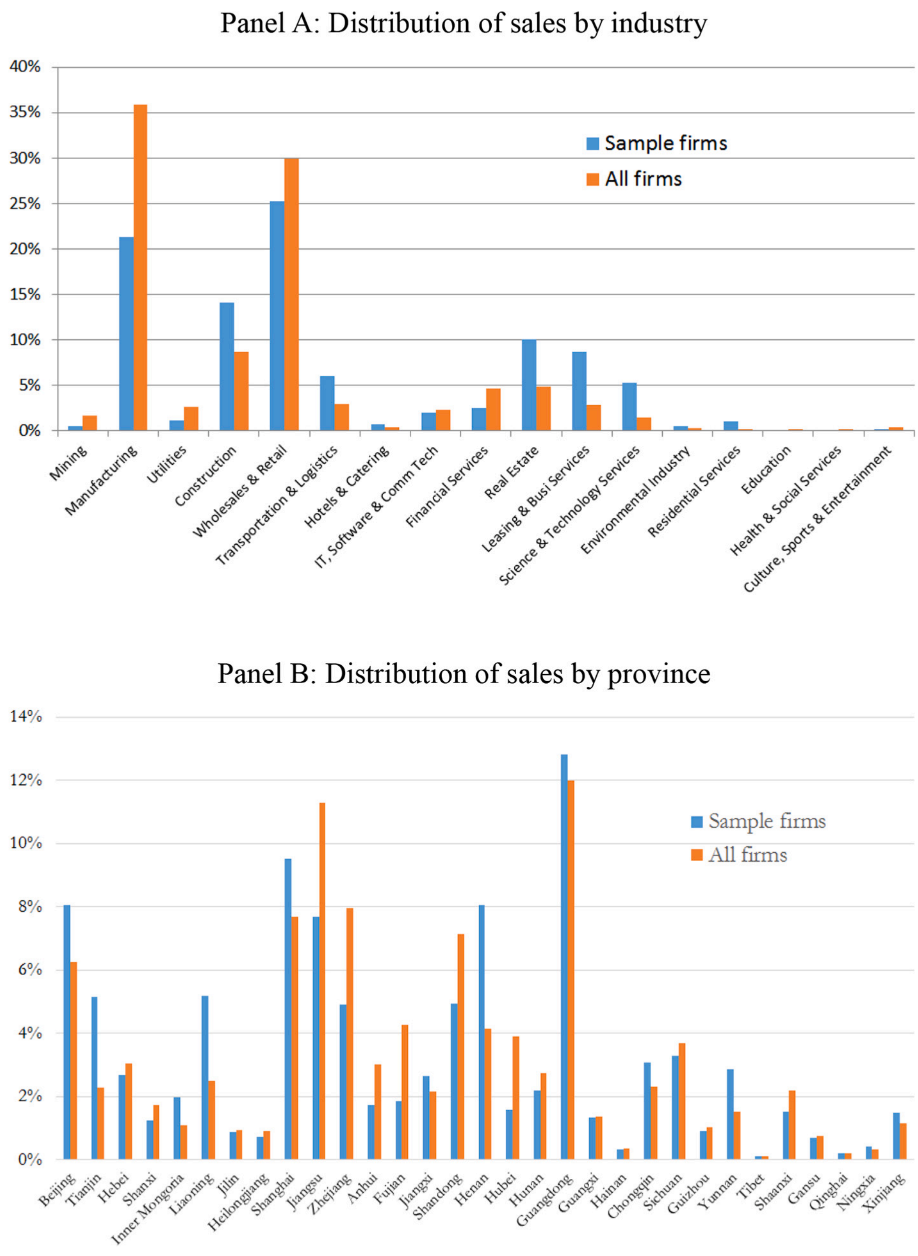
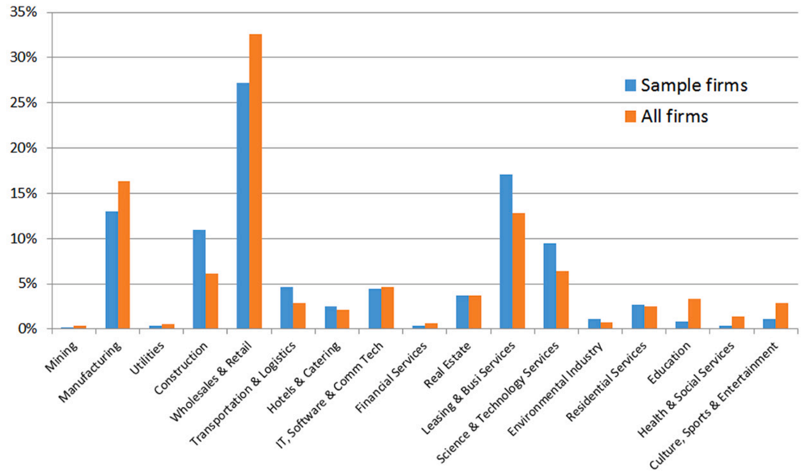
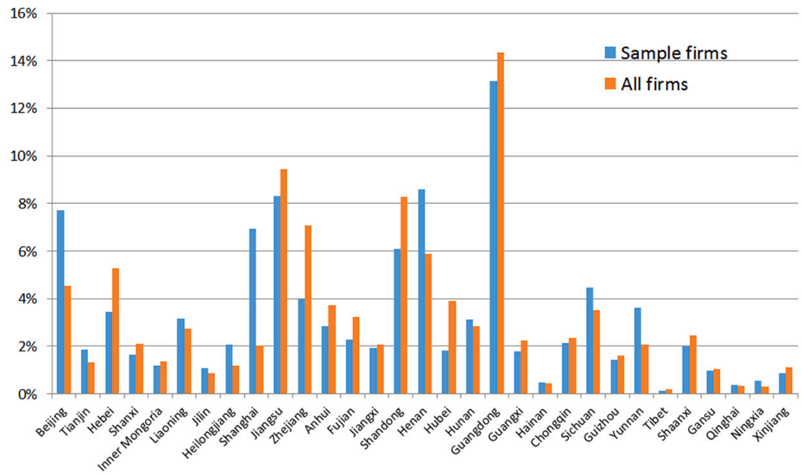


Fig. A1. Distributions of sales for the VAT-based sample and the full sample.
This figure plots the distributions of firms' sales by industry and province for the VAT-based and full samples. Panel A (B) plots the distributions of sales by industry (province) for our VAT-based and full samples for all firms in China. Data for the 2019 sales, which are aggregated from 1.5 billion VAT invoices, come from Daokou Fintech, a leading big data company. Data for the 2018 countrywide sales come from the Fourth National Economic Census, which the NBS conducts.

Panel A: Distribution of the number of firms by industry



Panel B: Distribution of the number of firms by province



Panel C: Distribution of the number of firms by registered equity capital

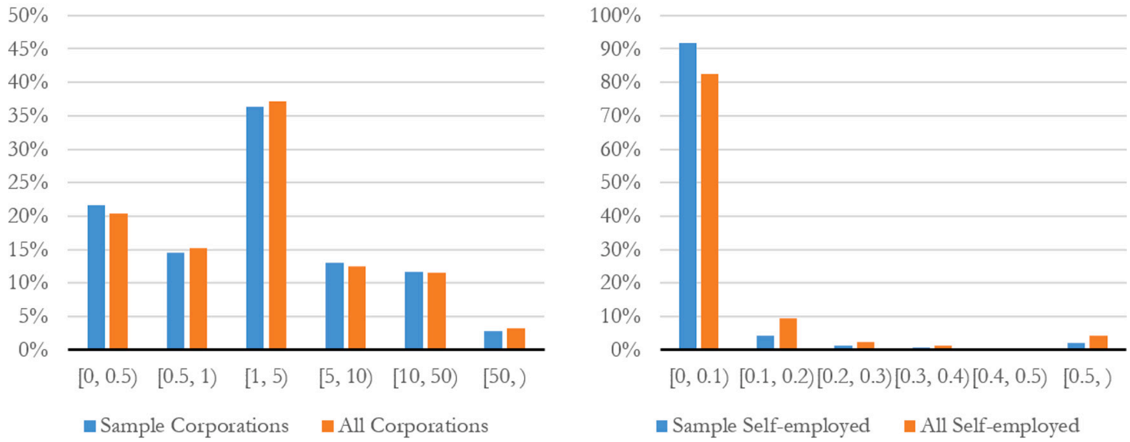


Fig. A2. Distributions of the number of firms for the VAT-based sample and the full sample.
This figure plots the distributions of the number of firms by industry, province, and size for the VAT-based sample and the full sample. Panel A (B, C) plots the distributions of the number of firms by industry (province, size) from our VAT-based and full samples for all firms in China. Firm size is measured by registered equity capital (RMB million). Data for the 2019 number of VAT-invoice-issuing firms come from Daokou Fintech, a leading big data company. Data for the 2018 countrywide number of firms come from the Fourth National Economic Census, which the NBS conducts. Registered equity capital data are from State Administration for Industry and Commerce.

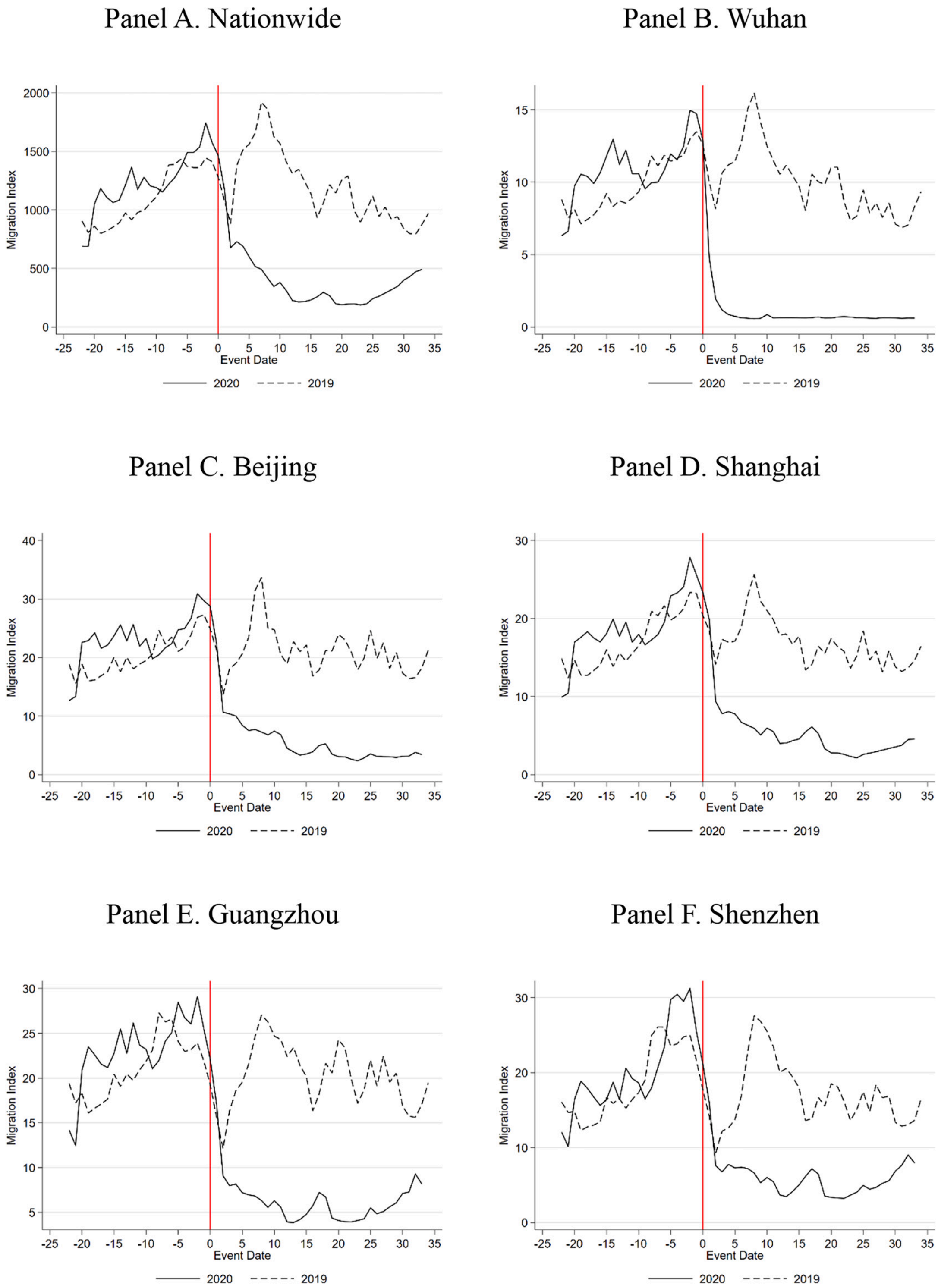


Fig. A3. The migration patterns before and after Wuhan lockdown.
This figure presents a comparative view of the migration index over a timeline where the event date indicates the Wuhan lockdown. The solid line represents the year 2020, while the dashed line denotes the year 2019 for reference. A significant decline in the migration index is observed post-event in 2020, indicating reduced travel willingness in response to the COVID outbreak in Wuhan.

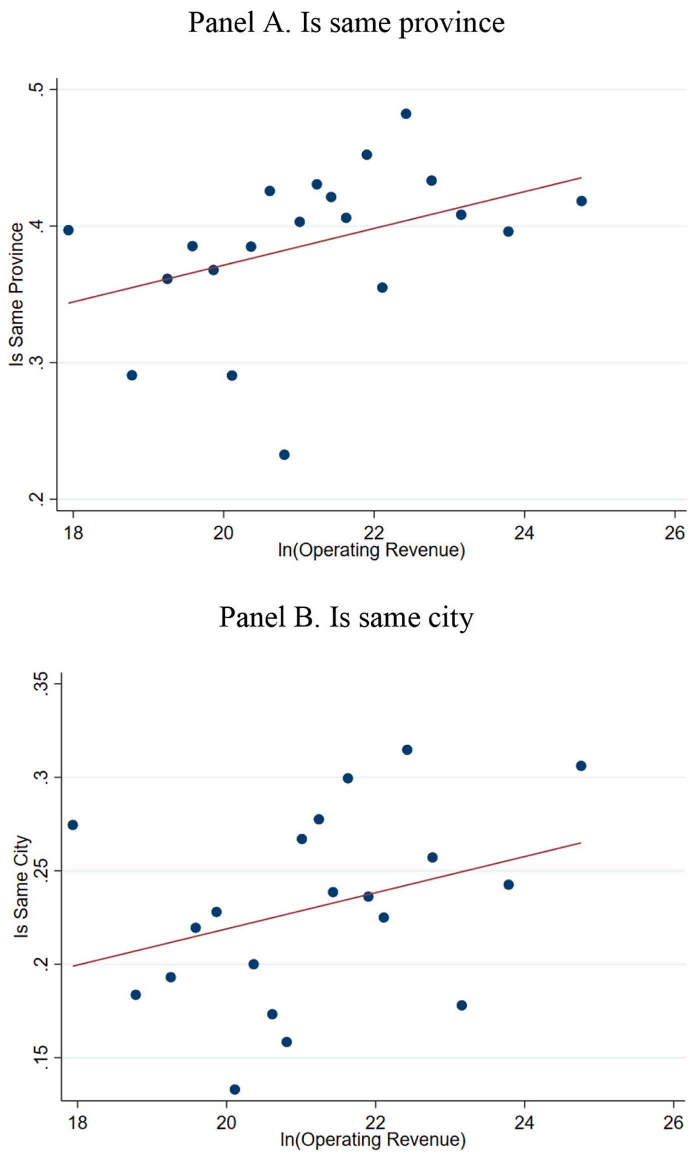


Fig. A4. Firm size and supply chain geographical concentration.
This figure shows the relationship between firm size and its supply chain geographical concentration degree. The horizontal axis represents the log value of the operating revenue of listed companies in 2019. The vertical axis indicates whether the listed company and its suppliers or customers are in the same city or the same province. All data are sourced from CSMAR.

Fig. A5. The relationship between FAI and share of construction industry.
This figure presents the correlation between a city's level of fixed asset investment and the proportion of its workforce employed in the construction industry. The horizontal axis represents the level of fixed asset investment in the city (in hundred million RMB), and the vertical axis shows the proportion of the workforce employed in the construction industry. Both variables are sourced from the city statistical yearbook in 2019. The dots represent observed values, and the red line is the linear fit line.

Table A1
NBS classification of firms by the four size categories.

Industry	Micro	Small	Medium-sized	Large
Agriculture	(0, 0.5)	[0.5, 5)	[5, 20)	[20, ∞)
Mining	(0,3)	[3,20)	[20, 400)	[400, ∞)
Manufacturing	(0, 3)	[3, 20)	[20, 400)	[400, ∞)
Utilities	(0, 3)	[3, 20)	[20, 400)	[400, ∞)
Construction	(0, 3)	[3, 60)	[60, 800)	[800, ∞)
Wholesale & retail	(0,1)	[1, 5)	[5, 200)	[200, ∞)
Transportation & logistics	(0, 1)	[1,10)	[10,300)	[300, ∞)
Hotels & catering	(0, 1)	[1,20)	[20,100)	[100, ∞)
IT, software & comm tech	(0, 0.5)	[0.5, 10)	[10,100)	[100, ∞)
Financial services	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Real estate	(0, 1)	[1, 10)	[10,2000)	[2000, ∞)
Leasing & services	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Science & Technology services	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Environmental industry	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Residential services	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Education	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Health & Social sciences	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Culture, sports & entertainment	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)
Public administration	(0, 0.5)	[0.5, 5)	[5, 100)	[100, ∞)

This table lists the sales cutoffs of large, medium-sized, small, and micro firms across 19 industries. The cutoffs are used in the Fourth National Economic Census, which the NBS conducts. The sales cutoffs are in RMB million.

Table A2
Impacts of COVID-19 on sales, robustness tests.

Panel A: Using cities' exact lockdown dates				
	Full		Subsamples	
	[1,12]	[1, 4]	[5, 8]	[9, 12]
	(1)	(2)	(3)	(4)
Micro firms β_1	−0.30***	−0.35***	−0.26***	−0.29***
	(−12.78)	(−12.56)	(−6.02)	(−7.50)
Small firms β_2	−0.26***	−0.29***	−0.22***	−0.28***
	(−11.97)	(−10.45)	(−5.51)	(−7.67)
Medium firms β_3	−0.36***	−0.42***	−0.29***	−0.38***

(continued on next page)

Table A2 (*continued*)

Panel A: Using cities' exact lockdown dates				
	Full		Subsamples	
	(−12.43)	(−12.93)	(−5.32)	(−8.95)
Large firms β4	−0.40***	−0.41***	−0.35***	−0.48***
	(−8.48)	(−6.09)	(−4.43)	(−7.11)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Size*$Post_t$	Yes	Yes	Yes	Yes
Obs.	219,563	135,541	135,998	109,876
Within R^2	0.09	0.07	0.04	0.04

Panel B: Day-of-the-month fixed effects				
	Full		Subsamples	
	[1, 12]	[1, 4]	[5, 8]	[9, 12]
	(1)	(2)	(3)	(4)
Micro firms β_1	−0.30***	−0.25***	−0.44***	−0.17***
	(−15.36)	(−10.24)	(−12.99)	(−6.27)
Small firms β_2	−0.24***	−0.21***	−0.35***	−0.13***
	(−13.18)	(−8.15)	(−10.43)	(−4.82)
Medium firms β_3	−0.34***	−0.35***	−0.48***	−0.17***
	(−18.03)	(−13.45)	(−14.26)	(−5.46)
Large firms β_4	−0.36***	−0.39***	−0.48***	−0.17***
	(−11.08)	(−6.78)	(−8.80)	(−3.69)
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Size*$Post_t$	Yes	Yes	Yes	Yes
Obs.	296,212	147,187	149,063	149,516
Within R^2	0.08	0.06	0.08	0.01

Panel C: City × Time fixed effects				
	Full		Subsamples	
	[1, 12]	[1, 4]	[5, 8]	[9, 12]
	(1)	(2)	(3)	(4)
Micro firms β_1	−0.29***	−0.27***	−0.43***	−0.17***
	(−12.12)	(−5.77)	(−14.00)	(−4.46)
Small firms β_2	−0.23***	−0.23***	−0.33***	−0.13***
	(−10.57)	(−4.99)	(−10.25)	(−3.69)
Medium firms β_3	−0.33***	−0.38***	−0.46***	−0.17***
	(−11.81)	(−7.55)	(−11.41)	(−3.50)
Large firms β_4	−0.35***	−0.42***	−0.47***	−0.17**
	(−8.27)	(−5.90)	(−6.56)	(−2.55)
City*Time FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Size*$Post_t$	Yes	Yes	Yes	Yes
Obs.	296,104	147,114	149,022	149,482
Within R^2	0.0883	0.0752	0.0997	0.0184

This table reports robust regression results for the average impacts of the COVID-19 lockdown on sales by firm size. The dependent variable is relative sales divided by the pre-lockdown 28-day average. In Panel A, the event day is set to the accurate lockdown timing in various cities. In Panel B and Panel C, the event day is set to January 23, 2020, when Wuhan was under lockdown, and a lunar-calendar-matched event day for 2019 is set to February 3, 2019. β1 measures the average impact at the city-day level for micro firms. The full sample period includes 4 weeks before ([−3,0]) and 12 weeks after ([1,12]) the event day. Three subsamples include daily observations in [−3,0] and [1,4], [5,8], and [9,12] weeks, respectively. Panel B presents the results with day-of-the-month fixed effects. Panel C presents the results with City × Time fixed effects, where Time includes fixed effects capturing the number of days to the event day and day of week. Heteroscedasticity-consistent *t-statistics* clustered by city and day are reported in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Table A3
Sales of publicly listed firms.

Industry	No. Firms	Sales 2019Q1	Sales 2020Q1	Growth
Agriculture	42	36,409	44,105	21.1%
Mining	76	1,664,607	1,442,055	−13.4%
Manufacturing	2289	3,817,057	3,366,865	−11.8%
Utilities	117	328,790	293,898	−10.6%
Construction	94	1,072,963	996,986	−7.1%
Wholesales & retail	169	1,055,744	946,976	−10.3%
Trans. & logistics	110	397,368	297,590	−25.1%
Hotels & catering	11	11,534	6452	−44.1%
IT & comm tech	279	232,303	206,246	−11.2%
Financial services	110	2,143,731	2,278,818	6.3%
Real Estate	128	372,473	359,767	−3.4%
Leasing & services	56	142,717	139,363	−2.3%
Sci & tech	44	16,083	15,272	−5.0%
Environmental	57	30,397	25,240	−17.0%
Resid. services	1	75	45	−39.4%
Education	8	3407	2590	−24.0%
Health services	12	8908	6737	−24.4%
Entertainment	57	43,346	29,098	−32.9%
Public Administration	16	10,718	9325	−13.0%
Aggregate	3676	11,388,632	10,467,427	−8.1%

This table presents the aggregate sales of publicly listed firms across 19 industries in China's A-share market. The sales are in RMB million for the first quarter in 2019 (2019Q1) and 2020 (2020Q1). Growth rates of sales in the first quarter of 2020 to that of 2019 are also reported.

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