Crisis Control in Top-down Bureaucracy: Evidence from China's Zero-Covid Policy

Da Gong* Andong Yan† Ziao Zhao ‡

November 1, 2023

Abstract

This study investigates the compliance of local Chinese officials with the zero-Covid policy throughout the COVID-19 pandemic. By examining biographical data from political elites and using a prefecture-day data set on risk levels – an indicator reflecting the status of zero-Covid policy - we discover a significant impact of prefecture leaders' promotion incentives on their response to COVID-19 outbreaks. Our empirical analysis reveals that leaders with stronger promotion incentives tend to exhibit increased reactions to emerging cases. Evidence shows that such a phenomenon is driven by the different choices of the prefecture leaders facing relatively larger-scale COVID-19 outbreaks. Furthermore, local governors whose jurisdictions are more economically developed tend to enforce more stringent mobility restrictions. However, for prefecture leaders who oversee more developed regions and possess strong promotion incentives, the combined effects of these two factors tend to balance each other out in terms of pandemic response. These results suggest a natural tension between demands for crisis management during the pandemic and routine performance in economic development within the political framework of China.

*Department of Economics, University of California, Riverside, E-mail: dgong005@ucr.edu

†Department of Economics, University of California, Riverside, E-mail: ayan013@ucr.edu

‡Department of Economics, University of Wisconsin-Madison

1 Introduction

The COVID-19 pandemic has had a profound impact on general economic activity, with restrictions on human mobility, ban on social gatherings, and closing of businesses. Recent literature has explored the economic consequences of the pandemic, such as unemployment, consumer spending, labor demand, and pollution. However, our understanding of how governments determine policies to combat the pandemic remains limited. This question is particularly complex in the context of China, which has a centralized, top-down hierarchical government structure. Although the central government prioritizes economic growth and evaluates the performance of local governments based on their GDP growth, the COVID-19 pandemic requires a slowing of economic development to curb the spread of the virus. This situation creates a tension between routine tasks and crisis control within the bureaucratic system. Our aim is to address this gap in the literature.

This paper examines the compliance of local Chinese officials with the zero-Covid policy during the COVID-19 pandemic. In China's political system, a conventional rule stipulates that governors at the prefecture level who are 58 years old or older become ineligible for further promotion. Consequently, officials whose ages are approaching this promotion eligibility threshold exhibit particularly strong incentives for advancement. Through an analysis of biographical data from prefecture party secretaries and a database at the prefecture-day level detailing the implementation of the zero-Covid policy, we find a significant influence of promotion incentives on the response of these leaders to COVID-19 outbreaks. Our empirical findings indicate that leaders with higher promotion prospects tend to exhibit an exaggerated response to emerging cases and maintain zero-Covid measures for extended periods. Compared to prefectures governed by leaders with fewer promotion incentives, those led by individuals with strong promotion incentives had a 0.727% higher chance of implementing the zero-Covid policy for every 7-day average daily case.

Interestingly, we observe a diminishing of these promotion incentives in regions that are more economically developed, signifying that these prefecture leaders have to pick a balance point between the mandate of pandemic control and the potential hazard to economic prosperity. Further analysis unveils that following the initiation of the zero-Covid policy, party secretaries with strong promotion incentives tend to enforce even stricter restrictions on traffic mobility when their jurisdictions are more economically developed, underscoring their desire to expedite pandemic containment to minimize its impact on the economy.

Our research contributes to three strands of literature. First, our research speaks to the studies on governance within a top-down bureaucracy, particularly when the system involves multitasking agency problems. Theoretically, within the multitasking framework, an agent will prioritize tasks that are strongly incentivized by clearly observed outcomes over poorly measurable, weakly incentivized ones (Holmstrom and Milgrom, 1991; Baker, 1992; Hart et al., 1997; Dewatripont et al., 1999). Whether governments could monitor their officials' multitasking efforts could significantly alter the execution of public policies and, subsequently, the overall social welfare (Dixit et al., 1997; Dixit, 2002).

However, for local officials facing multitasking in a pandemic scenario, the prediction is ambiguous, especially when efforts to contain the virus's spread could profoundly hurt economic development. Although rigorous anti-contagion measures may curb the pandemic's spread, the economic slowdown is evident, contrasting with the more intangible and less measurable efforts devoted to pandemic containment. Nevertheless, without prompt and effective interventions, the exponentially growing cases become another unwelcome outcome that local leaders aim to avoid. Our research sheds light on this complex multitasking circumstance, highlighting the deliberate balance that local officials strive to achieve between these competing priorities.

Second, our study contributes to the extensive body of literature examining the incentive role of personnel control in China's governance. Past studies indicate that local officials' drive for promotion in China has enhanced economic administration efficiency (Maskin et al., 2000; Blanchard and Shleifer, 2001; Li and Zhou, 2005). Empirical evidence also supports that local GDP performance stands as a pivotal benchmark for officials with marked promotion aspirations (Li and Zhou, 2005; Chen et al., 2005; Yao and Zhang, 2015). Given the outbreak of an unparalleled pandemic, one might wonder the efficacy of China's personnel-driven political system in crisis mitigation. Our study provides an affirmative answer to this question.

Moreover, zero-Covid policy is economically costly (Chen et al., 2022; Ke and Hsiao, 2022; Gong et al., 2022, 2023). This raises concerns about whether personal political incentives might spur local officials into outrageous actions, risking potential backfires. Existing literature indicates that political incentives can sometimes transform into policy radicalism detrimental to society at large (Kung and Chen, 2011) or lead officials to manipulate data, provide biased information, and distort official statistics for promotional gains (Zhou and Zeng, 2018; Suárez Serrato et al., 2019). However, our findings do not support the notion that promotion incentives encourage reckless actions among local officials concerning pandemic policy.

Lastly, our research delves into the political and economic determinants behind COVID-19 policy decisions, a field with limited literature to date. Since the onset of the pandemic, global policymakers have taken varying approaches to strike a balance between health concerns and economic implications. The interplay of political pressures, interest group dynamics, and population needs largely shapes these policy decisions. McCann and Wood (2022) underscore how the political-economic environment of states in the U.S. influences their COVID-19 policy choices. Grossman et al. (2020) examine the extent to which partisanship affects adherence to physical distancing in the U.S., while Bosancianu et al. (2020) offer insights into the political and social determinants that may account for variations in COVID-19 mortality rates.

Feng et al. (2023) is most related to our work. They analyze the role of local governors' patronage connection during China's nationwide stringent anti-contagion measures in the early stage of the pandemic. Their findings suggest that when a prefecture-level city leader maintained personal ties with the provincial supervisor, there was an increase in the stringency of the measures implemented. While their analysis focuses on the early 2020 phase of the pandemic in China, our study shifts the lens to the 2021-2022 period. During this time, local governors possessed greater flexibility over zero-Covid policy decisions. Our exploration sheds light on the nuance within China's COVID-19 policies, which were delegated to local officials who burdened the dual objectives of pandemic containment and economic vitality.

The remainder of the paper is structured as follows. Section 2 details the policy and institutional background. Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 presents the empirical results and robustness checks. Section 6 concludes the paper.

2 Policy and Institutional Background

2.1 China's zero-Covid Policy

In this section, we briefly introduce the background of China's zero-Covid policy.[1] In response to the initial COVID-19 outbreak in Wuhan, in early 2020, the Chinese government implemented unprecedented prefecture lockdowns to shut down the spread of the virus. Stringent measures were implemented in 58 out of 337 prefectures, including restrictions on outbound traffic, the imposition of stay-at-home orders, and the enforcement of quarantine measures (Fang et al., 2020; Qiu et al., 2020). Additionally, other anti-contagion policies, known as Community Stringent Measures (CSMs), were enforced in most prefectures nationwide. Unlike lockdowns, CSMs are less stringent measures that involve restrictions on human mobility, the establishment of body temperature checkpoints, neighborhood sanitization, monitoring of suspected COVID-19 cases, and other anti-contagious measures at the local community level. By February 20, 2020, 303 prefecture-level cities in China had implemented CSMs, covering 89.9% of all such cities (Qiu et al., 2020; Feng et al., 2023). The Chinese government introduced a policy package on February 18, 2020, aimed at precise containment of COVID-19 transmission at the community level.[2] As a result, the central government ceased to recommend prefecture-level lockdowns due to their harmful impacts on the economy. This research scope excludes the consideration of lockdown or CSM decisions made by local governments during this period since these were national policies directly announced and enforced by the central government, and not endogenous decisions made by local prefecture leaders.

After a one-month period of strict lockdowns and nationwide public health interventions, the central government sought to stimulate economic recovery and ease lockdown measures. The State Council and National Health Commission of China issued *Prevention Guidance for Novel Coronavirus Pneumonia (version 5)* on February 21.[3] This guidance mandated local governments

[1] Gong et al. (2023) provides a detailed documentation about the background and the description of the zero-Covid policy.

[2] *Guidelines on Scientific Prevention and Control, Precise Measures, Zone-Based and Tiered Approach for the COVID-19 Epidemic Prevention and Control*: https://www.gov.cn/xinwen/2020-02/18/content_5480514.htm

[3] *Prevention Guidance for Novel Coronavirus Pneumonia (version 5)*: http://www.nhc.gov.cn/jkj/s3577/202002/a5d6f7b8c48c451c87dba14889b30147.shtml

to assess COVID-19 risk at the community level. Communities reporting COVID-19 cases would be designated as either medium or high-risk zones, triggering the implementation of appropriate containment measures and closures. This is commonly known as the *zero-Covid policy*. In Figure 8, we present a time-series graph illustrating the count of prefectures with an ongoing pandemic and the number of counties implementing the zero-Covid policy. In principle, low-risk communities should primarily impose quarantines on individuals traveling from high or medium-risk areas and refrain from restricting the movements of residents or economic activities. The policy's objective is to eliminate COVID-19 transmission at the local level by assigning risk levels to each community and implementing corresponding measures.

To supplement the zero-Covid policy, in March 2020, the State Council of China published a national COVID-19 risk level system on the official website. This system classifies communities within the 2853 counties into high, medium, or low-risk areas and updates it daily.[4] All zero-Covid policy measures, including quarantine, public place closures, travel restrictions, and travel QR codes, were implemented based on this system. Specifically, local governments determine the risk level index (or non-risk) of a community based on recently reported confirmed and suspected cases of COVID-19, which is then reported to the National Health Commission of China. Local officials have some flexibility in adjusting the threshold for the risk level index and deciding whether to implement the zero-Covid policy. In certain situations, neighboring communities with no cases may still be classified as medium or high-risk areas; at the same time, areas that experienced outbreaks with dozens of cases could still be categorized as non-risk areas. Our research aims to investigate the endogeneity in this decision and understand how promotion incentives influence the choice of the local prefecture leaders regarding the zero-Covid policy when new COVID-19 cases emerge in their jurisdictions.

2.2 Promotion and Multitasking

The Chinese political system is both centralized and decentralized (Xu, 2011). On one hand, political appointments are typically determined by higher-level governments in China, with local

[4] State Council introduced risk level system on its official website: http://www.gov.cn/fuwu/2020-03/25/content_5495289.htm

leaders' career progression contingent on performance evaluations conducted by their superiors (Landry, 2008). For instance, provincial-level organizations oversee and assess the performance of prefecture-level officials. Therefore, this top-down hierarchical government structural manages to align the incentives of local officials with that of the party through centralized personnel control. This centralized personnel control allows the central government to align local officials' incentives with those of the party, a critical institutional foundation that has facilitated economic reforms in China since the 1980s (Blanchard and Shleifer, 2001; Enikolopov and Zhuravskaya, 2007).

On the other hand, economic decision-making and daily governance are highly decentralized in China's contemporary political-economic landscape. Local governments enjoy significant policy autonomy, driven by strong career-concern incentives for government officials. Economic and spending policies are predominantly decentralized, and local leaders hold substantial influence over local economic development (Jin et al., 2005). Party secretaries and mayors have a wide span of controls over policies that help boost the short term economic growth. The revenue-sharing arrangements within a decentralized fiscal system also motivates local leaders to promote economic growth (Qian and Weingast, 1997). In addition, the performance evaluation encompasses a broad range of tasks including social stability and public safety (Nie et al., 2013; Xi et al., 2018). In the 2014 version of the Central Committee of the Communist Party of China (CPC)'s guidelines, the significance of GDP as a performance metric was reduced. Instead, greater emphasis was placed on factors such as environmental protection, political loyalty, and government debt.

This duality of centralization and decentralization creates a multitasking challenge for local officials. When a potential crisis arises, such as the COVID-19 pandemic, the central government's crisis control objectives may clash with local leaders' personal incentives. While crisis control tasks demands containment of the virus and stability, local governors might still anticipate that their performance evaluations will cover various policy domains, including economic development. This unique multitasking dilemma, particularly faced by prefecture-level leaders, creates a complex situation. During the pandemic, they must strategically allocate their efforts across multiple policy areas, balancing central government directives with potential economic performance trade-offs.

2.3 Age Restrictions in Promotion

Age restrictions in China's cadre system have been frequently used to measure promotion incentive in recent literature (Xi et al., 2018; Zhou and Zeng, 2018; Shi and Xi, 2018; Huang et al., 2020; Shi et al., 2021). The CPC imposed restriction on the promotion of aging officials since the 1980s[5] and introduced age limits for officials in the 2000s (Kou and Tsai, 2014). Government policy explicitly states that "party and government cadres should resign from the position......upon reaching the age limit for assuming a position or the retirement age limit" (*Regulations on the Work of Selecting and Appointing Leading Party and Government Cadres*).[6] In his speech about the general election of the 17th CPC Conference in 2007, President Hu Jintao asserted that mayor-level officials aged 58 or more are ineligible for promotion and are subject to a mandatory retirement age of 60.[7] Moreover, it is a norm for officials in prefecture-level leadership roles to serve for a certain duration, typically three years or more, before being considered for promotion.[8] All the evidence mentioned above suggests that prefecture-level leaders aged 58 and older have little chance of promotion and are more likely to be reassigned to less critical ceremonial roles. Zhou and Zeng (2018) provide empirical findings indicating a significant decline in mayors' promotion probability once they surpass the age of 57, as shown in their original figure included in Figure A2.

In this study, we categorize party secretaries whose ages are close to the promotion eligibility cutoff age as having a strong promotion incentive. Since the appointments to vice-provincial level positions are typically announced during the provincial National People's Congress conference, which usually takes place before February every year, we consider a prefecture party secretary eligible for promotion if his or her age is 57 years or less by the time of the next provincial National People's Congress conference. Consequently, we define the age of the official as the age they attain by the time of the next provincial National People's Congress conference. In our

[5] *The Decision of the Central Committee of the Communist Party of China on Establishing a Retirement System for Senior Party Cadres*, 1982

[6] https://www.gov.cn/jrzg/2014-01/15/content_2567800.htm

[7] https://news.ifeng.com/mainland/200702/0210_17_75079_1.shtml

[8] In latest revision of *Regulations on the Work of Selecting and Appointing Leading Party and Government Cadres* (2014), "If a county-level or higher leadership position is to be appointed by a deputy-level official to a higher-level position, they should have worked in the deputy-level position for at least two years. If being appointed from a lower-level leadership position to a higher-level deputy position, they should have worked in the lower-level leadership position for at least three years."

primary specification, we generate a *Promotion* dummy variable and assign a value of 1 to party secretaries aged between 54 and 57, and a value of 0 to all others. This range is the last time window for prefecture leaders to be promoted (Shi and Xi, 2018), and we argue that it creates unique promotion incentives for party secretaries within this age range. In Section 4.4.3, we will further discuss details regarding the robustness of the age range we employed for the *Promotion* dummy variable and other potential concerns.

3 Data

3.1 COVID-19 Pandemic Data

We collect daily confirmed COVID-19 case data from the *Dingxiangyuan* website, which aggregates official reports of daily COVID-19 cases at the prefecture level. We define that an *outbreak* event of COVID-19 pandemic occurs in a prefecture when a new confirmed COVID-19 case is reported after a 14-day period with no reported cases in the same prefecture. The outbreak is considered to have ended when the prefecture maintains a clean record of confirmed cases for a consecutive 14-day period. By constructing event windows for these outbreaks, we can pinpoint the initial date of each outbreak in the prefectures. It is worth noting that many prefectures experience multiple such outbreaks.

3.2 Zero-Covid Policy Data

Our data regarding zero-Covid policy status (risk level index) are sourced from the *China's COVID Risk Level Database* (Gong et al., 2023). This database provides information on COVID-19 risk levels for communities within the 2853 counties on a daily basis, spanning from April 02, 2021, to December 15, 2022, which corresponds to the conclusion of the zero-Covid policies. To determine whether a prefecture has a zero-Covid policy in place, we look at whether at least one community within that prefecture is reported as a medium or high-risk level area. Additionally, we create three other variables related to zero-Covid policy: the percentage of zero-Covid policy coverage within each prefecture, the highest risk level index value within each prefecture, and the count of counties implementing the zero-Covid policy within each prefecture. The utilization of these three variables is discussed in further detail in Section 4.4.2. We present a heatmap plot illustrating the cumulative number of days under the zero-Covid policy at the county level, as of the end of both 2021 and 2022 in Figure 1.

3.3 Characteristics of Prefecture Leader

We obtained information about prefecture party secretaries' age, education, gender, and ethnicity from government websites, Baidu Baike, and Wikipedia. Their tenure start and end dates were manually collected to accurately assign the prefecture leader to each prefecture at every date in our panel data.[9] As mentioned in previous section, we categorize officials as having strong promotion incentives and assign a "Promotion" dummy variable equal to 1 if their age falls within the range of 54 to 57; otherwise, it is set to 0. We plot the distribution of prefecture leaders' age in Figure 2 and provide a map indicating which prefectures were governed by *Promotion* or non-promotion leaders by the end of 2021 and 2022 in Figure 3.

Before delving into a formal regression analysis, we employ a non-parametric approach to explore the relationship between the zero-Covid policy and the pandemic's scale, as well as its variations across groups of prefecture leaders with or without promotional incentives. Specifically, we conduct a local kernel regression on the status of the zero-Covid policy and its coverage using the natural logarithm of the 7-day average case count, segmented by groups defined by promotional incentives. The results are presented in Figure 4. We observe that officials with strong promotional incentives exhibit similar zero-Covid policy implementation patterns as their counterparts when the 7-day average case count is relatively low—below 50 daily cases. However, the divergence becomes notably significant once the scale of the pandemic surpasses this threshold. While this result does not represent a comprehensive analysis, it illuminates potential behavioral differences and lends credence to our forthcoming detailed analysis.

[9]There are few prefectures which do not have party secretary in position for few months. We classified these prefectures as non-promotion.

3.4 Mobility Data

Our traffic mobility data is originally from the Baidu Qianxi (Migration) website data and collected by Hu et al. (2020). This data is obtained by monitoring the characteristics of HTTP requests to the data server. It provides information on traffic flow between prefectures. Specifically, it includes two indices: inflow mobility, representing traffic flow towards the destination prefecture, and outflow mobility, indicating traffic flow away from the departure prefecture. To ensure comparability across time and prefectures, we standardized the inflow and outflow mobility indices within each prefecture. The data covers the period from September 23, 2021, to April 21, 2022.

3.5 Prefecture Characteristics and Sample Data

We gathered data on prefecture-level GDP, population, the share of the service sector in GDP, and the urbanization rate, all evaluated in 2019, from provincial and city yearbooks. To obtain our final sample data for empirical analysis, we excluded the four municipalities directly administered by the central government (Beijing, Shanghai, Tianjin, and Chongqing). Additionally, we calculated the total number of days each prefecture experienced pandemic outbreaks (defined in previous section 3.1) and excluded those with more than 500 days of outbreak. These outlier prefectures were either port cities for international flights during the pandemic or located close to such entry points. We removed them from our sample as they remained under outbreak conditions for most of our data period from April 02, 2021 to December 15, 2022 (622 days). We provide a scatter plot of each outbreak's duration and cumulative confirmed cases in Figure A3. Our focus is on the cluster of data points in the lower left corner of the graph[10] and most outlier points are dropped from our sample data. A statistical summary of the final sample data is provided in Table 1.

[10] A zoomed-in figure is in Figure A4

4 Empirical Strategies

4.1 Promotion Incentive

This research provides evidence that promotion incentives could influence the decisions made by prefecture leaders regarding the implementation of the zero-Covid policy. Our empirical analysis estimates the following regression:

$$ZeroCovid_{it} = \beta_1 Cases_{it} + \beta_2 Promotion_{it} + \beta_3 Cases_{it} \times Promotion_{it} + \gamma Cases_{it} \times X_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

where $ZeroCovid_{it}$ is a dummy indicating the zero-Covid policy status in the prefecture i at date t; $Cases_{it}$ is the 7-day running average number of Covid-19 cases in the prefecture i at date t; $Promotion_{it}$ is a dummy indicating the party secretary's promotion incentive of the prefecture i at date t, which assigns value of 1 if the secretary's age falls between 54 and 57 and 0 otherwise; X_{it} is a set of control variables, including a dummy of year 2022, prefecture leader's tenure in position, education, gender and ethnicity; μ_i is the prefecture fixed effect and θ_t is the time fixed effect. To further isolate the potential influence of provincial leaders' preferences for different governance objectives, we control for province-by-month fixed effects in all regression specifications.

Among the estimated coefficients, β_1 represents the effect of emerging cases of COVID-19 on the zero-Covid policy decision in the absence of strong promotion incentives. As the prefecture leader observes more cases, it will be a greater chance for the prefecture leader to announce the zero-Covid policy, thus β_1 is expected to be positive and significant. β_2 represents the probability difference in the declaration of a zero-Covid policy between prefecture leaders with and without promotion incentives regardless of the COVID-19 cases. The coefficient of interest for this research is β_3, which represents the impact of the promotion incentives of the prefecture leader on the marginal probability increase of a zero-Covid policy caused by the emerging cases of COVID-19. For prefecture leaders with high incentives, if promotion pressure leads to greater compliance with the zero-Covid policy facing the same scale of the pandemic, we should observe a positive and significant β_3.

4.2 Event Study

Another important identification assumption underlying our empirical strategy is that there are no other factors that generate a differential trend in zero-Covid policy decisions rather than the emerging COVID-19 cases. In other words, for the estimated effect to have a causal interpretation, the model requires a parallel trend assumption: the differential in policy decision between prefectures with or without new cases of COVID-19 is constant in the absence of a pandemic outbreak. In the context of China's zero-Covid policy, the NHS guideline explicitly describes the condition for a region to be classified as high or medium risk, which requires the detection of COVID-19 cases. This policy background relieves our concern that other unobservable factors determine the zero-Covid policy.

Additionally, although the parallel trend assumption is hard to verify empirically as we were unable to observe the counterfactual policy outcomes, we could employ an event study to display that there is no pre-trend in the zero-Covid policy outcome difference between prefectures which face new outbreaks of the pandemic or have no ongoing pandemic. Specifically, we estimate the following model for prefectures governed by party secretaries in high- and low-incentive groups separately:

$$ZeroCovid_{it} = \sum_{k=-7}^{-1} \beta_k D_{it}^k + \sum_{k=0}^{21} \beta_k D_{it}^k + \mu_i + \theta_t + \varepsilon_{it} \tag{3}$$

where D_{it}^k represents the indicator for the treatment status as k periods relative to initial outbreak, which takes value of 1 if date t is k days relative to the first day of an outbreak in prefecture i and 0 otherwise, and other notation remains identical to that of equation (1).

The event study could provide us two pieces of supportive evidence regarding the role of promotion incentive in the decision-making process related to the zero-Covid policy. Firstly, it could lend us confidence that the rising COVID-19 cases casually drive the adoption of the zero-Covid policy. Consequently, our estimation in equation (1) could identify differences in the choice of zero-Covid policy between party secretaries with and without strong promotion incentive facing a similar scale of the pandemic outbreak. Secondly, through an examination of the dynamic effect of a new COVID-19 outbreak on the implementation of the zero-Covid policy, we can determine the likelihood of the zero-Covid policy being implemented shortly after the first case emerged and the timeframe within which the local government responds. Conducting this event study separately for both groups of prefecture leaders enables us to explore any systematic variations in their behavior following the outbreak.

4.3 Multitasking

We are also interested in investigating whether the impact of promotion incentives varies across regions with distinct socioeconomic foundations, particularly when the zero-Covid campaign may impose a higher economic cost, leading to conflicting demands with regard to economic development. We estimate the following regression to explore this potential heterogeneity:

$$\begin{aligned} ZeroCovid_{it} &= \beta_1 Cases_{it} + \beta_2 Promotion_{it} + \beta_3 Cases_{it} \times Promotion_{it} \\ &\quad + \beta_4 Cases_{it} \times Promotion_{it} \times Z_i + \gamma Cases_{it} \times X_{it} + \mu_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{4}$$

where Z_i is the socioeconomic characteristic of prefecture i, and other notation remains the same as previous specifications. We select three factors that are likely to be correlated to the economic cost of the zero-Covid policy: GDP per capita, the share of the service sector in GDP, and the urbanization rate. These factors were evaluated in the year 2019, prior to the pandemic.

When initiating zero-Covid policy, prefectures with higher economic development would incur a higher loss in the slowdown of growth of GDP, service sectors are more vulnerable to stay-at-home orders or city lockdowns and urban areas would experience more disturbance than rural areas due to the containment measures and restrictions. When implementing the zero-Covid policy, prefectures with higher levels of economic development are likely to face more substantial setbacks in terms of the slow down in GDP growth. The service sector, being highly susceptible to stay-at-home orders and city lockdowns, is expected to be more vulnerable. Additionally, urban areas are likely to experience greater disruptions compared to rural areas due to the containment measures and restrictions. It is an empirical question that whether local governors, even when facing strong promotion pressures, will compromise on the implementation of the zero-Covid policy due to the economic burden it imposes. We aim to answer this question by estimating the coefficient β_4 in equation (4). This coefficient reflects the disparity in the response of emerging COVID-19 cases among prefectures with varying socioeconomic foundations, conditional on that the prefecture leaders are subject to strong promotion incentives.

4.4 Threats to Identification

4.4.1 Endogenous COVID-19 Cases

Our identification in equation (1) is based on a quasi-experimental design. While the emergence of a new wave of the pandemic is not entirely exogenous to prefecture-level factors, the number of confirmed COVID-19 cases shortly after the detection of the first case is semi-exogenous. It is plausible that, when the first case is detected, the virus has not yet spread widely among the population, resulting in a limited number of subsequent confirmed cases in the following weeks. Conversely, another scenario entails the virus quietly spreading for a period before the detection of the first case, leading to an exponential increase in confirmed cases until effective control measures are implemented. Given the uncertainty faced by party secretaries, who could not predict the specific condition they would encounter, we leverage this inherent randomness in the number of COVID-19 cases to identify variations in zero-Covid policy compliance as a response to the outbreak. This variation occurs among prefecture leaders with and without strong promotion incentives and we would like to identify the systematic difference between these two groups.

In the context of China's zero-Covid campaign, the primary objective is the dynamic elimination of the ongoing pandemic within each prefecture, ultimately reducing the number of confirmed cases to zero. Nevertheless, the implementation of the zero-Covid policy can exert a substantial influence on the trajectory of confirmed COVID-19 cases. Starting the zero-Covid policy earlier can potentially "flatten the curve" and expedite the termination of the outbreak. This implies that among the group of prefectures that were hesitant to implement the zero-Covid policy , they may eventually encounter with a larger number of confirmed COVID-19 cases for an extended period. This endogeneity between policy implementation and confirmed cases has the potential to introduce significant bias into our identification. For prefecture leaders with fewer promotion incentives, they might delay initiating the zero-Covid policy. Consequently, this delay could endogenously generate more observations with a large number of confirmed cases and no zero-Covid policy in place in the sample, resulting in an overestimate of the impact of promotion incentives in our estimation.

While we acknowledge that we cannot entirely eliminate the endogeneity issue from our estimation, we can mitigate it to some extent by constructing a subsample that consists of data from a short window after the first COVID-19 case is detected. By doing so, we exclude the period when the zero-Covid policy has already been implemented, which tends to suppress the number of confirmed cases. We also exclude the period when confirmed cases may have surged due to the exponential growth of the population affected by the virus. Before the implementation of the zero-Covid policy or the widespread transmission of the virus, the number of confirmed cases in this subsample closely approximates a randomized treatment in a natural experiment, which remains exogenous to other prefecture-level factors. During this selected period, prefecture leaders' decisions can better reflect their willingness to comply with the zero-Covid policy, as they have limited information about the actual outbreak situation. The regression results using this subsample could provide confidence in our identification of the impact of promotion incentives on the zero-Covid implementation.

4.4.2 Measurement of Zero-Covid Policy

There might be potential concerns regarding the measurement of the zero-Covid policy's implementation in our previous empirical analysis. We employed a binary variable to indicate whether a prefecture is subject to the zero-Covid policy, but this approach does not capture the depth and scope of the policy's application within the jurisdiction. It is plausible that a local governor might only impose restrictions in a limited area where recently diagnosed COVID-19 patients had visited, while the majority of the city and rural counties within the same prefecture remain unaffected by the zero-Covid policy.[11] Prefecture leaders driven by strong promotion incentives may decide to implement the zero-Covid policy in a limited area within their jurisdiction much more quickly

[11]This scenario was indeed prevalent in many cities during the pandemic. For instance, in Shanghai, prior to the extensive lockdown initiated on April 22, 2022, there were no city-wide restrictions or containment measures in place since the first confirmed COVID-19 case of this outbreak on March 1. During this 52-day period, except for areas classified as medium or high-risk, the remainder of the city was not subject to any restrictions.

compared to their counterparts with lower promotion incentives at the beginning of outbreaks. However, as the outbreak escalates and extends its reach, both groups may exhibit similar behavior in terms of expanding the coverage of the zero-Covid policy. Our binary measurement of the zero-Covid policy would lose track of this complexity of the policy decisions made by prefecture leaders, potentially exacerbating the influence of promotion incentives in their decision-making processes.

The granularity in our data provides us the possibility to examine the coverage and stringency of the zero-Covid policy implementation. To address potential biases caused by the measurement errors of the binary zero-Covid policy status, we propose an alternative approach. Instead of relying on the binary indicator for the zero-Covid policy status at the prefecture level, we could employ the county-level zero-Covid policy status and aggregating these data at the prefecture level.

Specifically, in equation (1), rather than utilizing a dummy indicator for the presence of the zero-Covid policy within the prefecture, we replace it by the percentage of county-level areas within the prefecture that have implemented the zero-Covid policy as the dependent variable of interest. This adjustment in equation (1) will enable us to analyze the influence of promotion incentives on the relationship between emerging COVID-19 cases and the extent of zero-Covid policy coverage within a prefecture. Then the estimated coefficient β_3 will represent the impact of the promotion incentives of the prefecture leader on the marginal percentage increase of a zero-Covid policy coverage at county level caused by the emerging cases of COVID-19. Moreover, to gain insight into the stringency of the implemented zero-Covid policy, we could also use the highest level of the zero-Covid policy risk level index within a prefecture to be the outcome variable in the regression of equation (1). This risk level index is categorized as "High", "Medium", and "Low" with corresponding assigned values of 2, 1, and 0, respectively, to serve as our dependent variable in this specification. In this context, β_3 represents the impact of the promotion incentives of the prefecture leader on the value of the highest risk level index associated with the zero-Covid policy, in response to emerging COVID-19 cases.

4.4.3 Measurement of Promotion Incentives

The primary assumption of our identification is that prefecture leaders experience a marked decline in promotion incentives as they surpass the age of 58, due to significantly diminished promotion prospects thereafter. While we could potentially exploit the discontinuity in promotion incentives linked with their age using a regression discontinuity design (RDD) to identify the causal impact of these incentives on policy results, we instead opt for measuring promotion incentives by age range because of two considerations.

First, the RDD approach relies on the assumption that the running variable—officials' ages—is not manipulated around the cut-off value. In the context of Chinese politics, this is questionable, as more competent and capable governors might advance in their ranks before nearing the age threshold. Figure 2 demonstrates that the distribution of officials around the threshold undergoes significant changes, which implies a potential breach of the no-manipulation assumption.

Second, in instances where the literature takes advantage of the age threshold's promotion incentive discontinuity, it is common to account for official fixed effects which controls official's talents, backgrounds, and other time-invariant personal traits. This allows for the identification of behavioral shifts for the same officials as they cross the age threshold. This approach is constrained in our case: our data cover only two years, as opposed to spanning multiple decades. In our dataset, only a select number of officials crossed the age threshold of 58 during the pandemic period.

Consequently, we choose to focus on officials nearing the promotion eligibility threshold, classifying them as our treatment group. We aim to estimate the average treatment effect of promotion incentives on the treatment group concerning zero-Covid policy compliance, drawing comparisons with a control group of officials either in the early stages of their career or past their final promotion opportunity. Though questions persist about the validity of the RDD in this context, we have included RDD approach regression findings in the Appendix.

There might be additional concerns regarding our chosen measure of promotion incentives in the baseline model. One potential concern suggests that younger officials may have different political motivations when making policy decisions (Alesina et al., 2019). To cope with the potential bias brought by other promotion incentives that are unobserved in our data, we propose several robustness checks. Firstly, we narrow our sample to officials aged 54 and above, drawing comparisons between officials at roughly equivalent career stages. Alternatively, we refine our treatment criteria to include all officials aged under 58. This strategy changes the scope to officials still holding promotion prospects against those with nearly no opportunities left. According to our assumption, the expected treatment effect on the likelihood of implementing zero-Covid policies should be positive under both these specifications.

5 Results

5.1 Main Results

We present the baseline estimates of the impact of promotion incentives on compliance with the zero-Covid policy in Table 2. In all specifications, we control for an interaction term of COVID-19 cases and the dummy of year 2022 and cluster the standard errors at the province-month level. In column (1), we estimate a two-way fixed-effect regression similar to that of equation (1), except that we did not include the interaction term between the COVID-19 case term and the promotion incentive dummy. The coefficient of $Promotion_{it}$ is not statistically significant. This suggests that prefecture leaders, whether with or without strong promotion incentives, do not exhibit a significant difference in their average probability of initiating the zero-Covid policy when controlling for the 7-day average confirmed COVID-19 cases. However, our primary interest lies in understanding how promotion incentives shapes the prefectures' response to the emerging outbreak of the pandemic as observed COVID-19 cases increase. Therefore, we aim to estimate the coefficient of $Cases_{it} \times Promotion_{it}$ in equation (1). Column (2) reports the estimates for the regression results of equation (1). The coefficient of $Cases_{it} \times Promotion_{it}$ is 0.00727 and statistically significant at the 0.01 level. This finding indicates that, for prefectures in the strong promotion incentive group, one average daily case in the past 7 days is associated with a 0.727% increase in the probability of implementing the zero-Covid policy compared to their counterparts in the low promotion incentive group. As we calculate a 7-day average daily case for $Cases_{it}$, we can construct a hypothetical scenario in which there have been 70 confirmed COVID-19 cases over the past 7 days. In this scenario, it would result in the strong promotion incentive group having a 7.27% higher probability of implementing the zero-Covid policy.

5.2 Dynamic Effects

As discussed in Section 4.3, our aim is to confirm whether the emergence of COVID-19 cases indeed drives the implementation of the zero-Covid policy, as opposed to other influencing factors. We employ an event study approach and estimate equation (3). Figure 1a presents the dynamic effects of the pandemic outbreak on the status of the zero-Covid policy, separately for prefectures in the strong and low promotion incentive groups. We establish the baseline as the date before the first confirmed case is found ($t = -1$). The coefficients $t = -7, ..., 21$ represent β_k in equation (3). From Figure 5a, it is clear that for both groups of prefectures, there is no pre-trend in the status of the zero-Covid policy leading up to $t = -1$. A noticeable coefficient jump occurs at $t = -1$, indicating an increased chance of implementing the zero-Covid policy just before the confirmation of the first COVID-19 case. This is reasonable given that test results could take time to conclude a positive COVID-19 case,[12] while local governments may initiate restrictions as soon as they receive reports of suspected COVID-19 cases. It is also possible that there may be delays in updating the number of confirmed cases.

At the same time, after the first COVID-19 case was confirmed, there is a rapid increase in the likelihood of zero-Covid policy in the subsequent days. Both groups of prefectures exhibit nearly identical patterns up to seven days after the outbreak. The coefficients for the low promotion group exhibit a declining trend starting from $t = 7$, whereas the coefficients for the strong promotion group remain relatively high for a few more days before declining. Within the observation window, the differences in coefficients between the two groups are not statistically significant.

Building upon the insights derived from the Figure 4, which indicated that prefecture leaders with stronger promotion incentives tend to exhibit a greater inclination to actively comply with the zero-Covid policy during larger-scale outbreaks, we conduct an event study analysis using a subsample of outbreaks with a total of more than 50 cases. We present the dynamic effects of

[12] The commonly used COVID-19 test in China, nucleic acid test, takes about 6 hours to get the result.

this specific analysis in Figure 5b. The overall trends in the dynamic patterns closely resemble those observed in Figure 5a. Consistent with the findings in Section 5.3, it is evident that when confronting larger pandemic outbreaks, the implementation of the zero-Covid policy in response to new outbreaks by prefectures in the strong promotion group displays a larger divergence from those in the low promotion group. The likelihood of the zero-Covid policy being implemented reaches its peak at almost 50%, significantly higher than the results obtained using the full samples, where it hovers around 25% at its peak. Furthermore, the strong promotion group extends the duration of the zero-Covid policy.

The dynamic patterns lend support to the argument that the implementation of the zero-Covid policy is driven by confirmed COVID-19 cases. On average, prefecture leaders with stronger promotion incentives tend to maintain the zero-Covid policy for a longer duration after the outbreak compared to their counterparts with less promotion incentives, while the difference between these two groups is not statistically significant.

5.3 Multitasking

In Table 3, we present the results of estimating the multitasking effect as described in Section 4.4. In columns (1), (3), and (5), we estimate the heterogeneous impacts of emerging COVID-19 cases on the zero-Covid policy decisions across prefectures, taking into account various economic factors, such as log of GDP per capita, the service sector's share of GDP, and the urbanization rate.

The coefficients of the interaction terms between the 7-day average cases and the economic factors are all statistically insignificant, suggesting that, on average, economic factors did not influence compliance with the zero-Covid policy. In columns (2), (4) and (6), we estimate the equation (4) by incorporating three-way interaction terms of confirmed cases, the dummy variable of promotion incentive, and the economic factors. We observe that the three coefficients hold values of -0.00918, -0.0543, and -0.0483, and are statistical significant at the 0.1, 0.05, and 0.01 levels, respectively. These findings suggest that, in a prefecture where the GDP per capita, the share of the service sector in GDP, or the urbanization rate is 1% higher than the average representative prefecture, and given that the prefecture's party secretary has a strong promotion incentive, the likelihood of implementing the zero-Covid policy per 7-day average confirmed cases will decrease by 0.918%, 5.43%, and 4.83%, respectively.

While it's important to only interpret these coefficients at the average value of these economic factors across all prefectures, the negative sign of all three coefficients suggests that prefecture leaders with strong promotion incentives also take into account the potential economic challenges raised by the zero-Covid policy. This result highlights the inherent tension that local governors face between pandemic restrictions and the target of economic prosperity. Although prefecture leaders may be incentivized by the prospect of promotion to closely follow the crisis control policies announced by the central government, they cannot completely neglect their daily tasks, including economic development, as economic performance may still be a part of their promotion evaluation.

5.4 Robustness Checks

5.4.1 Endogeniety Concern

In this section, we present robustness checks addressing the identification concerns discussed in the previous Section 4.2. We construct a subsample of data from a 7-day period before and a 28-day period after a COVID-19 outbreak. We then replicate the regressions from columns (1) - (3) in Table 2. In Table 4, we present the regression results for this robustness check.

As shown in column (2) of Table 4, the coefficient of $Cases_{it} \times Promotion_{it}$ remains positive and significant at the 0.01 level, with a value of 0.0125. This value is nearly twice the original coefficient value in column (2) of Table 2. This suggests that during the constructed window following the initial outbreak, prefecture leaders with strong promotion incentives exhibit a more proactive response to emerging COVID-19 cases, as compared to our original estimation in Table 2 covering the entire period. This alleviates our concern that endogeneity between the pandemic scale and the implementation of the zero-Covid policy could lead to an overestimation of the impact of promotion incentives.

Furthermore, we categorize the outbreaks based on their total confirmed COVID-19 cases, defining them as large outbreaks if the total cases exceed 50 and as small outbreaks otherwise.

Through this approach, our goal is to verify whether party secretaries exhibit similar behavior when facing small outbreaks, and whether secretaries with strong promotion incentives tend to demonstrate more proactive compliance with the zero-Covid policy specifically in the case of large outbreaks. Columns (4) - (5) focus on the subsample of large outbreaks, and columns (6) - (7) specifically analyze the subsample of small outbreaks.

In column (5) of Table 4, when analyzing the subsample of large outbreaks, we note that the coefficient of interest is slightly larger than that in column (2) and remains statistically significant. However, in column (7), the coefficient is notably smaller and not significant. Consequently, we conclude that promotion incentives do indeed play a differentiating role in the zero-Covid policy decisions of prefecture leaders, but primarily during large outbreaks.

5.4.2 Alternative Measurement of Zero-Covid Policy

To address the potential bias introduced by measurement errors in the zero-Covid policy status, we replicate the baseline regression presented in Table 2 using three distinct dependent variables: the percentage of zero-Covid policy coverage within the prefecture, the highest value of the risk level index within the prefecture, and the count of counties implementing the zero-Covid policy within the prefecture. The results are presented in columns (1) - (2) of Table 5, Table 6, and Table 7, respectively.[13] The estimations do not reveal significant discrepancies from the original findings.

We further replicate the multitasking regression outcomes as presented in Table 4, utilizing alternative measurements for the zero-Covid policy. These replicated results are displayed in columns (3) - (8) of Table 5, Table 6, and Table 7. Most of these results align closely with our main findings.[14]

---

[13] Figure 6 visually presents the comparison of the primary coefficients of β_3 in Equation 1 across various specifications.

[14] Figure 7 visually presents the comparison of the primary coefficients of β_4 in Equation 4 for different economic factors across various specifications.

5.4.3 Alternative Encoding and Subsample for Promotion Incentives

We present the robustness checks for potential measurement error in promotion incentives in Table 8. In columns (1) - (3), we display the results from Table 2 for reference purposes. In columns (4) - (6), we replicate the baseline regressions using the subsample of officials aged 54 or above; in columns (7) - (9), we use the full sample while relaxing the criteria of having high promotion incentives to all officials aged less than 58.

The findings remain consistent with our primary conclusions. For columns (4) - (6), the estimated coefficients increase in magnitude compared to their counterparts in the original results while remaining statistically significant. This suggests that younger officials—those excluded from this subset—might be less proactive in the zero-Covid policy, possibly due to a lack of pressing promotional aspirations. In contrast, columns (7) - (9) see the coefficients diminish substantially in magnitude, though they remain positive and significant. This reduction underscores that, in comparison to their promotion-eligible peers, older officials with minimal promotional prospects are the least motivated to align with the zero-Covid policy. The robustness check results emphasize that the most promotion incentive likely resides among officials aged between 54 and 57, further affirming the reliability of our baseline results.

5.5 Stringency of Zero-Covid Policy

To capture the heterogeneous effects of the zero-Covid policy on traffic mobility across prefectures within the strong and low promotion incentive groups, as well as those with different socioeconomic foundations, we estimate the following model:

$$\begin{aligned} Mobility_{it} = {} & \alpha_1 ZeroCovid_{it} + \alpha_2 Promotion_{it} + \alpha_3 ZeroCovid_{it} \times Promotion_{it} \\ & + \gamma ZeroCovid_{it} \times X_{it} + \mu_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where $Mobility_{it}$ is the measurement of traffic mobility for prefecture i at date t and other notation remains the same as previous specifications. Gong et al. (2023) have already estimated the impact of zero-Covid policy on traffic mobility. However, our focus lies on the coefficients α_3 and γ, which represent the differentials in the degree of mobility disruption following the implementation of the zero-Covid policy, influenced by promotion incentives and economic factors. We report the estimates of equation (5) in Table 9, where the dependent variable is the mobility inflow index (standardized traffic flow directed to the prefecture), and in Table 10, where the dependent variable is the the mobility outflow index (standardized traffic flow originating from the prefecture).

In column (1) of Table 9 and Table 10, both coefficients of $ZeroCovid_{it} \times Promotion_{it}$ in these two specifications are not statistically significant. This suggests that promotion incentives do not systematically influence the mobility restriction effect of the zero-Covid policy. In columns (2), (4), and (6), we observe that in more economically developed prefectures with higher GDP per capita, a greater share of the service sector in GDP, and a higher urbanization rate, the zero-Covid policy leads to a more significant decrease in traffic mobility. This is logical because economically developed, service-oriented, and urbanized prefectures tend to have stronger traffic connections with other regions, making them more susceptible to mobility reductions due to zero-Covid restrictions.

In columns (3), (5), and (7), we include the three-way interaction terms involving the zero-Covid policy status, promotion incentive dummies, and economic factors. The results consistently show negative coefficients, although none of them reaches statistical significance. This appears to be contradictory to the findings in Section 5.5, where prefecture leaders in more economically developed areas with strong promotion incentives tended to be less enthusiastic about implementing the zero-Covid policy. Meanwhile, in these same prefectures, we observe a larger decrease in traffic mobility following the initiation of the zero-Covid policy.

These seemingly conflicting results are inherent in the rationale of local governors with strong promotion incentives. The objective of these prefecture leaders is to earn favor in promotion evaluations by demonstrating their ability to control pandemics while also safeguarding the economy from substantial slowdowns, if not stimulating its growth. Therefore, when they assess it necessary to initiate the zero-Covid policy due to the emergence of confirmed cases, their aim is to swiftly control the pandemic, allowing for the reopening of the city as early as possible and ensuring economic growth. Our empirical findings can indeed offer evidence to support this narrative.

6 Conclusions

In conclusion, this study provides valuable insights into the complex interplay between crisis control and economic development in the context of China's zero-Covid policy. Our findings suggest that promotion incentives can significantly influence the response of local officials to emerging COVID-19 outbreaks, leading to a natural tension between crisis management and routine performance in economic development.

Specifically, we find that prefecture leaders who are closer to the promotion eligibility age threshold exhibit a higher propensity to adhere to the zero-Covid policy. Yet, they may be cautious if their jurisdictions are more vulnerable to the side effects of anti-contagion measures, given the potential for greater economic setbacks. Additionally, we observe that in economically advanced regions, the mobility constraints during the zero-Covid policy are more rigorous. This suggests that officials aim to swiftly curtail the virus's spread by limiting human activity, thereby mitigating the policy's economic impact.

Overall, this study contributes to the ongoing debate on the optimal balance between public health and economic growth in the face of pandemics, and underscores the need for effective policy and institutional frameworks to address these challenges. Future research could explore the generalizability of our findings to other countries and contexts, and investigate the role of other factors, such as political ideology and public opinion, in shaping pandemic response.

References

Alesina, A., Cassidy, T., and Troiano, U. (2019). Old and Young Politicians. *Economica*, 86(344):689–727. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ecca.12287.

Baker, G. P. (1992). Incentive Contracts and Performance Measurement. *Journal of Political Economy*, 100(3):598–614. Publisher: The University of Chicago Press.

Blanchard, O. and Shleifer, A. (2001). Federalism with and without Political Centralization: China Versus Russia. *IMF Staff Papers*, 48:171–179. Publisher: Palgrave Macmillan Journals.

Bosancianu, C. M., Hilbig, H., Humphreys, M., Kc, S., Lieber, N., and Scacco, A. (2020). Political and Social Correlates of Covid-19 Mortality.

Chen, J., Chen, W., Liu, E., and Luo, J. (2022). The Economic Cost of Locking down like China:.

Chen, Y., Li, H., and Zhou, L.-A. (2005). Relative performance evaluation and the turnover of provincial leaders in China. *Economics Letters*, 88(3):421–425. Publisher: Elsevier.

Dewatripont, M., Jewitt, I., and Tirole, J. (1999). The Economics of Career Concerns, Part I: Comparing Information Structures. *The Review of Economic Studies*, 66(1):183–198.

Dixit, A. (2002). Incentives and Organizations in the Public Sector: An Interpretative Review. *The Journal of Human Resources*, 37(4):696–727. Publisher: [University of Wisconsin Press, Board of Regents of the University of Wisconsin System].

Dixit, A., Grossman, G., and Helpman, E. (1997). Common Agency and Coordination: General Theory and Application to Government Policy Making. *Journal of Political Economy*, 105(4):752–69. Publisher: University of Chicago Press.

Enikolopov, R. and Zhuravskaya, E. (2007). Decentralization and political institutions. *Journal of Public Economics*, 91(11-12):2261–2290. Publisher: Elsevier.

Fang, H., Wang, L., and Yang (2020). Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China. Working Paper 26906, National Bureau of Economic Research. Series: Working Paper Series.

Feng, B., Lu, B., Wang, Z., and Yu, D. (2023). Patronage Networks and Multitasking Incentives: Evidence from Local Officials' COVID-19 Responses in China's Centralized Bureaucracy.

Gong, D., Shang, Z., Su, Y., Yan, A., and Zhang, Q. (2023). A Systematic Evaluation of the Economic Impacts of China's Zero-COVID Policies.

Gong, D., Yan, A., and Yu, J. (2022). Cost of Zero-Covid: Effects of Anti-Contagious Policy on Labor Market Outcomes in China. SSRN Scholarly Paper 4037688, Social Science Research Network, Rochester, NY.

Grossman, G., Kim, S., Rexer, J. M., and Thirumurthy, H. (2020). Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States. *Proceedings of the National Academy of Sciences*, 117(39):24144–24153. Publisher: Proceedings of the National Academy of Sciences.

Hart, O., Shleifer, A., and Vishny, R. W. (1997). The Proper Scope of Government: Theory and an Application to Prisons*. *The Quarterly Journal of Economics*, 112(4):1127–1161.

Holmstrom, B. and Milgrom, P. (1991). Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design. *Journal of Law, Economics, & Organization*, 7:24–52. Publisher: Oxford University Press.

Hu, T., Guan, W. W., Zhu, X., Shao, Y., Liu, L., Du, J., Liu, H., Zhou, H., Wang, J., She, B., Zhang, L., Li, Z., Wang, P., Tang, Y., Hou, R., Li, Y., Sha, D., Yang, Y., Lewis, B., Kakkar, D., and Bao, S. (2020). Building an Open Resources Repository for COVID-19 Research. *Data and Information Management*, 4(3):130–147.

Huang, Z., Liu, J., Ma, G., and Xu, L. C. (2020). *The Transformative Effects of Privatization in China: A Natural Experiment Based on Politician Career Concern.* Policy Research Working Papers. The World Bank.

Imbens, G. W. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635.

Jin, H., Qian, Y., and Weingast, B. (2005). Regional decentralization and fiscal incentives: Federalism, Chinese style. *Journal of Public Economics*, 89(9-10):1719–1742. Publisher: Elsevier.

Ke, X. and Hsiao, C. (2022). Economic impact of the most drastic lockdown during COVID-19 pandemic—The experience of Hubei, China. *Journal of Applied Econometrics*, 37(1):187–209. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/jae.2871.

Kou, C.-w. and Tsai, W.-H. (2014). "Sprinting with Small Steps" Towards Promotion: Solutions for the Age Dilemma in the CCP Cadre Appointment System. *The China Journal*, 71:153–171. Publisher: The University of Chicago Press.

Kung, J. K.-S. and Chen, S. (2011). The Tragedy of the Nomenklatura: Career Incentives and Political Radicalism during China's Great Leap Famine. *American Political Science Review*, 105(1):27–45.

Landry, P. F. (2008). *Decentralized Authoritarianism in China: The Communist Party's Control of Local Elites in the Post-Mao Era*. Cambridge University Press, Cambridge.

Lee, D. S. and Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, 142(2):655–674.

Li, H. and Zhou, L.-A. (2005). Political turnover and economic performance: the incentive role of personnel control in China. *Journal of Public Economics*, 89(9):1743–1762.

Maskin, E., Qian, Y., and Xu, C. (2000). Incentives, Information, and Organizational Form. *The Review of Economic Studies*, 67(2):359–378. Publisher: [Oxford University Press, Review of Economic Studies, Ltd.].

McCann, P. J. C. and Wood, A. K. (2022). The Political Economy of COVID-19 Policy Choices.

Nie, H., Jiang, M., and Wang, X. (2013). The impact of political cycle: Evidence from coalmine accidents in China. *Journal of Comparative Economics*, 41(4):995–1011.

Qian, Y. and Weingast, B. R. (1997). Federalism as a Commitment to Reserving Market Incentives. *Journal of Economic Perspectives*, 11(4):83–92.

Qiu, Y., Chen, X., and Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, 33(4):1127–1172.

Shi, X. and Xi, T. (2018). Race to safety: Political competition, neighborhood effects, and coal mine deaths in China. *Journal of Development Economics*, 131:79–95.

Shi, X., Xi, T., Zhang, X., and Zhang, Y. (2021). “Moving Umbrella”: Bureaucratic transfers and the comovement of interregional investments in China. *Journal of Development Economics*, 153:102717.

Suárez Serrato, J. C., Wang, X. Y., and Zhang, S. (2019). The limits of meritocracy: Screening bureaucrats under imperfect verifiability. *Journal of Development Economics*, 140(C):223–241. Publisher: Elsevier.

Xi, T., Yao, Y., and Zhang, M. (2018). Capability and opportunism: Evidence from city officials in China. *Journal of Comparative Economics*, 46(4):1046–1061.

Xu, C. (2011). The Fundamental Institutions of China’s Reforms and Development. *Journal of Economic Literature*, 49(4):1076–1151.

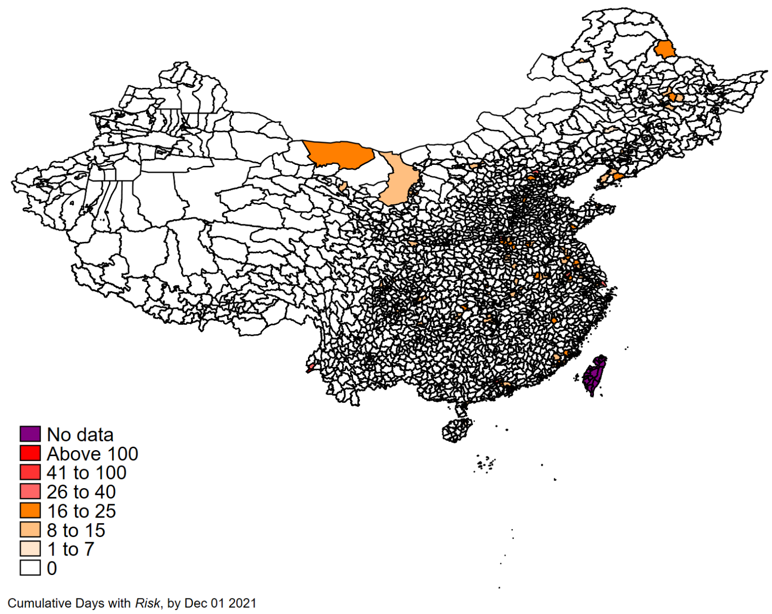
Yao, Y. and Zhang, M. (2015). Subnational leaders and economic growth: evidence from Chinese cities. *Journal of Economic Growth*, 20(4):405–436.

Zhou, Q. and Zeng, J. (2018). Promotion Incentives, GDP Manipulation and Economic Growth in China: How Does Sub-National Officials Behave When They Have Performance Pressure?

7 Figures and Tables

7.1 Figures

(a) Cumulative Days Under zero-Covid policy by end of 2021



(b) Cumulative Days Under zero-Covid policy by end of 2022

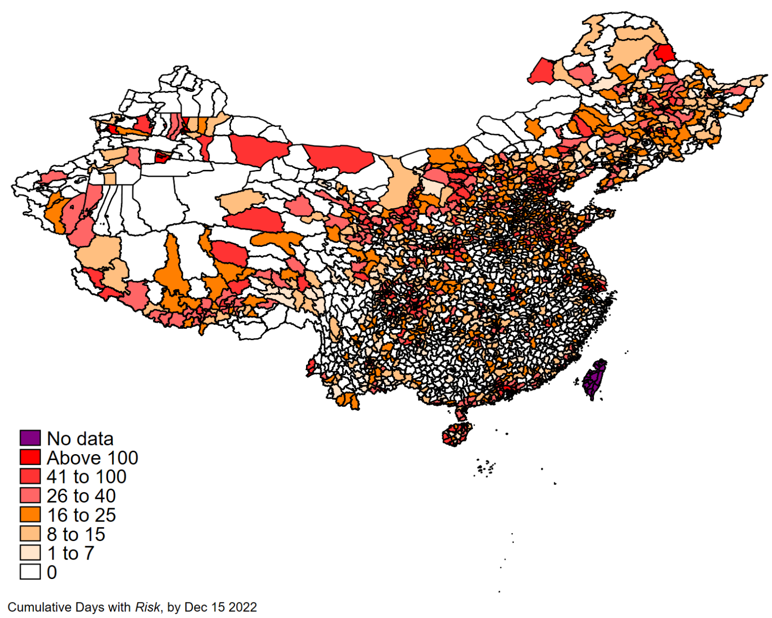


Figure 1: Cumulative Days Under Zero-Covid Policy at County Level

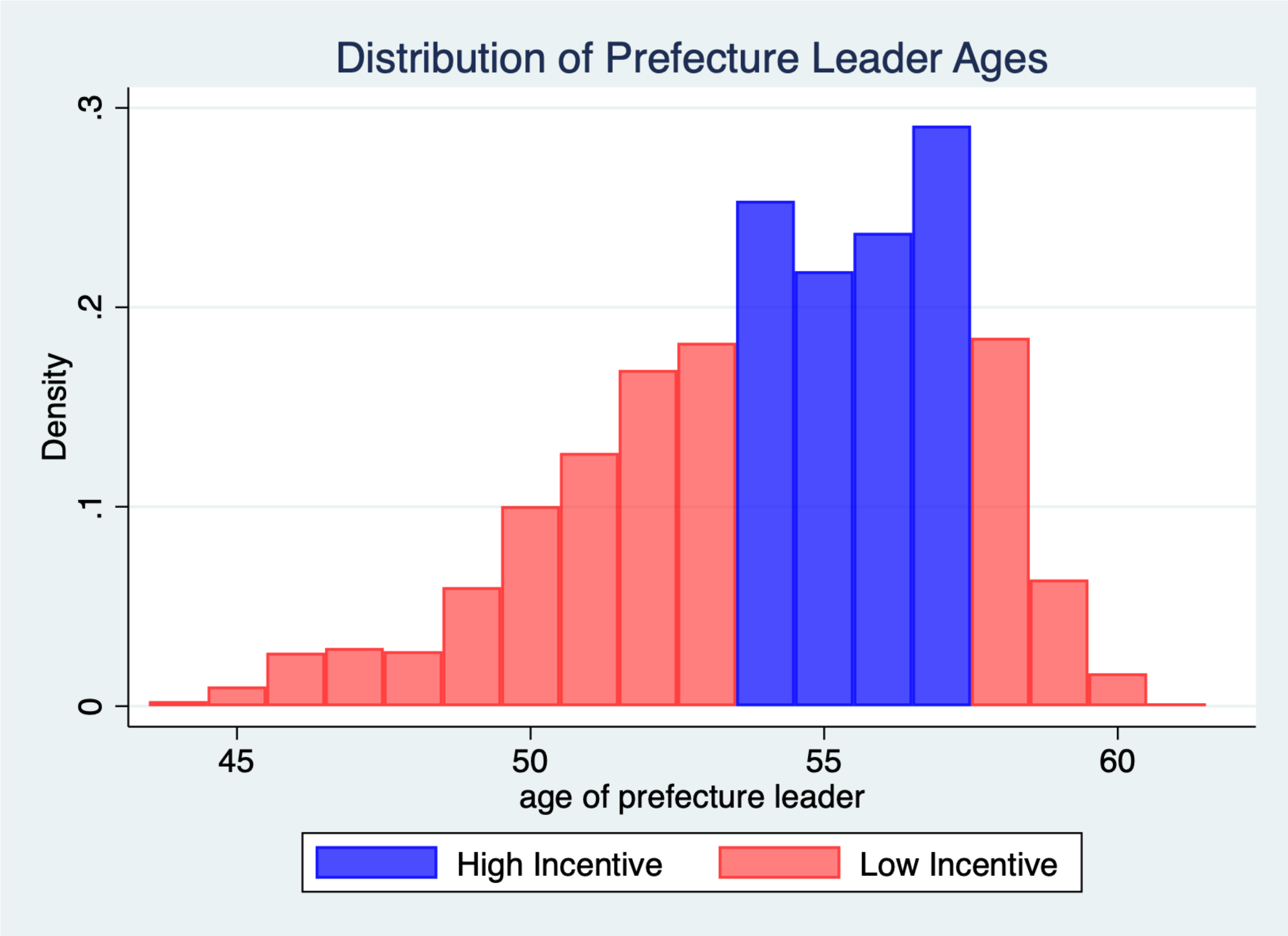
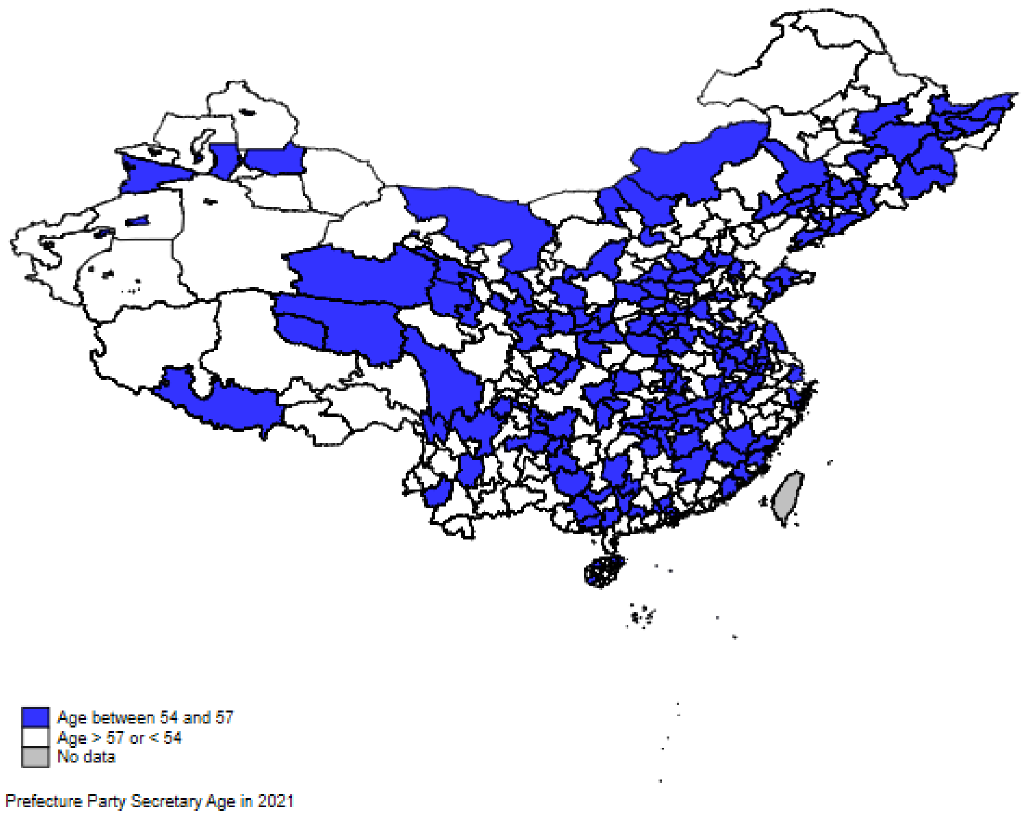


Figure 2: Prefecture Leader Age Categorized by Promotion Incentives

(a) Prefecture Leader Age in 2021



(b) Prefecture Leader Age in 2022

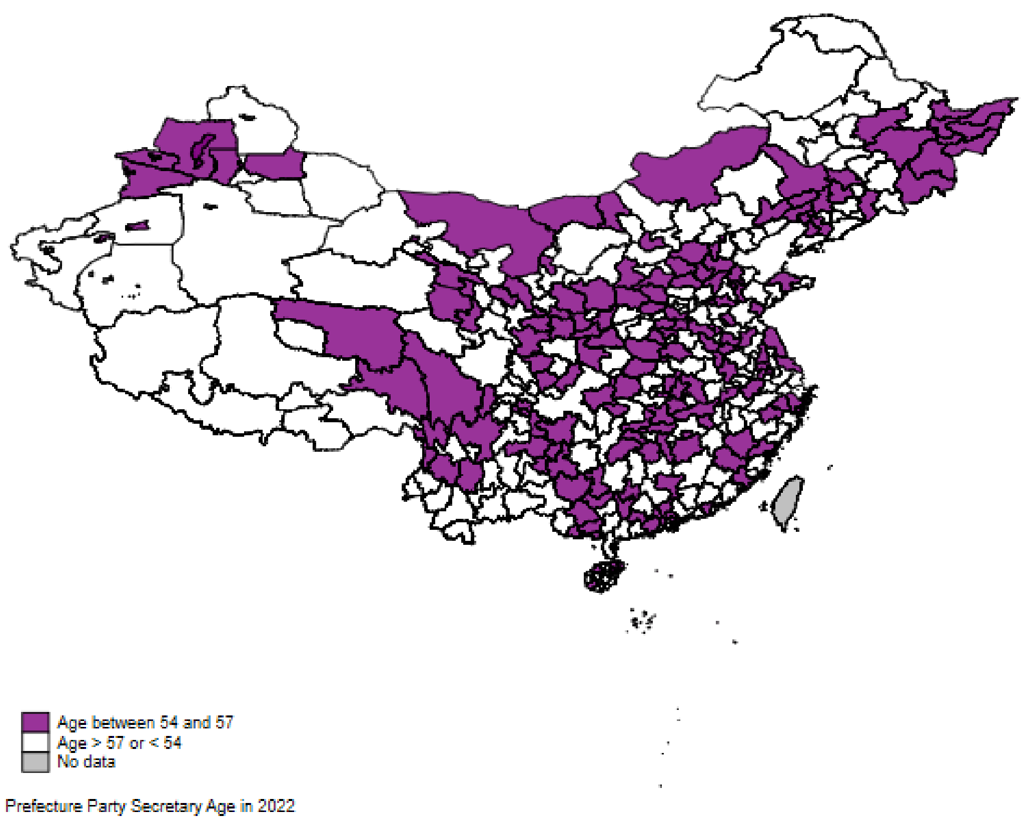
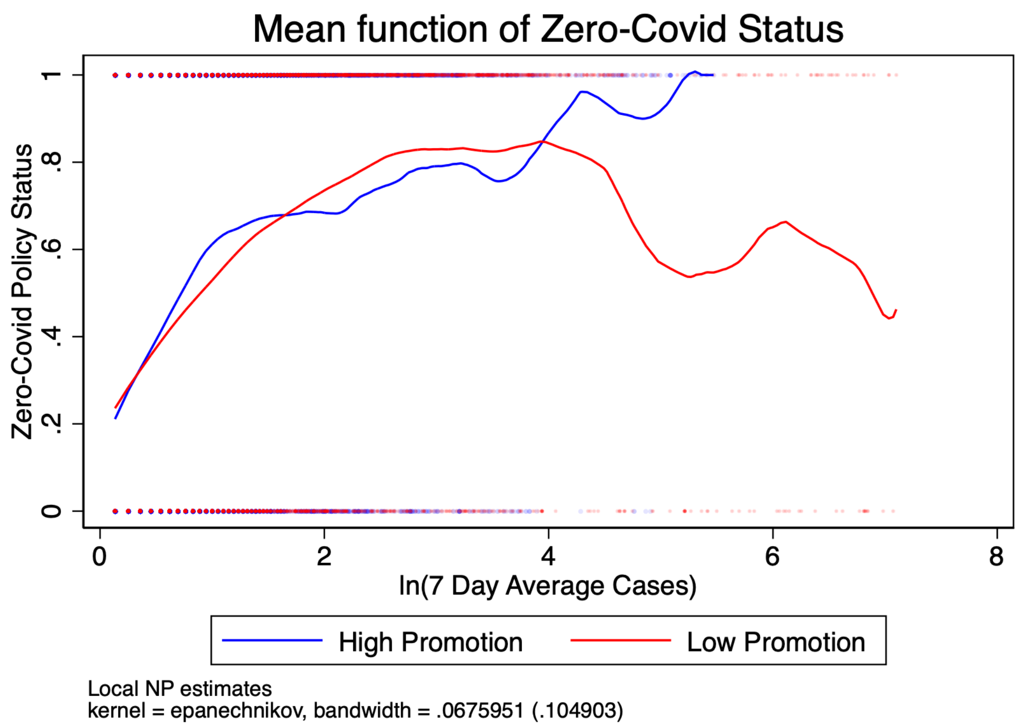


Figure 3: Prefecture Leader Age Categorized by Promotion Incentives

(a) Kernel mean of status of zero-Covid policy



(b) Kernel mean of portion of counties with zero-Covid policy

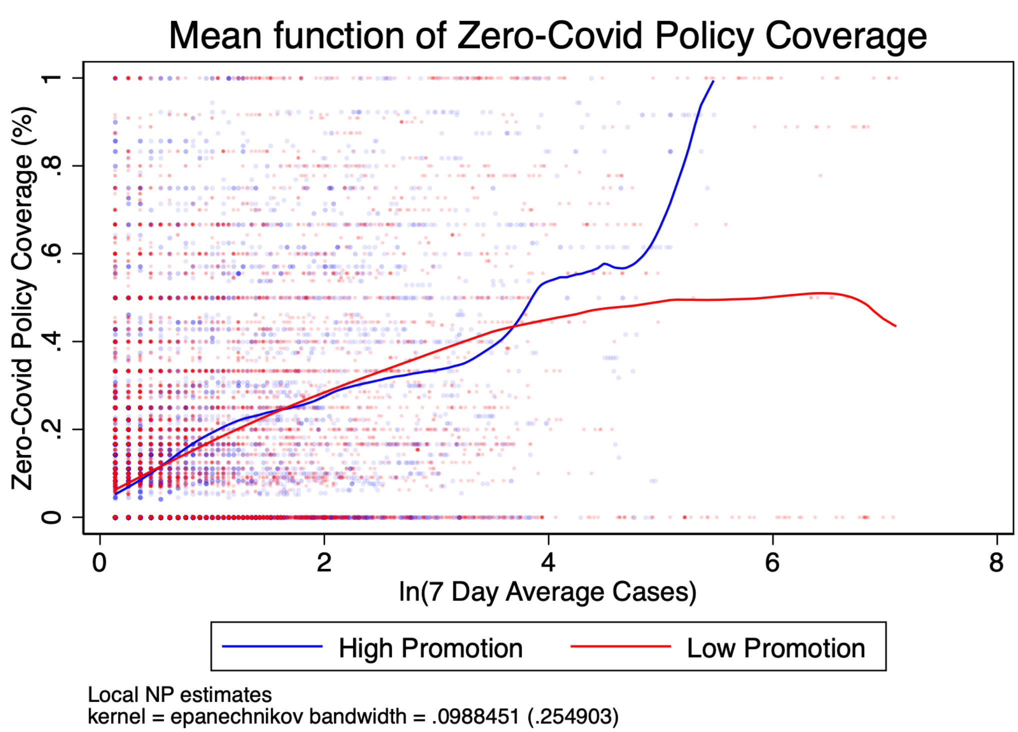
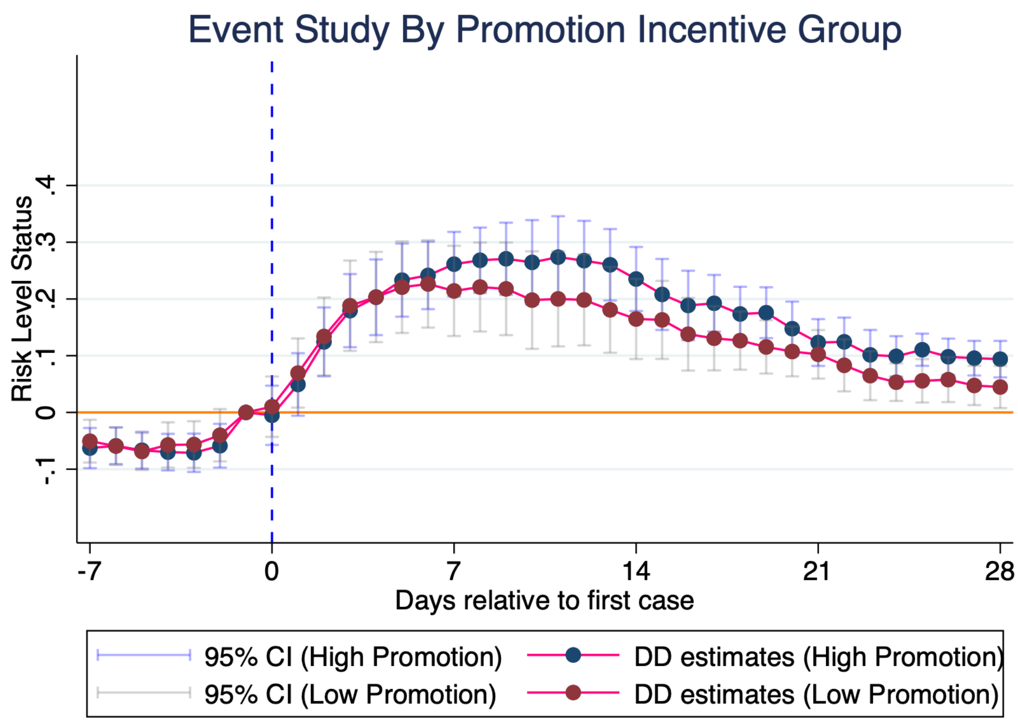


Figure 4: Non-parametric estimates of zero-Covid policy measurements on natural log of 7 day average cases

(a) Full Sample



(b) Sample of outbreaks with 50 or more cases

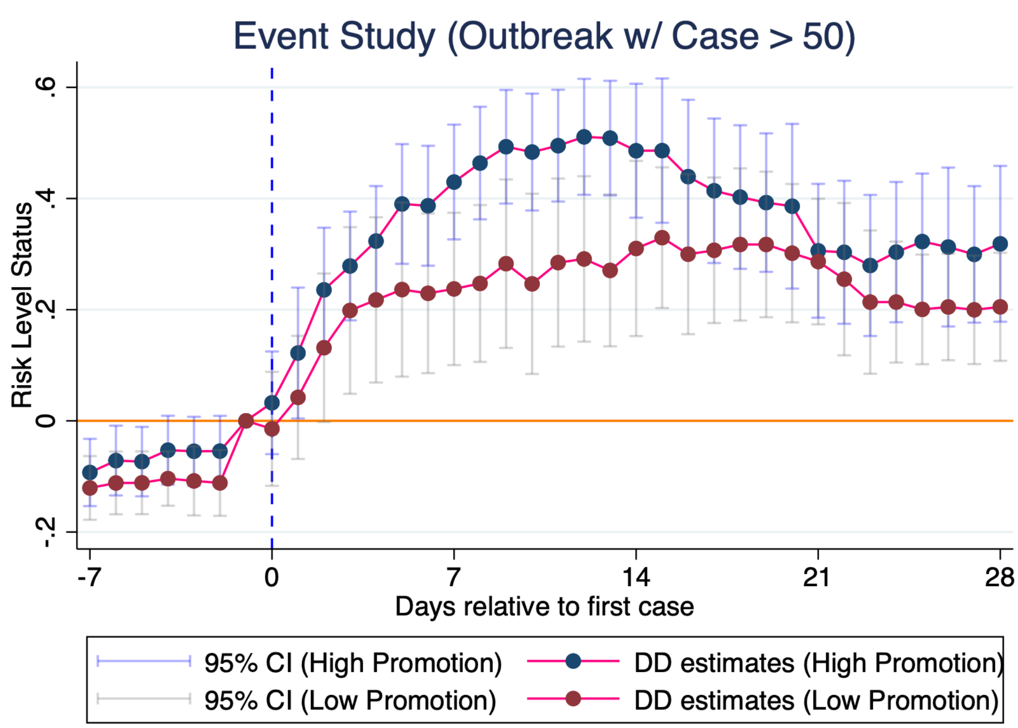


Figure 5: Plot of coefficients of the event study regression

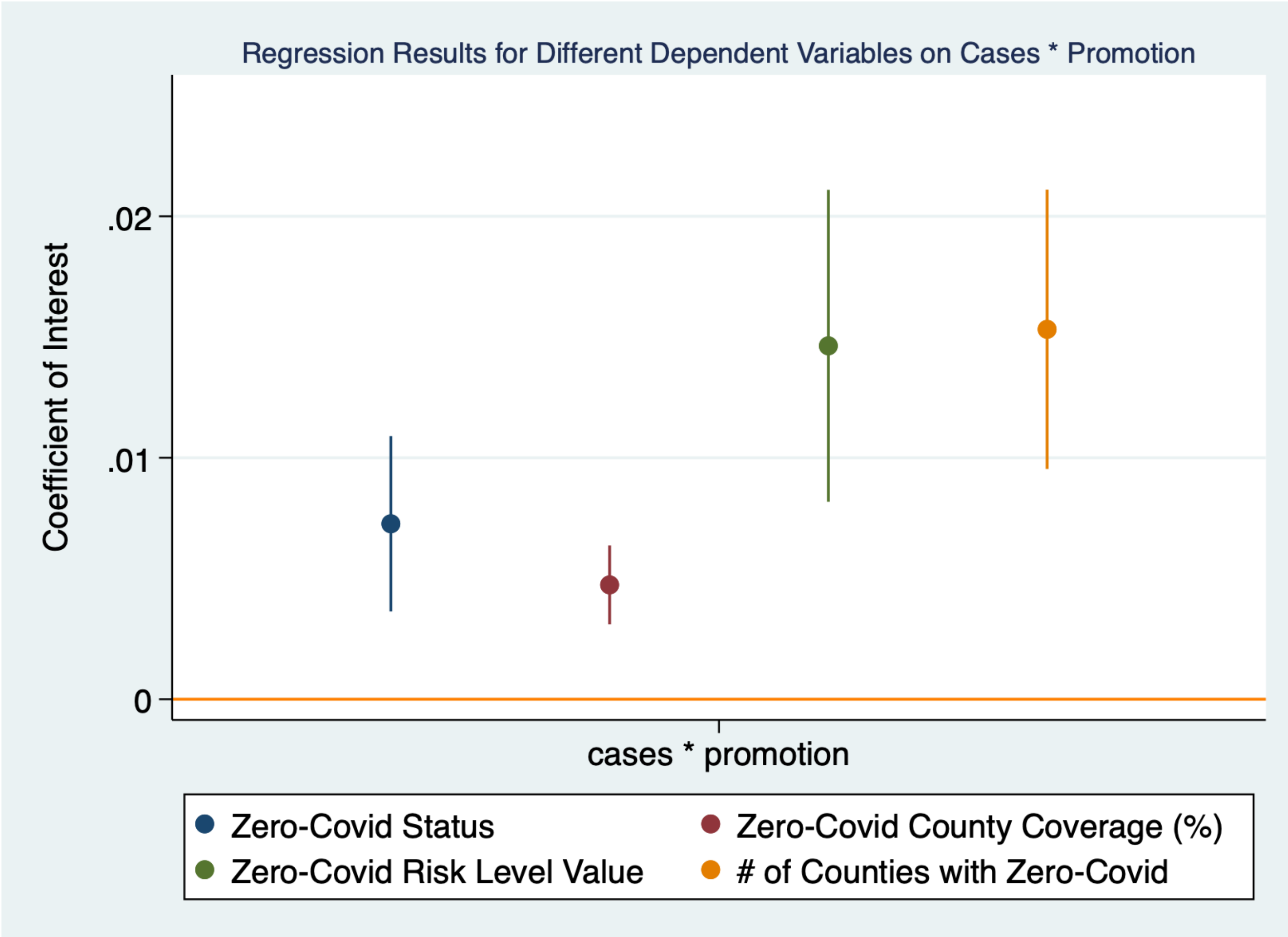
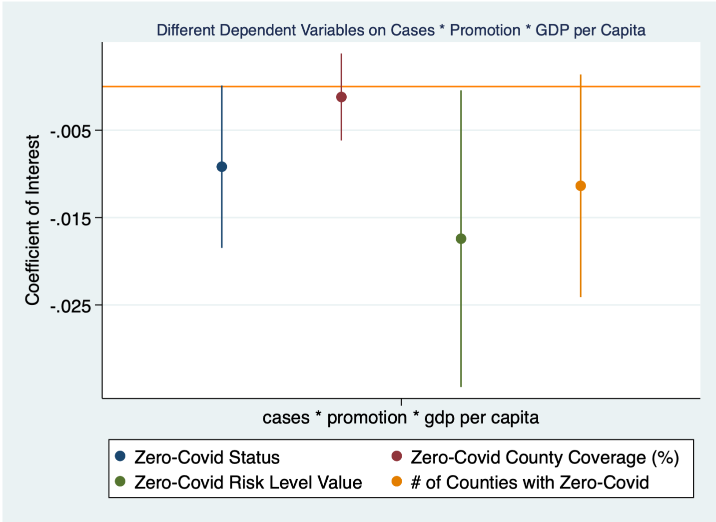
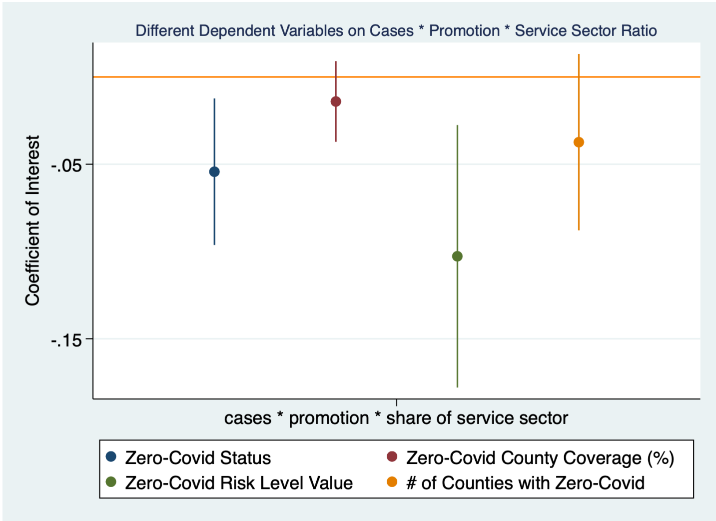


Figure 6: Main Regression Results for Alternative Dependent Variables

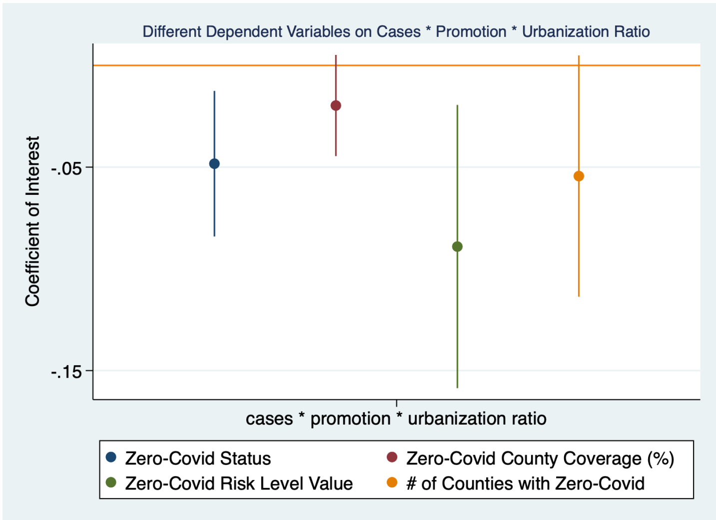
Figure 7: Multitasking Regression Results for Alternative Dependent Variables



(a) GDP per capita



(b) Share of service sector in GDP



(c) Urbanization ratio

7.2 Tables

Statistical Summary

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Panel A: Party Secretaries					
age of prefecture leader	451	54.58	3.278	45	61
promotion	451	0.437	0.497	0	1
female	451	0.0532	0.225	0	1
minor ethnicity	451	0.0732	0.261	0	1
Bachelor degree	451	0.208	0.407	0	1
Master degree	451	0.627	0.484	0	1
PhD degree	451	0.162	0.369	0	1
Panel B: Prefecture Characteristics					
population (Millions)	274	4.180	2.664	0.438	12.75
share of service sector	274	0.490	0.0726	0.285	0.805
urbanization ratio	274	0.605	0.121	0.351	0.954
GDP (Billion Yuan)	274	279.0	292.0	20.60	2,017
Panel C: COVID-19 Pandemic, Zero-Covid Policy and Mobility					
Zero-Covid Status	170,428	0.0717	0.258	0	1
Number of counties under zero-Covid	170,428	0.190	0.914	0	18
Percentage of counties under zero-Covid	170,428	0.0224	0.103	0	1
Highest Risk Level Value	170,428	0.125	0.465	0	2
Daily confirmed COVID-19 Cases	170,428	0.653	18.81	0	2,622
7-day Average Case	170,428	0.642	13.83	0	1,211
Outflow Mobility	63,294	0.0716	0.0674	0.00354	0.594
Inflow Mobility	63,294	0.0710	0.0658	0.00380	0.633

Table 1: Statistical Summary

Dependent Variable: Zero-Covid Policy Status

VARIABLES	(1)	(2)	(3)	(4)
7 day cases	0.0237***	0.0176**	0.0160**	0.0153*
	(0.00734)	(0.00803)	(0.00711)	(0.00778)
cases * Year_2022	-0.0225***	-0.0167**	-0.0160**	-0.0153**
	(0.00738)	(0.00803)	(0.00730)	(0.00765)
promotion	-0.00256	-0.00601	-0.00713	-0.000283
	(0.00653)	(0.00646)	(0.00694)	(0.00751)
cases * promotion		0.00727***	0.00913***	0.00920***
		(0.00184)	(0.00138)	(0.00167)
Observations	170,702	170,702	167,930	167,930
R^2	0.409	0.414	0.415	0.432
Prefecture FEs	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES
Cases * Control	NO	NO	YES	YES
Secretary FEs	NO	NO	NO	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prov-Month
Age Range	All	All	All	All

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Main Regression: Effect of Promotion Incentives on the choice of Zero-Covid Policy

Table 3: Main Regression: Heterogeneous Effect of Promotion Incentives on Zero-Covid Policy by GDP per capita, Share of service sector, Urbanization Ratio

	Dependent Variable: Zero-Covid Policy Status					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
7 day cases	0.0255*	0.0261**	0.0216***	0.0165**	0.0216*	0.0231**
	(0.0152)	(0.0110)	(0.00812)	(0.00721)	(0.0111)	(0.00981)
cases * Year_2022	-0.0226***	-0.0170**	-0.0224***	-0.0167**	-0.0223***	-0.0182**
	(0.00742)	(0.00814)	(0.00749)	(0.00702)	(0.00763)	(0.00755)
promotion		-0.00719		-0.00692		-0.00775
		(0.00643)		(0.00643)		(0.00644)
cases * promotion		0.111**		0.0385***		0.0438***
		(0.0539)		(0.0128)		(0.0134)
cases * gdp per capita	-0.000159	-0.000752				
	(0.00113)	(0.000676)				
cases * promotion * gdp per capita		-0.00918*				
		(0.00472)				
cases * share of service sector			0.00376	0.00206		
			(0.00511)	(0.00316)		
cases * promotion * share of service sector				-0.0543**		
				(0.0213)		
cases * urbanization ratio					0.00276	-0.00625
					(0.00940)	(0.00963)
cases * promotion * urbanization ratio						-0.0483***
						(0.0182)
Observations	170,702	170,702	170,702	170,702	170,702	170,702
R^2	0.409	0.415	0.409	0.416	0.409	0.417
Prefecture FEs	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prefecture	PPrefecture	Prefecture

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Main Regression Using Sample Data in the window of 7 days before till 28 days after an Outbreak

	Dependent Variable: Zero-Covid Policy Status					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
7 day cases	0.0129***	0.00229	0.0101***	-0.00353	0.215***	0.210***
	(0.00350)	(0.00305)	(0.00249)	(0.00577)	(0.0336)	(0.0349)
cases * Year_2022	-0.0110***	-0.000858	-0.00876***	0.00441	-0.0906**	-0.0899**
	(0.00363)	(0.00300)	(0.00263)	(0.00576)	(0.0390)	(0.0387)
promotion	-0.0433	-0.0623*	-0.127	-0.204*	-0.0495	-0.0528
	(0.0327)	(0.0326)	(0.108)	(0.115)	(0.0387)	(0.0386)
cases * promotion		0.0125***		0.0156***		0.0131
		(0.00386)		(0.00455)		(0.0317)
Observations	31,599	31,599	6,749	6,749	25,433	25,433
R^2	0.412	0.418	0.490	0.508	0.463	0.463
Prefecture FEs	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Subsample	Within 28 Days	Within 28 Days	Large Outbreak	Large Outbreak	Small Outbreak	Small Outbreak

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Dependent Variable: Portion of Counties with Zero-Covid

	Dependent Variable: Zero-Covid Policy Coverage							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
7 day cases	0.00952***	0.00551*	0.00832	0.0112*	0.00348	0.00137	-0.00141	8.62e-05
	(0.00250)	(0.00285)	(0.00979)	(0.00571)	(0.00389)	(0.00316)	(0.00526)	(0.00547)
cases * Year_2022	-0.00855***	-0.00475*	-0.00852***	-0.00481*	-0.00807***	-0.00477*	-0.00711**	-0.00499*
	(0.00253)	(0.00284)	(0.00256)	(0.00289)	(0.00280)	(0.00274)	(0.00279)	(0.00272)
promotion	0.000311	-0.00193		-0.00220		-0.00207		-0.00220
	(0.00258)	(0.00245)		(0.00245)		(0.00243)		(0.00244)
cases * promotion		0.00474***		0.0184		0.0124*		0.0187**
		(0.000829)		(0.0287)		(0.00697)		(0.00927)
cases * gdp per capita			0.000106	-0.000509				
			(0.000842)	(0.000463)				
cases * promotion * gdp per capita				-0.00119				
				(0.00253)				
cases * share of service sector					0.0107**	0.00803***		
					(0.00465)	(0.00301)		
cases * promotion * share of service sector						-0.0141		
						(0.0117)		
cases * urbanization ratio							0.0143**	0.00863
							(0.00576)	(0.00726)
cases * promotion * urbanization ratio								-0.0197
								(0.0126)
Observations	170,702	170,702	170,702	170,702	170,702	170,702	170,702	170,702
R^2	0.460	0.474	0.460	0.475	0.465	0.477	0.464	0.476
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Dependent Variable: Highest Value of Zero-Covid Risk Level

	Dependent Variable: Zero-Covid Policy Level							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
7 day cases	0.0378***	0.0254**	0.0426	0.0444**	0.0309**	0.0212*	0.0304	0.0344**
	(0.0112)	(0.0122)	(0.0296)	(0.0199)	(0.0131)	(0.0108)	(0.0192)	(0.0174)
cases * Year_2022	-0.0358***	-0.0241**	-0.0360***	-0.0246**	-0.0353***	-0.0242**	-0.0349***	-0.0267**
	(0.0113)	(0.0122)	(0.0114)	(0.0124)	(0.0117)	(0.0102)	(0.0118)	(0.0112)
promotion	-0.000347	-0.00728		-0.00960		-0.00894		-0.0104
	(0.0117)	(0.0116)		(0.0115)		(0.0116)		(0.0116)
cases * promotion		0.0146***		0.212**		0.0734***		0.0818***
		(0.00328)		(0.0985)		(0.0228)		(0.0258)
cases * gdp per capita			-0.000421	-0.00167				
			(0.00237)	(0.00143)				
cases * promotion * gdp per capita				-0.0174**				
				(0.00863)				
cases * share of service sector					0.0122	0.00841		
					(0.0108)	(0.00689)		
cases * promotion * share of service sector						-0.103***		
						(0.0382)		
cases * urbanization ratio							0.00979	-0.00957
							(0.0191)	(0.0205)
cases * promotion * urbanization ratio								-0.0890**
								(0.0354)
Observations	170,702	170,702	170,702	170,702	170,702	170,702	170,702	170,702
R^2	0.446	0.453	0.446	0.454	0.446	0.455	0.446	0.455
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Dependent Variable: Number of Counties Under Zero-Covid

	Dependent Variable: Zero-Covid Policy Number of Counties							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES								
7 day cases	0.0341***	0.0211**	0.0304	0.0358**	0.0212*	0.0145	0.00599	0.0137
	(0.00804)	(0.00961)	(0.0279)	(0.0163)	(0.0125)	(0.0103)	(0.0160)	(0.0158)
cases * Year_2022	-0.0315***	-0.0192**	-0.0314***	-0.0196**	-0.0305***	-0.0192**	-0.0278***	-0.0202**
	(0.00813)	(0.00960)	(0.00822)	(0.00972)	(0.00878)	(0.00913)	(0.00894)	(0.00922)
promotion	-0.000903	-0.00816		-0.00973		-0.00863		-0.00933
	(0.00886)	(0.00850)		(0.00844)		(0.00846)		(0.00845)
cases * promotion		0.0153***		0.144**		0.0361**		0.0547**
		(0.00294)		(0.0730)		(0.0148)		(0.0211)
cases * gdp per capita			0.000325	-0.00129				
			(0.00236)	(0.00123)				
cases * promotion * gdp per capita				-0.0114*				
				(0.00647)				
cases * share of service sector					0.0227	0.0127		
					(0.0152)	(0.00918)		
cases * promotion * share of service sector						-0.0374		
						(0.0257)		
cases * urbanization ratio							0.0368**	0.0129
							(0.0164)	(0.0197)
cases * promotion * urbanization ratio								-0.0544*
								(0.0301)
Observations	170,702	170,702	170,702	170,702	170,702	170,702	170,702	170,702
R^2	0.476	0.491	0.476	0.493	0.478	0.492	0.479	0.493
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre	Prefecutre

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Alternative Encoding and Subsample for Promotion Incentives

	Dependent Variable: Zero-Covid Policy Status								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES									
7 day cases	0.0176**	0.0160**	0.0153*	0.0134*	0.0192**	0.0181**	0.0218***	0.0140*	0.0133
	(0.00803)	(0.00711)	(0.00778)	(0.00749)	(0.00767)	(0.00833)	(0.00746)	(0.00833)	(0.00858)
cases * Year_2022	-0.0167**	-0.0160**	-0.0153**	-0.0129*	-0.00898*	-0.00874	-0.0213***	-0.0201***	-0.0195**
	(0.00803)	(0.00730)	(0.00765)	(0.00749)	(0.00501)	(0.00595)	(0.00746)	(0.00762)	(0.00778)
promotion	-0.00601	-0.00713	-0.000283	-0.0155*	-0.0185*	-0.0113	-0.00916	-0.0166*	-0.00885
	(0.00646)	(0.00694)	(0.00751)	(0.00796)	(0.0104)	(0.0111)	(0.00767)	(0.00974)	(0.0102)
cases * promotion	0.00727***	0.00913***	0.00920***	0.00778***	0.0113***	0.0113***	0.00193*	0.00600***	0.00595***
	(0.00184)	(0.00138)	(0.00167)	(0.00196)	(0.00232)	(0.00263)	(0.000998)	(0.00185)	(0.00223)
Observations	170,702	167,930	167,930	104,092	101,320	101,320	170,702	167,930	167,930
R^2	0.414	0.415	0.432	0.421	0.424	0.434	0.411	0.414	0.430
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cases * Control	NO	YES	YES	NO	YES	YES	NO	YES	YES
Secretary FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES
Clustered Standard Error	Prefecture	Prefecture	Prov-Month	Prefecture	Prefecture	Prov-Month	Prefecture	Prefecture	Prov-Month
Age Range	All	All	All	54 - 61	54 - 61	54 - 61	All	All	All
Promotion Criteria	54 - 57	54 - 57	54 - 57	54 - 57	54 - 57	54 - 57	< 57	< 57	< 57

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect of Zero-Covid Policy on Mobility Inflow

	Dependent Variable: Mobility Inflow						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES							
Zero-Covid	-0.176***	1.188***	0.941**	0.471***	0.363***	0.280***	0.173**
	(0.0451)	(0.371)	(0.471)	(0.125)	(0.0867)	(0.0921)	(0.0824)
Zero-Covid * Year_2022	0.0344	0.0391	0.0327	0.0220	0.0238	0.0292	0.0282
	(0.0352)	(0.0306)	(0.0351)	(0.0213)	(0.0259)	(0.0268)	(0.0321)
promotion	-0.00645	-0.00866	-0.00690	-0.00843	-0.00572	-0.00783	-0.00581
	(0.00607)	(0.00595)	(0.00596)	(0.00571)	(0.00544)	(0.00571)	(0.00572)
Zero-Covid * promotion	-0.0366		0.468		0.257		0.208
	(0.0461)		(0.689)		(0.229)		(0.144)
Zero-Covid * gdp per capita		-0.125***	-0.101**				
		(0.0337)	(0.0411)				
Zero-Covid * promotion * gdp per capita			-0.0454				
			(0.0642)				
Zero-Covid * share of service sector				-1.266***	-1.013***		
				(0.265)	(0.197)		
Zero-Covid * promotion * share of service sector					-0.594		
					(0.488)		
Zero-Covid * urbanization ratio						-0.706***	-0.515***
						(0.154)	(0.121)
Zero-Covid * promotion * urbanization ratio							-0.372
							(0.254)
Observations	63,294	63,294	63,294	63,294	63,294	63,294	63,294
R^2	0.929	0.930	0.930	0.932	0.933	0.931	0.932
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Effect of Zero-Covid Policy on Mobility Outflow

	Dependent Variable: Mobility Outflow						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES							
Zero-Covid	-0.212***	1.433***	0.913*	0.667***	0.556***	0.383***	0.260***
	(0.0568)	(0.456)	(0.473)	(0.151)	(0.103)	(0.112)	(0.0818)
Zero-Covid * Year_2022	0.0460	0.0522	0.0429	0.0289	0.0292	0.0392	0.0372
	(0.0424)	(0.0358)	(0.0418)	(0.0221)	(0.0292)	(0.0308)	(0.0384)
promotion	-0.00690	-0.00979	-0.00749	-0.00953	-0.00591	-0.00873	-0.00605
	(0.00714)	(0.00712)	(0.00704)	(0.00677)	(0.00637)	(0.00674)	(0.00667)
Zero-Covid * promotion	-0.0484		0.988		0.276		0.244
	(0.0553)		(0.811)		(0.253)		(0.161)
Zero-Covid * gdp per capita		-0.151***	-0.101**				
		(0.0413)	(0.0401)				
Zero-Covid * promotion * gdp per capita			-0.0934				
			(0.0757)				
Zero-Covid * share of service sector				-1.719***	-1.441***		
				(0.318)	(0.235)		
Zero-Covid * promotion * share of service sector					-0.664		
					(0.540)		
Zero-Covid * urbanization ratio						-0.923***	-0.695***
						(0.189)	(0.122)
Zero-Covid * promotion * urbanization ratio							-0.445
							(0.288)
Observations	63,294	63,294	63,294	63,294	63,294	63,294	63,294
R^2	0.927	0.929	0.929	0.934	0.934	0.932	0.932
Prefecture FEs	YES	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

A1. Regression Discontinuity Approach

To identify a casual effect of promotion incentives on the implementation of the zero-Covid policy, we also employ the regression discontinuity design (Imbens and Lemieux, 2008; Lee and Card, 2008) to verify the discontinuity that lies in the ineligible age of promotion of the prefecture leaders (i.e., 58). The following local regression was estimated for the subsample of party secretaries aged close to 58 years:

$$\begin{aligned} ZeroCovid_{it} = {} & \beta_1 Cases_{it} + \beta_2 Cases_{it} \times I(Year \leq 57)_{it} + \beta_3 Cases_{it} \times DAGE_{it} \\ & + \beta_4 Cases_{it} \times DAGE_{it} \times I(Year \leq 57)_{it} + \gamma Cases_{it} \times X_{it} + \mu_i + \theta_t + \varepsilon_{it} \end{aligned} \tag{A1}$$

where $DAGE_{it}$ is a running variable for the age of the party secretary of prefecture i at date t, specifically calculated by $DAGE =$ age of secretary -58; $I(Year \leq 57)_{it}$ is a dummy of secretary's age less than or equal to 57 years, and other notation remains identical to that of equation (A1). β_2 identifies the impact of promotion incentives on the prefecture leader's zero-Covid policy decision at the promotion eligible age cutoff point. We expect β_2 to be positive and significant if the age restriction creates a discontinuity in the promotion incentive and thus affects prefecture leaders' compliance with the zero-Covid policy.

In Table A1, we present the results of a regression discontinuity approach based on equation (A1). In columns (1) - (3), the estimation is conducted using a subsample of party secretaries aged between 55 and 61; and in columns (4) - (6), we used a subsample of officials aged between 56 and 60. In columns (1) and (4), the coefficients of $Cases_{it} \times I(Year \leq 57)_{it}$ are 0.0125 and 0.0215 and significant at the level 0.01 and 0.1, respectively. These results imply a discontinuity in the marginal increase in the probability of zero-Covid policy brought by the confirmed cases at the promotion eligible age cutoff point of 58 years. In prefectures with party secretaries aged 57 or younger, the probability of implementing the zero-Covid policy is approximately 2% higher for every 7-day average daily case compared to prefectures with older party secretaries. Using our previous hypothetical scenario in Section 5.1, this implies a 20% lower probability of implementing the zero-Covid policy when facing a pandemic outbreak with 70 cases over the past 7 days in prefectures with elder party secretaries.

In columns (2)(3)(5)(6), we add include interaction terms between 7-day average case and control variables and party secretary fixed effects. The regression results do not show substantial changes. Thus, we conclude that the estimation from our regression discontinuity approach is consistent with our baseline regression results in Section 5.1, giving credence to our overall findings.

A2. Appendix Tables

Dependent Variable: Zero-Covid Policy Status

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
7 day cases	0.0123*	0.0209**	0.0199**	0.0232***	0.0157	0.0153
	(0.00625)	(0.00904)	(0.00896)	(0.00769)	(0.0110)	(0.0110)
cases * Year_2022	-0.0118*	-0.00638*	-0.00626*	-0.0227***	-0.00458	-0.00511
	(0.00624)	(0.00335)	(0.00335)	(0.00769)	(0.0130)	(0.0129)
cases * I(age <= 57)	0.0125***	0.0185***	0.0189***	0.0215*	0.0244**	0.0243**
	(0.00422)	(0.00586)	(0.00604)	(0.0113)	(0.00941)	(0.00967)
cases * DAGE	0.135***	0.131***	0.133***	0.124***	0.131***	0.131***
	(0.0190)	(0.0183)	(0.0183)	(0.0188)	(0.0203)	(0.0197)
cases * DAGE * I(age <= 57)	-0.132***	-0.128***	-0.129***	-0.116***	-0.124***	-0.124***
	(0.0188)	(0.0183)	(0.0184)	(0.0175)	(0.0195)	(0.0192)
Observations	81,631	81,631	81,631	63,308	63,308	63,308
R^2	0.427	0.433	0.442	0.447	0.450	0.458
Prefecture FEs	YES	YES	YES	YES	YES	YES
Prov-Month FEs	YES	YES	YES	YES	YES	YES
Cases * Control	NO	YES	YES	NO	YES	YES
Secretary FEs	NO	NO	YES	NO	NO	YES
Clustered Standard Error	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Age Range	54-61	54-61	54-61	55-60	55-60	55-60

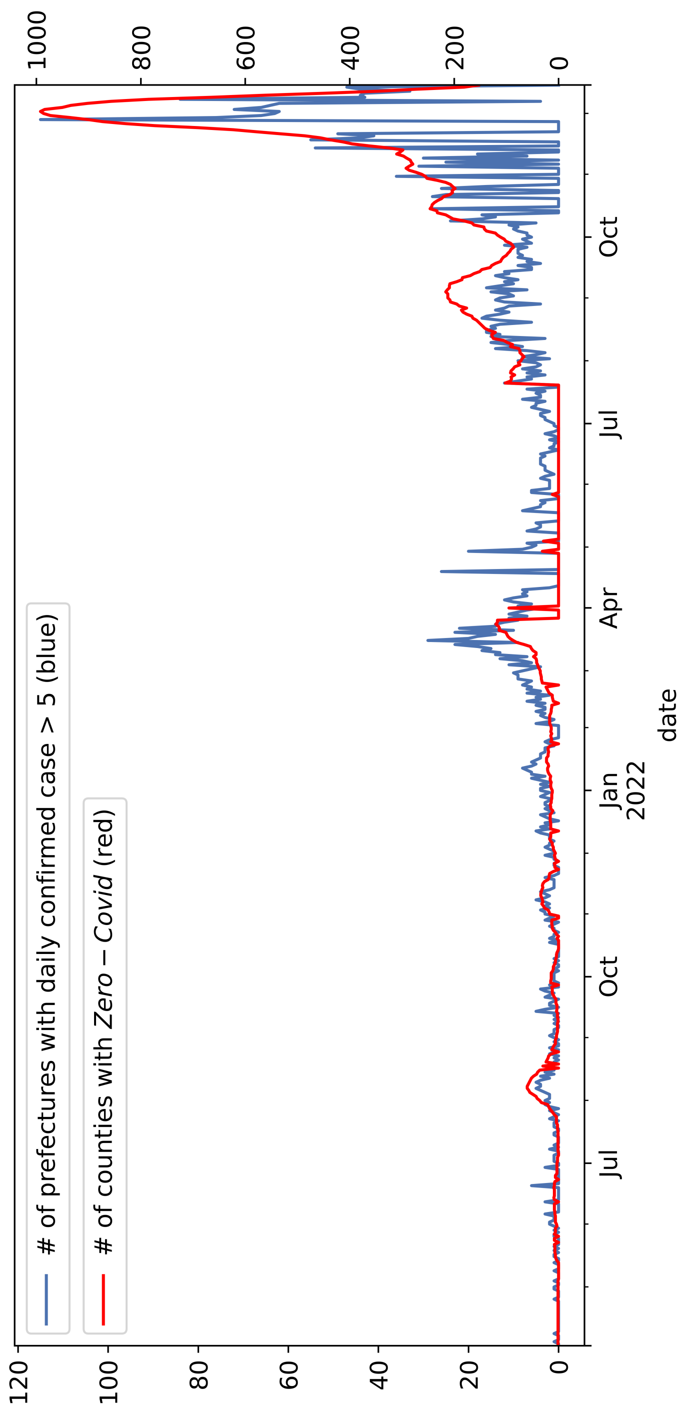
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A1: Regression Discontinuity: Effect of Promotion Incentives on the Choice of Zero-Covid Policy

A3. Appendix Figures

Figure 8: Timeline of Prefectures with Emerging COVID-19 Cases and Counties with Zero-Covid Policy



Note: The left y-axis represents the number of prefectures with daily confirmed COVID-19 cases exceeding five, while the right y-axis indicates the number of counties where the zero-COVID policy is in effect.

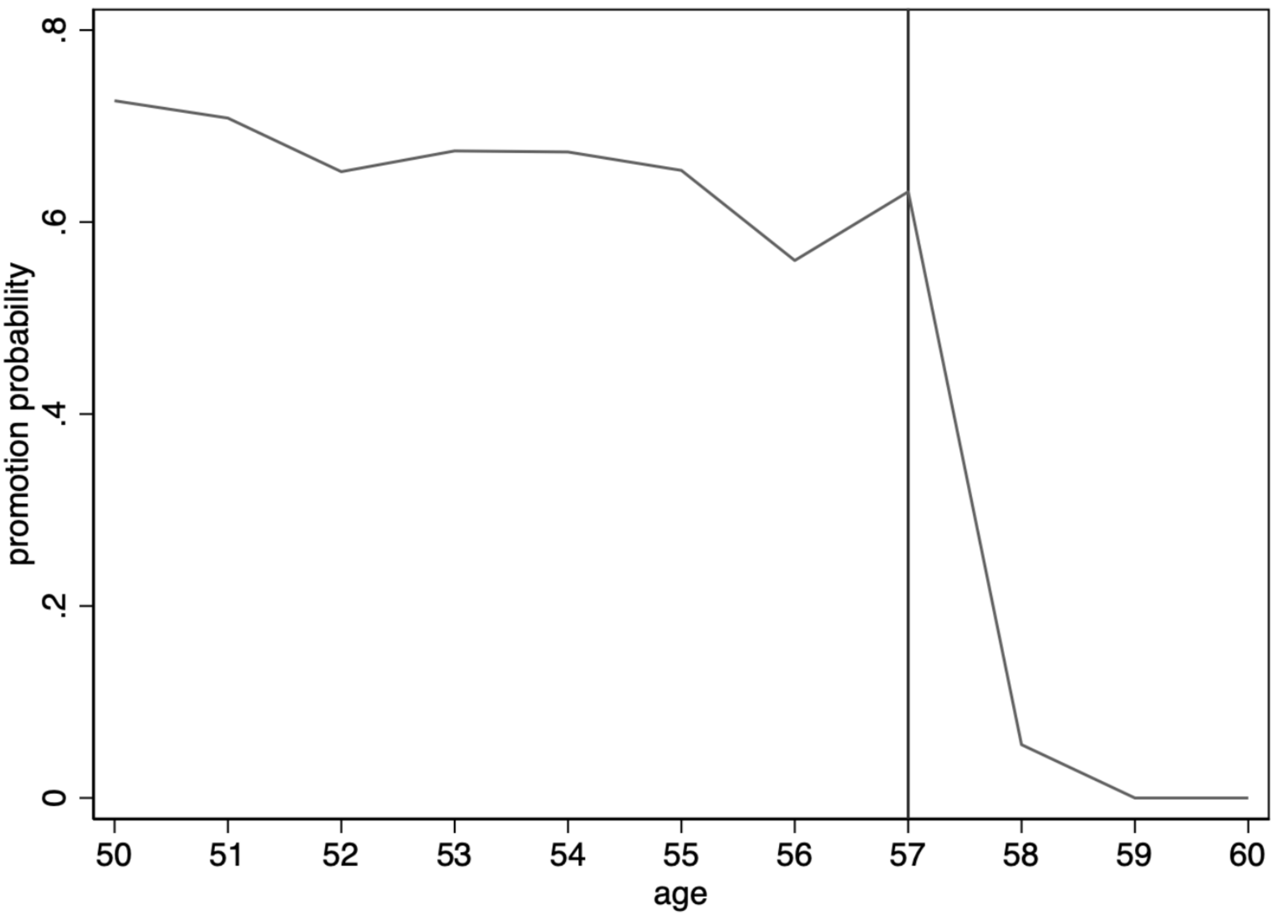


Figure A2: Promotion Probability of Mayors (Zhou and Zeng, 2018)

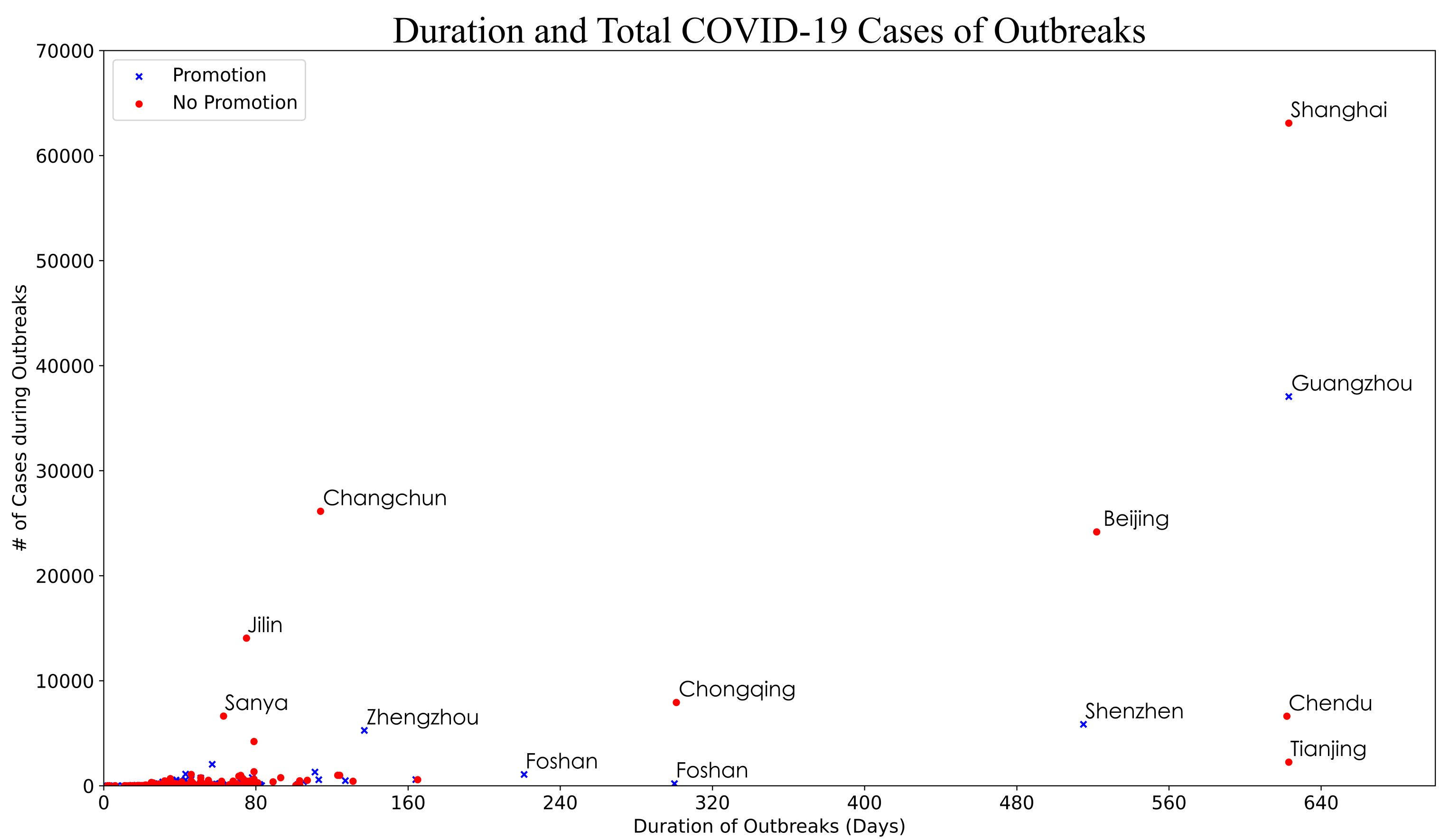


Figure A3: Distribution of Outbreak Duration and Cumulative Case Number

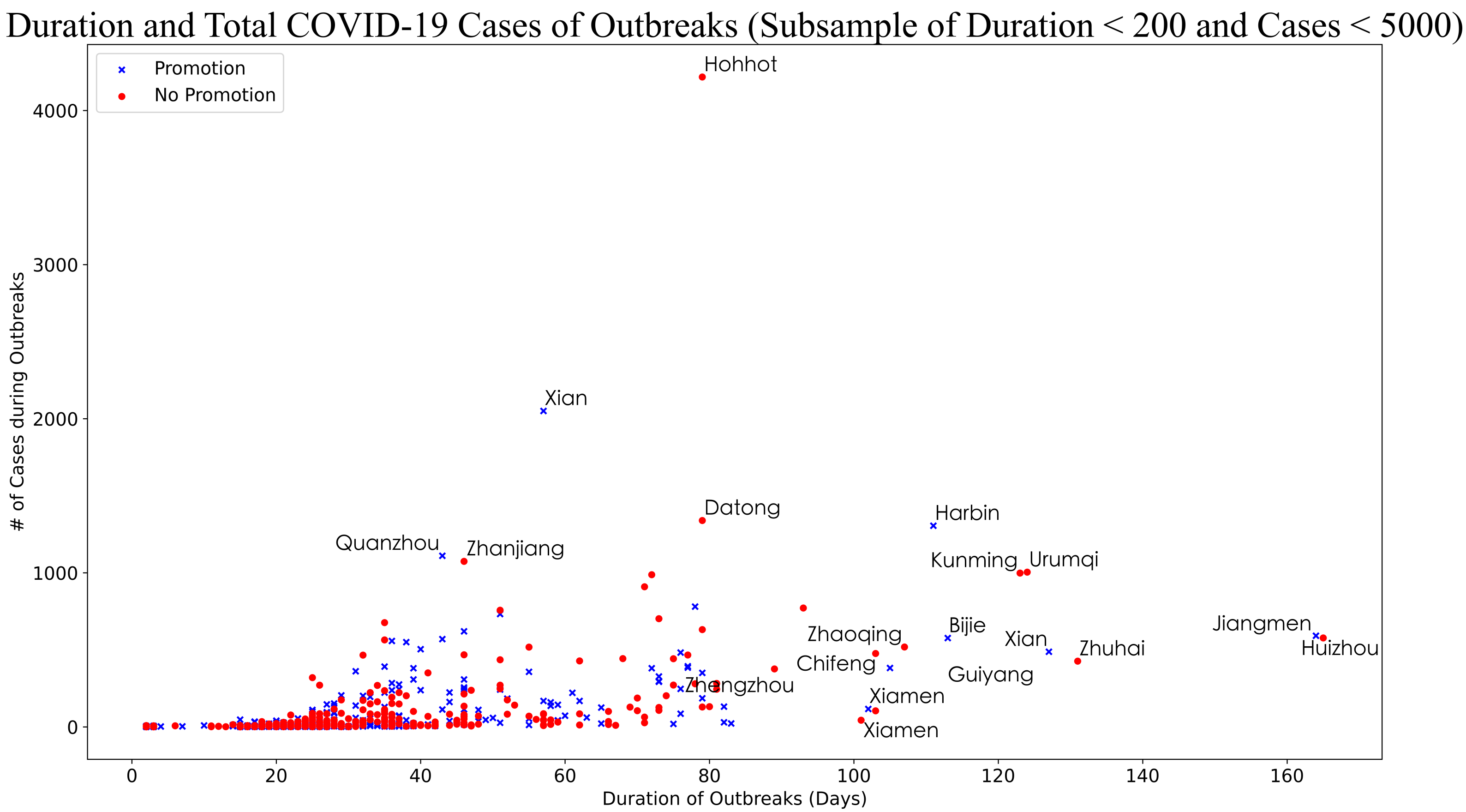


Figure A4: Distribution of Outbreak Duration and Cumulative Case Number (Subsample of Outbreaks with duration less than 200 and total COVID-19 cases less than 5000