Macroeconomic Impacts and Transmission Channels of an Epidemic Shock: Evidence from the Economic Performance of China during the 2003 SARS Epidemic

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- **Abstract:** This paper uses the 2003 Severe Acute Respiratory Syndrome (SARS)epidemic as a quasi-experiment to study the economic impact of epidemic shocks. It aims to answer the following three questions. 1) How does an epidemic affect various macroeconomic variable? 2) Does an epidemic have a lag effect on the economy? 3) What are the transmission channels through which the epidemic shock affected firms? We build an epidemic shock macroeconomic model and use a difference-in-differences (DID) estimator to estimate the impact of the 2003 SARS epidemic on the economic performance of China. We find that the SARS epidemic negatively affected China's GDP growth rates and its levels of consumption, investment, and productivity. The estimate implies that the SARS epidemic caused both a supply shock and a demand shock. Massive layoffs during the SARS epidemic due to liquidity constraints is an important reason for a lag effect on the economy. The lag time effect of SARS was very short because of the short duration of the outbreak and adequate liquidity. We isolate and compare the effects of the SARS epidemic from the perspectives of changes in business cycles, external financing conditions, and labor supply shocks on firms' economic performance using firm-specific sensitivity estimates prior to the SARS epidemic. We find that the SARS epidemic had a larger negative impact on firms with higher sensitivity to business cycles and labor supply shocks. The paper also discusses macroeconomic policies and nonpharmaceutical interventions (NPIs) during an epidemic shock. To avoid lag effects, the government should try to maintain normal market liquidity. Aggressive NPIs can not only lower mortality but also mitigate the adverse economic consequences of an epidemic.

Keywords: SARS 2003, COVID-19, Epidemic Shock, Borrowing Constraint, Demand Shock, Supply Shock

1. Introduction

The spread of coronavirus disease 2019 (COVID-19) in early 2020 has caused worldwide contractions of real economic activity, as reflected in real GDP. During the 1st quarter of 2020, China's GDP declined by 6.8% from the same period in 2019, representing the largest GDP decrease since China's reform and opening up. In the 2nd quarter of 2020, the U.S. GDP shrank 32.8%, record breaking decline in U.S. history. The COVID-19 outbreak is an unusual macroeconomic shock, i.e., a multiperiod shock that simultaneously disrupts supply, demand, and productivity. Worse pandemic situations mean larger macroeconomic shocks. Some nonpharmaceutical interventions (NPIs) perhaps exacerbate the size of recessions caused by epidemics. Policymakers are struggling with how to understand and manage COVID-19. Despite the catastrophic consequences of epidemics, the economic impacts of epidemics have been considerably under researched by economists until the COVID-19 outbreak. The ability to design policies to mitigate the economic impact of COVID-19 requires reference estimates of the effects of an epidemic shock. What are the real economic effects of an epidemic? Is there a lag effect for an epidemic shock? And if so, why? What are the transmission channels of an epidemic shock to firm performance? These questions need to be addressed to understand epidemic shocks.

In the neoclassical one-sector model, pandemics are considered of as a labor supply shock to the economy, leaving physical capital intact (Nie, Jiang et al. 2012, Karlsson, Nilsson et al. 2014).Pandemics have initial effects such as a reduction in labor supply, an increase in marginal products of labor and real wages, and a decrease in marginal products of capital and the rate of capital return. Capital per worker and output per worker also initially increase (Garrett 2009). Alfani and Percoco (2019) challenge the hypothesis that plagues are beneficial for the Italian economy; they find that when an epidemic shock in labor productivity decreases the labor demand, wages decrease after the shock.

A large set of papers has emerged on macroeconomic models in the context of the COVID-19 pandemic. Different from early pandemic studies that regarded a pandemic as just as a labor supply shock, most of the latest macro studies suggest that COVID-19 causes both a supply shock and a demand shock. Guerrieri, Lorenzoni et al. (2020) analysis of COVID-19 is based on the New Keynesian model and focuses on temporary shocks to supply due to shutdowns. Negative labor supply shocks can cause negative demand spillover under certain configurations of the elasticity of substitution with incomplete markets and liquidity-constrained consumers. Fornaro and Wolf (2020) study COVID-19 as a negative productivity shock using the New Keynesian model. The expected loss in future income reduces aggregate demand. Faria-e-Castro (2020) builds a calibrated DSGE New Keynesian model with financial frictions. The pandemic is modeled as a large negative shock to the utility of consumption. Baqaee and Farhi (2020) study the effects of supply and demand shocks in a general disaggregated model with multiple sectors, factors, and input-output linkages, focusing on complementarities and the associated nonlinearities from occasionally binding downward wage rigidity. Céspedes, Chang et al. (2020) build a minimalist model of the macroeconomics of a pandemic with two essential components: 1) productivity suffers if the virus forces firms to shed labor beyond a certain threshold and 2) credit market imperfection. Some papers extend the classic SIR model proposed by Kermack and McKendrick (1927), merging them into economic setting concerns and economic costs (Alvarez, Argente et al. 2020, Berger, Herkenhoff et al. 2020, Eichenbaum, Rebelo et al. 2020, Hall, Jones et al. 2020). Eichenbaum, Rebelo et al. (2020) suggest that containment policies reduce the severity of an epidemic but exacerbate the recession caused by the epidemic. These latest studies analyzed how epidemic shocks affect macroeconomy in theory and discussed the possible impacts of the COVID-19 pandemic on the economy and the optimal macro policy responses.

Due to data limitations, empirical studies of early epidemics focus on long-term economic effects. Past empirical researches on the Black Death (1347-52) confirm the neoclassical conclusion for the long term. The Black Death led to long-lasting increases in wages throughout Europe and triggered institutional innovation (Herlihy 1997, Epstein 2000, Pamuk 2007), which also altered the functional distribution of income favoring labor and then led to a decline in economic inequality (Malanima 2012, Alfani 2015). Alfani and Percoco (2019) find that Italian cities severely affected by the 1629-30 plague were displaced to a lower growth path because of the decrease in labor productivity. Using a dataset stretching back to the 14th century, Jordà, Singh et al. (2020) find evidence that pandemics reduce the real rate of interest.

Most empirical studies of epidemic shocks address the 1918 Spanish flu. The world's experience with the 1918 flu can be a reasonable upper bound for COVID-19 mortality and the economic effects (Barro, Ursúa et al. 2020).

Brainerd and Siegler (2003) find that states with higher 1918 influenza mortality experience stronger per capital income growth in the long run, from 1919 to 1929. Garrett (2009) finds that U.S. states and cities with more influenza exposure during the 1918 flu pandemic saw a relative increase in wages in the manufacturing sector between 1914 and 1919, consistent with the labor supply shock. However, using macroeconomic data from Sweden for the 1910-1930 period, Karlsson, Nilsson et al. (2014) find that the 1918 flu had a strong negative impact on capital income and a strong positive impact on the poorhouse rate during the immediate and medium-term but no effect on earnings. Guimbeau, Menon et al. (2020) find negative effects of the 1918 flu on long-term health and productivity in São Paulo, Brazil, with more disaggregated data. Correia, Luck et al. (2020) find that the pandemic reduced U.S. manufacturing employment and bank assets from 1914-1919, decreases that were driven by both supply and demand shocks. Cities that intervened earlier and more aggressively did not perform worse and grew faster after the pandemic was over. Barro, Ursúa et al. (2020) use country-level data for the 1901-1929 period and find that higher mortality during the 1918 flu pandemic lowered the real GDP and decreased the rate of return. Although many empirical studies focus on the 1918 flu to understand the macroeconomic effects of COVID-19, the complex nature of modern global supply chains, the larger role of services, and improvements in communication technology are mechanisms that cannot be captured in the analysis of the 1918 flu (Correia, Luck et al. 2020). Because of the absence of economic data for firms during early pandemics, economists are forced to use more aggregated data at the regional or national levels to study the relationship between pandemic incidence and economic outcomes.

Similar to COVID-19, Severe Acute Respiratory Syndrome (SARS) is a new disease caused by a previously unknown coronavirus subtype that cross species barriers with subsequent human-to-human transmission. During the SARS epidemic in 2003, there were 8,096 confirmed cases and 774 deaths in 29 countries and regions, with a case fatality rate of 9.56% (WHO 2003). More than 90 percent of these cases were reported in Asia. Compared with patients with COVID-19, patients with SARS present obvious symptoms (high fever and dyspnea), with few mild or asymptomatic patients. SARS has a higher mortality rate than COVID-19, but the R0 is lower. With much fewer infection and deaths throughout the world relative to COVID-19, SARS can only be regarded as a near-pandemic that highly affected some Asian regions. However, in the highly affected regions in China, SARS did have a large psychological impact on attitudes toward risk (Fan 2003). The economic impact of SARS is not a consequence of the epidemic itself but is rather the effect of the epidemic on the behavior of many people within these economies (Lee and McKibbin 2004). Limited attention has been given to the economic effects of SARS. Lee and McKibbin (2004) use the G-Cubed model to simulate the SARS shock on the Hong Kong economy. Chou, Kuo et al. (2004) use a multiregional CGE model to simulate the SARS shock to Taiwan services and manufacturing sectors. Both CGE simulation results assert that SARS could have significant short-run macroeconomic effects. Beutels, Jia et al. (2009) use a cross-correlation function to analyze the correlation between China SARS deaths and public transport, tourism, household consumption patterns and GDP growth and find significant correlation coefficients.

In this paper, we build a macroeconomic model and study the economic impact of SARS using a difference-in-differences (DID) estimator based on panel data for Chinese provinces and firms. Our study contributes to a better understanding of epidemic shock by addressing the following four aspects.

First, different from the other papers that study data from the 1918 flu or the Black Death (1347-1352), data from the 2003 SARS epidemic are adopted here to analyze the impacts of epidemic shocks. Although the impacts of SARS are specific to some Asian cities, there are several advantages for using SARS data to assess the impacts of a typical epidemic. (1) The data include the complex nature of the modern economy, such as global supply chains, the larger role of services, and improvements in communication technologies, which are missing in studies of the 1918 flu or the Black Death. (2) There are abundant economic data at different levels in China to evaluate the impacts of the SARS. Quarterly and monthly province panel data are important because of the short duration of SARS. Annual data tend to smooth out short-term effects, leading to a potential underestimate of disruption. We assess not only the monthly and quarterly province panel data but also firm-level data, enabling us to distinguish different transmission channels through which the epidemic shock influenced firms. (3) Seventeen years have passed since the 2003 SARS epidemic, allowing us to analyze the lag effects of the outbreak.

Second, we build a relatively simple macroeconomic model to analyze epidemic shocks and make four assumptions based on the model; then, we test the assumptions using SARS data. The epidemic shock is both a supply and demand shock, i.e., a real economy contraction. In the model, it is assumed that productivity would suffer if firms had to shed labor beyond a certain threshold during the epidemic (Guerrieri, Lorenzoni et al. 2020); this decrease in labor is the main cause for the lag effect of epidemic shocks. We do not address the important trade-offs between containment policies and economic cost with SIR but do discuss the economic impact of different probabilities of infection and expected outbreak durations in our model. The model is also used to analyze the transmission channels of an epidemic shock on business performance.

Third, we use quasi-experimental variation to assess the causal effects of SARS. Several papers have evaluated the association between SARS and economic results (Chou, Kuo et al. 2004, Lee and McKibbin 2004, Beutels, Jia et al. 2009). During the SARS epidemic, Beijing was highly exposed, but many provinces in China had few infected people. We use a DID estimator to estimate the different SARS infection rates among China provinces and assess the causality between their SARS infection rates and economic impacts. In this paper, we also conduct various robustness tests, including the synthetic control method (SCM) and the placebo test, and change the treatment and control group definitions, and we assess the lag effect of SARS on the economy.

Fourth, the nature of data regarding early pandemics makes it difficult to identify the exact channels through which pandemics affected the real economy. Here, firm-level data during the SARS epidemic make it possible to examine the various channels via which the epidemic affected the economy. We test three possible channels of epidemic impact: business cycle, liquidity shock, and labor supply shock.

With respect to the economic effects of the epidemic, we find that more severely affected provinces experienced more declines in GDP, consumption, investment, quantity of employment, and total factor productivity (TFP). Our findings imply that SARS led to a 1.3% reduction in China's GDP. These patterns are consistent with the notion that epidemics depress economic activities by reducing both supply and demand. Economic contractions are temporary, just occurring within a year after the outbreak. We note that the SARS epidemic had a larger negative impact on firms with greater sensitivity to business cycles and higher labor intensity. The empirical results support the theoretical hypothesis of this paper. The main concern with our empirical approach is that provinces with higher exposure to SARS is not arbitrary. This paper controls for province, time fixed effect, and some covariate variables, uses PSM for firm data, and tests the parallel trend assumption. Various robustness tests indicate the reliability of the empirical results.

The remainder of the paper is structured as follows. Section 2 discusses the background of SARS in China. Section 3 describes the macroeconomic model. Section 4 discusses the empirical strategy. Section 5 analyzes the dataset. Sections 6 and 7 present our empirical results for the economic effects of SARS. Section 8 offers concluding remarks.

2. Background of the 2003 SARS epidemic in China

2.1 The 2003 SARS epidemic in China

The earliest cases of SARS appeared in the southern Chinese province of Guangdong in mid-November 2002, marking the start of the SARS epidemic (Zhong, Zheng et al. 2003). Ultimately, 5327 SARS cases and 349 deaths were reported on mainland China between November 2002 and July 2003 (WHO 2003). SARS transmission in China consisted of three phases[1]. Phase I was the first quarter of 2003, with the outbreak occurring in Guangdong Province[2]. By the end of March, 1190 confirmed cases, accounting for 96.9% of the SARS cases in China, had been reported in Guangdong (1030 cases were in Guangzhou City). After February 2003, SARS cases started to appear in Hong Kong (Hung 2003) and seven other Chinese provinces: Guangxi, Jiangxi, Fujian, Hunan, Zhejiang, Sichuan, and Shanxi (Xu, He et al. 2004). On March 6, 2003, the first imported SARS case was detected in Beijing. Phase II was the massive outbreak of SARS cases in April 2003; the epidemic spread to many parts of North China, including Inner Mongolia, Shanxi, Beijing, Tianjin, and Hebei. Beijing became the new epidemic center. By the end of April, the total number of cases in China had reached 3303 (of which 1399 were in Guangzhou); Beijing had 1347 confirmed cases or 40.78% of the national total. Phase III was the epidemic stabilization period (May and June 2003), during which the number of daily new confirmed cases gradually declined and the epidemic was

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[1] Source of information: Speech by Qiang Gao, the Deputy Minister of the Ministry of Health of the People's Republic of China, at the WHO Global Conference on Severe Acute Respiratory Syndrome (SARS) on June 17, 2003 in Kuala Lumpur.

[2] Virus monitoring in Guangdong in February 2003 indicates that the SARS cases that met the WHO definition first appeared in mid-November 2002 (Zhong et al., 2003). Yet, no large-scale transmission occurred at that time.

gradually controlled. By the end of June, China had effectively controlled epidemic transmission, and by the end of August, all known patients had been treated and left hospitals (Huang 2004). Figures 1 and 2 illustrate the progress of the SARS epidemic in China and two major epidemic centers.

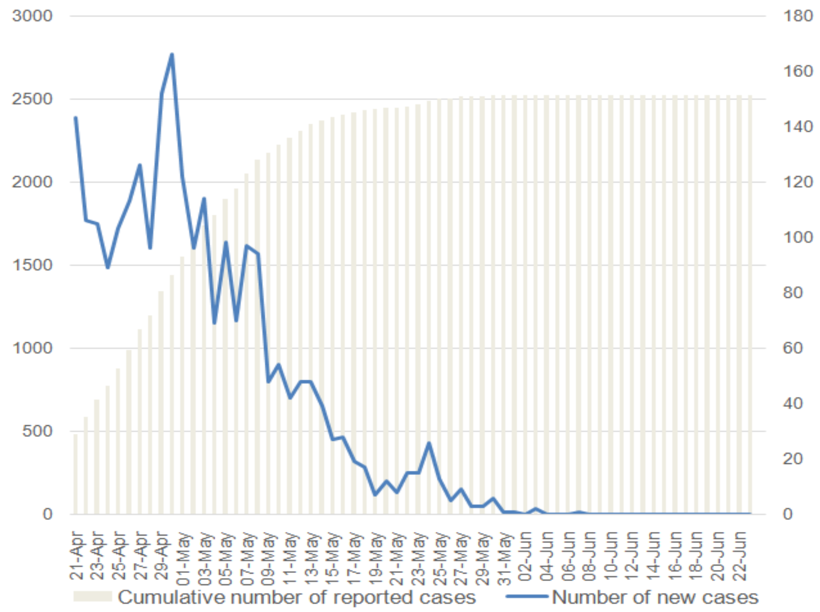

Fig. 1 Cumulative number of reported cases and new cases of SARS in Beijing

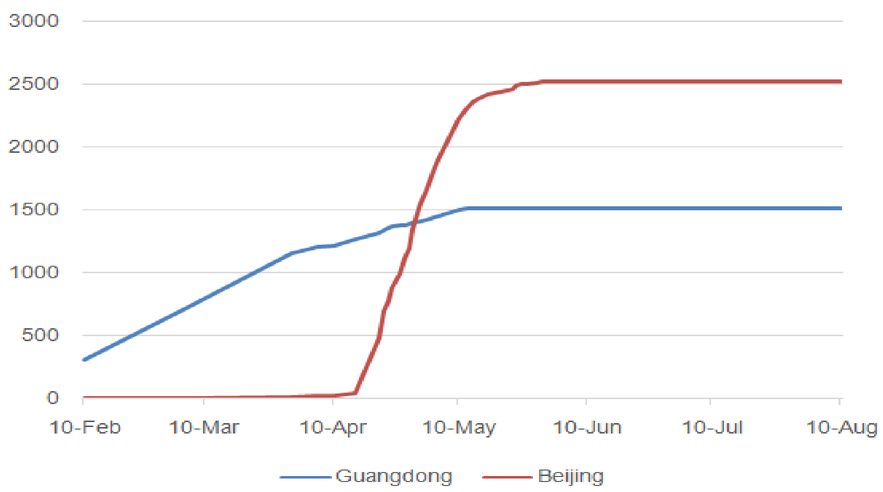

Fig. 2 Cumulative number of reported cases in Guangdong and Beijing

Note: The data for confirmed cases and deaths in February and March 2003 came from the News Office of the Ministry of Health of the People's Republic of China and public reports from www.people.com.cn; the data from April came from the WHO. None of the above data includes cases in Hong Kong, Macao, and Taiwan.

Figure 3 shows the geographical distribution of SARS cases in China (including Hong Kong, Macao, and Taiwan). Although SARS cases appeared in many parts of China in 2003, most were clustered in two regions: Guangdong Province and Beijing. Beijing, the city worst hit by SARS, had 2521 confirmed cases and 191 deaths. Guangdong Province reported 1512 confirmed cases and 58 deaths. The provinces neighboring Beijing also had high numbers of confirmed cases and deaths. For instance, Shanxi had 448 confirmed cases and 24 deaths, Inner Mongolia had 282 confirmed cases and 25 deaths, Hebei Province had 215 confirmed cases and 14 deaths, and Tianjin reported 17 5confirmed cases and 12 deaths. None of the other provinces in mainland China had more than 35 confirmed cases. The SARS epidemic caused not only many deaths but also left generated further sequelae, including osteonecrosis of the femoral head and pulmonary fibrosis, among the survivors. Many individuals who had SARS are still suffering from these sequelae.

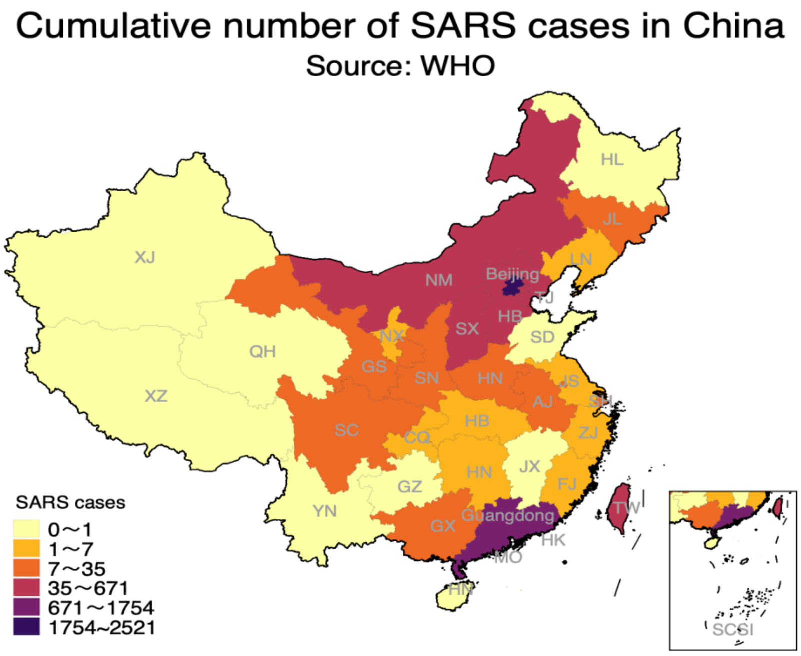

Fig. 3 The cumulative number of SARS cases in China

2.2NPIs during the SARS epidemic

During the initial phase of the SARS outbreak, the Chinese government did not pay much attention because of a lack of understanding of its transmission characteristics. It was not until April 2003, when SARS spread quickly and became a massive outbreak, that the Chinese government started to implement numerous control policies and measures. The Ministry of Health (MOH)of the

People's Republic of China approved of listing SARS as an infectious disease on April 8. A “SARS control and prevention headquarters" was set up to coordinate national control efforts on April 23 (Liang, Zhu et al. 2004). China's NPIs effectively stopped the interprovince transmission of SARS and ended the SARS epidemic in a short amount of time. The main policies and measures were as follows. 1) Travel was restricted to and from quarantined villages in China (Rothstein, Control et al. 2003). In some rural areas, entire villages, such as in Hebei Province, were cordoned off (Rothstein, Control et al. 2003). The measure was effective, and only 155 confirmed cases appeared among the eight million migrant workers who returned to their home villages. 2) From April 9, 2003, medical workers from the China Center for Disease Control and Prevention (China CDC) started to trace potential close contacts of individuals with confirmed cases, i.e., individuals who came in contact with individuals with SARS during the two weeks prior to symptom onset. Early case detection followed by rapid and effective isolation was a key measure for controlling the spread of SARS. Close contacts of individuals with probable and suspected SARS underwent a mandatory 10-to-14-day home quarantine. 3) A daily health condition reporting system was set up for public places with high population aggregation, such as schools and restaurants. In the event that individuals with confirmed or suspected SARS case were detected, the relevant schools and restaurants were closed. 4) China initially required all hospitals to be prepared for isolating and treating individuals with SARS and later devoted entire hospitals for the isolation of patients with SARS.

Beijing, as the epidemic center of SARS, enforced strict NPI policies. On April 23, 2003, the Beijing Municipal Education Bureau required all primary and middle schools in the city to be closed for two weeks and later extended the school closure. On April 26, Beijing closed over 3500 public places, such as libraries, cinemas, bars, and indoor sports centers. On April 28, Beijing imposed closed management for all universities and colleges in the city and strictly controlled access by external people to campuses and traced the health conditions of all students that had left the campuses. Government agencies, firms, public institutions, and schools and universities were prohibited from organizing any external conferences, travels, or site visits and were required to cancel all nonessential business travel. From late April onwards, the government screened anyone from Beijing traveling within the country by air, rail, road, ferry, etc. and set up checkpoints at all 71 roads connecting Beijing to other parts of the country (Pang, Zhu et al. 2003). Bell (2004) believes that active use of conventional public health interventions, such as case reporting and the isolation of close contacts, controlled the SARS transmission. Wang, McMichael et al. (2006) report that the dramatic decreases in confirmed SARS cases after 20 April in Beijing corresponded to the enhanced control measures by the government.

Provincial governments other than Beijing and Guangdong mainly curtailed SARS transmission by restricting the entry of people from Beijing and Guangdong, the centers of the SARS outbreak. They also isolated individuals with suspected cases and the close contacts of individuals with confirmed or suspected cases. Shanghai, for instance, placed people from Beijing under quarantine even in the absence of symptoms (Huang 2004). These policies and measures effectively prevented the interprovince transmission of SARS.

2.3 Macroeconomic policies during the SARS epidemic

The fiscal policies introduced during SARS include tax reduction and exemption and increased government procurement. According to the 2003 Chinese fiscal report, governments at various levels arranged 13.6 billion CNY of fiscal funds for SARS prevention and treatment. The central government established a 2-billion-CNY SARS Control and Prevention Foundation and implemented a policy of free SARS treatment for farmers and low-income urban residents. This measure effectively reduced the medical costs for households and reduced social panic. During the SARS epidemic, the Beijing municipal government waived the valued-added tax, urban maintenance and construction tax, educational surtax, and personal income tax for micro-businesses for individual vegetable sellers in Beijing. From May 1 to September 30, 2003, the government also reduced and exempted businesses in the restaurant, hotel, tourism, entertainment, civil aviation, road passenger transport, waterway transport, and taxi industries from the urban utility surtax, the urban and local educational surtax, the cultural development levy, as well as some other surtaxes and fund contributions for various industries.

As for monetary policies, although the Chinese central bank did not lower its official reserve ratio and interest rate, it maintained interest rate stability and implemented a policy of reasonable increases in financial lending, especially lending to industries and regions badly affected by the SARS epidemic. The growth rate of bank loans increased from 15.8% at the end of 2002 to a peak of 23.9% in August 2003. The growth rate of M2 rose from 16.8% at the end of 2002 to a peak of 21.6% in August 2003.

3. Theoretical Model

Our model includes a two-sector closed economy: households and firms. The model does not consider government and international trade. We introduce nominal rigidities into the model; the nominal wages are downwardly rigid; and the labor market may deviate from demand and supply balance in the short-term. The Chinese central bank adjusts the money supply based on market demands to secure a stable interest rate during SARS[3]. The issue of credit constraints exists. When businesses face liquidity shortages, they cannot maintain an optimal employment level, and excessively low employment levels can lower businesses' productivity levels. The severity of epidemic exposure can affect the macroeconomic performance of a country or region. The model has two variables related to the severity of epidemic: the probability of infection and the expected outbreak duration.

The economy lasts two periods, and subscripts 1 and 2 indicate periods 1and 2, respectively. Before the outbreak, the economy was in long-term equilibrium. In the first period, a pandemic strike and causes both a supply shock and a demand shock, hurting overall productivity. The pandemic subsides in the second period, allowing productivity to recover. The model uses comparative statics for the epidemic shock and assesses the impact of the epidemic shock on the macroeconomic variables. Under the conditions of credit constraints, the model determines the factors that explain the lag effect. It also explores the transmission channels through which the epidemic shock influences business performance. Although the model does not cover government, we investigate the macroeconomic policies and the economic costs of NPIs.

3.1 Environment and equilibrium

Household

If ρ is the subjective discount rate and θisthe marginal disutility of labor supply, households maximize

$$U(C_1, n_1)+\frac{U(C_2,n_2)}{1+\rho} \qquad (1)$$

[3] During the SARS epidemic, the interest rate remained unchanged, but commercial banks increased their lending.

with respect to consumptions C_1 and C_2 and labor supplies n_1 and n_2, subject to the constraint

$$C_1 + \frac{C_2}{1+r} \leq f + w_1 n_1 + \frac{w_2 n_2}{1+r} \qquad (2)$$

r is the real interest rate, and f is the initial holding of the bond by households. In equilibrium, the real interest rate is equal to the subjective discount rate, and the real wage in each period is equal to the marginal disutility of labor supply θ.

$$\gamma = \rho$$

$$w_1 = w_2 = \theta$$

Firm

The production function of the firm is:

$$y = zF(k, n) \qquad (3)$$

y is the output, z is the Hicks-neutral productivity shifter, k is capital, and n is labor.

Following Guerrieri et al.(2020), firm productivity z is given by

$$z = \begin{cases} z^l \text{ if } 0 \leq n \leq \tilde{n} \\ z^h \text{ if } \tilde{n} \leq n \leq \bar{n} \\ 0 \text{ otherwise} \end{cases} \qquad (4)$$

where $z^h > z^l > 0$; therefore,firms have a maximum scale of operation given by$\bar{n}$,and they also have a minimum efficient scale $\tilde{n}$. If in response to a shock the firm has to shed crucial employees and lower the employment level to $\tilde{n}$ or below,its productivity will drop. The capital accumulation is:

$$K_2 = (1-\delta)K_1 + I_1 \qquad (5)$$

In t=2, the firm sells its capital $(1-\delta)K_2$.

The firm's profits during the two periods are:

$$\pi_1 = Y_1 - wn_1 - I_1 \qquad (6)$$

$$\pi_2 = Y_2 - wn_2 + (1-\delta)K_2 \qquad (7)$$

In equilibrium, the rule for investment and employment demand optimization is:

$$MPL = \frac{dY}{dL} = zF_L = w \qquad (8)$$

$$\mathrm{MPK} = \frac{dY}{dK} = zF_k = r + \delta \qquad (9)$$

Financial markets and frictions

Firms can borrow in the financial markets but face borrowing constraints. Lenders will demand λ share of the asset value as collateral.

π_1 could be negative, which means that a firm borrows d with interest rate r from the bank in t=1:

$$d = wn_1 + I_1 - Y_1 \qquad (10)$$

$$\pi_2 = Y_2 - wn_2 + (1 - \delta)K_2 - rd \qquad (11)$$

An entrepreneur can borrow a share of λ of the net value of the firm.

$$d \leq \lambda v \qquad (12)$$

The value of the firm is the discounted value of firm profits:

$$v = \pi_1 + \frac{\pi_2}{1+r} \qquad (13)$$

If in equilibrium, the borrowing demand for firms can be satisfied. The borrowing constraint does not bind. Firms can maximize their profits and have optimal employment and investment. Nevertheless, sometimes they may face borrowing constraints, meaning the conditions are:

$$d_1 = wn_1 + I_1 - Y_1 = \lambda v = \lambda\left(\pi_1 + \frac{\pi_2}{1+r}\right) \qquad (14)$$

The level of employment must be:

$$n_1 = \frac{\lambda v + Y_1 - I_1}{w} \qquad (15)$$

if $\tilde{n} < n_1 < \bar{n}$, future productivity is high. However, if $0 < n_1 < \tilde{n}$,the firm has to shed crucial employees and lower the employment level to $\tilde{n}$ or below in response to a shock; therefore, future productivity is low.

Equilibrium

The aggregate demand for the current period is:

$$y^d = C^d(r, w, f) + I^d(r) \qquad (16)$$

The aggregate supply for the current period is:

$$y^s = zF(k, n) \qquad (17)$$

The equilibrium is:

$$y^s = y^d \tag{18}$$

3.2 Comparative statics for the epidemic shock

We provide comparative statics with respect to the epidemic shock, starting at an initial equilibrium. The epidemic can be captured as a combination of negative supply and demand shocks.

Supply effect

Government lockdowns, working from home, travel restrictions, the isolation or quarantine of infected employees, more leave requests by employees, and declines in capital utilization will reduce the productivity of firms because of fewer person-to-person interactions (Baqaee and Farhi 2020) (dz_1<0).

With a productivity shock, the marginal product of labor (MPL) decreases. Full employment means a decrease in w, but w is rigidity. As MPL declines, labor quantity demand decreases (dn_1d<0). The epidemic exposes people who are working to the virus (Eichenbaum, Rebelo et al. 2020). The marginal disutility of labor supply θ increases with the probability of infection during the epidemic. People react to that risk by reducing their labor supply (dn_1s<0). Both the demand and supply of labor will decrease during the outbreak, but the demand will decrease more with a low epidemic mortality rate. There will be more unemployment in t=1.

An epidemic is both a productivity and labor supply shock; therefore, the output will decrease based on the production function.

$$dy_1 < 0$$

Demand effect

The demand effect arises because the epidemic exposes people to the virus when they go shopping. People react to that risk by reducing their consumption (Eichenbaum, Rebelo et al. 2020). When workers lose their income because of the epidemic shock, they reduce their spending, which causes a contraction in demand. Current and expected future income declines from supply-side disruptions will weigh negatively on demand, especially that for durable goods (Correia, Luck et al. 2020). Hence, consumption is reduced after an epidemic shock($dC_1 < 0$).

With the labor supply and productivity shocks, the marginal product of capital (MPK) and the return on capital (r_k) decrease. As MPK declines, investment (I) demand also decreases.

$$dMPK = d(zF_k) = r_k + \delta < 0$$

$$dI_1 < 0$$

An epidemic shock decreases both consumption and investment demand. Therefore, the output will shrink based on the aggregate demand function.

The influences of epidemic severity

We introduce two indicators for this aspect: the probability of becoming infected Φ[4] and the expected outbreak duration (ω).

Because purchasing consumption goods and working bring people into contact with other, people are more willing to engage in market activities with lower risks of infection. The longer the expected outbreak duration, the greater is the loss in expected income, and the less people consume and investment.

$$\frac{dC_1}{d\Phi} < 0, \frac{dC_1}{d\omega} < 0, \frac{dI_1}{d\omega} < 0, \frac{dn_s}{d\Phi} < 0$$

High epidemic severity can increase economic losses. Strict isolation measures increase the recession but also shorten the outbreak duration and reduce the probability of being infected, which will reduce the economic cost of an epidemic.

3.3 Lag effect

Each firm's staff is the result of previous search and recruitment activities. With a productivity shock, MPL decreases, and a firm will need fewer labors. Nevertheless, finding and hiring the right workers takes time and is costly after an epidemic. Suppose a firm fire workers during the epidemic and is unable to achieve an optimal employment level in the future. In that case, the labor loss will lead to a productivity decrease during the second period (t=2), causing a lag effect.

To keep the high productivity z^h in t=2, if the expected outbreak period is not too long, an entrepreneur would opt to retain most workers. To keep

[4] In reality, different types of activity involve different amounts of contact with other people. For simplicity, we abstract from this type of heterogeneity.

employees and stay current on debt payments, a firm will have to borrow even more money.

Consider a financially constrained equilibrium, the entrepreneur will borrow:

$$d_1 = wn_1 + I_1 - Y_1 = \lambda v = \lambda(\pi_1 + \frac{\pi_2}{1+r}) \qquad (19)$$

The market value of a firm(v) depends on its anticipated profits. If the market expects a low v, lenders lend little, and firms must fire more worker during t=1. As a result, firms lose future productivity. That confirms initial expectations. If lenders expect high asset values and high productivity, firms can keep more workers and expect large future productivity. Therefore, those expectations are also rational and self-fulfilling.

The lag effect of an epidemic depends on firms' future productivity. If firms can retain most workers during an outbreak, the lag effect is shorter. Therefore, policies that mitigate these liquidity problems or improve firm balance sheets, while providing an incentive to retain workers, may improve that outcome. If credit does not flow, millions of jobs will be lost, and massive amounts of entrepreneurial capital will be lost (Céspedes, Chang et al. 2020). There will be a large lag effect resulting from the epidemic shock.

Apart from market liquidity, epidemic severity also influences lag effects. During an epidemic shock, entrepreneurs compare the cost and revenue of firing a worker. The cost is the productivity decrease in the future, t=2, while the revenue is the cost-savings($w-MPL_1$)*ω during t=1. The longer the expected outbreak duration ω, the more likely it is that businesses will fire workers. A longer expected outbreak duration also reduces entrepreneurs' confidence in the future of the economy. If the market expects a low v, lenders lend less, and the businesses must fire more workers during t=1. However, such situations also worsen the lag effect. The NPIs for epidemic control and prevention may exacerbate recessions in the short term. However, they can lower the mortality rate and infection rate and help build optimism in the market, which can reduce the recession and, in particular, shorten lag effects.

3.4 Transmission channel analysis

An epidemic can affect firms' economic performance. Based on the above analysis, we identify three possible influencing channels:

1) Business cycle shock

Epidemic shocks take the form of negative demand shocks and supply shocks and affect the real economy. The firms that are more sensitive to business cycles are more vulnerable to such shocks.

2) Labor supply shock

Epidemics today rarely cause high numbers of death among the labor force. However, if one or more confirmed cases appear in a company, the likelihood of infecting other employees is high, and clusters of confirmed cases might lead to a large-scale shutdown of businesses. Such situations cause labor supply shocks and a decrease in business output.

3) Liquidity shock

During an epidemic, firms' economic performance declines, and they may face liquidity stress due to credit constraints. As market expectations influence the market valuation of assets, banks may further tighten their credit constraints, which may worsen the credit access of firms and cause liquidity shocks. When firms face liquidity stress and have to fire employees, the firing may affect their normal operations, cause productivity declines, and generate lag effects.

Based on the model, we have made the following suppositions:

1)An epidemic is both a supply shock and a demand shock, and it causes decreases in consumption, investment, productivity, and output. Wages have a downward rigidity, and the number of labors decreases during an epidemic. Firms are willing to retain most of their workers if they expect that an epidemic shock is temporary.

2) The lag effect of an epidemic shock can vary, depending on the unemployment rate and the borrowing constraints during the outbreak.

3) At the firm level, epidemic shocks may manifest in multiple ways, for example, a sudden drop in demand and productivity (business cycle shock), shutdowns of production facilities because of the epidemic shock (labor supply shock), or borrowing constraints (liquidity shock).

In the next section, we will verify these suppositions based on data for the 2003 SARS epidemic.

4. Empirical identification strategy

Using panel data for different provinces and companies in China, we employ the DID estimator to analyze the different epidemic exposures among provinces in China. This section presents our empirical strategy and discusses various threats to our identification strategy.

The results are reliable if the regional exposure to SARS was essentially random and, in particular, if there was no correlation with potential outcomes. However, the exogeneity assumption may not be fully satisfied; some characteristics of the region may influence the spread of the epidemic. Unlike ordinary least squares (OLS), DID does not require the random distribution of SARS cases in different provinces; however, it requires the assumption of parallel trends between the treatment group and the control group to be satisfied. This paper conducts an ex-ante common trend test. To address selection bias and to make the trends for the treatment group and the control group as parallel as possible, we control the necessary covariates in the model. The changes in other policies or the unobserved characteristic variables in some regions can also make the parallel trend assumption invalid. We isolate the changes in unobserved regional characteristic variables by controlling the regional fixed effects and the correlations between the regional fixed effects and the time dummy. We also carry out a series of robustness tests to guarantee the credibility of the results.

The other goal is to distinguish different transmission channels through which epidemic shocks affect the economy by using firm-level data. We examine three possible channels: a business cycle channel, a labor supply shock channel and a liquidity channel. To make it easier for the business performance in different regions to satisfy common trends, we match the firms in the control group using propensity score matching (PSM).

4.1 The methodology for an empirical study using provincial panel data

(1) Baseline DID model

The basic DID model for provincial panel data is as follows:

$$y_{it} = \alpha_i + \beta_{it}\mathrm{Treat}_{it}\mathrm{T}_t + \gamma_t + \varepsilon_{it} \qquad (20)$$

where y_{it} is the variable representing various economic outputs; α_i is the fixed effects of the province I; γ_t is the fixed effect of time; and ε_{it} is the random disturbance. $Treat_{it}$ is the treatment variable, and for provinces with high numbers of cases, it is 1; for other provinces, it is 0.T_t is the time dummy, and during the SARS outbreak, it is 1; during other periods, it is 0. If the treatment group and the control group satisfy the common trend assumption, then β_{it} is the economic impact of the epidemic.

y_{it} represents the macroeconomic variables on which this paper focuses, including growth rate of GDP, consumption, investment, TFP, and employment, wage, and return on capital.

(2) Including a covariate and interactive fixed effect

We introduce a covariate to control the influence of other variable' on the economic outputs. As a result, equation (20) changes to:

$$y_{it} = \alpha_i + \beta_{it} Treat_{it} T_t + \theta_i X_{it} + \gamma_t + \varepsilon_{it} \tag{21}$$

For provincial panel data, X_{it} is the covariate for different provinces. In the analysis of firm level data, the covariates include firm characteristic variables.

As the provinces enact different economic policies at different time, a term representing the province-year interactive fixed effect, $\alpha_i\gamma_t$, is introduced into equation (21) to isolate the policy differences of different provinces.

$$y_{it} = \alpha_i + \beta_{it} Treat_{it} T_t + \theta_i X_{it} + \gamma_t + \alpha_i\gamma_t + \varepsilon_{it} \tag{22}$$

In the above equation, when conducting provincial data analysis, $\alpha_i\gamma_t$ represents the province-year interactive fixed effect. When analyzing firm data, a sector-year interactive fixed effect is further introduced into $\alpha_i\gamma_t$.

(3) The DID model with a dynamic effect

We introduce a dynamic effect into the DID so that the estimator coefficient β for the treatment effect can change with time.

$$y_{it} = \alpha_i + \sum_{t=2000}^{2006} Treat_{it} T_t \beta_t + \rho Treat_{it} T_t I_i + \theta_i X_{it} + \gamma_t + \alpha_i \mu_t + \varepsilon_{it} \tag{23}$$

The common trend assumption appears more plausible if provinces with different exposure to SARS have the same development trends before SARS.

Common trend assumptions of all outcome variables are tested before 2003[5]. If β_{it} is not significant before the epidemic, then the two groups generally have common trends. In other words, there is no significant difference between the treatment group and the control group before the SARS epidemic.

To determine whether the SARS epidemic caused lag effects, equation (23) considers the lag effects after an epidemic. It evaluates how an epidemic affects various macroeconomic variables during various post-epidemic periods.

(4) SCM

Apart from using the DID to estimate the epidemic's economic impacts, we also apply the SCM proposed by Abadie and Gardeazabal (2003) to artificially create a "synthetic" Beijing that has a very similar economic performance as Beijing before the epidemic and thus use it as a control group. This method also includes all the provinces not affected by external impacts in the scope of control group options. Then, we take the provincial characteristics, such as the population density, urbanization level, and industrial structure, as predictor variables and the weighted combination of the control group options as a counterfactual group. The advantage of this methodology is creating a control group through a data-driven approach to eliminate deviations due to subjective selection.

We also perform a placebo test on the basis of SCM tests. By counterfactually assuming a highly exposed province, we get a placebo test. A nonsignificant but precisely estimated placebo coefficient suggests an acceptable size, whereas an estimate that is significantly different from zero either suggests that the common time trend assumption is violated or that false positives are an issue (Karlsson, Nilsson et al. 2014).

(5) Other robustness tests

Unlike ordinary macro policy studies, in an epidemic study, there is no definite treatment group and control group. This paper uses two other treatment group definitions in the robustness tests. One method is defining Guangdong Province as the treatment group, the other method is defining 0 confirmed province as the control group.

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[5] For annual data, the common trend assumption pre-2003 is tested; for quarterly data, the assumption before the 2nd quarter of 2003 is tested; and for monthly data, the ex-ante common trend test for datapre-March 2003 is conducted.

4.2 The methodology for an empirical study using firm level data

(1) PSM

Using PSM, we match the firms in the epidemic area with other firms of similar propensities but located outside the epidemic area. This methodology creates a reasonable counterfactual framework and hence is able to effectively reduce the influence of selection bias on the accuracy of parameter estimation. However, the application of PSM needs to satisfy the ignorable conditional independence assumption (CIA)[6] (Rosenbaum and Rubin 1983) which implies that conditional on the observable attributes, whether the sample accepts the intervention must be independent of the potential outcome. It can be expressed as follows:

$$(Y_i^T, Y_i^C) \perp T_i | X_i$$

Although we cannot test this assumption, we can help satisfy this assumption by controlling more covariates that may affect treatment participation of the sample. Meanwhile, to guarantee the validity of the PSM, balancing property of the propensity score needs to be met: when the propensity scores are controlled, the distribution of different sample covariates should be the same. This condition guarantees that when different samples have the same propensity scores, their probabilities of receiving interventions are the same. This can be expressed as follows:

$$X_i \perp T_i | p(X_i)$$

where $p(X_i)$ is the corresponding propensity score of the sample. To test whether this condition is satisfied or not, after matching, the balance of covariates and the overlapping degrees of propensity scores is checked. Before conducting sample matching, the propensity score for different samples is estimated. We apply the Iterative Comparison Method proposed by Imbens and Rubin (2015) to choose the covariates for matching[7]. The first step is to choose some basic covariates and to include them in the equation for propensity score estimation. In this paper, covariate selection is based on variables representing firm characteristic in the theoretical models. The second step is to include the covariate options of other available data in the equation for propensity score estimation and conduct likelihood ratio tests[8] between the new equation and

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[6] Multiple terms are used to describe this hypothesis, such as conditional independence and unconfoundedness.
[7] The method is essentially a covariate screening approach combining theory-driven and data-driven practices.
[8] The original assumption of this test is that the estimated value of an additional covariate coefficient is 0.

the basic estimation equation. The results are the likelihood ratio statistics[9]. Finally, we compare the largest likelihood ratio statistics with the established threshold[10]. If the former is larger than the threshold, then we include the corresponding covariate in the estimation equation and repeat the above process. Therefore, the binary Logit model for estimating the propensity score is as follows:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 \mathrm{Basic} + \beta_2 \mathrm{Other} + u_i \qquad (24)$$

where $p_i = p(X_i) = \Pr(T_i = 1|X_i)$ represents the propensity score of a sample business; Basic includes the integrated basic covariates, and Other indicates other covariates that are integrated after the iterative comparison.

In this paper, we use one-to-one nearest neighbor matching for selection to test whether the values of the covariates are significantly different between the treatment group and the control group. A deviation of less than 10% indicates that the datasets pass the balance test. After the common support domain is defined, the control group for successful matching can function as the counterfactual result.

(2) Transmission channel test

We use firm-level data for the channel analysis. In reference to Claessens, Tong et al. (2012), our basic empirical strategy is to determine whether ex-ante classifications of firms, in terms of their intrinsic characteristics, i.e., degree of sensitivity to business cycles, exposure to labor supply shocks, and financial dependence, help to explain changes in their ex-post "performance".

If different transmission channels imply different firm-level effects related to firm characteristics, there is a better chance of isolating and quantifying the different channels. If the SARS epidemic represents a negative business cycle shock in macroeconomics, it should be reflected in relatively worse performance for those firms that are more business-cycle-sensitive than for those firm that are less so. If labor supply shock played an important role during the SARS epidemic, it should affect more of the firms that are labor-intensive. If liquidity shortage played an important role during the SARS epidemic, it should affect more of the firm that rely more on external finance.

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9 The statistical indicator follows the chi-square distribution.

10 Imbens, G. W. and D. B. Rubin (2015). Causal inference in statistics, social, and biomedical sciences, Cambridge University Press. chose a threshold value of 1, but he believes his threshold value choice is not necessarily better than other values.

The basic empirical strategy is to determine ex-ante classifications of firms in terms of their intrinsic characteristics, i.e., degree of sensitivity to business cycles ($Cycle_i$), labor intensity ($Labor_i$), and financial dependence(Lev_i).

$$y_{it} = \alpha_i + \beta_{it}\mathrm{Treat}_{it}T_t + \delta_{it}Cycle_i\mathrm{Treat}_{it}T_t + \lambda_{it}Labor_i\mathrm{Treat}_{it}T_t + \phi_{it}Lev_i\mathrm{Treat}_{it}T_t + \theta_i X_{it} + \gamma_t + \alpha_i\mu_t + \varepsilon_{it} \quad (25)$$

y_{it} is the variable for firm performance, α_i is a firm's individual fixed effect, γ_t is the annual fixed effect, and ε_{it} is the random disturbance.$\mathrm{Treat}_{it}$is the treatment variable; it is 1 for firms in provinces with high numbers of cases and 0 for firms in other provinces. T_t is the time dummy; it is 1 during the epidemic and 0 for any other time. The above equation introduces a Difference-in-Difference-in-Difference (DDD)estimator to the standard DID（equation 22） to distinguish the influencing channels.

We proxy these sensitivities using a firm's own history as realized over 1999-2002. An advantage of this approach is that it incorporates information about heterogeneity across firms within a sector. A disadvantage is that the firm-specific sensitivity measures can reflect omitted variables and be endogenous to the firm's performance. We include the firm characteristics in the X_{it}, in order to rule out the obvious omitted variables.

(3) Robustness test

During firm data selection, to guarantee the existence of common trends, an ex-ante trend test is conducted. Apart from the one-to-one nearest neighbor matching method, caliper matching and one-to-four nearest neighbor matching are utilized to test the robustness.

In the baseline transmission channel test, we use specific firm data to indicate a business's sensitivity level. As an alternative, we proxy these sensitivities relying on the sector characteristics of firms before SARS, which are more exogenous to individual firm.

5. Data and variables

In this paper, we create monthly and quarterly panel data for different provinces, and at the firm level, we obtained annual panel data for industrial firms. The data for confirmed SARS cases and deaths in February and March 2003 were obtained from the News Office of the Ministry of Health of the

People's Republic of China and public reports on www.people.com.cn; the data for April and later were obtained from the WHO (none of the data include cases in Hong Kong, Macao, and Taiwan). The data regarding the final number of confirmed cases and deaths were obtained from the summary report by the WHO on August 15, 2003. In this paper, we use Beijing, the region with the highest number of confirmed SARS cases as the treatment group and selected 19 provinces and cities that had zero or less than 10 confirmed SARS cases as the control group[11]. The duration of the SARS outbreak in Beijing was the second quarter of 2003.

5.1 Provincial panel data

Provincial panel data consist of monthly data and quarterly data[12]. To facilitate the ex-ante common trend assessment and the lag effect analysis, the data span from early 2000 to the end of 2006. The provincial data mainly originated from the National Statistics Bureau of the People's Republic of China and EPS China Database.

Using Correia, Luck et al. (2020) as a reference, we use the following covariates in this paper: per capita GDP, urbanization rate[13] and industrial structure. Fang, De Vlas et al. (2009) and Wang, McMichael et al. (2006) believe that population density and highways can influence epidemic transmission. Therefore, we also introduce two additional covariates: population density and highway mileage. In this paper, we further add local fiscal spending and financial institutions' lending as covariates, to control the differences in local monetary policies and fiscal policies. The description of a series of variables in provincial level is shown in Table 1.

Table 2 provides summary statistics of all the variables at the provincial level. As shown in Table 2, Beijing's growth rate of GDP, investment, employment, salary, return on capital, industrial structure, monetary policy, per capita GDP, population density, and urbanization rate all have significant difference from the control group provinces. OLS estimates are affected by

[11]Including two municipalities (Shanghai and Chongqing), 14 provinces and autonomous regions (Gansu, Liaoning, Jiangsu, Hubei, Hunan, Zhejiang, Fujian, Jiangxi, Shandong, Heilongjiang, Qinghai, Hainan, Yunnan, and Guizhou), and three autonomous regions (Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, and Tibet Autonomous Region).

[12]We delete the provinces and industries that lack data on multiple key indicators. We use average values to smooth out the lack of data for other indicators. We omit Liaoning Province, and the Tibet Autonomous Region due to lack of quarterly GDP data for these areas.

[13]As the *China Statistical Yearbook*s only provide the urban population shares during 2005-2012, we use the methodology described by Zhou and Tian (2006) and correct the data for 2000 based on the Fifth National Population Census of China. The data for 2001 to 2004 are corrected using the methodology provided by the United Nations.

endogeneity problems. In this paper in order to control the influences of these factors on the estimation results, we use these factors as covariates.

Table 1 Description of the variables (province panel data)

Variables		Explanation
Dependent variables	GDP (Q)	Year-on-year GDP growth rate for a province (Quarterly)
	Consumption (M)	Year-on-year consumption growth rate(monthly)
	Investment (M)	Year-on-year investment growth rate (monthly)
	Employment level (Q)	Annual growth rate of total employment(Quarterly)
	Provincial TFP (Q)	Annual growth rate of total factor productivity (Quarterly), which is calculated using growth accounting[14]
	Return on capital (Q)	$t\_return_{st} = \frac{DP_{st} - Wage_{st}}{K_{st}}$ where DP_{st} is the total output based on the income approach, $Wage_{st}$ is the labor wage in the total GDP based on the income approach; and K_{st} represents a province's total capital stock in the year.
	Salary growth rate (Q)	The annual growth rate of per capita salary among employed people (Quarterly).
Core independent variables	Did the region have a severe SARS outbreak?	During the 2nd quarter of 2003, Beijing had a severe SARS outbreak.
Characteristic variables	Per capita GDP	GDP per capita for a province (Quarterly)
	Urbanization rate	The proportion of people living in rural areas
	Industrial structure	The proportion of the added value of the secondary and tertiary industries in the total added value of the province
	Population density	The ratio of total population to area (per square kilometer)
	Highway mileage	The total length of expressway(10000 km)
	Fiscal spending	The ratio of local policy fiscal expenditure to regional GDP
	Balance of outstanding loans by financial institutions	Provincial financial institutions loan balance value

Note: "*" signifies that in the model, the indicator value takes the logarithmic form. Q, quarterly data; M, monthly data; and Y, yearly data.

[14] $TFP_{st} = Y_{st} - \alpha L_{st} - (1-\alpha)K_{st}. Y_{st}$. This equation is used to calculate the TFP growth rate of a province with the province's total output index. In the equation, α is the share of labor income, which is measured with the share of labor income in the total output based on the income-based approach; L_{st} is the growth rate of labor input and is measured with the number of people employed in each province; andK_{st} is the capital stock growth rate based on constant price.

Table 2 Summary Statistics (province panel data)

Variables		Control group		Treatment group		Difference
		Mean	Std. dev.	Mean	Std. dev.	
Dependent Variable	GDP growth rate	0.109	0.019	0.117	0.013	-0.009**
	Consumption growth rate	0.118	0.041	0.119	0.068	-0.001
	Investment growth rate	0.268	0.201	0.188	0.097	0.080***
	Quantity of employment growth rate	-0.014	0.045	0.018	0.037	-0.031***
	TFP growth rate	0.045	0.023	0.05	0.021	-0.004
	Return on capital	0.077	0.039	0.072	0.058	0.005
	Salary growth rate	0.136	0.045	0.159	0.023	-0.023***
Control variable	GDP per capita*	12130.89	9081.44	36128.57	8896.47	-23997.68***
	Urbanization rate	0.417	0.149	0.812	0.025	-0.395***
	The proportion of secondary industry in GDP	0.433	0.085	0.299	0.018	0.135***
	The proportion of tertiary industry in GDP	0.409	0.05	0.684	0.022	-0.275***
	Population density*	376.100	603.826	893.184	48.077	-517.084***
	Highway mileage	0.088	0.076	0.046	0.011	0.042*
	Fiscal expenditure	0.188	0.141	0.149	0.006	0.039
	Balance of outstanding loans by financial institutions*	4439.09	4325.572	10832	3280.264	-6392.91***

Notes：*、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

5.2Firm-level data

This paper uses micro data from the China Industry Business Performance Database for the 1998-2006 period. The database covers data for all industrial firms above the scale threshold in China, which are all annual data. We matched the multiyear data from the database with unbalanced panel data. First, we use the methodology of Brandt, Van Biesebroeck et al. (2012) and apply the sequential recognition method to create the unbalanced panel. Specifically, we use legal entity registration numbers of firms as clues to identify different firms. If the matching fails or if there are duplicate legal entity registration numbers (i.e., two or more firms share the same registration code), then the firm names are used in the matching. If matching again fails or if there are duplicate names, then the following combinations are used for matching: "legal representative name + region code", "region (county) code + telephone number + year of registration", and "postcode + main product + registration year". Second, we follow the examples of such scholars as Cai and Liu (2009), Nie, Jiang et al. (2012), and (Lu and Lian 2012) and eliminate the abnormal or missing data from the samples. 1) The key indicators include total asset, intermediate input, total industrial output, and number of employees. Samples missing key indicator values or samples with key indicator values of zero are eliminated. 2) Samples with unreasonable indicator values, for example, the total assets are less than the value of the liquid assets, the accumulative depreciation is less than the depreciation of the current period, the current year's depreciation is negative, the total liability is less than the long-term liability, or the actually received capital contribution is zero or negative, are omitted. Third, we follow the practice of existing studies and use estimates as substitutes for missing key indicator values for specific years[15]. The total industrial output and the intermediate input are deflated with an output deflator and a sectoral deflator[16].Matching results in 1053110 observed values for 298539 firms.

The core economic explanatory indicators for firms include sales revenue, added value, average wage, return on capital, number of employees, and firm TFP. Based on provincial covariates, we add firm age and ownership as firm-level covariates. We choose the following matching variables for firm characteristics: firm scale, capital-labor ratio (Lnkl), asset-liability ratio (Lev), profitability (Prf), firm age, and exporter or not (Exp), state-owned or not (State).

We now define our index for a firm's relative sensitivity to the business cycle. A regression analysis is conducted for each firm regarding the change in its (log) real sales and the change in (log) GDP during the 1999-2002 period and then use the coefficients as firm-level measures of business cycle sensitivity. We calculate, at the individual firm level, the median debt-to-assets ratio during the 1999-2002 period as the financial dependence index and the median employment quantity-to-assets ratio as the labor intensity index. The description of a series of variables in firm level is shown in Table 3.

[15] To estimate the added value in 2004, we follow the example by Liu (2008). The calculation formula is as follows: added value = sales revenue + ending inventory - opening inventory - intermediate input + value-added tax.

[16] Before price index matching, we converted the 2-digit industry codes in 1994GB to those in 2002GB for industry consistency purposes.

Table 3 Description of the variables (firm level data)

Variables		Explanation
Dependent Variable	Sales growth rate	Annual growth rate of “Sales revenue” data
	Added value growth rate	Annual growth rate of “industrial value added ” data
	Quantity of employment growth rate	Annual growth rate of “average number of all employees” data
	Capital return rate	$t\_return_{it} = \frac{VA_{it} - wage_{it}}{K_{it}}$, where VA_{it} is the industrial added value of the firm, and $wage_{it}$ is the total payable wages of the firm. K is the actual capital stock of the firm calculated by perpetual inventory method[17]
	Average wage growth rate	Average wage= Gross pay/ annual average number of all employees
	TFP growth rate	Refer to OP method (Olley and Pakes,1996)
Independent Variable	Business cycle	Regress each firm’s sales volume on GDP of the province where the firm locates in over the period 1999 to 2002, and then use the coefficients as the firm-level measure of business cycle sensitivity
	Labor intensity	The ratio of original value of fixed assets and employment
	Financial dependence	The ratio of firm-level total liabilities and total assets
Control variable	Firm scale*	Total assets
	Lnkl*	The ratio of the original value of fixed assets to the annual average number of all employees
	Lev	the ratio of firm-level total liabilities and total assets,
	Prf	The ratio of operating profit to gross sales
	Firm age*	Current year minus business opening year
	Exp	If the enterprise had exported before 2003, then exp=1, otherwise exp=0. The export value is not provided in the China Industry Business Performance Database, we use export delivery value instead.
	State	If the holding status of the firm from 1998 to 2006 has been state holding, then it is considered a state-owned firm, state=1, otherwise state=0

Notes： “*” signifies that the indicator value takes the logarithmic form in the econometric model

[17] $K_{it}=(1-\delta)K_{it-1}+I_{it}$

In the equation, I_{it} represents the investment of a firm in year t, K_{it} represents the actual capital stock of the firm, and δ represents the rate of depreciation. The values are deflated by using the price indices of investment in the fixed assets of each province. The original fixed asset values in the year that each firm first appeared in the database are converted to the actual values and used as the initial capital stock of each firm.

Table 4 shows that the control group and the treatment group are significantly different. Except for export, the industrial firms in the control group outperform their peers in Beijing in all operational variables. When we perform the DID estimation at the firm level, to better guarantee the common trend between the control group and the treatment group, we firstly apply the PSM to select matching firms in the control group for the firms in Beijing and then combine with the DID technique.

Table 4 Summary Statistics (firm level data)

Variables		Control group		Treatment group		Difference
		Mean	Std. dev.	Mean	Std. dev.	
Dependent Variable	Sales growth rate	0.190	0.367	0.141	0.349	0.049***
	Added value growth rate	0.182	0.654	0.096	0.678	0.086***
	Quantity of employment growth rate	0.080	0.427	0.045	0.379	0.036***
	Return on capital	0.181	1.317	0.066	1.471	0.115***
	Average wage growth rate	0.219	0.666	0.180	0.557	0.040***
	TFP growth rate	0.038	0.382	0.026	0.443	0.012***
Independent variable	Business cycle	1.546	23.022	2.826	25.468	-1.28**
	Labor intensity	0.099	2.107	0.151	1.683	-0.052***
	Financial dependence	1.086	0.795	0.956	0.710	0.129***
Control variable	Firm scale*	75359.4	828268.8	148198.4	4366344	-72839***
	Lnkl*	126.313	1219.539	142.823	133.096	-16.51***
	Debt ratio	1.086	0.795	0.956	0.710	0.129***
	Profit rate	0.016	0.112	-0.003	0.149	0.019***
	Firm age*	10.504	12.251	11.322	12.347	-0.818***
	Export firm	0.138	0.345	0.291	0.454	-0.153***
	State-owned firm	0.228	0.419	0.132	0.338	0.096***

Notes： *、**、***indicate significance at the 10%, 5%, and 1% level, respectively. “*” signifies that the indicator value takes the logarithmic form in the econometric model while it takes original value form in summary statistics.

6. Results based on the provincial panel data

6.1 Common time trend Test

Figure 4 indicates that the common trend is a reasonable assumption. The confidence interval for the treatment group's estimated coefficient before 2003 is generally close to 0, indicating that the common trend assumption is satisfied.

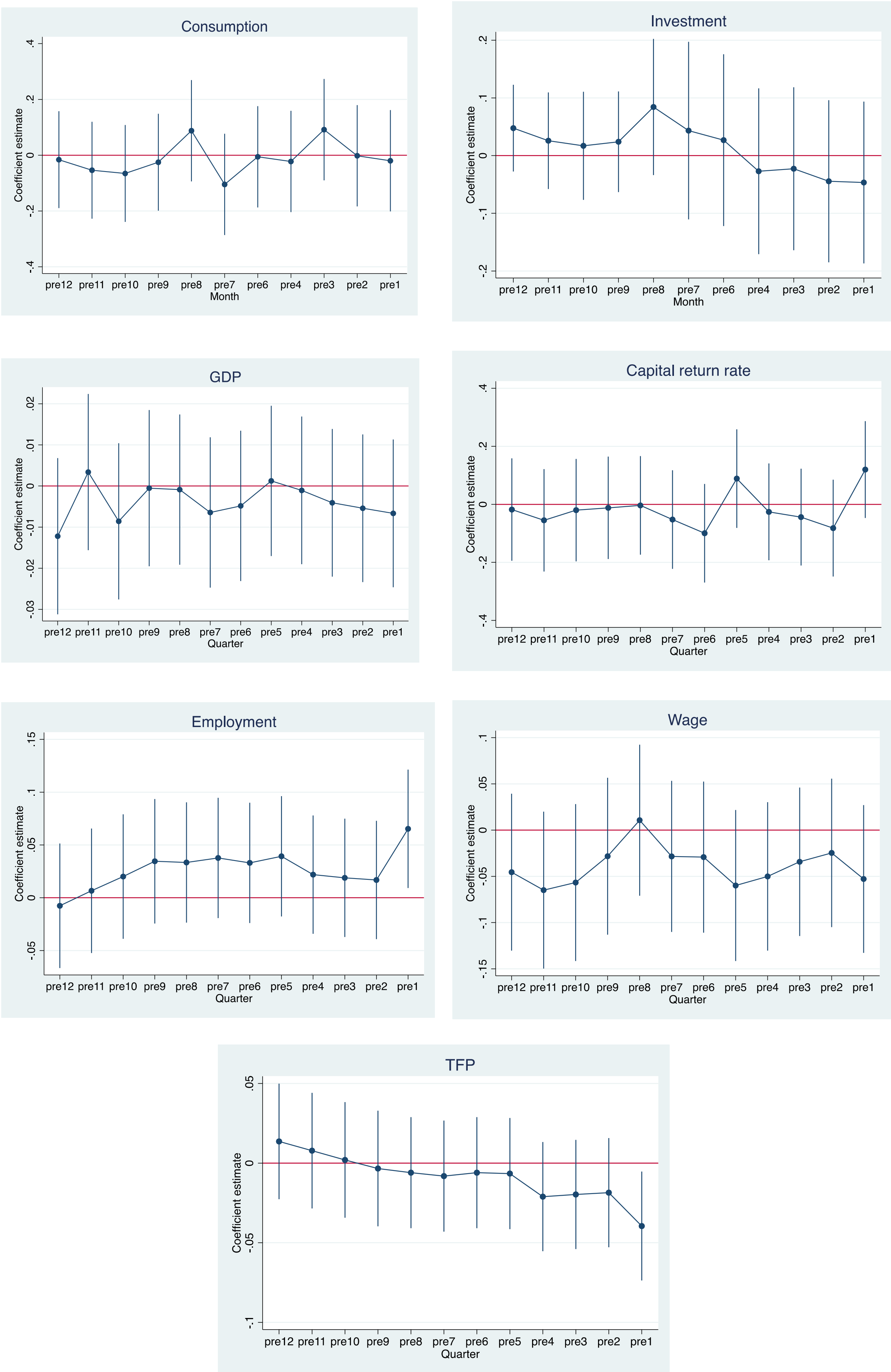


Fig. 4 Common time trend for all variables in province panel data

6.2 Baseline results for the provincial panel data

According to the baseline results in table 5, the SARS epidemic caused a recession in the real economy: a 1.3% drop in the GDP growth rate. The SARS epidemic was a demand shock. It led to a 11.2% drop in the consumption growth rate and an 8.5% drop in the investment growth rate. The SARS epidemic was also a supply shock and led to a productivity decrease: a 1.1% drop in the TFP growth rate.

Consistent with the sticky-price assumption, there was no significant decrease in the wage level during the epidemic. During the SARS outbreak, the Beijing Municipal Human Resource and Social Security Bureau required that all employees in quarantine should be entitled to full-paid leave, i.e., the infected employees' absence due to SARS exposure should be treated as sick leave. This policy limited the epidemic's impacts on the wage level in Beijing. The decline in the return on capital and the number of employed people is tiny and nonsignificant. Under a loose monetary policy, the majority of firms did not resort to immediate firing or wage decreases. Despite output declines, thanks to the loose fiscal and monetary policies, firms' return on capitals did not significantly decline. However, TFP dramatically declined. The TFP levels reflect both the changes in technology changes and the changes in the utilization rate of production factors. During the SARS outbreak, although the firms in Beijing did not immediately fire employees or lower wage levels, the ineffective utilization of capital and labor is reflected in the TFP declines. The introduction of the province-time interactive fixed effect does not cause significant changes to the coefficient, indicating satisfactory robustness of the results.

Table 5 The impact of SARS on Province Macroeconomic

Variables	(1) Con.	(2) Con.	(3) Con.	(4) Inv.	(5) Inv.	(6) Inv.	(7) GDP	(8) GDP	(9) GDP
did	-0.141***	-0.112***	-0.112***	-0.165***	-0.085***	-0.085***	-0.025***	-0.013***	-0.013***
	(0.008)	(0.011)	(0.011)	(0.039)	(0.016)	(0.016)	(0.002)	(0.001)	(0.001)
Controls	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Province FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

N	1,396	1,396	1,406	1,414	1,414	1,425	500	500	504
Adjusted R-squared	0.084	0.049	0.050	0.131	0.386	0.378	0.718	0.866	0.871

Notes：Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5 *(Continued)*

Variables	(1) Cap.	(2) Cap.	(3) Cap.	(4) Empl.	(5) Empl.	(6) Empl.	(7) Wage	(8) Wage	(9) Wage	(10) TFP	(11) TFP	(12) TFP
did	0.003	0.005	0.005	-0.017***	-0.008	-0.008	0.001	0.001	0.001	-0.049***	-0.011***	-0.011***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.010)	(0.007)	(0.007)	(0.006)	(0.001)	(0.001)
Controls	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Province FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
N	393	393	396	500	500	504	500	500	504	500	500	504
Adjusted R-squared	0.622	0.640	0.644	0.123	-0.027	-0.020	0.278	0.497	0.505	0.335	0.846	0.847

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

6.3 Dynamic effects

To determine whether there is a lag effect, we conduct a regression analysis on the lag period on top of the basic regressions. The consumption and investment data have some temporary lag effect, but the lag effect is less than one year. The investment, consumption, GDP and TFP also experienced faster growth after the lag impact of the epidemic ended.

In the model analysis in Section 3, we expect the existence of lag effects because new employee recruitment takes time and cost. During an epidemic, the decrease in employment can lead to declines in future productivity and generate a lag effect. The basic regression shows that the firms did not carry out massive layoffs or introduce substantial salary decreases during the SARS epidemic because of the short outbreak duration and sufficient liquidity supply from the government. Therefore, after the outbreak, business and consumer confidence quickly recovered, and the economy resumed normal operations shortly.

Table 6[18] The impact of SARS on Province Macroeconomic with lag effects (monthly data)

Variables	(1) Con.	(2) Con.	(3) Inv.	(4) Inv.
did	-0.143***	-0.159***	-0.165***	-0.069***
	(0.007)	(0.024)	(0.043)	(0.013)
after1	-0.054***	-0.071**	-0.105**	-0.010
after2	-0.032***	-0.049**	-0.096**	-0.000
after3	-0.073***	-0.090***	-0.055	0.041**
after4	-0.029***	-0.046*	-0.021	0.075***
after5	-0.008*	-0.025	0.232***	0.217***
after6	-0.031***	-0.048**	-0.009	-0.024
after7	-0.471***	-0.400***	0.038	0.022
after8	-0.075***	-0.003	0.043	0.028
after9	0.237***	0.309***	0.011	-0.004
after10	0.419***	0.491***	-0.023	-0.038***
after11	0.022***	0.093***	-0.012	-0.027***
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Time and Province FE		Yes		Yes
N	1,396	1,396	1,414	1,414
Adjusted R-squared	0.128	0.098	0.126	0.382

Notes：Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6*(Continued)*

The impact of SARS on Province Macroeconomic with lag effects (quarterly data)

Variables	(7) Cap.	(8) Cap.	(5) GDP	(6) GDP	(9) Empl.	(10) Empl.	(11) Wage	(12) Wage	(13) TFP	(14) TFP
did	0.005	-0.009	-0.026***	-0.030***	-0.018***	0.000	0.005	0.035**	-0.047***	-0.011***
	(0.041)	(0.026)	(0.002)	(0.002)	(0.005)	(0.009)	(0.011)	(0.016)	(0.006)	(0.001)
after1	-0.030	-0.044	-0.025***	-0.029***	-0.004	0.014	0.014	0.044**	0.020***	0.007***
after2	0.059	0.046	-0.018***	-0.022***	-0.007	0.011	0.028**	0.058***	0.017**	0.004**
after3	0.032	0.042	0.005*	0.002	0.005	0.015	0.036***	0.020*	0.019**	0.006
after4	-0.021	-0.012	0.018***	0.015***	-0.006	0.004	0.018*	0.002	0.015	-0.001

[18] Since the lag impact of all variables is less than one year, this table shows the estimated results with a lag of one year.

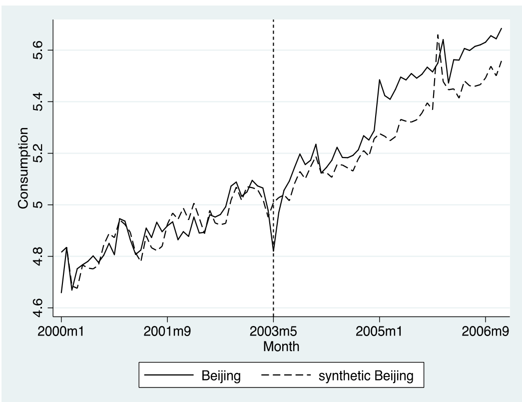
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Province FE		Yes		Yes		Yes		Yes		Yes
N	500	500	500	500	500	500	500	500	500	500
Adjusted R-squared	0.062	-0.146	0.727	0.872	0.116	-0.037	0.274	0.495	0.346	0.854

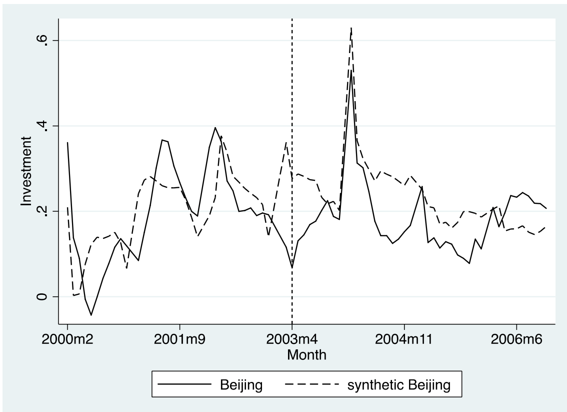
Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

6.4 SCM results and the placebo test

We further apply the SCM and artificially create a control group that is similar to Beijing's economic development before the SARS epidemic for comparison. The predictor variables in this paper include multiple factors that reflect a region's economic situation, such as per capita GDP, population density, shares of industrial and service in the local economy, fiscal policies, monetary policies, and highway mileage.

Figure 5 illustrates an economic situation comparison between Beijing and the synthetic control group during the entire study period. Overall, the dependent variables in the synthetic control group maintain similar growth rates as those in Beijing before the SARS outbreak. In other words, the data satisfy the assumption of common trends. During the epidemic, Beijing reported much lower consumption, investment, GDP, and TFP than did the synthetic control group. These findings further prove the robustness of the basic results of the DID analysis.





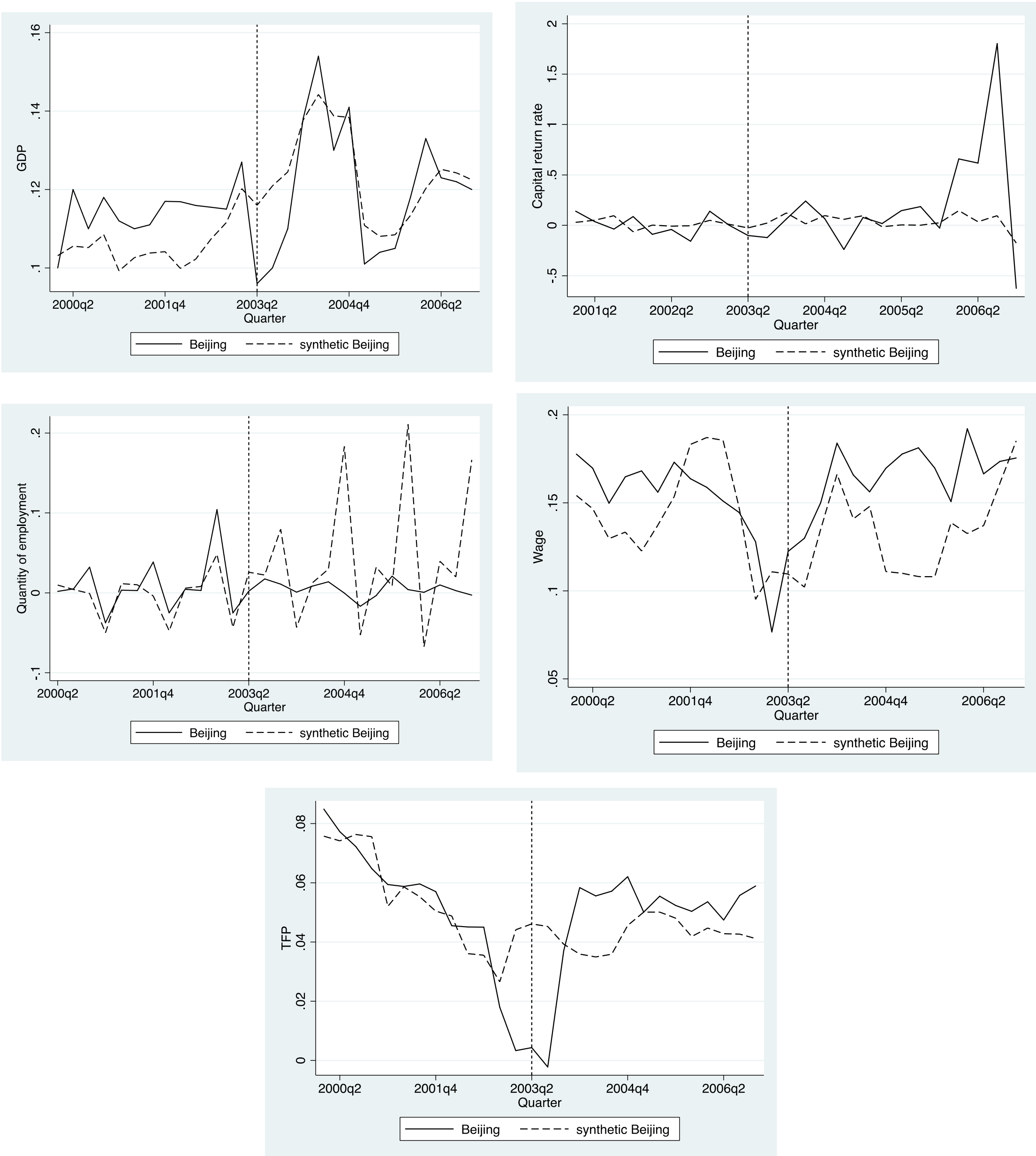
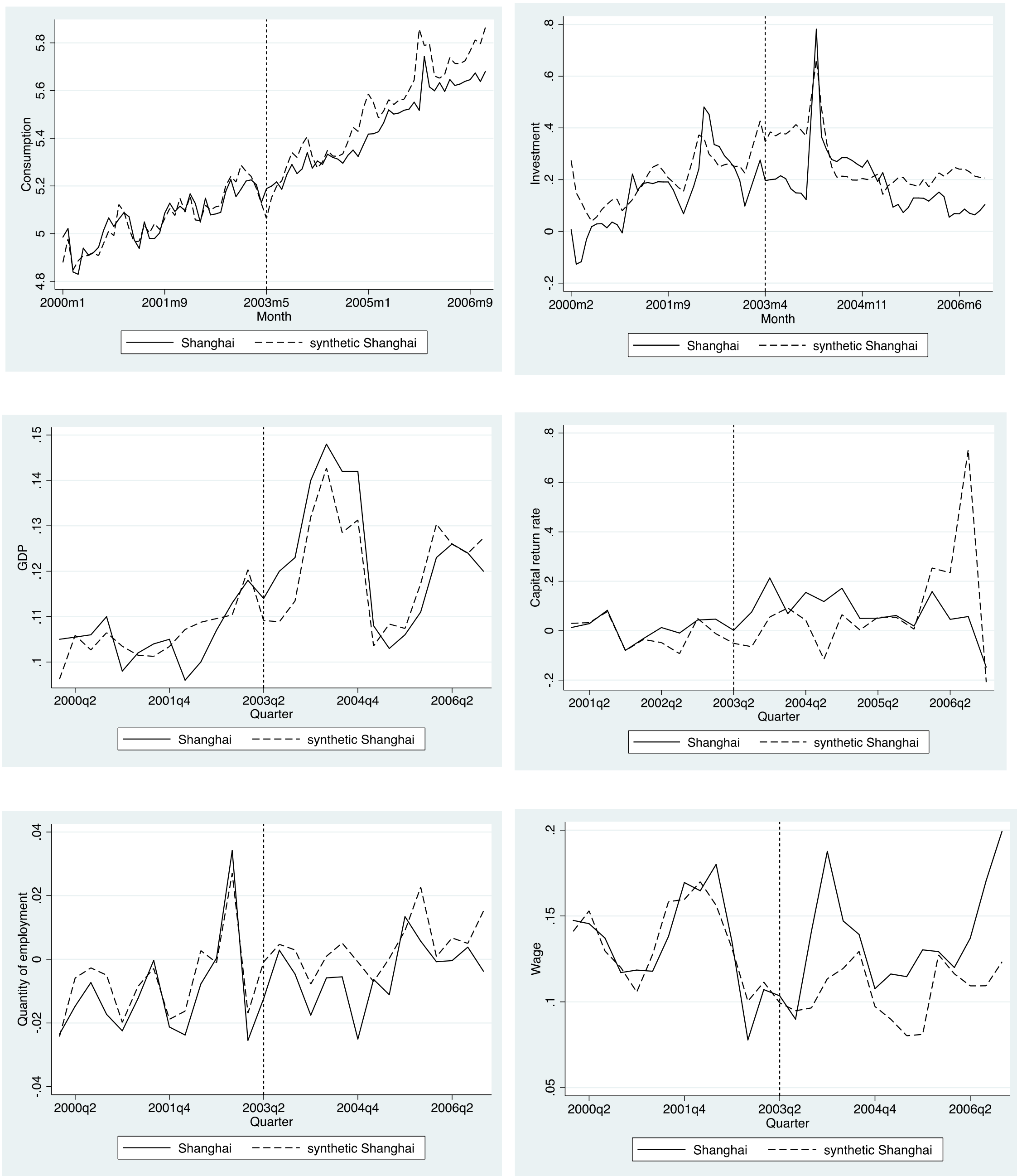


Fig.5. Economics Gap between Beijing and Synthetic Beijing.

In this paper, we use the approach reported by Abadie and Gardeazabal (2003) and conduct a placebo test on province-level data based on the SCM. The actual operations are as follows. We assume that the regions with low numbers of SARS infections in 2003 were subject to SARS shocks and thus take them as the treatment group. We then create a control group based on the SCM and determine whether there exist significant differences in the economic level between the treatment group and the control group during the SARS outbreak. If our hypothesis that the epidemic affected the economic levels in Beijing is true, then we should not observe any significant difference in the group subject to the placebo test. We select Shanghai as the region for the placebo test, and

Figure 6 shows the test results. Shanghai and its synthetic group maintained the same development levels during the SARS epidemic, and the trend did not change because of the epidemic. There is no significant economic level difference between the two groups. The test results indicate that the SARS epidemic caused some short-term shocks to economic development in Beijing; however, it did not have significant impacts on regions with few confirmed SARS cases.



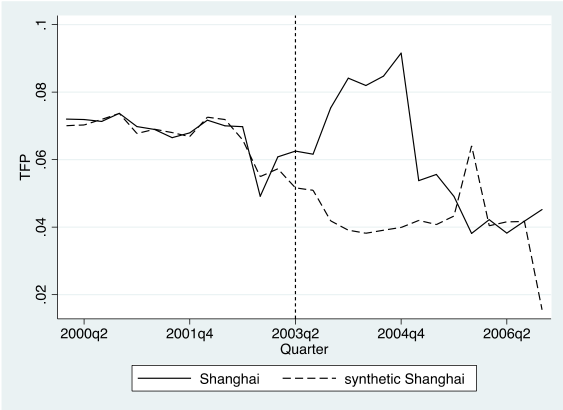


Fig. 6 Economic gap between Shanghai and synthetic Shanghai

6.5 Robustness tests

In the robustness test, we further change the definition of the treatment group and the control group. We tried two definition changes: taking Guangdong, which is the province with the second highest number of diagnoses, as the treatment group; only keeping the provinces without confirmed cases in the control group. Table 7 and 8 show the robustness test results. Although the change in definitions of the treatment group and control group leads to changes in the DID coefficient, the direction and significance level of the coefficient remain the same.

The province-level test shows that the SARS epidemic dramatically reduces the consumption, investment, GDP growth rate, and TFP growth rate in the epidemic core region; however, it does not have a significant effect on the region's employment, salary levels, and return on capital.

Table 7 The robust test: Guangdong as the treatment

Variables	(1) Con.	(2) Con.	(3) Inv.	(4) Inv.	(5) GDP	(6) GDP	(7) Cap.	(8) Cap.	(9) Empl.	(10) Empl.	(11) Wage	(12) Wage	(13) TFP	(14) TFP
did	-0.012**	-0.008	-0.150**	-0.133**	0.002	-0.015***	-0.009	0.025	0.001	0.000	-0.649	-0.777	0.003	-0.015***
	(0.032)	(0.135)	(0.063)	(0.050)	(0.004)	(0.003)	(0.013)	(0.025)	(0.005)	(0.007)	(0.374)	(0.513)	(0.005)	(0.005)
Controls	Yes	Yes	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	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Province FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	1,454	1,454	1,454	1,454	500	500	393	393	500	500	483	483	500	500
Adjusted R-squared	0.569	0.627	0.157	0.394	0.696	0.828	0.378	0.301	0.149	0.003	0.093	-0.111	0.329	0.499

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8 The robust test: provinces without confirmed cases as control group

Variables	(1) Con.	(2) Con.	(3) Inv.	(4) Inv.	(5) GDP	(6) GDP	(7) Cap.	(8) Cap.	(9) Empl.	(10) Empl.	(11) Wage	(12) Wage	(13) TFP	(14) TFP
did	-0.064***	-0.101***	-0.102	-0.058**	-0.025***	-0.028***	0.002	0.004	-0.024**	-0.018	0.038	0.032	-0.039***	-0.010***
	(0.010)	(0.010)	(0.056)	(0.023)	(0.047)	(0.056)	(0.007)	(0.008)	(0.008)	(0.012)	(0.023)	(0.027)	(0.008)	(0.002)
Controls	Yes	Yes	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	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Province FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	542	542	584	542	186	186	151	151	192	192	192	192	192	192
Adjusted R-squared	0.351	0.391	0.100	0.233	0.085	0.103	-0.044	-0.220	0.060	-0.110	0.992	0.991	0.378	0.869

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

7. Channel analysis empirical results

7.1 PSM of firm data

Figure 7 illustrates the covariate standard deviation changes before and after the propensity matching of sample firms[19]. Before matching, most covariates' standard deviations are larger than 10%, and their average value reaches 12.98%. After matching, the standard deviations of all covariates are less than 4%, and their average value dramatically declines to 2.25%. Additionally, the t-test also shows that after matching, all the average values for different groups' covariates are no longer significantly different, further proving that matching dramatically improves the covariate balance. Figure 8 shows that after matching, the kernel density distribution of propensity scores for the treatment group and control group largely overlap each other, indicating that the PSM

[19] For the definition of standard deviation, please refer to the article by Imbens, G. W. and D. B. Rubin (2015). Causal inference in statistics, social, and biomedical sciences, Cambridge University Press..

eliminates the selection bias of sample in some degree.

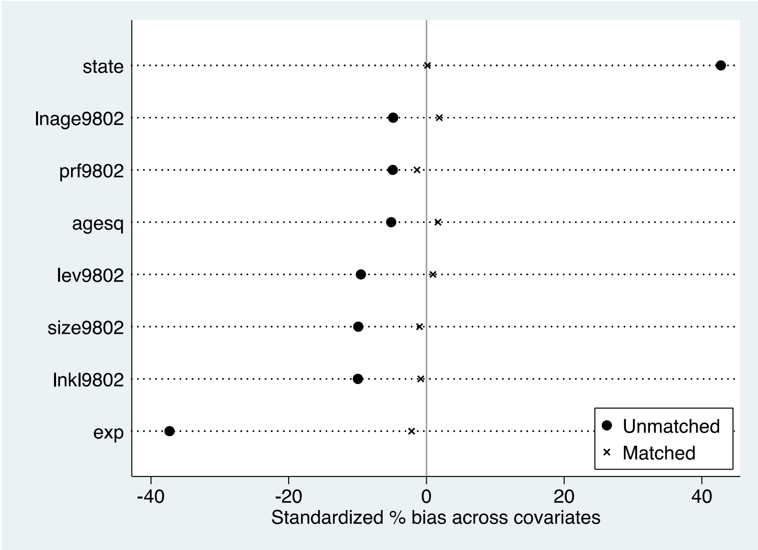


Fig. 7 Standardized % bias across covariates

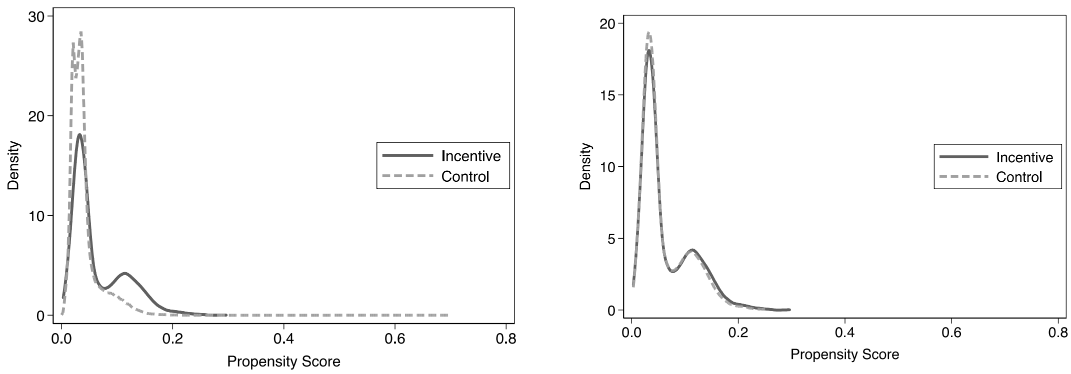


Fig.8 Density distribution of propensity score

7.2 Common trend test

The firm data for the control group and the treatment group after PSM meet the requirements of an ex-ante common trend based on the Fig 9.

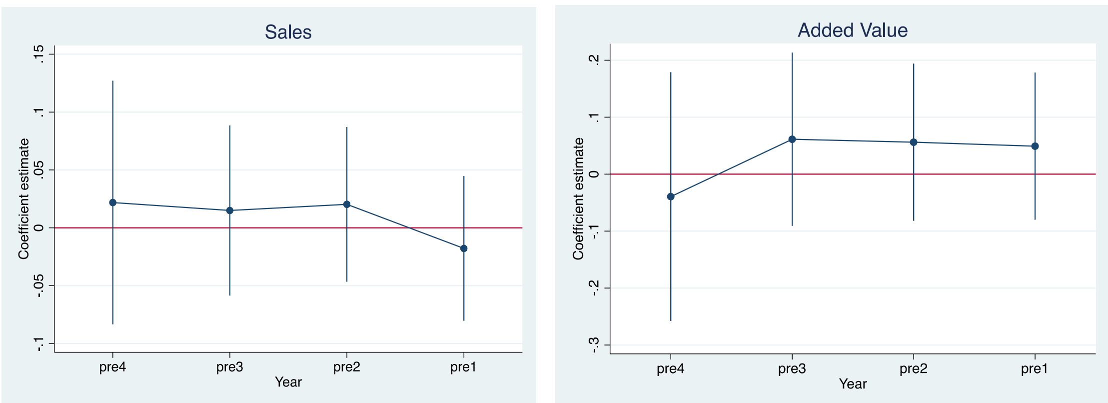


Fig.9 Common time trend for all variables in enterprise micro data

7.3 Channel analysis baseline results

We start with our basic regression, which examines how various firm features relate to changes in firm performance during the epidemic shock. These results are reported in Table 9.

The research results suggest that the SARS shock is a typical negative shock to the real economy. Firms more sensitive to economic cycles suffer more impacts; in addition to declines in their added value, these salaries provided to workers at these firms also decrease (the threshold of significance is 10%). An increase of one standard deviation in business cycle leads to a 6.6% decline in sales growth rate, a 7.4% fall in value added growth rate, and a 0.2% reduction in wage growth rate. The coefficients on return on capital, quantity of employment, TFP are close to zero and not significant. The employee numbers for the firms remained stable; however, the firms relieved the stress of sales revenue decline by shortening employees' work hours and thus reducing labor costs. This result suggests that there was indeed a significant channel of business cycle sensitivity during the epidemic shock.

Labor-intensive firms are susceptible to epidemic impacts, and our research results indicate their sales revenue and TFP significantly decrease. An increase of one standard deviation in labor intensity is associated with a 2.6% fall in value added growth rate and an around 4% decline in TFP growth rate. Although the number of employees, wages, and return on capitals for these firms remain stable during the epidemic, their TFP significant declines. Labor-intensive firms are more likely to shut down their factories or reduce the number of employees on duty. They did not choose to implement massive layoffs or reduce wages; however, insufficient labor usage is reflected in decreases in TFP and reductions in sales revenue.

The most interesting findings are for the firms with high debt ratios. Compared with their counterparts with low debt ratios, they had better business performance, higher value-added, higher return on capitals, and higher TFP during the SARS outbreak. An increase of one standard deviation increase in debt paying ability induces a 3.9% higher value-added growth rate, a 6.4% rise in capital return growth rate and a 5.3% increase in TFP growth rate. We believe the following factor explains this phenomenon: during the SARS epidemic, the government adopted loose monetary policies on the affected firms. The government not only satisfied firms' demand for financial credits but also reduced interest rates on loans. These measures helped reduce the financial costs of firms with high debt ratios, leading to better business performance. During the SARS epidemic, due to the Chinese central bank's loose monetary policies, a liquidity shortage did not occur.

Table 9 The impact of SARS on firm performance (One-to-one Nearest neighbor matching)- firm feature

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.018	-0.123***	-0.231**	-0.005	-0.092***	-0.088
	(0.020)	(0.042)	(0.103)	(0.010)	(0.030)	(0.062)
cycledid	-0.001***	-0.002**	-0.000	-0.000	-0.000	-0.002*
labordid	0.697	-1.013**	1.211	0.279	-0.909***	2.311
financedid	0.013	0.105*	0.350**	-0.009	0.084*	0.067
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,915	32,179	28,270	29,259	27,717	33,415
Adjusted R-squared	0.122	0.008	0.034	0.113	0.036	-0.030

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively. ‘Cycledid’, ‘labordid’ and ‘financedid’ are three interaction terms between three transmission channels (business cycle, labor intensity and financial dependence) respectively and 'did' term

The business cycle, labor supply shock and liquidity shock could be related. In order to give the different channel that the maximum chance to reveal itself, we consider only one channel in regression. Table 10 report the single channel test results. We find that the coefficients for different channel remain almost the same as in table 9, suggesting that our business cycle sensitivity, labor sensitivity and financial sensitivity indexes capture somewhat different aspects.

Table 10 The impact of SARS - business cycle channel

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.005	-0.074***	-0.022	-0.002	-0.053***	-0.029
	(0.012)	(0.025)	(0.061)	(0.008)	(0.017)	(0.041)
cycledid	-0.001***	-0.001**	-0.000	-0.001***	-0.000	-0.002*
	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,915	32,179	28,270	29,719	27,717	33,415
Adjusted R-squared	0.122	0.008	0.034	0.130	0.036	-0.030

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10*(Continued)* The impact of SARS - labor intensity

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.016	-0.068***	-0.031	-0.008	-0.044***	-0.054
	(0.013)	(0.026)	(0.062)	(0.009)	(0.017)	(0.053)
labordid	0.828	-1.051**	0.935	0.481	-0.971***	2.331
	(0.639)	(0.416)	(0.983)	(0.380)	(0.235)	(4.194)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,915	32,179	28,270	29,719	27,717	33,415
Adjusted R-squared	0.122	0.008	0.034	0.130	0.036	-0.030

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10*(Continued)* The impact of SARS-financial dependence

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.016	-0.143***	-0.214**	0.002	-0.105***	-0.067
	(0.020)	(0.042)	(0.101)	(0.014)	(0.029)	(0.062)
financedid	0.013	0.115*	0.340**	-0.010	0.092*	0.059
	(0.028)	(0.064)	(0.155)	(0.019)	(0.048)	(0.088)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,915	32,179	28,270	29,719	27,717	33,415
Adjusted R-squared	0.122	0.008	0.035	0.130	0.036	-0.030

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

7.4 Robustness tests

One-to-one nearest neighbor matching is used in the baseline model, we tried caliper matching and one-to-four nearest neighbor matching as the robust test. Table 11 reports the results of caliper matching, the magnitude and significance of most coefficients are close to the base regression. The wage for financial sensitivity firms is now significantly negative at the 1% level. But the coefficients on value-added for the business-cycle sensitivity firms, return on capital for the financial sensitivity firms are not significant now. Table 12 reports the results for one-to-four nearest neighbor matching, the coefficients are almost the same with the baseline results.

Table 11 The impact of SARS on firm performance (Caliper matching)

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.023	-0.124***	-0.123	-0.013	-0.083***	0.021
	(0.021)	(0.041)	(0.086)	(0.008)	(0.022)	(0.030)
cycledid	-0.001***	-0.001	-0.001	-0.000	-0.000	-0.001*
labordid	0.933	-1.154***	0.291	0.173	-0.890***	-2.149***
financedid	0.014	0.134**	0.188	0.001	0.081**	-0.022
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	32,683	31,438	27,475	26,241	26,948	32,693

Adjusted R-squared	0.112	0.010	0.036	0.123	-0.006	-0.048

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

Table 12 The impact of SARS on firm performance (One-to-four nearest neighbor matching)

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.027*	-0.140***	-0.283***	-0.011	-0.091***	-0.052
	(0.016)	(0.038)	(0.093)	(0.008)	(0.027)	(0.054)
cycledid	-0.001***	-0.002**	-0.000	-0.000	-0.000	-0.002*
labordid	0.732	-0.988**	1.052	0.040	-0.844***	2.754
financedid	0.018	0.107*	0.351**	0.002	0.088*	0.080
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	68,429	75,905	65,041	55,992	63,825	78,779
Adjusted R-squared	0.112	0.006	0.035	0.148	0.031	-0.010

Notes: Robust standard errors in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

In the baseline channel analysis, we use the values for specific firm indicators to indicate different firms' sensitivity. In table 13, we replace the firm-level measures with sector-level measures. We calculate the mean sensitivity index for all firms in each three-digit SIC sector, and use it as a measure of sector-level sensitivity. This approach assumes that sensitivity is an intrinsic property of a sector, and therefore the index derived from the pre-epidemic data is applicable to firms in the sector.

We find that the value-added is significantly lower for more business cycle sensitive firms. This is consistent with the baseline result where we used firm-level business cycle sensitivity. However, the coefficient on sales and wages is now not significantly. Again, we find the value-added and TFP is significantly lower for more labor sensitive firms. The coefficients are consistent with the baseline results, but significant at 1%. The results of financial dependence firms are different from the baseline results. The coefficients on value-added and return on capital are not significantly, but the sales of financial dependence firms increase significantly.

Relative to sector-level sensitivity data, the firm-level measures could be subject to some endogeneity issues, but which can consider the heterogeneity of the firms within a sector. Although the findings of sector-level sensitivity analysis in table 13 differ some from the baseline results in table 9, it is reassuring that the role of business cycle and labor shock sensitivity during the epidemic shock. We can also find that monetary stimulus helps to mitigate the impacts of financial dependence shock.

Table 13 The impact of SARS on firm performance – sector features

Variables	(1) Sales	(2) Val. Ad.	(3) Cap.	(4) Empl.	(5) TFP	(6) Wage
did	-0.372**	-0.465	0.979	-0.206	0.172	0.040
	(0.173)	(0.462)	(0.970)	(0.173)	(0.260)	(0.590)
cycledid	-0.003	-0.018**	0.025	-0.001	-0.006	-0.004
labordid	0.812	-1.003***	0.869	0.471	-0.949***	2.341
financedid	0.638**	0.773	-1.877	0.351	-0.354	-0.146
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry and time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30,915	32,179	28,270	29,719	27,717	33,415
Adjusted R-squared	0.121	0.006	0.033	0.129	0.035	-0.032

Notes: Robust standard errors clustered at the industry level in parentheses. *、**、***indicate significance at the 10%, 5%, and 1% level, respectively.

8. Conclusion and Discussion

The paper builds a macroeconomic model of an epidemic and examines the impact of the 2003 SARS epidemic on real economic activity. Using variation across China provinces, this study provides several key results. First, epidemics lead to a fall in real economic activity. We find negative effects on output, consumption, investment, and TFP, means that an epidemic depresses economic activity through both supply and demand-side effects. Our main findings are generally very robust. Second, if there is substantial unemployment during an epidemic, the adjustment cost after the outbreak will lead to lower productivity in the future. The borrowing constraints of firms and the expected outbreak duration will affect the level of lag effects. There are no obvious lag effects on China's economy resulting from the 2003 SARS epidemic because the expected outbreak duration is short and liquidity is adequate. Profit subsidies and employer-side payroll tax cuts are effective for keeping businesses afloat and preventing closures. Monetary policies that lower debt interest payments and provide more credit can help prevent businesses from closing. Third, we analyze three channels through which an epidemic shock may affect firms: a business cycle channel, a liquidity shock channel, and a labor supply shock channel. Firms that are more sensitive to business cycles or are labor-intensive are more susceptible to negative economic shocks. Adequate liquidity during an epidemic even improve the performance of firms that depend on external financing. A healthy banking system can provide liquidity, mitigating the severity of the decline in demand and production.

Our theoretical analysis and empirical study show that the key macroeconomic policies for reducing an epidemic's economic impacts are to maintain employment market stability and sufficient liquidity for firms and the financial market during the epidemic. An epidemic's economic costs depend on the duration, range and severity of the epidemic. NPIs can reduce the rates of infection but perhaps exacerbate the size of the recession caused by an epidemic in the short run. Existing studies indicate that there is an inevitable trade-off between the severity of the recession and the health consequence of the epidemic (Eichenbaum, Rebelo et al. 2020, Gourinchas 2020). However, in view of the economic lag effect of an epidemic and the negative impacts of a severe epidemic on economic behaviors and market confidence, NPIs can reduce the economic costs of an epidemic. They can also benefit the economy by reducing the probability of infection and the duration of the outbreak. Timely measures that mitigate the severity of a pandemic can reduce the severity of the persistent economic downturn. However, NPIs are more than simply lockdown. China's experiences with the SARS epidemic indicate that it is optimal to adopt "smart containment" without delay, which is consistent with the conclusion by Eichenbaum, Rebelo et al. (2020). The early detection and isolation of individuals with confirmed and suspect cases. Isolation policies allow susceptible people to work without the risk of becoming infected. China prohibits travel from outbreak areas to other regions, which effectively slows the spread of the epidemic among regions. "Herd immunity" is not necessary to end an epidemic. It is possible, based on experience with SARS, to end an epidemic by adopting containment measures. Although extreme NPIs cause a recession in the short run, they can shorten the outbreak duration, which can prevent a medium-to-long-term economic crisis.

Our theoretical model is simplified and aims to analyze how epidemic shocks affect economic functions and tests the theoretical conclusions with empirical studies. A cost of that simplicity is that we cannot study many important epidemic-related policy issues. Our models do not cover impacts on trade; they include no variable regarding the government's macro policies; and they do not conduct policy simulation with specific production functions and utility functions. When interpreting our findings, there several important caveats. First, our firm data include only industrial firms without services. After an epidemic shock, compared with industrial firms, service firms will have impacts that are more negative. Second, the psychological shock of the SARS epidemic, however, rippled to other provinces rather than affecting only the heavily exposed provinces because the provinces are closely linked by travel and trade. Our DID result may underestimate the economic impact of the epidemic. Third, while there are important economic lessons to be learned from the 2003 SARS epidemic and applied to the COVID-19 pandemic, we stress the limits of external validity. The number of deaths from SARS and the number of confirmed SARS cases are much lower than the number of deaths caused by COVID-19 and the number of confirmed COVID-19 cases, and the duration of the 2003 SARS epidemic was much shorter than the duration of the COVID-19 pandemic, suggesting more severe economic impacts from COVID-19. Despite these limitations, studying the effects of the SARS epidemic can provide insights into epidemic shocks and be helpful in establishing appropriate policy responses.

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