Social Media and Government Responsiveness: Evidence from Vaccine Procurement in China*

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September 1, 2024

Abstract

This paper studies how public opinion on social media affects local governments' procurement of vaccines in China during 2014-2019. To establish causality, we exploit city-level variation in the eruption of online opinion on vaccine safety, instrumented by quasi-random early penetration of social media. We find that governments in cities exposed to stronger social media shocks increased the share of more-transparent procurement and shifted procurement from small local suppliers to reputable nonlocal suppliers. The effect is driven by posts expressing anti-government sentiment instead of posts containing investigative information and is larger in cities where local officials face higher top-down political pressure.

JEL Code: H4, H7, I1, P2

Keywords: Social media, Government responsiveness, China, Procurement, Public health

*This work benefits greatly from comments and suggestions from Ruben Durante, Jin Li, Ruixue Jia, John Matsusaka, Juanjuan Meng, Joris Mueller, Michael Zheng Song, David Stromberg, and seminar and conference participants at CUHK, HKUST, HKU, NUS, Peking University, UCSD, USC, the JADE-CEPR-TIME Development Economics Conference, and China Economics Summer Institute.

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1 Introduction

The lack of transparency and truthful communication in an authoritarian regime is often viewed as a major obstacle to public accountability in nondemocracies. It has been argued that this problem can be mitigated by allowing a relatively free media, which helps authoritarian rulers monitor local officials and rectify policy oversights (e.g., Egorov et al., 2009; Lorentzen, 2014). Such an argument is challenged by the fact that the media in nondemocracies typically fails to provide information that is useful for holding officials accountable because of the monopoly of state-owned media and the intervention of local governments (Qin et al., 2018). However, in the era of social media, the monitoring role of the media is not necessarily deemed a failure because the new technology has substantially facilitated the production and dissemination of political information from the grassroots (Howard, 2010; Morozov, 2011; Shirky, 2011). In this paper, we examine the accountability-enhancing function of social media in China by estimating the causal effect of public opinion expressed on social media on the responsiveness of Chinese local governments in their procurement of vaccines.

In democracies, politicians are held accountable to the electorate, and the media has the inherent ability to inform voters about politicians' behavior and attributes, enhance the transparency of political processes, and bring instances of misconduct to the forefront of public attention (e.g., Besley and Burgess, 2002; Besley and Dray, 2022; Snyder and Strömberg, 2010; Strömberg, 2004). Thus, the media serves as a powerful tool to foster government responsiveness to the needs of citizens.[1] In contrast, local leaders of authoritarian governments are accountable to national leaders who appoint them. Such upward accountability may evolve into public accountability only when informed national leaders align their concerns with those of citizens. Therefore, in domains where the regime and citizens share mutual interests, such as public health, social media has the potential to discipline local politicians' misconduct and enhance public accountability in a nondemocratic country. The key question is to what extent bottom-up information on social media can generate top-down pressure on local governments and compel them to respond to public demands.

Our study on the procurement of vaccines by the Chinese government provides a unique opportunity to investigate the effect of relatively free information flows over social media on government accountability in an authoritarian regime. Government procurement assumes an important role in the provision of essential goods and services directly relevant to the well-being of the population (Best et al., 2023; Bosio et al., 2022). Ensuring accountability in this process remains a prominent social problem in many developing countries (Gerardino et al., 2017; Szucs, 2023). In China, vaccines are exclusively admin-

[1] For surveys on the political effects of the media, see Dellavigna and Gentzkow (2010); Dellavigna and La Ferrara (2015); Prat and Strömberg (2013); Strömberg (2015a,b).

istrated by the government, and widespread discontent regarding the safety and quality of vaccines can undermine citizens' trust and support for the regime. In areas where the issue is not politically sensitive and the regime has the same concern as the public, information flows on social media are largely unrestricted. Evidence shows that public discussions about vaccine safety on social media were not subject to censorship until vaccines became a sensitive topic in China during the COVID pandemic. We restrict our study to the pre-COVID period.

We compiled a dataset documenting the procurement of over 23,000 vaccine-related items by Chinese city-level (prefectural) governments from 2014 to 2019. Since 2005, a national regulation has mandated that all vaccines, along with related products and services, must be procured by governments before being supplied to healthcare providers. However, the specific procurement arrangements are decentralized to city governments. This decentralization gives rise to discretionary policy execution and the potential for corruption. Notably, the regulation requires normal vaccine procurement to be administered through the open-bid (competitive auction) format. However, many local governments deviate from this prescribed regulatory guidance, opting for less transparent procurement formats such as invited bidding and private negotiation. Our main outcome variables are the frequency and share of open-bid procurement conducted by city governments on a monthly basis.

Regarding the social media data, we obtained more than three million posts referencing "vaccine" published on Sina Weibo (Weibo for short)—the Chinese equivalent to Twitter—during our sample period. Previous studies have documented that Weibo is abundant in general discussions about social problems as long as these discussions do not challenge the authority of the Chinese Communist Party (CCP), target top political leaders, or incite collective action (King et al., 2013, 2014; Qin et al., 2017). Given the central government's direct control over social media, subnational governments have limited influence over information flows on Weibo. Instead, many local governments resort to acquiring massive information-processing software or AI systems to monitor public opinion on social media. In our study, we employ two commonly used machine learning techniques, which we suspect bear resemblance to those monitoring systems used by Chinese local governments, to extract Weibo users' opinions about vaccine safety and to assess public sentiment towards city governments.

To identify causal effects, we leverage drastic transformations in the information landscape on social media triggered by sudden events. During regular periods, social media discussions about vaccines are scant and evenly distributed across regions. Upon an unexpected shock (e.g., a scandal), social media discussions are dramatically heated up. The resulting uneven and varied informational distribution across regions, after controlling for predetermined economic and social conditions as well as evolving trends, can be used to identify the media effect. Specifically, we measure the strength of public opinion on vaccine safety in a city by the per-capita number of vaccine posts originating from that city and classified by our machine learning algorithms as "monitoring posts" (i.e., expressing public grievances and questioning government misconduct). We then construct a city-specific information shock on Weibo (Weibo shock hereafter) by calculating the change in our strength measure following a vaccine scandal within a narrow time window. Finally, we interact this cross-section Weibo shock with a dummy variable indicating the event timing to construct a difference-in-differences (DID) estimation. In addition to city fixed effects and year-month fixed effects, we control for province-specific time trends and general informational flows on social media over time to isolate the effect of the event-induced Weibo shock. To strengthen the identification, we instrument the Weibo shock with a measure of Weibo penetration during its initial entry period, which is arguably exogenous after controlling for economic, technological, and educational factors.

Our main empirical analysis focuses on a vaccine scandal in March 2016. It involved a drug ring from northern China, which had been illicitly selling defective and expired vaccines for years. The scandal remained concealed until it was unexpectedly leaked to the public by an online media outlet on March 18. This sudden revelation led to a significant surge in Weibo posts referencing vaccines, with the number jumping from 1,045 on March 17 to 75,506 on March 22. Despite the scandal originating at the local level, it triggered national discussions of vaccine-related issues on Weibo. Many posts accused governments of procuring vaccines behind the scenes and failing to monitor the circulation of vaccines.

Applying the aforementioned DID estimation to this event setting produces three results. First, in cities experiencing a stronger Weibo shock, local governments significantly increased both the frequency and share of open-bid procurement. Putting the effect in perspective, in a city with an average population of 4 million, if one out of 10,000 citizens tweeted one more post talking about vaccine safety in a month, the local government would have increased the share of open-bid procurement by around 10%. There are no pretrends, and the result is robust to the use of instrumental variables and the scrutiny of potential confounding factors such as the event itself, tightened policy implementation, and other information channels.

Second, upon a stronger Weibo shock, city governments reduced their "home bias" by procuring more vaccines from nonlocal suppliers, particularly from reputable large companies, to ensure vaccine quality. Third, following the Weibo shock, local governments swiftly intensified their blogging efforts to alleviate government distrust, shifting from routine reporting to a focus on public accountability regarding vaccine issues.

Paradoxically, although social media facilitates widespread information diffusion across the nation, the effect of Weibo shocks on government behavior remains localized. Somewhat surprisingly, the media effect appears to stem from government responses to public sentiment rather than verifiable information—the vast majority of Weibo posts on vaccine safety are general and emotional discussions that do not mention specific government entities, firms or individuals. These "puzzles" can be rationalized by local governments' sensitivity to top-down pressure. When there is a visible display of anti-government sentiment within a locality, it raises the likelihood of inspections from upper-level authorities, which can pose a threat to the career prospects of local officials. Along this line, the localized effect of social media is consistent with the facts that top-down inspection tends to target a select group of "at-risk" governments and that Chinese local governments actively monitor social media to better assess the risk of being inspected.

To verify the mechanism of top-down pressure, we examine a number of heterogeneous effects related to local politicians' perceived probability and consequence of being inspected. First, we find that the effect of the Weibo shock on local governments' adoption of more-transparent procurement is stronger in cities where there were more anti-corruption allegations prior to the Weibo shock. Second, the effect is more pronounced in cities where political leaders held lower positions in the government or had higher prospects for promotion. Third, governments in regions with more extensive internet censorship prior to the event exhibited a stronger response, consistent with the view that governments facing informational disadvantages were more susceptible to heightened top-down pressure during a public opinion crisis. These effects also help rule out the explanation that local governments respond directly to public needs uncovered on social media.

Our analysis reveals that the top-down-pressure mechanism is activated by anti-government sentiment contained in Weibo posts. In another vaccine-safety scandal in 2018, which lacked anti-government sentiment and instead focused on a manufacturer's production of substandard vaccines, we find a muted effect of social media on vaccine procurement. When examining the entire period from 2014 to 2019, we observe a positive correlation between the volume of Weibo discussion about vaccine safety originating from a city and the local government's adoption of open-bid procurement. However, this correlation is only statistically significant when Weibo information specifically targets the government.

This paper contributes to the emerging study of the political effect of social media. The focus of this strand of literature has been on how social media affects citizens' political views and participation (e.g., Allcott et al., 2020; Bakshy et al., 2015; Bursztyn et al., 2019; Yanagizawa-Drott et al., 2021) and grassroots collective action (e.g., Acemoglu et al., 2018; Enikolopov et al., 2020; Qin et al., 2021).[2] Several recent papers study the effect of online information flows on government behavior and public accountability in democracies. Gavazza et al. (2019) examine the impact of the internet on local elections and government policies in the UK. Petrova et al. (2021) show that opening a Twitter account helps politicians compete for campaign contributions in the US. Bessone et al.

[2]See Zhuravskaya et al. (2020) for a recent survey.

(2020) investigate how legislators respond when their constituencies have access to 3G mobile technology in Brazil and find that politicians increase their interaction with voters on Facebook but reduce their offline effort.

Our paper advances this literature by providing some of the first causal studies of the effect of social media on government responsiveness and accountability in nondemocracies.[3] Our findings demonstrate that, in China, social media can serve as an effective channel for enhancing government responsiveness to citizens' needs, whereas traditional media fails. The likely reason is that social media facilitates the communication between top leaders and citizens, which in turn mitigates agency problems within the authoritarian government. Furthermore, we show that citizens' expression of sentimental opinions on social media, even without revealing any concrete information about specific government entities or politicians, causes local governments to increase policy compliance and address public needs. This suggests that understanding the political effect of social media cannot be confined to the wisdom derived from the study of traditional media, which emphasizes that the media influences governments and politicians through informing the public of specific government conduct (Ferraz and Finan, 2008; Strömberg, 2004) or a politician's type (Besley and Burgess, 2002; Snyder and Strömberg, 2010), through affecting voter behavior (Ash and Galletta, 2023; Ellingsen and Hernæs, 2018), and through providing truthful information about certain social problems (e.g., Besley and Dray, 2022).

Our study is also related to the research on the political economy of nondemocracies. How information is distributed across government layers is key to the functioning of an authoritarian regime (Egorov and Sonin, 2023). One notable problem concerns subnational governments' informational advantages, which on the one hand encourage local experimentation and adaptation but, on the other hand, create policy noncompliance and corruption (Xu, 2011). Several experimental studies in China show that verifiable and issue-specific information sent by citizens to relevant governments is useful for monitoring officials and firms (Anderson et al., 2019; Buntaine et al., 2022, 2021; Chen et al., 2016). However, communication of verifiable and specific information is costly, lacking visibility, and susceptible to the intervention of local governments. In contrast, social media communication, albeit coarse, is rapid, cheap, visible, and direct. Thus, the political impact originating from social media is likely to be more frequent and far-reaching. Our finding that an information outbreak on social media caused better policy compliance (the use of open-bid procurement) across the entire nation suggests that social media is highly valuable for the central government to increase policy implementation, but it may bear the cost of policy rigidity and over-reaction. This tradeoff is essential in the theoretical

[3] Several studies provide indirect evidence on the effect of social media on government accountability in nondemocracies. For instance, Qin (2013) finds a correlation between social media penetration and the number of bad drugs detected by local drug administrations in China. Enikolopov et al. (2018) show that social media exposure of corruption in large state-controlled firms in Russia was associated with improvements in corporate governance of these firms.

study of the role of information in authoritarian governments (e.g., Maskin et al., 2000; Qian et al., 2006).

The remainder of this paper proceeds as follows. Section 2 provides a brief description of the institutional background. Section 3 describes the data and the empirical strategy. Section 4 reports the basic results to test the main hypothesis, and Section 5 presents further evidence to shed light on the mechanisms. Section 6 concludes.

2 Background

2.1 Vaccination in China

China stands as the second largest global market for vaccines, surpassed only by the United States. However, concerns over vaccine safety and drug quality have consistently ranked among the highest priorities for Chinese citizens. Over the past decade, numerous scandals have emerged, revealing the circulation of substandard and faulty vaccines that pose significant risks to the health of inoculated children.

The Chinese government classifies vaccines into two categories. Category-I encompasses 14 vaccines, including DPT and MMR. Vaccination with Category-I vaccines is mandatory and freely provided by the government. Category-II comprises common vaccines such as chickenpox, flu, and rabies, as well as some enhanced versions of Category-I vaccines. Vaccination with Category-II vaccines is voluntary, and individual consumers bear the cost. Across China, the vaccination rates for Category-I vaccines exceed 95% and reach 100% in major cities. Nevertheless, the vaccination rates for Category-II vaccines remain below 20%, even in the developed regions (Fu, 2021). In 2019, the sales of the Category-II vaccines in China amounted to 7.81 billion US dollars with an annual growth rate of 33% over the past five years (Frost & Sullivan, 2022). In our sample period, 35 vaccine manufacturers supplied Category-II vaccines in China. Among them, 66% were domestic private firms, 25% were state-owned enterprises, and 9% were multinational firms such as Merck and Pfizer.

Despite its large size, the Chinese vaccine market is highly fragmented due to the involvement of local governments. Entry into a regional market is challenging for a manufacturer without collaboration with established distributors and service suppliers who maintain strong relationships with local authorities. As a result of these high agency costs, it is estimated that the prices of Category-II vaccines, which consumers ultimately bear, are more than double the factory prices.

The lucrative nature of the vaccine business, coupled with extensive government involvement, creates fertile ground for corruption. A notable example occurred in 2007 when over 100 children in Shanxi province either died or suffered disabilities following vaccination. Despite protests from outraged parents, these incidences were covered up by local governments until 2010 when an investigative journalist from Beijing revealed that the children's adverse health outcomes were caused by vaccines that had been improperly exposed to high temperatures but were still approved for use. The Chinese vaccine market grapples with persistent issues such as defective and substandard products and inadequate storage and transportation practices.

2.2 Public Procurement

In China, public procurement constitutes an important part of government expenditure. In 2019, government procurement accounted for 10% of the overall fiscal expenses and 3.3% of the GDP. According to a law enacted in 2003, goods and services purchased with public money above certain thresholds (determined by local governments) are required to undergo formal procurement. The default format is open-bid procurement, wherein the government publicly announces the procurement, and qualified and interested suppliers compete through auctions (typically sealed-bid). Other procurement formats include invited-bid in which only a small number of supplies are invited to bid; private negotiation, involving negotiation between the government and selected suppliers; and assigned procurement in which a specific supplier is assigned the procurement task. By regulation, these other formats are permitted only in exceptional circumstances, as the regulatory emphasis is on open-bid procurement to increase transparency and reduce corruption.

In 2005, the Chinese government mandated that all vaccines and related products (equipment) and services (storage and transportation) must be procured through government channels. Supplies are prohibited from selling their products and services directly to health providers. The procurement of vaccines follows the general regulation of public procurement as described above. However, the decisions on the quantity, producers, and format of procurement are decentralized to the prefectural Centers for Disease Control and Prevention (CDCs), under the supervision of the corresponding Bureau of Public Health (Fu, 2021).

In practice, local governments frequently depart from the open-bid format, citing various reasons. One common reason is that open-bid procurement is insufficiently swift to meet sudden spikes in demand (e.g., during flu seasons) or financially impractical for small-scale purchases. Another justification is the need for specialized and localized services, such as customized storage solutions that can only be provided by specific suppliers. Nevertheless, such departures from the default open-bid format are often viewed as potential avenues for rent-seeking, because invited-bid and private negotiation processes are opaque and difficult to monitor.

2.3 Monitoring of Policy Oversight

In China, the implementation of national policies is primarily decentralized to local governments, and the central government assesses their performance and makes promotion decisions based on a set of metrics related to different policy objectives (Ang, 2016). This approach provides regional governments with a certain degree of flexibility to tailor a national policy to their specific contexts. However, it can also result in policy oversight and distorted implementation (Xu, 2011).

The central government often uses top-down monitoring to align local governments' policy implementation. One important tool is the so-called "inspection and appraisal" mechanism, in which higher authorities deploy inspection teams to assess the performance of the subordinate bureaus (Zhou et al., 2012). In many cases, this inspection-and-appraisal process is triggered by large-scale incidents or widespread public sentiment towards certain social problems (Ai, 2011; Zhou et al., 2012). Receiving a low evaluation in an inspection poses a significant threat to the career of a local official. The high stakes associated with inspections create substantial top-down pressure on local officials, especially those in lower-ranking positions (Zhou, 2022).

In ordinary time, local governments' procurement of vaccines follows a regular bureaucratic procedure as long as it maintains a certain level of quality control and operational efficiency. However, when serious safety problems catch public attention, vaccine procurement can escalate from bureaucratic operation into a political issue and become subjects of top-down inspection. In the aforementioned 2007 vaccine scandal, the inspection from the central government following the event led to the demotion of several high-rank officials.

2.4 Social Media

Among the various social media platforms in China, Sina Weibo is the most prominent platform for public discourse on societal matters. Launched in August 2009, it experienced rapid expansion in the subsequent years, and reached its pinnacle with over 500 million users in 2012 (CNNIC, 2013). Although Weibo has lost some ground to other social media since 2013, it continues to hold its influence as a platform for the public discussion of social issues.

Unlike traditional media, Chinese social media operates under the direct control of the National Office of Information Control. Local governments exert limited influence over Weibo's censorship practices.[4] China's censorship of social media is widely recognized as strategic (King et al., 2013, 2014). Qin et al. (2017, 2021) document that a large volume of posts discussing political issues, such as corruption, strikes, and protests, circulate on Weibo for extended periods of time. It appears that the Chinese government does not systematically censor discussions about social problems as long as they do not challenge the political doctrines of the CCP.

[4]There has been anecdotal evidence showing that local government officials bribed Sina Weibo employees to delete unfavorable posts targeting specific governments and officials. However, such interventions are sporadic and have a limited impact on a small number of posts.

This information-control strategy is particularly applicable to issues where both the central government and the public share a common interest. Vaccination (drug and food safety more broadly) falls into this category as it directly affects people's well-being. The failure to address these issues can lead to public dissatisfaction with the leadership of the CCP and erode trust in the regime. For citizens, drug and food safety problems are often attributed to corrupt local officials and unscrupulous companies. As a result, citizens have a strong incentive to voice their concerns, and the central government allows relatively free discussions about these issues.

Monitoring posts (i.e., posts that discuss social problems and have implications for government accountability and corporate behavior) can affect government responsiveness through several channels. First, these posts serve as a source of information for the central government and the public, shedding light on the consequences of policies and misconduct by local officials. Second, when these posts are aggregated at a regional level, they can reflect widespread public sentiment against specific local governments. Third, public opinion provides information for top leaders to detect discontent and incipient insurrection in a locality. These channels can trigger top-down inspections that directly impact the career prospects of local officials. Consequently, it has become crucial for local governments to monitor information flows and gauge public opinion on social media. One common approach is to assign dedicated personnel to search for relevant posts originating from specific localities. Weibo even offers location-based search functions to facilitate the collection of locality-specific information. In addition, there has been increasing government procurement of information technology with the regime's desire to enhance surveillance (Beraja et al., 2022). Since 2010, local governments have made substantial investments to increase their capacity to collect and analyze social media data.

3 Data and Empirical Strategy

3.1 Data

3.1.1 Vaccine-related Data

Vaccine procurement Our main outcome variables concern the procurement of vaccines and related products by a city government. In accordance with regulations, all procurement of vaccines and related products must be made public through government websites. We collected relevant procurement documents from both national and subnational government websites from 2014 to 2019.

Each procurement is accompanied by an announcement notice and a deal-closure notice. These public announcements serve as commitments, and it is rare for a government to announce one procurement format and then implement a different format in the final deal. From the announcement notice, we extracted key information such as the name of the procuring government entity (typically a local CDC), the specific item to be procured, the date of the announcement, and the chosen procurement format. From the deal-closure notice, we obtained the names of the winning companies and, if available, the procurement amount.[5] Unfortunately, the price information for specific procured items is largely missing. A significant number of final notices do not provide the transaction value of the procurement, and even for those that do, the reported value combines multiple items. Thus, we are unable to use price differentials for homogeneous items to infer administrative effectiveness and potential corruption.

We obtained a total of 23,035 item-level observations from 2014 to 2019 across 273 cities. These items are classified into three categories: Category-I vaccines, Category-II vaccines, and supplements (supplemental materials, facilities, and services). We aggregate the item-level information at the city-month level.

Table 1 presents the basic summary statistics for the count and share of open-bid procurement (as opposed to the less transparent procurement) at the city-month level. The number of observations is limited to 1,630 as we exclude city-month observations without vaccine procurement. On average, the open-bid format is used 4.3 times per city-month, accounting for 53% of total vaccine procurement. The share of open-bid procurement is slightly higher for Category-II and supplements, but it is still far below the level desired by the central government.

3.1.2 Social Media Data

Our key explanatory variables concern social media coverage of vaccine issues. We collected posts referencing "vaccine" in Chinese published on Weibo from 2014 to 2019. The data was obtained from a specialized third-party provider that collected social media data in China. To ensure data quality, we compared it with the posts we scraped from Weibo for the period of January to June 2014 using the exact same keyword. The two data sources yielded very similar sets of posts, with our data accounting for approximately 95% of the third-party data. We decided to use the more comprehensive third-party data for our analysis.

We believe that social media discussions about vaccine issues, unless they contain anti-regime content, are barely censored by the Chinese government. To verify this claim, we conducted a test by searching the word "vaccine" on a website exclusively accessible outside mainland China. This website compiled Weibo posts that appeared briefly on the official Weibo platform before being removed. We found an absence of posts referencing vaccines on this website until 2021, when the COVID-19 vaccination became a politically sensitive issue. In contrast, when we searched for other keywords related to political leaders, protests, or disasters, we consistently discovered posts dating as far back as 2012. This evidence, coupled with the surge of vaccine-related posts during significant

[5] We further utilized various external information sources to gather additional details about the winning companies, including their location, ownership, size, and age.

events, supports our contention that information flows concerning vaccine issues were largely free on Weibo during our study period.

Our dataset comprises a total of 3,328,889 posts referencing vaccines. For each post, we obtained information regarding its content, posting time, and the city-level user location. User-location data was obtained from the users' self-reported information on their Weibo profiles. To validate its accuracy, we selected a subset of users who granted Weibo permission to track their real-time locations and compared them to their self-reported locations. Our analysis revealed a 93% match between the self-reported and real-time locations of these users.

After reading a randomly drawn sample of 1,000 posts, we observed that these posts can be broadly categorized into three main groups. First, a considerable portion of the posts indeed discuss concerns about vaccine safety, such as expressing suspicions about the quality of vaccines and criticizing corruption and inadequate government inspection. Second, many posts simply share personal vaccination experiences and information on vaccine availability. Third, some posts consist of scientific information and product descriptions. We will use the posts belonging to the first category to gauge public opinion on vaccine safety. For convenience, we refer to these posts as "monitoring posts." Additionally, we will aggregate all three types of posts to serve as a proxy for the overall attention given to vaccine-related issues within a region.

We employed a supervised machine-learning approach to differentiate the monitoring posts from the others. Specifically, we manually labeled 12,000 randomly selected Weibo posts from our dataset. Then, we created a training dataset to train a support vector machine (SVM) classifier, which assigned each post to either the monitoring posts or the others. After conducting cross-validation, we applied the SVM classifier to the entire dataset. The detailed procedure can be found in Appendix B. The performance evaluation, as depicted by the confusion matrix and ROC curve (Figure B3), demonstrates a reasonably high classification accuracy. While more advanced machine learning techniques may potentially enhance accuracy, our classification exercise aims to imitate the capability of Chinese governments in gauging public opinion. According to industry experts, SVM is the most commonly utilized approach in the development of information monitoring software employed by local governments. Furthermore, we apply sentiment analysis to the vaccine posts to capture public sentiment, which is also of interest to Chinese governments. See Appendix B for details.

The last three rows of Table 1 report the summary statistics for the three measures of Weibo discussions about vaccines. On average, there are approximately 173 posts referencing vaccines in a city-month, with considerable variance. The mean of "Monitoring-Posts (ML)," which represents the number of monitoring posts identified by the machine-learning approach, is only 24, less than 1/7 of the mean value of the total number of posts. The average number of posts with a negative sentiment is approximately 63, more than double the mean number of monitoring posts. The two variables, "Monitoring-Posts (ML)" and "Negative-Sentiment-Posts," are strongly correlated, as illustrated in Figure B4. Throughout this paper, we use "Monitoring-Posts (ML)" as our baseline measure for Weibo discussions about vaccine safety. Results obtained using "Negative-Sentiment-Posts" remain qualitatively the same.

Figure 1 plots the monthly time-series of the three Weibo variables mentioned above. Of particular significance are the two spikes, resulting from vaccine scandals. These spikes were unlikely to have occurred if there were government censorship of public discussions about vaccine issues. The spikes appear so abrupt that they substantially shift the information landscape on Weibo for a brief period. We will explore the regional variations stemming from such shifts to identify the social media effect.

3.2 Empirical Strategy

In this section, we first describe the background of the focal event that we use to draw causal implications. After discussing the identification assumptions, we specify the econometric estimation. Finally, we discuss the use of an instrumental-variable (IV) approach to strengthen identification.

3.2.1 Event Setting

Our identification strategy relies on an outbreak in public opinion on social media led by the occurrence of a vaccine scandal. On March 18, 2016, an online media outlet, The Paper, exposed a vaccine distributor from Shandong province for selling defective or expired vaccines worth 88 million US dollars across 18 provinces over a period of six years. The vaccines involved in this scandal were mostly category-II vaccines and related services, which were highly lucrative businesses. This news leak immediately sparked heated discussions about vaccine issues on Weibo. As depicted in Appendix Figure A1, the number of Weibo posts referencing "vaccine" remained relatively low (around 1,000) prior to the news leak. However, it surged to 14,825 on March 18, peaked at 75,506 on March 22, and declined rapidly after one week.

We also plot the number of articles discussing vaccine issues published on WeChat public accounts and newspapers.[6] The dynamics of these articles mirror the pattern observed in Weibo posts, indicating that the information outbreak on Weibo was triggered by the news leak and was unexpected to the public and government.

In mid-April 2016, the central government undertook two measures to enhance regulations surrounding vaccine procurement and distribution. First, the procurement of vaccine-related products was mandated to be reported on the provincial digital platform.

[6] WeChat is the most popular Chinese social media platform known for private messaging within a restricted group. We searched for vaccine-related articles published on 59 prominent WeChat public accounts specializing in healthcare. For newspaper data, we retrieved articles mentioning "vaccine" from Wisenews, a digital archive of Chinese newspapers based in Hong Kong. During our sample period, Wisenews covers 87 general-interest newspapers from 31 cities in Mainland China.

Second, stricter inspections were imposed on the qualification of vaccine distributors, leading to the disqualification of many lower-tier distributors. However, local governments still kept the decision rights regarding vaccine suppliers and procurement format. While the new regulations were announced in April, they were not implemented in most provinces until the end of 2016.

Within a few months after the news on the scandal, the central government sent inspection teams to investigate the problems of vaccine safety in several regions. Following the investigations, a total of 355 individuals (including 64 civil servants) involved in the scandal were arrested and prosecuted.

3.2.2 Identification Strategy

In the above setting, the release of news regarding the vaccine scandal created a strong and unforeseen information shock to each city. This regional variation in information shocks serves as the basis for our identification strategy. In Figure 2, we present the landscape of public opinion on vaccine safety in China, as measured by the number of monitoring posts published by Weibo users in each city from February to May 2016. In February, there were minimal public discussions about vaccine issues, with only a few central cities showing some engagement. However, the landscape underwent a dramatic shift in March, with a surge in vaccine-related discussions accompanied by noticeable regional disparities. In the subsequent two months, the intensity of discussions on Weibo gradually diminished and returned to the pre-event levels. Our identification leverages the abrupt change in Weibo discussions on vaccine issues within a city during this period, with cities experiencing more pronounced shifts regarded as receiving stronger treatment.

The key identification assumption is that, absent the region-specific and vaccine-related information shock caused by the event, local governments would not alter their behavior in vaccine procurement. The main threats to this assumption arise from factors that align with the regional distribution of the Weibo shock during the event and also impact local government procurement practices. For instance, in regions where there is already heightened public attention to vaccine issues, local governments are likely to respond more strongly to the event even without Weibo. Another confounding factor is the presence of other information channels, such as newspaper coverage, which can prompt local governments to react. Additionally, changes in local social and economic conditions at the time of the event may confound the effect of social media. It is important to note that information circulated on social media might reflect, rather than alter, existing local conditions that drive changes in government behavior. We regard this as part of the media effect, as long as these local conditions remain undisclosed to the public in the absence of social media information.

To address these identification concerns, we use three approaches. First, in our regression analyses, we control for province-specific time trends in addition to city fixed effects and year-month fixed effects. Second, we use an IV to isolate the impact of Weibo. Third, we conduct falsification tests to rule out the influence of various potential confounding factors.

3.2.3 Econometric Specification

We estimate a panel of 237 cities from March 2015 to March 2017 with the following DID econometric specification:

$$y_{it} = \alpha + \beta WeiboShock_i \times Event_t + X_{it}'\gamma + \lambda_i + \eta_t + \epsilon_{it}, \tag{1}$$

where the subscript i indicates a city and t indicates year-month. The dependent variable y_{it} is the number (in logarithm) or the share of open bids. The key independent variable is the interaction term $WeiboShock_i \times Event_t$. $Event_t$ is a dummy that equals 1 if an observation is in and after the event month (March 2016). It is not identifiable when year-month fixed effects are included. $WeiboShock_i$ is measured by the difference between the per-capita number of monitoring posts published by users in city i in the event month and the same measure averaged over the three months before the event. This variable captures the intensity of information shock to a city at the timing of the event and is time-invariant. It is not identifiable in the presence of city fixed effects. What we aim to identify is β, the coefficient of the interaction term.

In the baseline regressions, we include city-fixed effects, λ_i, and year-month fixed effects, η_t, as well as X_{it}', which is a set of time-variant city characteristics including population density, GDP per capita, government expenditure, foreign direct investment, the numbers of internet users, mobile phone users, land-line users, and students, the share of college students among all students, and the share of the secondary industry in GDP.[7] Importantly, we include the number of total posts mentioning vaccines in each city in a month. This variable captures the time-variant general attention to vaccine issues in a city, and controlling for it helps purify the effect of information eruption on social media. We also control for province-specific time trends. ϵ_{it} is the error term, clustered by city.[8]

3.2.4 Instrumental Variable

To further isolate the effect of the Weibo shock, we use Weibo penetration (the number of posts per capita) across cities during the early stages of Weibo's entry into the market in 2009 as an instrument for the variable $WeiboShock_i$. In essence, this IV is similar to that used by Kearney and Levine (2015), who utilize local area MTV ratings from a pre-period as an IV for the current ratings of a specific MTV reality show (16

[7] These variables are sourced from the Chinese City Yearbooks and are available at the yearly level. In the regressions, government expenditure, foreign direct investment, and the numbers of internet users, mobile phone users, land-line users, and students are all weighted by population and applied a logarithmic transformation.

[8] Clustering the standard error at the province level or two-way clustering at both the city and year-month levels barely changes the statistical significance of the coefficients of the main variables.

and Pregnant) to identify its effect on teen childbearing. The identifying assumption is that Weibo penetration in a city in 2009 is unrelated to vaccine procurement in that city in 2016, except through the outbreak of vaccine-related posts that have monitoring implications. We next discuss the validity of this assumption.

Weibo was introduced by Sina Corporation in August 2009 as a response to the blocking of Twitter and Facebook in China, as well as the closure of several domestic micro-blogging services. At its inception, Weibo was unknown to most Chinese and primarily attracted a small group of young, well-educated individuals who had prior experience with micro-blogging platforms. As shown in Appendix Figure A2, during 2009-2010, Weibo users were predominantly people in their twenties. Consequently, conditional on economic and social factors that affected young individuals' engagement with microblogging (e.g., the numbers of college students and internet users per capita), the initial penetration of Weibo in a city is arguably independent of unobservable regional factors that may subsequently impact local governments' vaccine procurement after a span of seven years. We further validate this assertion below.

We measure the early penetration of Weibo in a city by the per-capita number of Weibo posts, encompassing all kinds of topics, published by users in the first three months following Weibo's launch (August–October 2009).[9] Panel (a) of Appendix Figure A3 illustrates the residuals derived from regressing our measure of early Weibo penetration on the numbers of college students, internet users, mobile phone users, and land-line users in 2009, against a city's GDP per capita in 2009. The analysis reveals that the early penetration of Weibo is barely correlated with a city's level of economic development, which was a crucial determinant of Weibo usage in subsequent years. Similarly, in Panels (b) and (c), we observe no significant correlation between the residuals and a city's government expenditure and foreign direct investment in 2009, respectively. In Panel (d), we depict the correlation between the aforementioned residuals in 2009 and the same residuals in 2012, a period of rapid expansion for Weibo usage. The correlation between these two sets of residuals is weak. Collectively, this evidence supports our conjecture that early Weibo penetration, conditional on observable regional characteristics, can be considered quasi-random.

The IV-relevance condition necessitates a sufficiently strong correlation between the early Weibo penetration and the Weibo shock in the 2016 event. Figure A4 depicts the relationship between the registration time of Weibo users and their total number of posts and followers by the end of 2019. Evidently, users who registered in 2009 exhibited a considerably higher number of posts and a larger follower base compared to users who registered in subsequent years.

[9]The data on the total number of Weibo posts is obtained from a database compiled by Weibook, which has been validated for its accuracy and reliability. See Qin et al. (2017) for further details.

4 Main Results

In this section, we focus on the above event-study setting to examine whether the eruption of Weibo information caused local governments to adopt more-transparent formats for vaccine procurement. We first present the results from the baseline regressions, followed by the IV estimation and a series of robustness checks. We then report results concerning outcomes other than procurement formats.

4.1 Baseline Estimation

Table 2 reports the results obtained from the estimation of specification (1). In Panel A, the dependent variable is the share of open-bid procurement. The panel is unbalanced at the city level because some cities procured vaccines only before or after the event during the sample period. To assess the potential bias caused by the unbalanced data, we report the estimated effects controlling for province fixed effects (in the odd-numbered columns) and city fixed effects (in the even-numbered columns), respectively. The inclusion of provincial fixed effects is due to the fact that there is always vaccine procurement before and after the event at the provincial level. The first column reveals that the Weibo shock increases a local government's share of open-bid procurement by 10.3% at the 1% significance level. This coefficient remains virtually unchanged when the province fixed effects are replaced with the city fixed effects in the regression (Column (2)). The estimated magnitude shows that one additional monitoring post published per 10,000 people in a city leads to approximately 10% increases in the share of open-bid, or a 17% increase relative to the pre-event average (60.6%).[10]

The next two columns report the effects on Category-I vaccines. Regardless of the fixed effects included in the regression, the estimates are small and statistically insignificant. The last two columns report the effects on the procurement of Category-II vaccines and supplements (equipment and services). We combine these two categories into one outcome variable because local governments have substantial discretion in procuring Category-II vaccines and supplements, and vaccine safety issues encompass both of them. The effects in both regressions are sizeable and statistically significant at the 1% level. Given that the estimated Weibo effects are comparable in Columns (5) and (6), we focus on the estimates with control for city fixed effects, unless otherwise specified. Column (6) shows that in cities where one additional monitoring post per 10,000 people is published

[10] Admittedly, interpreting the magnitude of the Weibo effect poses some challenges. First, a single post may be read many times and retweeted extensively, leading to a substantial information shock even with a small number of original posts. Second, the eruption of monitoring posts was short-lived, resulting in a relatively low average number of monitoring posts in a city over the event month. However, if we consider the number of posts during the event week and extrapolate it to a monthly scale, the count would be much higher. Third, the effect of Weibo posts is not necessarily linear, and the marginal effect may be disproportionately large when the number of posts is small. Lastly, the effect of the Weibo shock persists over a long period, and the cumulative effect is sizeable even if the effect in a single period is modest.

in a month, the share of open-bid increases by 19.6%, which is substantial in view of the mean share (0.64).

Clearly, the positive effect of Weibo on overall procurement (Columns (1) and (2)) is attributed to Category-II vaccines and supplements. This is reasonable because Category-I vaccines are compulsory and local governments have little room to exercise discretion. We further verify this result in Panel B, where the dependent variable is the logarithm of the count of open-bid (or nonopen-bid) procurement. The results align with those in Panel A, indicating that the Weibo shock increases the frequency of open-bid procurement without increasing the frequency of other procurement formats. For Category-II vaccines and supplements, there appears to be a shift from non-open to open bids. As a robustness check, we also estimate the effect on the frequency of procurement in a balanced panel where we assign zero to the city-month in which there is no vaccine procurement (see Appendix Table A1). The coefficients are qualitatively consistent with those in the baseline estimation.

Discrete measure of Weibo shock In Appendix Table A2, we report the regression results using the same specification but replacing the continuous measure of Weibo shock with a dummy equal one if the magnitude of the Weibo shock is above the mean level. The results are qualitatively the same as those in Table 2. Table A2 also reports the event effect, which necessitates excluding time fixed effects in the regression. The event appears to have a negative effect on the share of open-bid procurement regardless of the Weibo shock. This can be explained by the fact that the vaccine scandal itself caused a nationwide vaccine shortage, prompting local governments to opt for non-open bids to expedite procurement. We will show evidence supporting this explanation in Section 4.4.2. Importantly, the event itself does not confound the effect of the Weibo Shock as shown in Section 4.3.

Dynamic effects Figure 3 plots the dynamics of the DID estimates around the event using the share of open-bid procurement for Category-II vaccines and supplements as the dependent variable. Specifically, we interact $WeiboShock_i$ with a sequence of time dummies indicating a period before, during, and after the event. To more precisely estimate the dynamics, we choose a two-month interval for each period. We normalize the effect seven months before the event to zero. In Appendix Table A3, we also report the dynamic effects with one-month intervals. Figure 3 and Table A3 show no significant pretrends before the event, and the effect becomes apparent immediately after the event and remains significant even up to eight months later. Such a speedy reaction is plausible because a local government can promptly announce the use of a specific procurement format and initiates the actual procurement months later.

In the above dynamic analysis, we use the calendar month to construct the time series. This is particularly useful for testing pretrends. However, not all cities procure vaccines at the monthly level, and the time series based on calendar month may not capture the actual dynamic effects. To address this concern, we reconstruct the panel so that the time series is arranged by the sequence of procurement and re-estimate the dynamic effects in the same way. As seen in Appendix Figure A5, the results are qualitatively similar to those reported in Figure 3 and Table A3.

4.2 IV Estimation

We exploit the aforementioned IV based on the early penetration of Weibo conditional on a set of predetermined conditions. Specifically, we extract the residuals from regressing Weibo penetration during August-October 2009 on the numbers of college students, internet users, mobile phone users, and land-line users in 2009. We then use these residuals interacted with "$Event_t$" to instrument "$WeiboShock_i \times Event_t$" in the estimation of equation (1), following a two-stage-least-squares (2SLS) regression.[11]

Table 3 presents the results of our IV estimation. The IV estimates reported in Column (1) (overall procurement) and Column (2) (category-II vaccines and supplement) are remarkably similar to their counterparts in the baseline estimation (Table 2). The Kleibergen-Paap rk Wald F statistic is large, indicating a strong first stage, as displayed in Appendix Table A4.

To further purge the potential influence from latent factors that might simultaneously affect Weibo information flows and government procurement, we introduce a new interaction term, "$Weibo2012 \times Event$," into our baseline regression. This term indicates the interaction between Weibo penetration (number of users per capita) across cities in 2012 and the 2016 event dummy. As noted before, the number of Weibo users stabilized in 2012. Therefore, the regional variation in underlying social and economic conditions that affected the regional development of Weibo is captured by the variation in Weibo penetration in 2012. In Columns (3) and (4), we report the results of the extended OLS regressions with this newly added term. The effect of Weibo penetration in 2012 on procurement formats is negligible and insignificant, while the effect of the Weibo shock in 2016 remains virtually unchanged.

Columns (5) and (6) present the IV estimates in the extended specification. The K-P rk Wald F-statistic remains large, although it is considerably reduced by the inclusion of Weibo penetration in 2012 because long-term Weibo penetration naturally has a significant impact on subsequent information outbreaks on Weibo. This is evident in the first-stage regression in Table A4. Despite this change, the direct effect of Weibo penetration in 2012 on vaccine procurement remains small and insignificant, and the effect of the Weibo shock is only marginally weakened. This result suggests that the initial

[11]In the presence of city fixed effects, we can only instrument "$WeiboShock_i \times Event_t$" with "$residuals_i \times Event_t$" because the estimation absorbs time-invariant residuals in the presence of city-fixed effects. Alternatively, we can use province fixed effects in lieu of city fixed effects in specification (1) to instrument simultaneously "$WeiboShock_i$" and "$WeiboShock_i \times Event_t$" with "$residuals_i$" and "$residuals_i \times Event_t$". Implementing this version of IV estimations generates similar results.

penetration of Weibo generates a long-lasting impact on the information outbreaks in 2016, likely because many earlier users became active bloggers of public issues.

The IV estimation provides reassuring evidence that endogeneity in the baseline estimation is not a serious concern. Moreover, it indicates the source of the social media effect: whether the effect is driven by a specific information outbreak or by the long-term Weibo penetration. Existing studies (e.g., Bessone et al., 2020; Gavazza et al., 2019) tend to stress the long-term effect of the internet or social media penetration through a gradual effect on the preferences and behavior of voters and politicians. In contrast, our findings underscore the predominance of the short-term effect of information outbreaks. This is likely because in an authoritarian regime, citizens' direct influence on local governments is limited; the effect, if existent, is channelled through the spontaneous intervention from upper-level governments. We will investigate such a mechanism in Section 5.

4.3 Robustness Checks

In this section, we present evidence that rules out a number of prominent confounding factors: (1) event effect, (2) policy effect, (3) other information channels, and (4) coordination and peer effect.

Event effect One potential confounding factor is the event itself: aware of the scandal, governments would have responded even without being influenced by public opinion. To address this confounder, we leverage the variation in the impact of the scandal across cities. As previously mentioned, the vaccine distributor responsible for the scandal operated in 18 provinces, selling defective vaccines. Therefore, we include an interaction term between the event timing indicator and a dummy indicating whether a city is located in one of the affected provinces. The results, as shown in Panel A of Table A5, reveal that the coefficient of this newly added interaction term is statistically insignificant, while the estimated Weibo effect remains unchanged.

Policy effect As noted in Section 3.2.1, subsequent to the event, the central government implemented stricter regulations regarding vaccine procurement. If cities with stricter implementation of the new regulations coincidentally experienced a larger Weibo shock, our estimated effects could be spurious. To address this concern, we consider the timing of the implementation of the new regulations in each province.[12] In our dataset, we observe a large significant variation in the timing of implementing the new regulation; many cities did not implement the central government's new regulation until six months after the event. As demonstrated in Panel B of Table A5, the timing of policy implementation does not have a direct impact on the share of open-bid procurement and does not affect the Weibo effect in any significant way.

[12]This information was collected from the official websites of provincial Food and Drug Administration. We exclude the observations from Ningxia, an inland province with a relatively lower level of economic development, as the exact timing of implementing the new policy was not announced.

Other information channels Local governments may respond to information from other sources, such as traditional media, WeChat, and the Internet. In Appendix Figure A1, we illustrate that WeChat discussion and newspaper coverage did not precede the outbreak of Weibo posts about vaccine safety. Panel C of Table A5 reports the result of a regression that extends the baseline DID estimation by including two interaction terms: (1) the interaction of the event timing dummy with the change in local newspapers' coverage of vaccine issues and (2) the interaction of the event dummy with the change in the intensity of search of keywords related to vaccines on Baidu, the Chinese equivalent to Google. Despite including these additional information sources, the estimated Weibo effect remains close to the baseline estimation, while the effects of newspaper coverage and Baidu searching are insignificant.

Coordination and peer effect Another potential concern is that after the scandal, city governments were guided by the coordinated effort of the provincial government or reacted to the action of its peer governments, and the locality-specific Weibo shocks are somehow correlated with these coordination or peer effects. If this is the case, we should have observed little within-province variation in the format of vaccine procurement after the event. Figure A6a plots the mean and 95% confidence interval for the standard deviation of the share of open-bid procurement within a province at the quarterly frequency. The persistent within-province variations reject the conjecture of collective responses. We also show that the estimated effect of Weibo shock is not negatively correlated with the initial level of open-bid procurement. This is evidence against the coordination or peer effect explanation because all cities within a province adopting the same level of open-bid procurement after the event would imply a catching-up effect for cities with a lower initial level of open-bid procurement.

4.4 Other Outcomes

Considering the strong Weibo effect on the format of government procurement, it is reasonable to expect that the outbreak of Weibo information following the event has a notable impact on other outcome variables, such as governments' stance on vaccine safety and the vaccine supply in the market.

4.4.1 Government blogging about vaccine issues

Since 2011 when social media gained popularity in China, the central government has encouraged local governments to engage with the public through platforms like Weibo. In 2012, there were approximately 50,000 Weibo accounts operated by government offices or individual officials (Sina Weibo 2013). Concerned about the potential for public sentiment to arouse anti-government collective action or trigger top-down inspection, local governments have a strong incentive to promptly alleviate online sentiment. Therefore, the eruption of public grievances on Weibo is likely to affect local governments' blogging activities on their Weibo accounts.

To investigate local governments' blogging activities, we examine the content of government posts referencing vaccines. We first use a machine-learning approach to identify the posts published by Weibo accounts representing governments.[13] Then, we apply the Latent Dirichlet Allocation (LDA) topic modeling approach to the machine-identified government posts. Regardless of the number of topics chosen for the modeling, two topics emerge as being closely related to vaccine safety and public accountability, while others predominantly relate to governments' routine work of disease prevention and regular vaccination. This distinction is evident in the five-topic model reported in Appendix B, where posts assigned to the first three topics with high probability are referred to as "routine-work posts," and those assigned to the last two topics are referred to as "accountability posts." The eruption of government posts following the event primarily stems from the accountability posts.

To formally estimate the effect of the Weibo shock on governments' posting activities, we run a regression analogous to the baseline DID estimation, but at a daily level within a short time frame (February to April 2016). We create two timing dummies: "2016.3.18-2016.3.21" being a dummy for the 4-day period from March 18 to 21, 2016, and "After 2016.3.22" being a dummy for the time period starting from March 22, 2016, onwards. This division is based on the fact that March 22 marked the date when the National FDA issued an official announcement regarding the scandal. Therefore, government posts published during the first time window reflect a local government's expressed attitude prior to the central government's intervention. Note that the government posts only account for a tiny share (0.7%) of the monitoring posts, and the concern of reverse causality is mitigated.

The regression results, presented in Table 4, show that in cities where discussions about vaccine safety on Weibo increased more on the event date, local governments responded by publishing a greater number of posts on vaccine-related issues. Additionally, the content of these posts shifted from routine work to matters of public accountability. Interestingly, after the National FDA's official announcement, local governments responded to the eruption of monitoring posts by refocusing more on routine work to align with the National FDA's guidance.

[13]There are two types of Weibo accounts representing governments: government official accounts and private accounts operated by individual officials. The former can be easily identified from the user profile but the latter can only be judged based on post content. Therefore, we use a supervised machine learning approach to identify government users, with the training data labelled by research assistants according to the user profile and post content. Our estimated presence of government posts is approximately 4.81% of all posts referencing vaccines. This estimate is comparable to Qin et al. (2017). Details of this classification exercise can be found in the online appendix.

4.4.2 Trade-off between product quality and operational efficiency

Local protectionism One important distinction between open-bid procurement and other less-transparent formats is the larger pool of participants involved in open bidding. This helps alleviate the problems of local protectionism, the phenomenon where regional governments, driven by the desire to stimulate local GDP growth, prefer to procure goods and services from firms operating within their administered regions. Such a phenomenon is prevalent in China, resulting in a widespread supply of lower-quality vaccines offered by non-reputable small local firms.

Measuring vaccine quality is challenging due to the limited availability and accuracy of price information. Therefore, we focus on the effect of the Weibo shock on the composition of vaccine suppliers. Table 5 reports the regression results for different classifications of producers: large vs. small firms and non-local vs. local firms.[14] The econometric specification follows the baseline model, with the dependent variable being the share of procurement frequency by different types of firms.

Panel A shows that cities experiencing a greater Weibo shock are more likely to procure vaccines from reputable large firms. The effect is sizeable and statistically significant for both open-bid and nonopen-bid procurement. Panel B reveals that a stronger Weibo shock led city governments to procure vaccines from nonlocal firms more frequently. Interestingly, the effect is primarily driven by nonopen bid procurement. This is not unexpected because open-bid has encouraged wider participation and local protectionism is more pertinent to nonopen procurement. Overall, the results in Table 5 show that in response to the Weibo shock, local governments actively sought vaccines with higher quality.[15]

Operational efficiency One potentially detrimental consequence of open-bid procurement is the protracted duration due to its requirement for extensive participation and thorough review. This may lead to a delay in the supply of vaccines to the market and potentially even temporary shortages. Table A7 reveals a substantial positive effect of Weibo on the duration of open-bid procurement at the 1% significance level.

The extended duration of vaccine procurement coincides with reports of vaccine supply shortages, as indicated by anecdotal evidence. Complaint data filed with local leaders' offices in certain cities indicate a shift in the proportion of complaints related to vaccine shortages. Prior to the vaccine scandal in 2016, the share of such complaints stood at 12.3%, increasing to 35.1% thereafter. To further investigate this issue, we selected a

[14] Local firms, in this context, refer to companies whose registration address is located within the administrative regions of the procuring government. These firms encompass both vaccine manufacturers and distributors. Large firms are defined based on their size, specifically those whose sales exceed the median; all the listed companies fall under the category of large firms.

[15] Appendix Table A6 presents the effects on the monetary value of procured vaccines, which are largely consistent with the findings in Table 5. But given the smaller number of observations, the effects are less accurately estimated.

subset of Weibo posts that contained keywords related to vaccine shortages. The average number of posts expressing concerns about shortages rose from approximately 50 posts before the event to nearly double that number afterward. Notably, a spike in Weibo posts discussing vaccine shortages was observed in July 2016, which was approximately a quarter after the scandal.

5 Mechanisms

The above findings reveal a consistent body of evidence pointing to the responsiveness of Chinese local governments in the realm of vaccine procurement, triggered by an information shock from social media. This effect is intriguing for two reasons. First, although the originating event is local, the media's impact reverberates nationwide, even encompassing cities unaffected by the event itself. Second, social media discussions regarding vaccine safety are mostly emotional and vague, without offering verifiable information concerning specific government entities or firms.

The key to understanding the effect of Chinese media on government behavior lies in the top-down pressure inherent in China's authoritarian political system. In China, local politicians are accountable to their supervisors, and the central government deploys a combination of performance metrics and subjective evaluations to create incentives and monitor local politicians (Ang, 2016; Li and Zhou, 2005). However, in cases where metrics are difficult to gauge or susceptible to manipulation, the central government must rely on external information sources to align the actions of local politicians with its objectives (Xu, 2011). Several experimental studies show that citizens' complaints targeting specific government entities or individuals with reference to their supervisors generate significant top-down pressure to affect local officials' policy implementation (Buntaine et al., 2021; Chen et al., 2016). This channel, akin to a petition system, is very costly to operate and difficult to scale up (Chen et al., 2016; Heurlin, 2016). In contrast, the Chinese traditional media, although being a cheaper way to gather verifiable information from the bottom up, falls short in conveying public grievances and policy oversights due to the capture of the media by local governments (Qin et al., 2018).

As noted in Section 2, Chinese social media serves as a more-direct and less-costly channel for political communication between the regime and the grassroots. Therefore, Chinese leaders have an incentive to allow for relatively unfettered social media usage to gather information for surveillance and monitoring. This aligns with the theory of strategic media control in autocracies (e.g., Egorov et al., 2009; Egorov and Sonin, 2023; Lorentzen, 2014) and is substantiated by numerous case studies (Yu, 2012) and some empirical evidence (Qin et al., 2017). While not necessarily disseminating factual or verified information, Chinese social media has evolved into a platform for people to voice discontent and propagate anti-government sentiments, potentially mobilizing unauthorized collective actions and eroding public trust in the regime (Qin et al., 2021). To the extent that the central government considers public grievances and dissent in its promotion decision, widespread information and sentiments on social media will exert top-down pressure, compelling local politicians to respond.

In this section, we present empirical evidence aimed at elucidating the top-down pressure mechanism. We test several hypotheses that corroborate this mechanism but contradict competing mechanisms, particularly those that posit that benevolent governments respond directly to citizen needs as their political goals or bureaucrats address public demands as part of their job responsibilities.

5.1 Hypotheses

One way to gauge the extent of top-down pressure on local politicians is to investigate their perceived probability of being inspected. Since 2013, the Chinese central government has initiated a series of anti-corruption campaigns with the policy objective of dismantling patronage networks within a region. In these anti-corruption campaigns, a city tends to draw increased attention from top-down inspections when there are frequent corruption allegations in that region (Jiang et al., 2022). Therefore, local politicians in areas that have recently experienced more of these anti-corruption actions are likely to be more sensitive to negative shocks. Based on this premise, we propose the following hypothesis.

Hypothesis 1 ***(Top-down inspection)*** *In cities recently experiencing more anti-corruption allegations, local governments are more likely to increase the transparency of vaccine procurement in response to social media information.*

Testable hypotheses can also be formulated based on city characteristics. As noted in Section 2.1, Category-II vaccines are costly and self-financed, with their coverage focusing on well-developed urban areas. Therefore, if the media's impact is propelled by local governments' direct attention to citizen needs, it should be more pronounced in metropolitan areas compared to smaller cities. Conversely, the top-down-pressure mechanism posits the opposite scenario: ensuring policy compliance in vaccine procurement holds less significance for a metropolitan government, which is responsible for a broader spectrum of responsibilities than its smaller city counterparts.

Additionally, another characteristic of cities can help discriminate between mechanisms. In the Chinese government hierarchy, local leaders' rankings are determined by the administrative level of their cities. For instance, Beijing, Shanghai, Tianjin, and Chongqing are four special municipalities directly under the supervision of the central government. These municipalities hold a higher rank than provincial capital cities, which, in turn, outrank other cities. Given that lower-ranked governments are subject to more inspections by upper-level governments, we propose the following hypotheses that support the top-down-pressure mechanism.

Hypothesis 2a ***(City size)*** *Relative to governments of other cities, governments of* *metropolitan cities are less likely to increase the transparency of vaccine procurement in response to social media information.*

Hypothesis 2b ***(City rank)*** *Relative to higher-ranked governments, lower-ranked governments are more likely to increase the transparency of vaccine procurement in response to social media information.*

In China, a political leader's career advancement hinges on both their competence and loyalty, with loyalty becoming increasingly vital as a politician progresses in their career (Ang, 2016; Jia et al., 2015). In the earlier stages of their career, politicians face greater pressure from top-down policy inspections because they have not yet amassed sufficient performance metrics to demonstrate their competence. This holds particularly true for politicians in their first term in a new position. In contrast, politicians approaching the end of their career or tenure are more inclined to align with the central government's policies to showcase their loyalty and, consequently, are less susceptible to top-down pressure. Thus, we formulate the following hypothesis for testing.

Hypothesis 3 ***(Career concerns)*** *In cities in which political leaders are younger and in the earlier term of tenure, local governments are more likely to increase the transparency of vaccine procurement in response to social media information.*

The information asymmetry between the central and local governments offers another avenue for testing the top-down-pressure mechanism. The agency problem within the government hierarchy primarily arises from lower-level governments' possession of private information concerning local conditions. Absent such informational advantages, a local government is more likely to be apprehensive about top-down inspections because it is less capable of addressing issues stemming from unexpected information shocks. The efficacy of this mechanism is contingent on local governments' perception that the central government possesses the necessary information. Therefore, we formulate the following hypothesis.

Hypothesis 4 ***(Information asymmetry)*** *In cities where public information about social problems is scarcer, local governments are more likely to increase the transparency of vaccine procurement in response to social media information.*

5.2 Evidence from the focal event

We test the above hypotheses within the same event-study framework in Section 4. In particular, we extend the baseline DID regression (1) to a triple-differences model to estimate a series of heterogeneous treatment effects, specified as follows:

$$\begin{aligned} y_{it} = \alpha &+ \theta WeiboShock_i \times Event_t \times Condition_i \\ &+ \beta_1 WeiboShock_i \times Event_t + \beta_2 Condition_i \times Event_t + X_{it}^{'}\gamma + \lambda_i + \eta_t + \epsilon_{it}. \end{aligned} \tag{2}$$

Here, we introduce a new variable $Condition_i$, indicating a predetermined city condition used to assess a specific hypothesis. All other variables are the same as previously defined. The coefficient attributed to the triple-interaction term, θ, represents the heterogeneous treatment effects of interest. We incorporate an identical set of control variables as used in (1), and we continue to cluster the standard errors by city. Table 6 reports the regression results.

Top-down inspection To test Hypothesis 1, we collected data on the anti-corruption allegations at the provincial level from the Procuratorial Yearbooks of China. We find that the number of anti-corruption allegation cases is uncorrelated with the share of open-bid procurement after controlling for basic provincial characteristics such as GDP per capita and government expenditure. We define a dummy variable, $Inspection$, which equals one if the number of anti-corruption allegations in a province within three years prior to the vaccine event is above the median level among all provinces.[16] We then interact this measure with "$WeiboShock_i \times Event_t$"—the baseline interaction term. As displayed in Panel A, the estimated coefficient of the triple interaction term is positive, sizeable, and statistically significant, thereby providing evidence in support of the top-down-pressure mechanism.

City size and rank Panel B presents the results aimed at testing Hypotheses 2a and 2b. We define a dummy variable, $Metropolitan$, which equals one if a city falls within the top two tiers of the 5-tier hierarchical classification of Chinese cities.[17] In total, there are 52 cities categorized in the first two tiers. Their GDP per capita substantially surpasses that of other Chinese cities. Therefore, it is reasonable to assume that the demand for high-quality vaccines is notably higher in these cities. We define another dummy variable, $High\ Rank$, to identify cities among the four special municipalities and 15 sub-provincial cities. The political leaders (Party Secretary and Mayors) of these 19 cities hold positions that are ranked one or two levels above leaders in regular prefectural cities. These higher-ranked governments enjoy a considerably greater degree of autonomy in policy implementation and legislation. As a result, they are subject to less top-down intervention pressure than their lower-ranked counterparts. As reported in Columns (1) and (3), while metropolitan city governments exhibited a stronger response to the event than other governments, this heightened responsiveness did not dilute the impact of the Weibo shock. The negative and significant coefficient of the triple-interaction term demonstrates that, compared to governments in regular cities, metropolitan city governments responded less to the Weibo shock. In fact, the Weibo effect is almost entirely attributed to regular prefectural governments, as evidenced by the coefficients' magnitude and a formal F-test evaluating the sum of the main Weibo effect and the triple-

[16] The estimated effects are robust when we normalize the anti-corruption measure by dividing the aggregate number of anti-corruption allegations by the number of employees in the public sector.

[17] Officially recognized by the Chinese government, the China Business Network(CBN) has classified 337 Chinese cities into five tiers based on various criteria, including economic development, urbanization, agglomeration, and population.

differences effect. Similarly, Columns (2) and (4) reveal that, lower-ranked cities respond strongly to the Weibo shock while the response of higher-ranked cities is considerably smaller. These findings square with Hypotheses 2a and 2b.

Career concerns Panel C presents the results aimed at testing Hypothesis 3. To gauge a local political leader's career concerns, we define two variables based on detailed personnel information derived from the CVs of the mayors in our sample cities.[18] The first variable, $Pre-retirement$, is a binary indicator that assesses the likelihood of a mayor receiving a promotion. According to the promotion rule, a prefectural leader who is above the age of 54 typically serves for one additional term before retirement, making it improbable for them to attain further promotion.[19] This age threshold coincides with the median age of mayors in our sample. The second variable, $First\ Term\ of\ Tenure$, serves as an indicator of whether 2016 falls within a city mayor's initial term in office. As shown in Columns (3) and (4), the Weibo effect on the procurement of Category-II vaccines and supplements is less pronounced for local governments headed by leaders aged 54 or older, while it is more pronounced during the first term of their tenure. This differentiated effect is less conspicuous when we incorporate the procurement of mandatory Category-I vaccines into the analysis (Columns (1) and (2)). These results confirm Hypothesis 3.

Information asymmetry Generally speaking, in regions with less transparent informational environments, local political leaders are more likely to be unaware of infrequent local problems, such as vaccine safety. To measure the transparency of the informational environment in a region, we use the share of Weibo posts deleted in a province as a proxy for the scarcity of local information available to cities in this province. This variable is collected from Bamman et al. (2012), who tracked the deletion of a substantial number of Weibo posts across provinces in 2011. Qin et al. (2017) have demonstrated a strong correlation between this provincial-level measure of censorship and the long-term pro-government bias of local newspapers. Hence, a higher rate of post deletion indicates a more tightly controlled media environment and likely, a greater shortage of bottom-up information. We define a dummy variable, $Delete\ Post\ above\ Mean$, which equals one if the proportion of deleted posts is higher than the mean level across all provinces. As observed from Panel D (Column (2)), the positive and highly significant coefficient of the triple-interaction term indicates that the Weibo effect is more pronounced for governments operating in regions with poorer informational environments. This finding aligns with Hypothesis 4.

[18]We have opted to focus on city mayors, rather than party secretaries because the responsibility of supervising public procurement and vaccine safety is undertaken primarily by the mayor.

[19]The result we report remains robust even when we exclude the four municipalities directly governed by the central government, which have a more lenient retirement rule for political leaders.

5.3 Evidence from other events

In our argument, the top-down pressure arises from the prevalent anti-government sentiment on social media. This sentiment not only informs the central government about the severity of the issue but also reflects a lack of trust in the government. Thus, it is likely to trigger top-down inspections into possible misconduct by local governments. If this mechanism is the primary driver, social media discussions that do not express anti-government sentiment, even if they contain information regarding vaccine safety, will not propel local governments to respond. To test this conjecture, we leverage another surge of information on Weibo.

In July 2018, a public vaccine manufacturer, Changsheng Bio-Technology Co., located in Jilin province, was discovered to have provided false information about the production of a significant quantity of rabies vaccine. This incident was reported to the top leaders, leading to a comprehensive investigation. Ultimately, the company was delisted, and 15 senior managers were sentenced to imprisonment. This event sparked intense discussions on Weibo and received extensive coverage from traditional media outlets. However, public opinion during this time primarily centered on the issue of corporate accountability.[20]

We employ the same event-study approach to analyze this new context, with the Weibo shock being defined as the difference between the per-capita number of monitoring posts in a city during the event month (July 2018) and the average number of posts from three months prior to the event. Table A8 shows that, across all specifications, the effects of the Weibo shock on the share of open-bid procurement are minimal and statistically insignificant. Note that the average share of open-bid procurement before 2018 is comparable to that before the focal event in 2016. It is not the case that the lack of government responsiveness is due to the share of open-bid procurement having reached a sufficiently high level with no further room for adjustment. Consistent with this primary finding, we observe that the Weibo shock had limited impact on other outcome variables. These findings suggest that when public sentiment does not generate top-down political pressure, the influence of media is subdued.

5.4 Evidence beyond event study

Figure A6b plots the time series depicting the share of open-bid procurement of vaccines throughout our entire sample period. The noticeable fluctuations suggest that local governments do not consistently institutionalize their vaccine procurement practices, even though they exhibit increased policy compliance during periods of information outbreaks. Instead, their adherence to procurement regulations appears to vary over time,

[20] In terms of the number of related posts, the ratio of content targeting government to content targeting firms is 3.84 in 2016 and 0.68 in 2018. In terms of word frequencies, the ratio is 7.19 in 2016 and 0.45 in 2018.

with periods of strict compliance followed by deviations from these regulations. We investigate whether this variability in local governments' adoption of open-bid procurement is associated with fluctuations in information flows on Weibo.

Table A9 reports the results of the OLS regressions of the per-capita numbers of Weibo posts (referencing vaccine and containing negative sentiment) in the preceding three months on the present vaccine procurement period from January 2014 to December 2019. The periods encompassed in this analysis exclude the Weibo-information outbreak periods spanning March to August 2016 and July to December 2018. The regressions account for city and time fixed effects, provincial time trends, as well as time-varying city characteristics. In line with our hypothesis that local government responsiveness is influenced by top-down pressure arising from anti-government sentiments on social media, we use relevant keywords to construct two distinct sub-samples of Weibo posts: (1) posts targeting the government and (2) posts targeting firms. Notably, we identify a strong correlation between the number of government-targeted posts (with a two-month lag) and the share (and frequency) of open-bid procurement (Columns (1)-(3)). However, this correlation vanishes when government-targeted posts are replaced with firm-targeted posts (Columns (4)-(6)). Although these results do not have causal implications, they, alongside the findings from the two event studies, highlight that information specifically pertaining to the government is a critical factor for social media to influence the behavior of local politicians in China.

6 Conclusion

Government accountability is a central issue in the debate about the competency of authoritarian regimes. The emergence of social media has led to a redistribution of political information, granting authoritarian leaders greater control over bottom-up information flow. In this paper, we demonstrate that social media serves as a channel to enhance the responsiveness and accountability of Chinese local governments in areas where the central government and the public share common interests, such as vaccine procurement. This finding aligns with the theoretical argument that authoritarian governments can improve their governance by allowing for freer information flows from the bottom up (e.g., Egorov et al., 2009; Lorentzen, 2014).

Furthermore, our study reveals that the social media effect on government responsiveness is predominantly driven by how local government responds to top-down pressure. We demonstrate four findings. First, the social media effect is more pronounced in cities with more recent anti-corruption allegations. Second, the effect is weaker in metropolitan areas and provincial capital cities, where political leaders face less top-down monitoring pressure despite higher demand for high-quality vaccines. Third, the social media effect is stronger in cities where political leaders are younger or in their early terms of tenure.

Last, the effect is also more pronounced in regions where pre-existing public information on social problems is scarcer. These findings substantiate the top-down-pressure mechanism—Public sentiment amplified through social media prompts local officials to be concerned about potential top-down inspections, which could jeopardize their careers. Thus, they are compelled to address public grievances and citizens' needs. This insight, in line with theoretical studies on authoritarian politics (e.g., Egorov and Sonin, 2023; Gehlbach et al., 2016; Xu, 2011), can likely be applied to other authoritarian contexts.

It may seem that, as long as governments respond to public opinion and citizen's concerns within their jurisdictions, the effect of social media in our study resembles the effect of a free media in democracies. Such a comparison, however, can be misleading. In a democratic system, a politician striving for re-election responds to media information that reflects citizens' needs. This response is likely localized, but it serves to address genuine preferences and solve real problems, as unsatisfied citizens will continue to provide information that holds politicians accountable. In contrast, a politician focused on career advancement in an autocracy reacts to media information that generates top-down monitoring pressure. This response can extend beyond a specific administration. Herein lies the power of social media, which swiftly disseminates information nationwide and triggers a cascade of reactions, even in regions where citizens' genuine concerns may not warrant such attention. The media effect, in this context, is a response to potential top-down intervention, which heightens the risk of policy rigidity. Local governments, driven by substantial top-down pressure, may overreact, leading to the failures of flexible policy adaptation. One striking example is China's exceptionally strict lockdown policies during the COVID-19 pandemic. In this sense, free information flows on social media, even if they do not pose a threat to the regime, act as a double-edged sword within an authoritarian regime.

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Figures and Tables

Figure 1: Time Trend of Weibo Posts on Vaccines

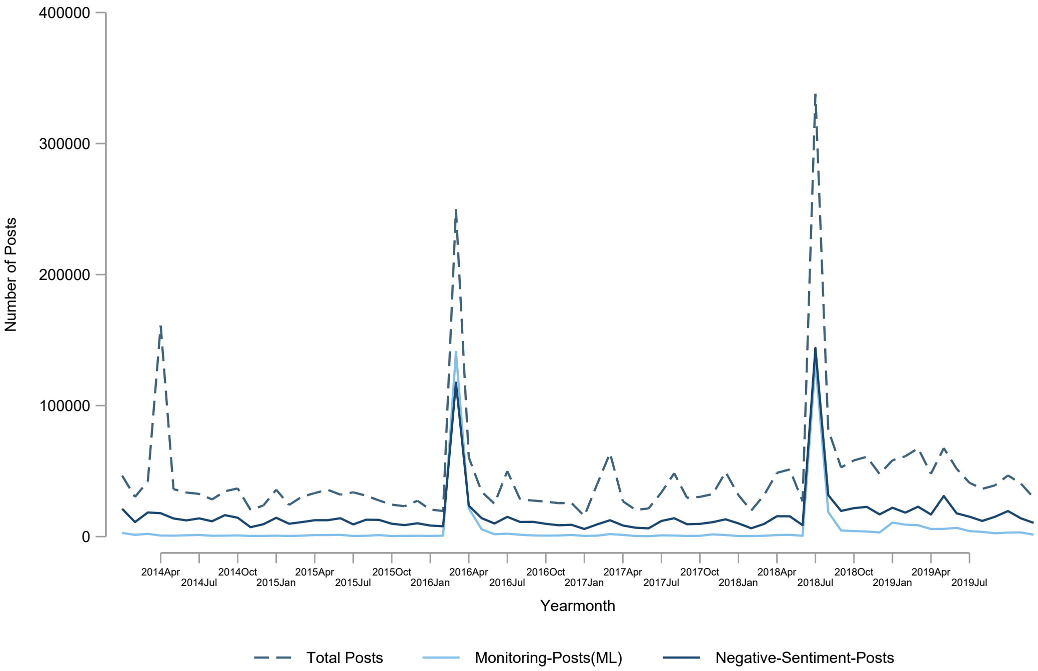


Figure 2: Changes in the Landscape of Monitoring Posts in 2016

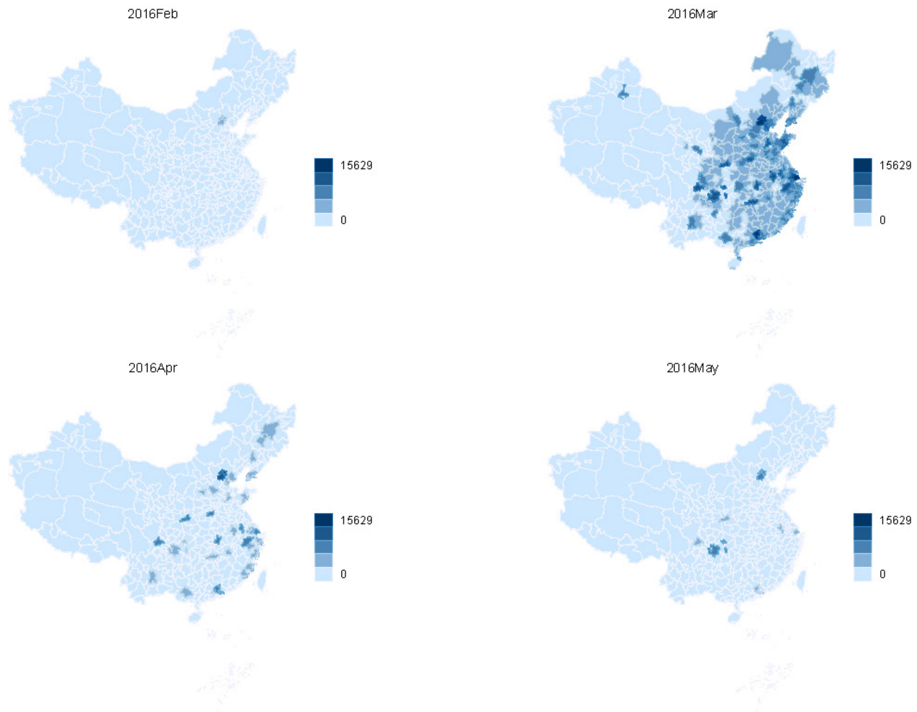


Figure 3: Dynamic Effects of the DID Estimation

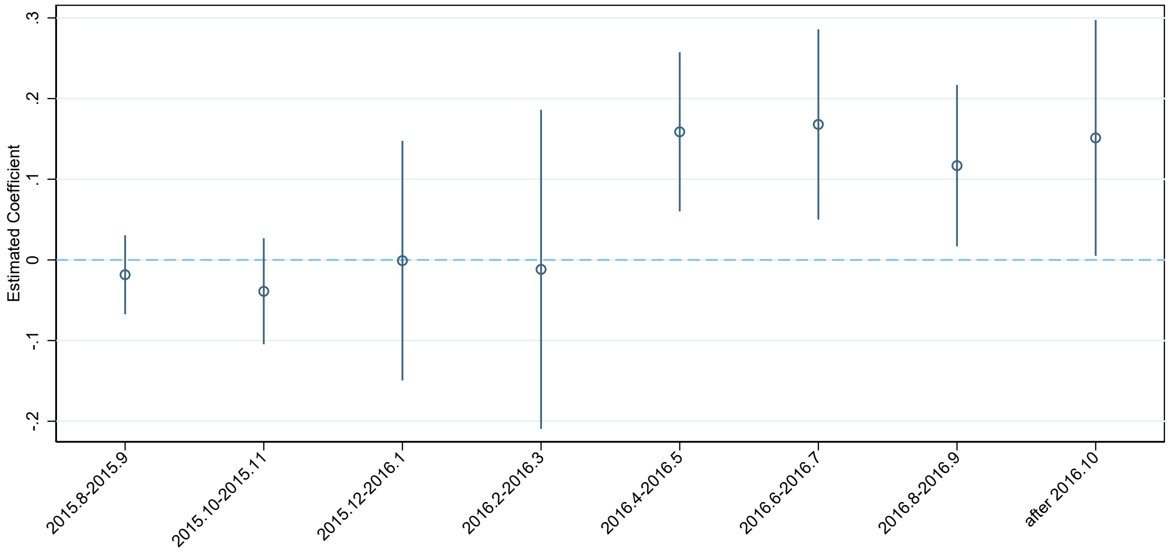


Table 1: Summary Statistics for Main Variables

	count	mean	sd	min	max
Procurement Variables					
Number of procured items	1630	6.640	13.849	1	200
Number of open-bid procurement	1630	4.292	12.225	0	200
Share of open-bid procurement	1630	0.530	0.473	0	1
Weibo Variables					
Total posts	17064	173.280	835.604	0	55422
Monitoring-Posts(ML)	17064	24.148	242.368	0	15629
Negative-Sentiment-Posts	17064	62.528	286.221	0	18138

Note: The unit of observation is city-month. The time frame is from January 2014 to December 2019. "Number of procured items" is the count of total procured items. "Number of open-bid procurement" is the count of open-bid procured items and "Share of open-bid procurement" is the share of open-bid procured items. "Total posts" is the count of posts referencing the Chinese word for vaccine. "Monitoring-Posts(ML)" is the count of posts referencing vaccine and having monitoring implications identified by a supervised machine learning approach. "Negative-Sentiment-Posts" is the count of posts referencing vaccine and containing a negative sentiment identified by automated sentiment analysis.

Table 2: Baseline Results of DID Estimation

Panel A: Share of open-bid procurement

	Overall		Category-I		Category-II and Supplement	
	(1) open bid	(2) open bid	(3) open bid	(4) open bid	(5) open bid	(6) open bid
WeiboShock × Event	0.103***	0.099***	0.006	−0077	0.133***	0.196***
	(0.020)	(0.029)	(0.065)	(0.053)	(0.033)	(0.035)
Observations	471	471	181	181	367	367
DV Mean	0.606	0.606	0.583	0.583	0.641	0.641
R^2	0.332	0.499	0.600	0.655	0.429	0.644
Regional FE	Province	Prefecture	Province	Prefecture	Province	Prefecture
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Frequency of procured items in different formats

	Overall		Category-I		Category-II and Supplement	
	(1) log(open)	(2) log(nonopen)	(3) log(open)	(4) log(nonopen)	(5) log(open)	(6) log(nonopen)
WeiboShock × Event	0.293***	−0029	−0064	0.146	0.299***	−0235***
	(0.065)	(0.064)	(0.165)	(0.139)	(0.091)	(0.080)
Observations	471	471	181	181	367	367
DV Mean	1.103	0.581	1.113	0.561	1.025	0.497
R^2	0.570	0.462	0.691	0.585	0.701	0.599
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Results of IV Estimation

	IV (Baseline)		OLS (Extended)		IV (Extended)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Cate-II and Suppl.	Overall	Cate-II and Suppl.	Overall	Cate-II and Suppl.
WeiboShock × Event	0.095**	0.188***	0.102	0.180**	0.090	0.169**
	(0.040)	(0.033)	(0.073)	(0.076)	(0.087)	(0.084)
Weibo2012 × Event			−0.003	0.016	0.006	0.024
			(0.057)	(0.067)	(0.066)	(0.080)
Observations	426	319	426	319	426	319
K-P rk Wald F statistic	244.439	244.039			39.306	53.315
Full Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. "Weibo2012" is measured by the per-capita number of Weibo posts (covering all kinds of subjects) in 2012. The interaction term "$WeiboShock_i \times Event_t$" is instrumented by the interaction term between residuals and "Event", where residuals are obtained from regressing Weibo penetration in Aug.–Oct. 2009 on the (log) numbers of college students per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, and (log) number of land-line users per capita in 2009. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Weibo Effect on Government Blogging by Topics

		Routine-work Posts			Accoutability Posts	
	(1)	(2)	(3)	(4)	(5)	(6)
	Overall	Topic1	Topic2	Topic3	Topic4	Topic5
WeiboShock(Daily) × 2016.3.18-2016.3.21	3.668***	−0.124**	0.167	0.218	2.403***	3.378***
	(0.711)	(0.049)	(0.137)	(0.181)	(0.438)	(0.535)
WeiboShock(Daily) × After 2016.3.22	1.285***	0.278***	0.185**	0.609***	0.318***	1.132***
	(0.271)	(0.096)	(0.086)	(0.114)	(0.098)	(0.269)
Observations	9840	9840	9840	9840	9840	9840
R^2	0.705	0.409	0.417	0.489	0.582	0.701
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-date level. The time window of the regression is from February 2016 to April 2016. "WeiboShock(Daily)" is measured by the difference between the per-capita number of monitoring posts published by users in a city on the day 2016.3.18 and the number of posts published one day before. "2016.3.18-2016.3.21" is a dummy that equals 1 if an observation is between 2016.3.18 and 2016.3.21 and 0 otherwise."After 2016.3.22" is a dummy that equals 1 if an observation is on and after 2016.3.22. Control variables include city fixed effects and date fixed effects. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Weibo Effect on Vaccine Procurement by Company Size and Locality

Panel A: Share in Terms of Procurement Frequency, Large Company

	Overall	Open Bid	Non-open Bid
	(1)	(2)	(3)
WeiboShock × Event	0.068**	0.118**	0.161***
	(0.029)	(0.049)	(0.049)
Observations	304	143	200
R^2	0.612	0.782	0.809
Full Baseline Controls	Yes	Yes	Yes

Panel B: Share in Terms of Procurement Frequency, Non-local Company

	Overall	Open Bid	Non-open Bid
	(1)	(2)	(3)
WeiboShock × Event	0.009	−0.033	0.105***
	(0.028)	(0.056)	(0.036)
Observations	304	143	200
R^2	0.541	0.696	0.656
Full Baseline Controls	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Evidence on Mechanisms: Heterogeneous Treatment Effects

Panel A: Top-down Inspection

	Overall	Category-II and Supplement
	(1)	(2)
WeiboShock × Event	0.102***	0.139***
	(0.036)	(0.037)
Inspection × Event	−0.081	−0.707***
	(0.290)	(0.265)
WeiboShock × Event × Inspection	−0.005	0.165***
	(0.065)	(0.057)
Observations	471	367
R^2	0.499	0.652
F Test (row1+row3=0)	0.075	0.000

Panel B: City Size and Rank

	Overall		Category-II and Supplement	
	(1)	(2)	(3)	(4)
WeiboShock × Event	0.582***	0.198*	0.596***	0.339***
	(0.167)	(0.103)	(0.199)	(0.113)
Metropolitan × Event	0.256		0.191	
	(0.212)		(0.291)	
WeiboShock × Event × Metropolitan	−0.478***		−0.393**	
	(0.164)		(0.196)	
High Rank × Event		0.202		0.288
		(0.293)		(0.300)
WeiboShock × Event × High Rank		−0.115		−0.168
		(0.108)		(0.117)
Observations	471	471	367	367
R^2	0.506	0.501	0.649	0.647
F Test (row1+row3/row5=0)	0.003	0.012	0.000	0.000

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. "Inspection" is a dummy that equals 1 if the number of anti-corruption allegations in a province within three years before the event is above the median level among all provinces. "Metropolitan" is a dummy that equals 1 if a city belongs to the top two city tiers and 0 otherwise. "High Rank" is a dummy that equals 1 if a city belongs to the four special municipalities or 15 sub-provincial cities and 0 otherwise. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Evidence on Mechanisms: Heterogeneous Treatment Effects (Cont'd)

Panel C: Career Concerns

	Overall		Category-II and Supplement	
	(1)	(2)	(3)	(4)
WeiboShock × Event	0.157***	−0.028	0.336***	−0.093
	(0.042)	(0.087)	(0.059)	(0.086)
Pre-retirement × Event	0.023		0.293	
	(0.205)		(0.252)	
WeiboShock × Event × Pre-retirement	−0.078		−0.201***	
	(0.049)		(0.068)	
First Term of Tenure × Event		−0.022		−1.319**
		(0.509)		(0.583)
WeiboShock × Event × First Term of Tenure		0.139		0.316***
		(0.090)		(0.093)
Observations	471	471	367	367
R^2	0.502	0.504	0.654	0.653
F Test (row1+row3/row5=0)	0.022	0.001	0.006	0.000

Panel D: Information Asymmetry

	Overall	Category-II and Supplement
	(1)	(2)
WeiboShock × Event	0.092***	0.194***
	(0.029)	(0.038)
Delete Post above Mean × Event	−0.353	−0.479*
	(0.265)	(0.282)
WeiboShock × Event × Delete Post above Mean	0.168	0.474***
	(0.222)	(0.160)
Observations	471	367
R^2	0.500	0.652
F Test (row1+row3=0)	0.251	0.000

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. "Pre-retirement" is a dummy that equals 1 if the age of the city mayor is above 54 and 0 otherwise. "First Term of Tenure" is a dummy that equals 1 if the city mayor is in his/her first tenure and 0 otherwise. "Delete Post above Mean" is a dummy that equals 1 if the proportion of posts being deleted is above the mean level of all provinces. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendices (Not for Publication)

A Additional Empirical Results

Figure A1: Information Eruption during the 2016 Event

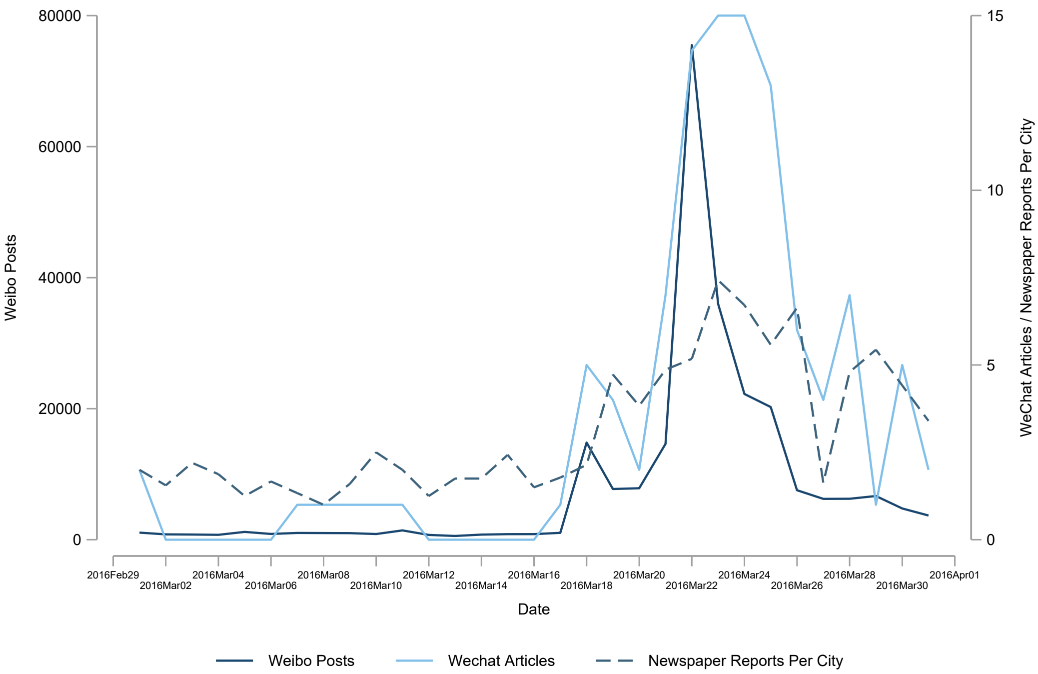


Figure A2: Age Distribution of Early Weibo Users

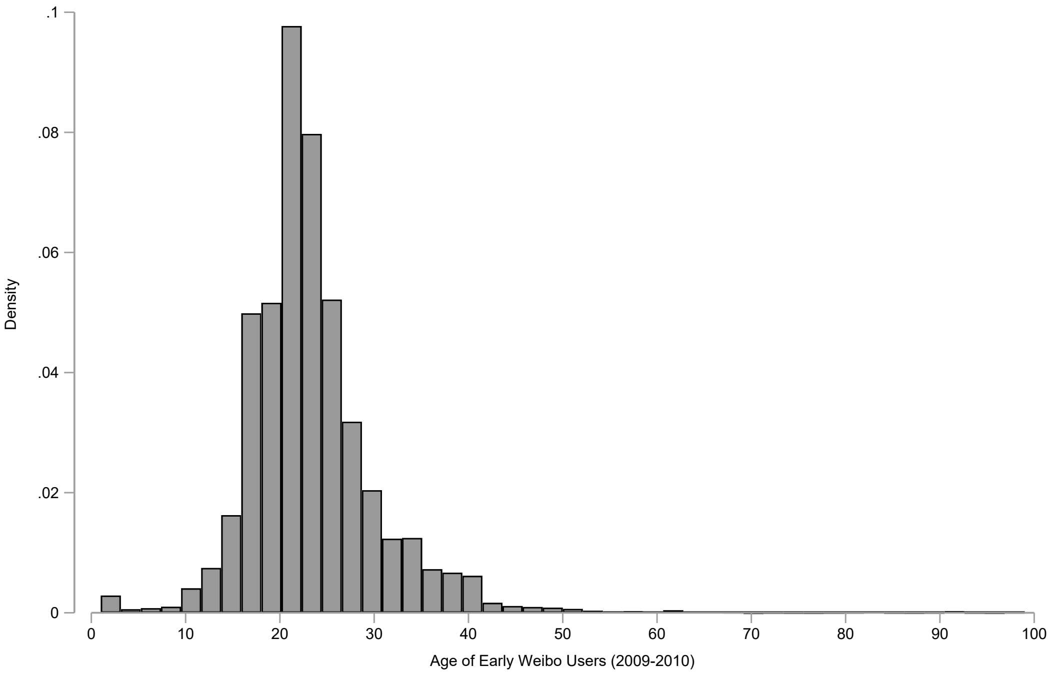
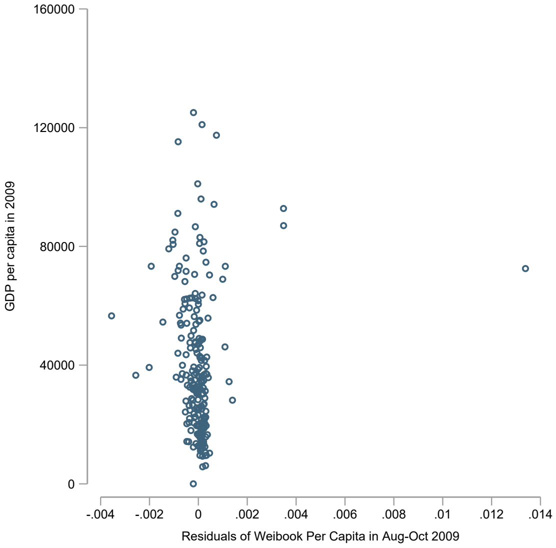
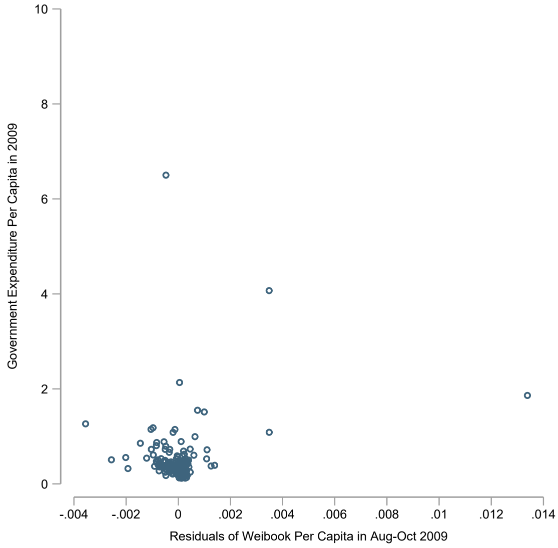


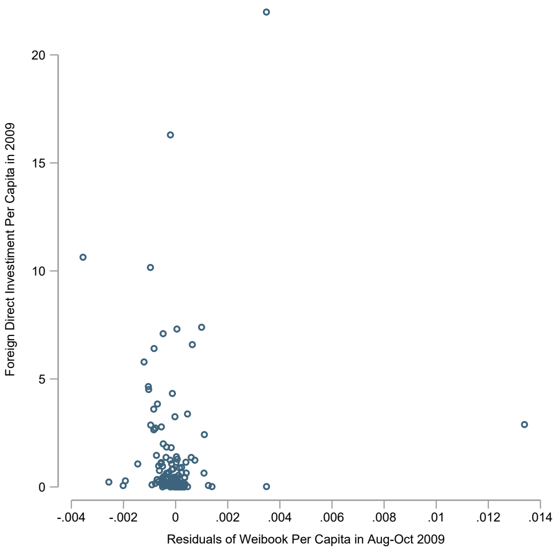
Figure A3: Randomness of Weibo Penetration



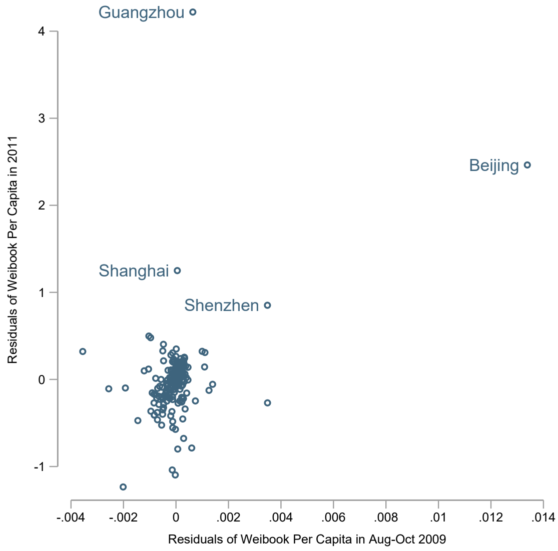
(a)



(b)



(c)



(d)

Figure A4: Key Opinion Leaders (KOLs) and Registration Time

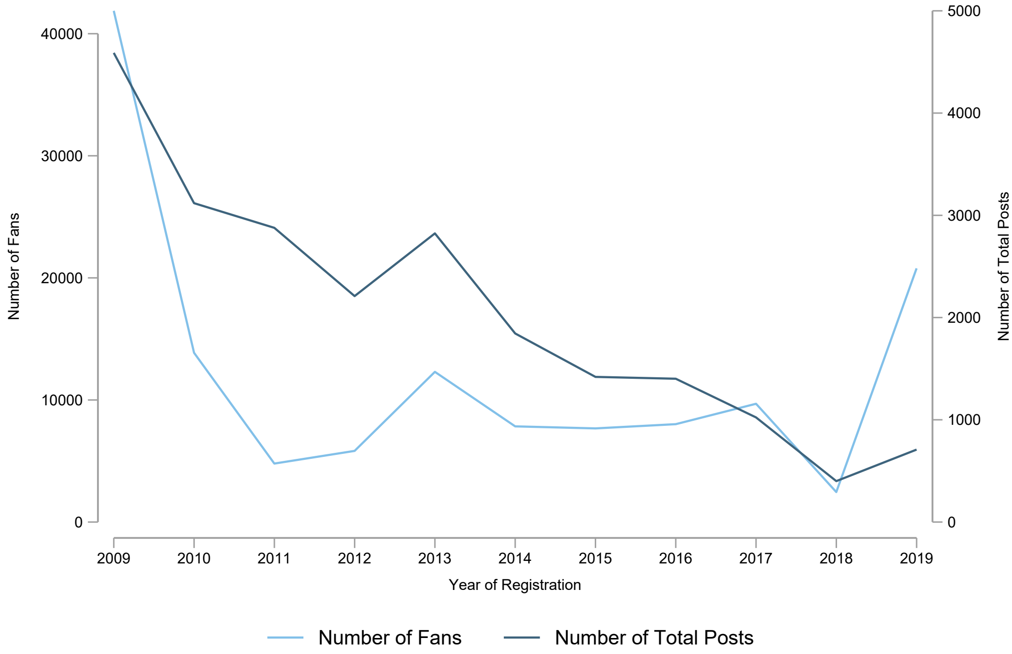


Figure A5: Dynamic DID Estimates by Procurement Sequence

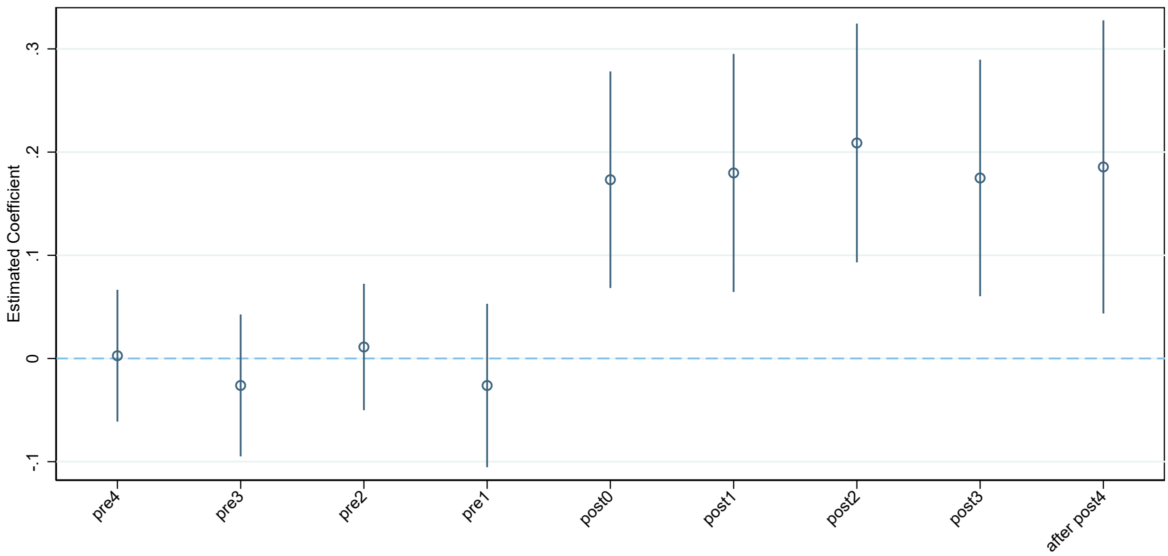
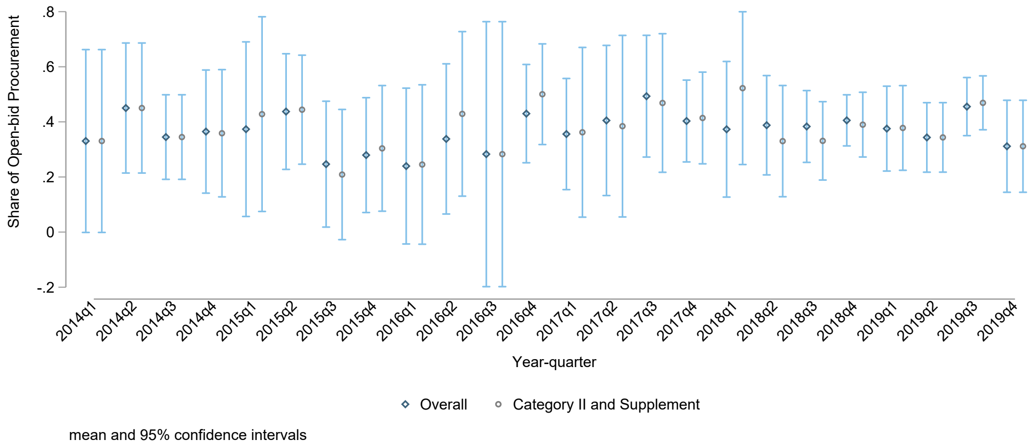
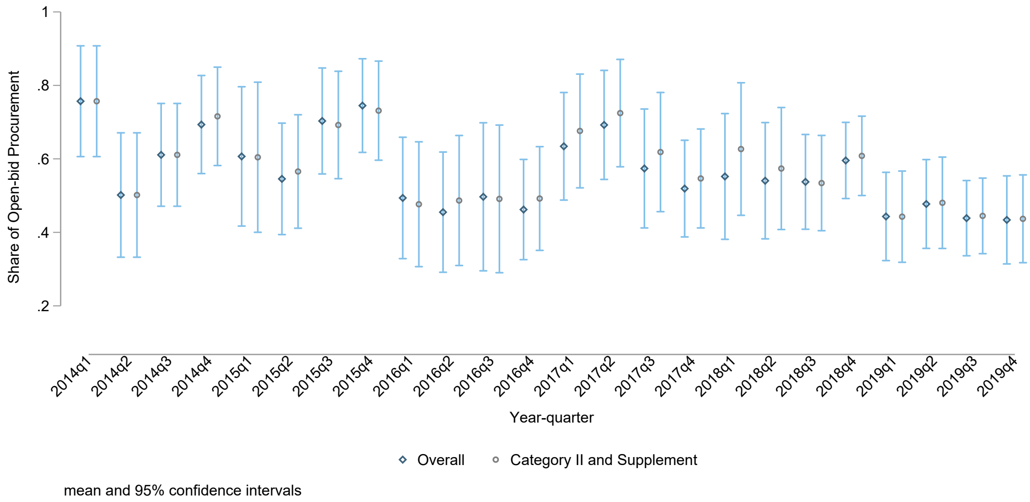


Figure A6: Share of Open-bid Procurement over Time



(a) within province



(b) overall

Table A1: Baseline Results of DID Estimation: Balanced Panel

	Overall		Category-I		Category-II and Supplement	
	(1)	(2)	(3)	(4)	(5)	(6)
	log(open)	log(nonopen)	log(open)	log(nonopen)	log(open)	log(nonopen)
WeiboShock × Event	0.037**	0.023	0.021*	0.024**	0.022*	0.001
	(0.016)	(0.014)	(0.012)	(0.010)	(0.013)	(0.012)
Observations	5375	5375	5375	5375	5375	5375
DV Mean	0.088	0.046	0.030	0.015	0.067	0.032
R^2	0.171	0.179	0.158	0.162	0.134	0.126
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Effect with Discrete Measure of Weibo Shock

	Overall		Category-I		Category-II and Supplement	
	(1)	(2)	(3)	(4)	(5)	(6)
	open bid	open bid	open bid	open bid	open bid	open bid
WeiboShockDmy × Event	0.309***	0.385**	0.397**	−0.371	0.314***	0.488*
	(0.093)	(0.188)	(0.184)	(0.365)	(0.104)	(0.267)
WeiboShockDmy	0.027		−0.348*		0.087	
	(0.097)		(0.193)		(0.102)	
Event	−0.363***		−0.495***		−0.339***	
	(0.078)		(0.165)		(0.085)	
Observations	471	471	181	181	367	367
R^2	0.095	0.495	0.135	0.656	0.118	0.624
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	Yes	No	Yes	No	Yesd
Year-Month FE	No	Yes	No	Yes	No	Yes
Provincial Time Trend	No	Yes	No	Yes	No	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShockDmy" is a dummy variable indicating that the Weibo Shock (the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event) is above the mean level among all cities. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Dynamics Effect of DID Estimation

	Overall	Category-II and Supplement
	(1)	(2)
WeiboShock × 2015.11	0.032	−0.002
	(0.041)	(0.053)
WeiboShock × 2015.12	−0.039	0.059
	(0.126)	(0.112)
WeiboShock × 2016.01	−0.034	0.051
	(0.084)	(0.063)
WeiboShock × 2016.02	−0.061	−0.022
	(0.077)	(0.069)
WeiboShock × 2016.03	−0.013	0.161
	(0.110)	(0.183)
WeiboShock × 2016.04	0.023	0.126**
	(0.057)	(0.057)
WeiboShock × 2016.05	0.160***	0.204***
	(0.037)	(0.049)
WeiboShock × 2016.06	0.071	0.267***
	(0.047)	(0.066)
WeiboShock × after 2016.07	0.092	0.170***
	(0.056)	(0.054)
Observations	471	367
R^2	0.511	0.652
Full Baseline Controls	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. The time period variables are a set of dummies that equals 1 if an observation is within the specific time period indicated by the timing variable name and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: First Stage of IV Estimation

	IV (Baseline)		IV (Extended)	
	(1) Overall	(2) Cate-II and Suppl.	(3) Overall	(4) Cate-II and Suppl.
Residuals(penetration) × Event	0.713***	0.680***	0.356***	0.359***
	(0.046)	(0.043)	(0.057)	(0.049)
Weibo2012 × Event			0.613***	0.610***
			(0.072)	(0.075)
Observations	426	319	426	319
F Statistic	243.440	244.040	39.310	53.310
City Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Residuals(penetration)" are obtained from regressing Weibo penetration in Aug.-Oct. 2009 on the (log) numbers of college students per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, and (log) number of land-line users per capita in 2009. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "Weibo2012" is measured by the per-capita number of Weibo posts (covering all kinds of subjects) in 2012. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Robustness Checks

Panel A: Event Effect

	Overall		Category-II and Supplement	
	(1)	(2)	(3)	(4)
WeiboShock × Event		0.100***		0.196***
		(0.028)		(0.037)
Province Involved × Event	0.013	−0.061	0.187	−0.001
	(0.218)	(0.211)	(0.223)	(0.239)
Observations	471	471	367	367
R^2	0.489	0.499	0.617	0.644
Full Baseline Controls	Yes	Yes	Yes	Yes

Panel B: Policy Effect

	Overall		Category-II and Supplement	
	(1)	(2)	(3)	(4)
WeiboShock × Event		0.102***		0.193***
		(0.030)		(0.036)
WeiboShock × Vaccine Policy	0.036**	0.040**	0.041**	0.032
	(0.017)	(0.017)	(0.020)	(0.024)
Observations	471	471	367	367
R^2	0.491	0.502	0.619	0.646
Full Baseline Controls	Yes	Yes	Yes	Yes

Panel C: Other Information Channels

	Overall		Category-II and Supplements	
	(1)	(2)	(3)	(4)
WeiboShock × Event	0.127**	0.089*	0.172*	0.164***
	(0.054)	(0.046)	(0.090)	(0.047)
Newspaper Shock × Event	0.008		0.021	
	(0.022)		(0.041)	
Search Index Shock × Event		0.059		0.223
		(0.237)		(0.233)
Observations	180	471	126	367
R^2	0.441	0.499	0.676	0.646
Full Baseline Controls	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. "Newspaper Shock" (or "Search Index Shock") is similarly defined using the number of newspaper reports (or the per-capita Baidu search index) in lieu of the number of relevant Weibo posts. "Province Involved" is a dummy that equals 1 if a city is located in a province that was affected by the company involved in the vaccine scandal.. "Vaccine Policy" is a set of dummy variables measuring the timing of the implementation of the new vaccine policy in each province. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effect on Vaccine Procurement by Company Size and Locality

Panel A: Share in Terms of Winning Value, Large Company

	Overall	Open Bid	Non-open Bid
	(1)	(2)	(3)
WeiboShock × Event	0.001	0.295***	0.097
	(0.046)	(0.071)	(0.114)
Observations	243	121	149
R^2	0.590	0.809	0.842
Full Baseline Controls	Yes	Yes	Yes

Panel B: Share in Terms of Winning Value, Non-local Company

	Overall	Open Bid	Non-open Bid
	(1)	(2)	(3)
WeiboShock × Event	−0.033	−0.013	0.075
	(0.043)	(0.093)	(0.114)
Observations	243	121	149
R^2	0.502	0.765	0.707
Full Baseline Controls	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effect on the Duration of Procurement

	Overall	Open Bid	Non-open Bid
	(1)	(2)	(3)
	log(days)	log(days)	log(days)
WeiboShock × Event	0.324***	0.362***	0.122
	(0.078)	(0.097)	(0.093)
Observations	471	471	470
R^2	0.543	0.502	0.518
Full Baseline Controls	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from March 2015 to March 2017. The duration of open-bid procurement refers to the time frame starting from the announcement date of procurement and ending on the expiration date of the announcement notice, which usually coincides with the procurement deadline. Given that the duration of other types of procurement cannot be defined in the same way, the result in Column 3 should be interpreted with caution. "Event" is a dummy that equals 1 if an observation is in and after the event month (March 2016) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. Full baseline controls include time-variant city characteristics as well as year-month fixed effects, city fixed effects, and provincial time trends. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Effect of Weibo Shock during the Vaccine Scandal in 2018

	Overall		Category-I		Category-II and Supplement	
	(1)	(2)	(3)	(4)	(5)	(6)
	open bid	open bid	open bid	open bid	open bid	open bid
WeiboShock × Event	−0014	0.006	0.068	0.036	−0028	−0011
	(0.021)	(0.029)	(0.124)	(0.110)	(0.022)	(0.023)
Observations	564	564	166	166	484	484
DV Mean	0.512	0.512	0.439	0.439	0.568	0.568
R^2	0.210	0.453	0.494	0.520	0.266	0.545
Regional FE	Province	Prefecture	Province	Prefecture	Province	Prefecture
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from November 2017 to July 2019. The starting month is not extended to an earlier period to avoid overlapping with a precedent mild information outbreak. The ending month is chosen for practical reasons to ensure enough observations in the panel regression with city fixed effects. "Event" is a dummy that equals 1 if an observation is in and after the event month (July 2018) and 0 otherwise. "WeiboShock" is measured by the difference between the per-capita number of monitoring posts published by users in a city in the event month and the average number of posts published three months before the event. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Correlation between Weibo Posts and Government Procurement

	(1) log(open)	(2) log(nonopen)	(3) openshare	(4) log(open)	(5) log(nonopen)	(6) openshare
L1.#govt-specific posts pca	−0179	−0000	−0078			
	(0.167)	(0.162)	(0.136)			
L2.#govt-specific posts pca	0.500***	−0193	0.263**			
	(0.166)	(0.251)	(0.124)			
L3.#govt-specific posts pca	−0322*	0.048	−0046			
	(0.187)	(0.108)	(0.085)			
L1.#firm-specific posts pca				0.164	−0254	0.159
				(0.421)	(0.329)	(0.190)
L2.#firm-specific posts pca				0.411	0.636*	−0066
				(0.414)	(0.355)	(0.166)
L3.#firm-specific posts pca				−0416**	−0252	−0010
				(0.196)	(0.198)	(0.106)
Observations	1185	1185	1185	1185	1185	1185
R^2	0.330	0.243	0.314	0.328	0.244	0.310
City Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial Time Trend	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are at the city-month level. The time window of the regression is from January 2014 to December 2019, excluding the Weibo-information outbreak periods of March-August 2016 and July-December 2018. "L1.#govt-specific posts pca" is one-period lag of the per-capita number of negative-sentiment posts referring vaccine and specifically targeting government. "L2.#govt-specific posts pca" and "L3.#govt-specific posts pca" are similarly defined with two-period and three-period lags of the per-capita number of posts, respectively. "L1.#firm-specific posts pca" is one-period lag of the per-capita number of negative-sentiment posts referring vaccine and specifically targeting firms. "L2.#firm-specific posts pca" and "L3.#firm-specific posts pca" are similarly defined with two-period and three-period lags of the per-capita number of posts, respectively. The time-variant city characteristics include the (log) population density, (log) GDP per capita, (log) government expenditure per capita, (log) foreign direct investment per capita, (log) number of internet users per capita, (log) number of mobile phone users per capita, (log) number of land-line users per capita, (log) number of students per capita, the share of college students among all students, and the share of the secondary industry in GDP. Standard errors (in parentheses) are clustered by city.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B Details on Textual Analysis

In this section, we provide details on the textual analysis process, which yields two crucial inputs for our empirical analysis: (1) monitoring posts, which are Weibo posts that capture public grievances and have the potential to monitor government behavior and (2) government posts, referring to posts published by government entities.

B.1 Monitoring Posts

We employ two commonly used machine-learning methods to identify the monitoring posts. Our objective is to simulate the functionality of the massive-information-monitoring software or AI systems utilized by Chinese local governments. Based on insights gathered from interviews with industry experts, sentiment analysis and the support-vector-machine (SVM) algorithm are the most prevalent methods employed by social media information-monitoring software.[1]

B.1.1 Sentiment Analysis

We employed sentiment analysis on all Weibo posts mentioning "vaccine" within our sample period (2014-2019). To facilitate this analysis, we used HowNet, a pre-trained dictionary widely used in natural language processing in the Chinese context, to identify sentiment words.[2] For sentiment calculation, we employed a straightforward approach known as sentiment word-count. The sentiment polarity of a given text is determined by the difference in the count of negative words and positive words. A higher sentiment score in a post indicates a stronger negative sentiment.

B.1.2 Classification

We used a binary classification method to distinguish monitoring posts from other posts. Initially, we obtained a random sample of 12,000 posts from our Weibo data, specifically from the year 2016, which was the focal year of the scandal examined in our study.[3] A preliminary sample of 1,000 Weibo posts was manually labeled to identify monitoring content, assigning a label of 1 to posts with monitoring content and 0 to others. Based on the experience gained from this pilot sample, we developed a comprehensive instruction for the labeling task. Subsequently, two research assistants were hired to

[1] Although more advanced techniques such as neural networks and reinforcement learning could potentially enhance the accuracy of classifying monitoring posts, they were less commonly utilized by massive-information monitoring software during our sample period.

[2] Several other Chinese dictionaries are available for sentiment analysis, including the Chinese Sentiment Word Weight Table from BoYuan of Tsinghua University, the Chinese Emotional Vocabulary developed by Dalian University of Technology Information Research Laboratory, and the National Taiwan University Sentiment Dictionary. All these other dictionaries produce similar sentiment analysis results.

[3] To ensure an adequate number of monitoring posts, we limited our post selection to the year 2016. This decision was made to address the potential scarcity of monitoring posts during non-scandal periods. By focusing on 2016, we were able to capture the variation in monitoring posts specifically during the event period within that year.

independently label the remaining 11,000 Weibo posts in the random sample following the provided instructions. Approximately 87% of the posts received the same label from both research assistants. In cases where inconsistencies arose, we resolved them through careful reading and discussion. Ultimately, the labeled dataset consisted of 4,633 monitoring posts, which accounted for 38.61% of the entire sample.

The labeled dataset was divided into 10 folds, with 7 folds used for training and 3 folds for testing purposes. Pre-processing of the data involved segmenting the text and removing alphabets, numbers, punctuation, and other irrelevant characters. The corpus was then vectorized into a word frequency matrix. We applied various machine-learning algorithms, including Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Decision Tree, Random Forest, and AdaBoost, to train the classifier. As depicted in Figure B2, SVM demonstrated superior performance in terms of both recall and precision. This advantage of SVM has been observed in other classification tasks as well, particularly in the classification of short social media posts (Dumais et al., 1998; Joachims, 1998; Sebastiani, 2002).

Hence, we selected SVM as the baseline algorithm for classifying the monitoring posts. Figure B3a presents the confusion matrix, while Figure B3b displays the Receiver Operating Characteristic (ROC) curve and the Precision-Recall curve. Both figures demonstrate that the SVM classifier exhibits a good fit and achieves a high level of classification accuracy. Subsequently, we apply the trained SVM classifier to predict the labels of posts in our entire dataset. These predicted monitoring posts are used to calculate the regional variation in the Weibo shock for our empirical analysis. As shown in Figure B4, at the city level, this measure of monitoring posts demonstrates a strong correlation with the negative-sentiment posts identified through our sentiment analysis.

B.2 Government Posts

A straightforward approach to identifying government posts is through user information. Official government accounts on Weibo are typically operated by users whose profiles clearly indicate their identity, such as a specific government division. However, relying solely on user names to identify government posts may lead to an underestimation of the number of posts published by governments, as some government entities may use private user names or require government employees to post official messages. To address this issue, we employ a machine-learning approach to identify government posts.

B.2.1 Classification

We employed a similar supervised machine learning approach to classify government posts as we did for monitoring posts. The key is to create an accurately labeled sample to train the classifier. We used two methods to label a selective sample of 12,000 posts from our vaccine dataset.[4] The first method relied on user information, where a post was labeled as a government post if it was published by a user with a clear indication of government identity in their user profiles. The second method involved manual coding based on the content of the post, determining whether it discussed messages and announcements from the government. Two research assistants independently labeled the selected posts, achieving a high consistency rate of 94%. In the final dataset used for machine learning, 22.84% (3287 posts) were identified as government posts.

Similarly, we divided the labeled dataset into 10 folds, using seven folds for training and three folds for testing. SVM was employed once again for the classification of government posts, yielding a very high accuracy.

B.2.2 Topic Modeling

In Section 4.4.1 of the paper, we conducted an analysis of governments' blogging activities in response to the information outbreak. In order to gain a deeper understanding of the content of government posts, we used the Latent Dirichlet Allocation (LDA) topic modelling method. By applying LDA to the government posts obtained through the aforementioned textual classification process, we were able to uncover the underlying topics and themes present in these posts. LDA is a widely employed unsupervised machine learning technique in textual analysis within the Chinese context.

In the baseline version of LDA, we opted for five topics to analyze the content of government posts. This choice was motivated by the simplicity and concentration of the posts, allowing for easier interpretation. Figure B5 presents the distribution of the top 10 words for each topic. The first line displays the Chinese words, the second line provides their English translation, and the third line shows the proportion of each word contributing to the topic. Topic 1 primarily revolves around words such as *work, carry out, preventive vaccination*, indicating a focus on government routine work. Topics 2 and 3 mainly consist of specific vaccine names and vaccination-related terms. On the other hand, Topics 4 and 5 exhibit distinct characteristics. Topic 4 includes words such as *problem, children (kids), parents, and flow*, suggesting a connection to vaccine safety. Topic 5 clearly relates to the government's response to vaccine issues, as evidenced by words like *illegal (business), legal cases, FDA, Bureau of General Administration, and announcement*. Based on the interpretation of the topic words, we classify Topics 1-3 as pertaining to government routine work and Topics 4-5 as relating to vaccine safety and government accountability. Since each post is associated with a probability distribution of topic weights, we assign a post to a specific topic based on the highest topic weight. For example, if Topic 1 carries the highest weight in a post, we classify the post as belonging

[4] Because government posts account for only a small fraction of our dataset, using a randomly selected sample will lead to substantial asymmetries between the two classes in our classification exercise. Therefore, I used a selective sample to increase the representation of government posts in the training data.

to Topic 1. Following this post-topic assignment, we label posts under Topics 4 and 5 as "accountability po and those under Topics 1-3 as "routine-work posts." These measures are employed in the regression analysis presented in Section 4.4.1.

In alternative versions of LDA, we explored different numbers of topics. Despite varying the number of topics to 10 or more, the distinction between "routine-work" and "accountability" topics remained clear.

References

Dumais, S., J. Platt, D. Heckerman, and M. Sahami (1998). Inductive Learning Algorithms and Representations for Text Categorization. *Proceedings of the Seventh International Conference on Information and Knowledge Management*, 148–155.

Joachims, T. (1998). Making large-scale SVM learning practical. Technical report.

Sebastiani, F. (2002). Machine Learning in Automated Text Categorization. *ACM Computing Surveys 34*(1), 1–47.

Figure B1: Machine Learning Procedure

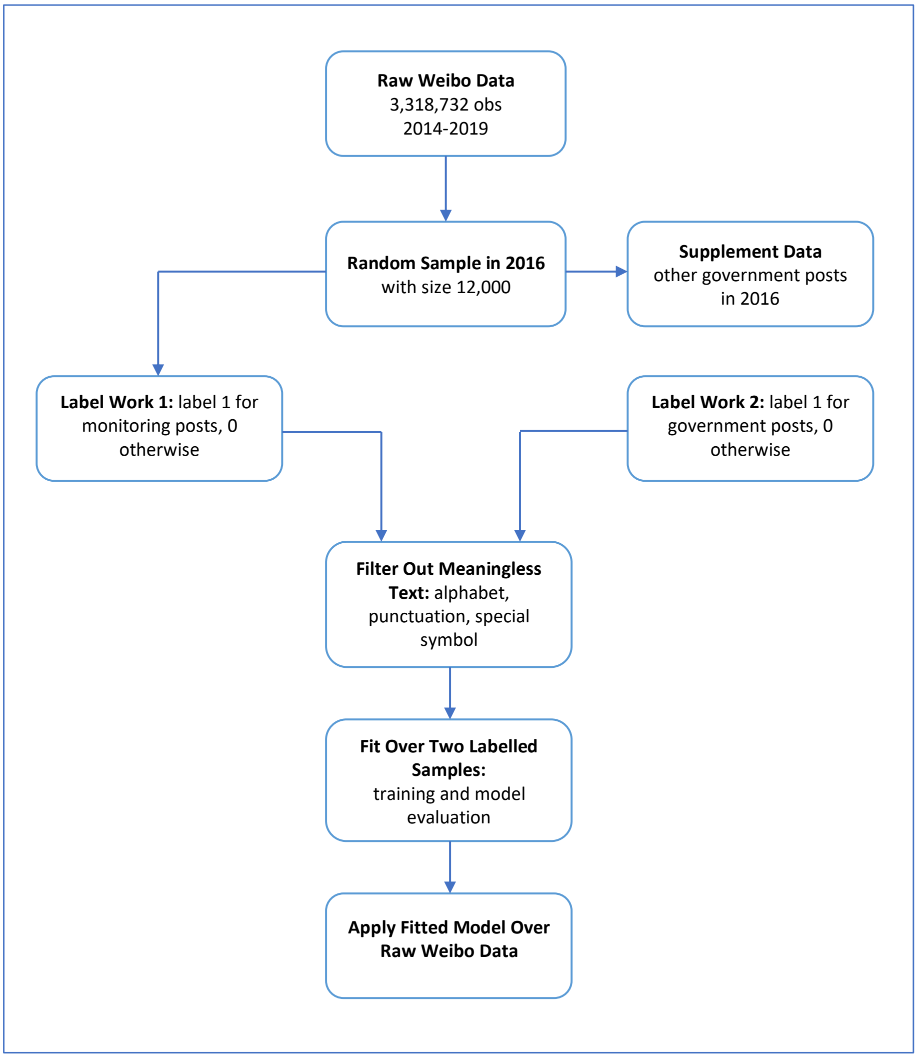


Figure B2: Comparison of Model Performance

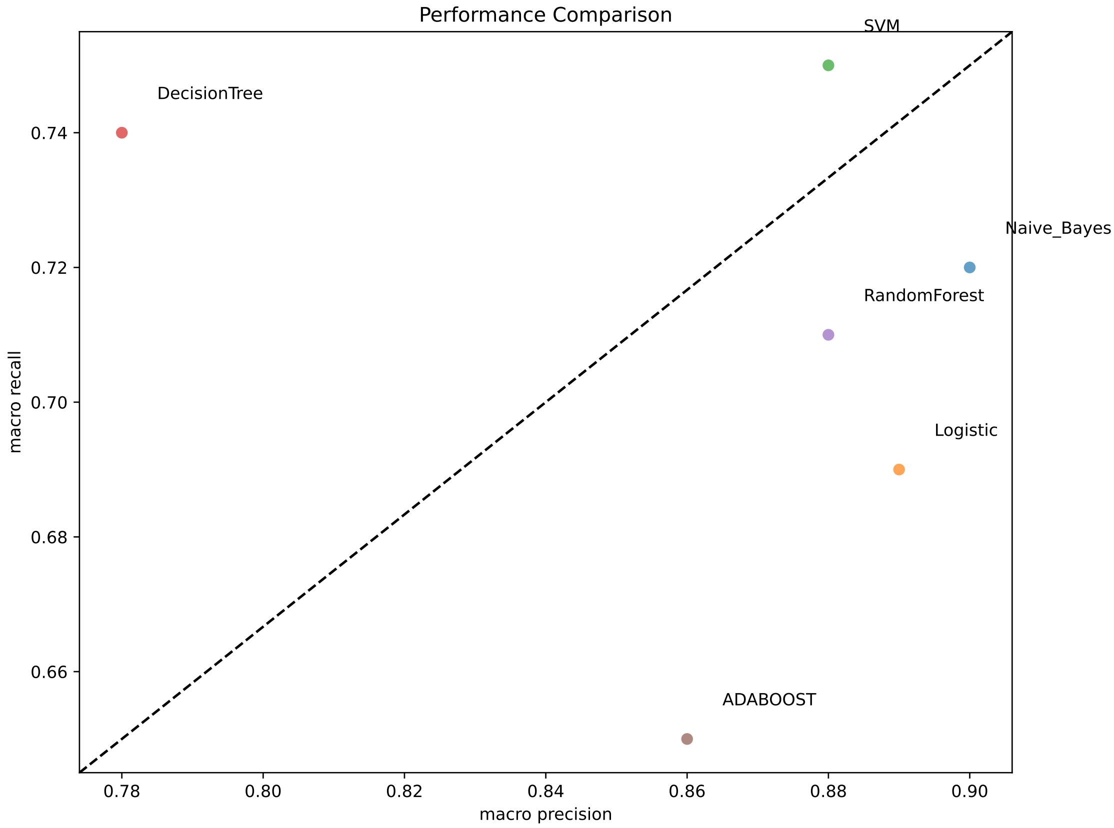
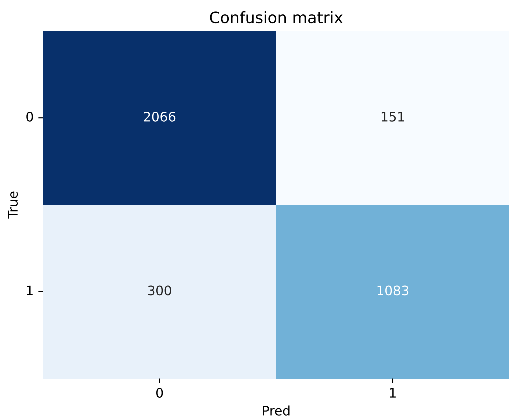
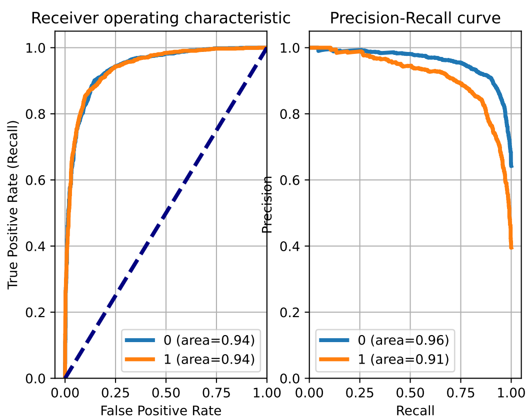


Figure B3: Performance Evaluation for Trained SVM Model



(a) Confusion Matrix



(b) ROC Curve and PR Curve

Figure B4: Correlation between Monitoring-Posts(ML) and Negative-Sentiment-Posts

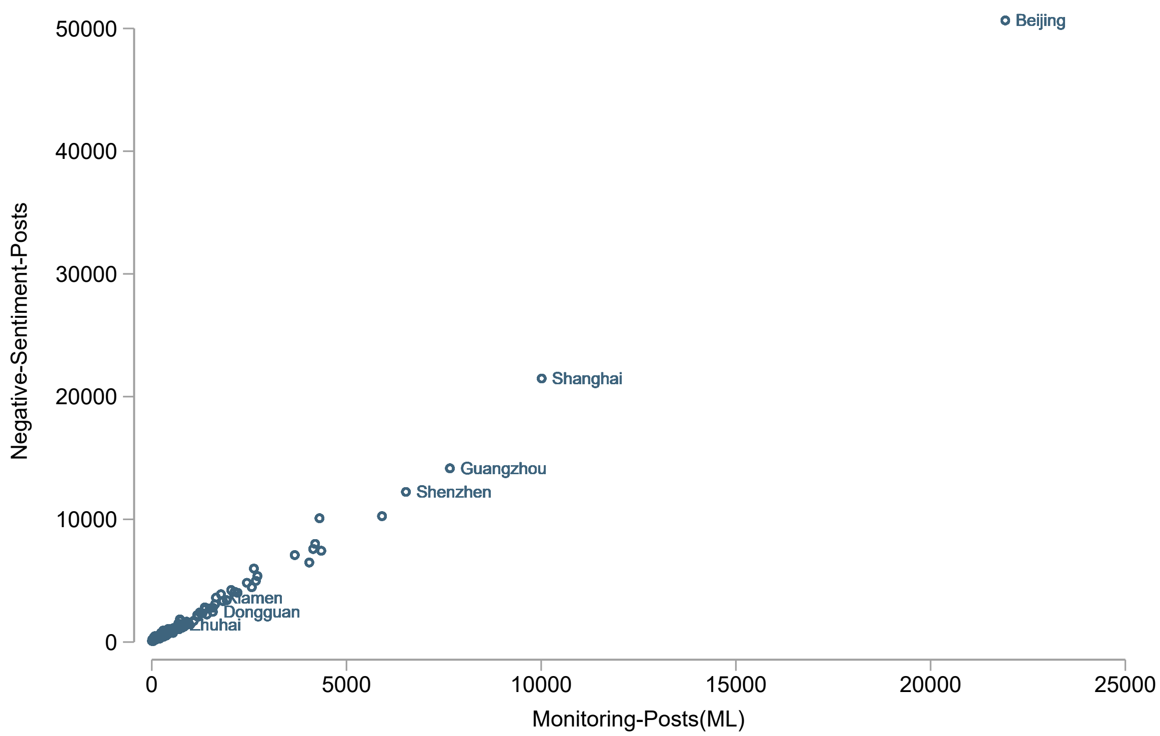


Figure B5: Words Distribution of Each Topic

Topic	Top 10 Words									
	接种	工作	免疫	开展	进行	检查	流感	预防接种	免费	疾病
1	vaccination	work	immune	carry out	proceed	inspection	flu	preventive vaccination	free	disease
	0.039	0.015	0.012	0.011	0.010	0.010	0.010	0.009	0.008	0.008
	接种	狂犬病	预防	麻疹	补种	注射	咬伤	病毒	反应	出现
2	vaccination	rabies	prevent	measles	revaccinate	injection	bite	virus	react	appear
	0.022	0.018	0.014	0.013	0.009	0.008	0.008	0.007	0.007	0.007
	接种	活疫苗	预防	脊灰	国务院	脊髓灰质炎	国家	链接	网页	减毒
3	vaccination	valid vaccines	prevent	polio	state department	poliomyelitis	country	link	website	attenuation
	0.020	0.014	0.013	0.013	0.010	0.009	0.009	0.009	0.009	0.008
	接种	问题	疾控中心	儿童	预防接种	家长	孩子	手足口	门诊	流入
4	vaccination	problem	CDCs	children	preventive vaccination	parents	kids	hand-foot-mouth	outpatient service	flow
	0.052	0.016	0.016	0.014	0.013	0.011	0.011	0.010	0.010	0.009
	山东	非法经营	非法	公布	涉案	问题	食药监	总局	案件	药品
5	Shandong	illegal business	illegal	announce	involve the case	problem	FDA	general administration	law case	drug
	0.037	0.029	0.022	0.018	0.016	0.014	0.013	0.013	0.011	0.010