Economic Impacts of China's Zero-COVID Policies *

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Abstract

This paper presents an investigation of the economic consequences of the zero-COVID policy implemented by the Chinese government as a pilot experiment in using big data for country management from 2020 to 2022. Our study includes an original county-daily panel data set on the COVID-19 *Risk Level* issued by the State Council of the People's Republic of China (PRC). To measure economic activities, we used satellite data on night lights and PM2.5, and geographical data on population mobility. Our findings indicate that the zero-COVID policy did not result in significant economic loss in 2021. However, in 2022, when the Omicron variant emerged, a stricter zero-COVID policy led to a 30% decline in mobility, a 1.17% decrease in PM2.5 and a 7.7% reduction in night lights. Based on our calculations, China experienced a 3.9% loss in GDP as a consequence of the implementation of the zero-COVID policy in 2022.

Keywords: COVID-19, zero-COVID policy, Air pollution, Human mobility, Night lights

JEL codes: I18, D04, Q53

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1 Introduction

The COVID-19 pandemic severely disrupted general economic activity as human mobility was restricted, social gatherings were banned, and businesses were halted. However, research that examines the effects of the pandemic on the economy has focused primarily on specific areas, such as unemployment, consumer spending, labor demand, and pollution. There is a demand for a comprehensive assessment of the economic consequences of the pandemic and the corresponding anti-contagion policies. Additionally, most of the research has focused only on the year 2020 and has not considered the subsequent periods 2021 and 2022. Our paper aims to fill this gap.

In this paper, we compile a unique dataset of China's COVID-19 risk level on prefecture/county level, which is constructed based on big data provided by the State Council of the People's Republic of China (PRC). We examine the impact associated with China's COVID-19 policies on several salient economic indicators from 2020 to 2022. Specifically, we analyze the effects on mobility, air pollution measured by the concentration of fine particulate matter (PM2.5) and night lights. We rely on a difference-in-differences framework for identification, with the assumption that, conditional on daily confirmed COVID-19 cases and other prefecture-day level controls, the difference in economic indicators between regions with and without COVID-19 containment policies would remain stable over time.

From February 17, 2020, after one month of the pandemic outbreak and a series of strict lockdown measures, China has utilized big data and established a nationwide risk-level system, which aimed to contain the spread of the virus within communities while keeping the economic costs to a minimum, also referred to as "zero-COVID" policy. To be specific, China implemented a nationwide risk response system that mandated local officials to classify communities into low-, medium-, and high-risk levels based on recent confirmed COVID-19 cases and other factors. Areas rated as medium- and high-risk imposed more stringent containment measures compared to low-risk areas, such as stay-at-home order, mass testing, contact tracing and mobility restrictions. Therefore, the classification of an area as *risk* or non-risk is closely linked to the stringency of the zero-COVID policies enforced by local authorities.

It is important to evaluate the economic consequences of zero-COVID policy in the context of both economics and politics. Zero-COVID policies are considered as the Chinese government's pilot experiment in using big data for national management and crisis response.[1] In 2021, China's media outlets portrayed the low mortality rate from COVID-19 as the success of this risk-level system. Moreover, China's GDP growth rate reached 8.1% in 2021. The Chinese government has been promoting their zero-COVID policies as a model for the rest of the world to follow, claiming that it has been effective in both preserving lives while maintaining economic growth. However, in 2022, the emergence of the Omicron variant resulted in shutdowns of financial, manufacturing, and exporting centers, including Shanghai, Shenzhen, Guangzhou, and Changchun, leading to the failure of China's zero-COVID policy to safeguard people's lives and economic vitality (Mark and Schuman, 2022).

Using an original daily panel data at the prefecture/county-level on COVID-19 risk levels collected from the website of the State Council, our study firstly shows that on average the zero-COVID policy took 21 days to eliminate local COVID-19 cases in 2021, but it took approximately 50 days in 2022. Our second finding reveals a 30% reduction in inter-prefecture traffic flow after a prefecture has been classified as a *Risk* region in either 2021 or 2022. Furthermore, our study revealed that the probability of being classified as a *Risk* region was positively and significantly associated with changes in PM2.5 and night lights in 2021, while the effects of the zero-COVID policy are negligible. However, in 2022, the zero-COVID policy led to a decrease in PM2.5 concentration by 1.17% and a reduction in night lights by 7.7%. The differences in policy effects observed between 2021 and 2022 can be primarily attributed to differences in the stringency of the zero-COVID policy. In 2022, with the emergence of the Omicron variant and stricter zero-COVID policies, the negative policy effects on economic activities became significantly larger. Our back-of-the-envelope calculations indicate that the zero-COVID policy caused China to experience a reduction of around 3.9% in GDP in 2022.

The previous studies on COVID-19 pandemic in China have two limitations. First, the majority of studies draw their conclusions focusing on lockdown policies in the early stage of 2020 rather than zero-COVID policies in 2021 and 2022.[2] To date, only one paper has estimated the economic

[1] Check out the coverage provided by state-controlled media: https://www.tsinghua.edu.cn/info/1182/51343.htm

[2] For example, see Fang et al. (2020a); He et al. (2020); Fang et al. (2020b); Liu et al. (2020). For a systemic

impacts using truck flows in 2020 and 2021 (Chen et al., 2022a). However, it is worth noting that the policy object under study in this paper is prefecture-level city lockdown, rather than zero-COVID policy, therefore it could not account for less stringent policies such as 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. Second, they primarily focused on the economic consequences of COVID policies from a single aspect. Dang et al. (2023); Gong et al. (2022); Zhang (2021) focus on the COVID-19 policies' adverse effects on labor market outcomes such as unemployment, wage, and labor market participation. Using high-frequency transaction data, Chen et al. (2021) provided evidence that the pandemic has caused a sharp decline in consumption immediately after the COVID outbreak. Fang et al. (2020b) documented that the human mobility restrictions imposed by Chinese government in the early phase of the pandemic effectively controlled the spread of the virus. Despite the seemingly high economic and social costs, researchers have also shown that the COVID-19 pandemic significantly improved air quality and reduced environmental pollution (He et al., 2020; Brodeur et al., 2021).

This paper makes three primary contributions. First of all, to be best of our knowledge, our paper is the first empirical study that examines the economic impact of the zero-COVID policy spanning from 2020 to 2022. We offer evidence of the heterogeneous outcomes linked to the implementation of the zero-COVID policy during the three-year pandemic. This research provides insight into the efficacy of the zero-COVID strategy in contributing to China's rapid economic recovery in 2021, and also highlights the disruptions caused by the escalating pandemic and the frequent re-imposition of the zero-COVID policy in 2022. Second, we compiled a unique dataset that reflects the stringency of China's zero-COVID policy. Our dataset provides daily risk level indices at the county level in China from April 2021 to December 2022, including 2853 counties and 368 prefecture-level cities. Local governments have implemented various anti-contagion policies based on risk ratings. The granularity of our dataset could provide new insights and serve as a valuable tool for future research in general to better understand the economic consequences of the pandemic and the zero-COVID policies in China. Lastly, our paper contributes to the

review, see Huang et al. (2023)

existing literature with an in-depth analysis of the economic impact of the COVID-19 policies along three dimensions: human mobility, air pollution, and night lights. The three outcomes in our research offer varying insights into economic performance, such as transportation, manufacturing, and service sectors. Furthermore, the inter-prefecture traffic mobility index and PM2.5 can be used as proxies for short-term economic activities, particularly human mobility and factory productions. On the other hand, night lights can be used as proxies for medium-term economic activities.

The remainder of this paper is structured as follows. Section 2 details the policy background and data. Section 3 delineates the identification strategy. Section 4 presents the main results and performs robustness checks. Section 5 concludes.

2 Policies and Data

In this section, we cover basic facts and data source. Initially, we outline China's COVID-19 policies, encompassing lockdown and the zero-COVID. Then, we describe the sources of data for mobility, pollution, and night lights. Finally, we describe the control variables, which include daily confirmed cases and weather.

2.1 China's COVID-19 Policy — Lockdown (Jan 23 — Feb 16, 2020)

With the initial COVID-19 outbreak in Wuhan in 2020, the Chinese government implemented unprecedented prefecture lockdown to contain the virus. Stringent measures were put in place in the locked-down prefectures, including the prohibition of traffic leaving, the imposition of stay-at-home orders, and the enforcement of quarantine measures. It's worth mentioning that anti-contagion policies were also enforced in prefectures without lockdowns, albeit with less strict measures compared to the locked-down ones. According to Qiu et al. (2020), by February 16, 2020, more than 250 prefectures had implemented such measures.[3] Starting from February 17, 2020, the Chinese government implemented a policy package to precisely contain COVID-19 transmission at the community level. As a result, the central government no longer recommended prefecture-level

[3]"In all Chinese cities, the Spring Festival holiday was extended, and people were advised to stay at home when possible, enforce social distancing and maintain good hygiene." (He et al., 2020)

lockdowns, as they were considered too detrimental to the economy.

The "Lockdown" in this study is defined as China's major COVID-19 policy from January 23 to February 16, 2020. Our data on lockdowns come from He et al. (2020), who originally collected from Wikipedia, various sources of news media and government announcements.

2.2 China's COVID-19 Policy — zero-COVID (Feb 17, 2020 — Dec 25, 2022)

Following the one-month-long enforcement of strict lockdowns and nationwide public health interventions, the central government sought to revive the economy and loosen the lockdown measures. (Gong et al., 2022). On February 17, Prevention Guidance for Novel Coronavirus Pneumonia (version 5) was issued by the State Council and National Health Commission of China.[4] This guidance mandated local governments to classify COVID-19 risk at the community level. Any community that reported COVID-19 cases would be categorized as either a medium- or high-risk zone, and corresponding containment measures and closures would be enforced. However, in principle, low-risk communities should only impose quarantines on individuals traveling from medium- or high-risk areas and should not limit the traveling of residents or economic activities. The objective of this policy is to eradicate COVID-19 transmission at the local level by assigning each community a risk level and implementing corresponding measures. This is commonly known as the zero-COVID policy.

In order to comply with the guidance, starting from March 2020, the State Council of China began to release a national COVID-19 risk level system on a regular basis through its website. This system categorizes communities within the 2853 counties into high-, medium-, or low-risk groups and updates on a daily basis. All zero-COVID policies, including quarantine, closures of public places, travel restrictions, Travel QR Codes, etc., were implemented based on this system.[5] The COVID-19 risk level system is viewed as a pilot experiment in utilizing big data for national

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

[5]Check out the news from State Council's website: http://www.gov.cn/fuwu/2020-03/25/content_5495289.htm

management and crisis response.[6] In particular, the risk level is reported by local governments and compiled by National Health Commission of China.[7] The criteria used to designate a community as either a *Risk* or non-risk area are based on the presence of confirmed cases of COVID-19 reported within recent days. It is important to note that local officials have some flexibility to adjust the coverage range of medium- or high-risk areas. In cases of overreaction, neighboring communities without any cases may still be classified as medium- or high- risk.

Our data on risk level information are drawn from *China's COVID-19 Risk Level Database*, a newly constructed database containing COVID-19 risk level information for communities within the 2853 counties on a daily basis from April 02, 2021 to December 15, 2022, which marks the end of the zero-COVID policies. This information was collected from the State Council's website (see Appendix A for more details). To the best of our knowledge, this is the first dataset to document China's county-level daily implementation of the zero-COVID policy during 2021 and 2022.[8] We define a county as *Risk* region on a given day if it contains at least one community categorized as medium- or high- risk according to the aforementioned criteria. We define a prefecture as *Risk* region on a given day if at least one community within it is categorized as *Risk* area.

Table 1 shows that on average, from April 02, 2021 to December 15, 2022, 74 counties were classified as *Risk* regions on a daily basis. Averagely, each county was classified as *Risk* region for a duration of 16 days by December 15, 2022 (the end of zero-COVID). Figure 1 shows that the aggregate nationwide daily confirmed cases correlates positively with number of counties with *Risk* areas.[9] Furthermore, we have noticed a steep rise in the number of counties categorized as *Risk* regions beginning in July 2022, while the number of confirmed cases experienced a sharp surge starting only after October 2022. These trends suggest that, comparing to 2021, local officials may be more inclined to enforce stricter zero-COVID policies or potentially overreact with their policies in response to the more transmissible Omicron variant in 2022. This finding is further supported by Figure 2, which illustrates a comparison between the green bar and blue bars. The results show

[6]Check out the coverage provided by state-controlled media: https://www.tsinghua.edu.cn/info/1182/51343.htm

[7]The term "risk" used in this context is distinct from its traditional usage in economic research, which involves prediction and expectation. Here, "risk" refers to the assessment of COVID-related risk based on the current presence of COVID-19 cases.

[8]The previous research mainly focus on 2020 or lockdowns, rather than 2021 and 2022 or zero-COVID.

[9]Shanghai is excluded from the sample due to a skyrocketed increase in COVID-19 cases during April 2022.

that in 2022, there were much more counties classified as *Risk* regions for longer duration compared to 2021. Additionally, Figure A2 indicates that only a small fraction of counties were classified as *Risk* regions in 2021, whereas by the end of 2022, 1700 out of 2853 counties were classified as *Risk* regions.[10]

There are three things worth noting. Firstly, our binary variable of a county classified as *Risk* or non-risk region does not differentiate the level of intensity of treatment. For instance, a county with only one community designated as *Risk* area and another county with 100 communities designated as *Risk* areas are likely to receive varying impacts from zero-COVID policies. Although there will be differences in the treatment, we are unable to distinguish between them. Secondly, our risk level data does not provide information on the specific zero-COVID policies implemented in each county. For example, if two counties with the same number of communities are classified as *Risk* areas, County A may require all residents to stay home, while County B may only quarantine individuals who have tested positive for COVID-19. The bottom line is that as long as a county/prefecture is categorized as *Risk* region, corresponding zero-COVID policies will be implemented in this region. Finally, a prefecture-wide lockdown remains as an option within the zero-COVID policy framework for the years 2021 and 2022,[11] despite variations in official terminology like "citywide static management", "silence period" and so on. Our research does not aim to differentiate between lockdown and other aspects of the zero-COVID policy during 2021 and 2022. Instead, we regard our estimates as capturing the average impact of a range of interventions, including both stringent measures like lockdowns and milder restrictions.

2.3 Mobility

We use the data from the Baidu Qianxi (Migration) website, which is publicly shared by Hu et al. (2020), to construct our measures of human mobility. Baidu is the largest search engine in mainland China. Their migration data are based on real-time location records for every smart phone that uses the company's mapping app, and thus can accurately reflect population mobility

[10]See Panel B of Table 1

[11]Prominent cities such as Xi'an and Shanghai implemented lockdown measures, with Xi'an being in lockdown for approximately a month starting from the end of 2021, and Shanghai undergoing a lockdown for about four months during the first half of 2022.

between cities.

The Baidu Qianxi data set covers 120,142 pairs of prefecture-level cities per day for 364 such cities. For each prefecture-level city, Baidu Migration provides the following two sets of information: (1) the top 100 origination cities for the population moving to the target city and the corresponding percentages of the inflow population that originated from each of the top 100 origination cities; (2) the top 100 destination cities for the population moving out of the city and the corresponding percentages of the outflow population that go into each of the top destination cities (Fang et al., 2020b). The mobility data used in this research cover the periods from January 1, 2020, to March 27, 2021 and from September 2, 2021, to April 21, 2022.

To achieve our research objectives, we converted the raw mobility data into two daily indices at the prefecture level: inflow mobility and outflow mobility. To compute the inflow mobility index for a given prefecture-level city, e.g. City A, we averaged the outflow values from all other cities directed toward City A, based on Baidu Qianxi data for a specific date.[12] Specifically, this average is derived from the percentages of outflow population originating from cities that include City A in their list of top 100 mobility destinations. Similarly, for the outflow mobility index, we followed the same procedure but substituted inflow values for outflow values in the Baidu Qianxi data. When City A implements the zero-COVID policy and assuming inter-city traffic among other cities remains constant, the share of population mobility associated with City A relative to the total population mobility of other cities is likely to decline due to imposed restrictions. This anticipated decrease would be reflected in the mobility indices we have devised.

2.4 PM2.5

The county-level weekly data on PM2.5 is derived from the Aerosol Optical Depth (AOD) data, which are from NASA's Global Modeling and Assimilation Office (GMAO) released Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2). Comparing to station-level PM 2.5 data, satellite data cover all the counties in China and are widely used

[12]In this context, the outflow mobility from other cities to City A is essentially considered as inflow mobility for City A.

in economic research.[13] The data is reported with a nested resolution of 50km $\times$ 60km at a hourly base. Firstly, the grid-level PM2.5 concentration is computed using the formula provided by Buchard et al. (2016). Next, to achieve a higher resolution, we split each grid into smaller grids of 5km x 6 km using an upsampling method.[14] Lastly, we adopt the *Raptor Join* method described in Singla et al. (2021) to aggregate the data from the smaller grids into county-level for each hour and compute the weekly sum for each county.[15]

2.5 Night Lights

China's government has not released any county or prefecture-level GDP data for the years 2020 to 2022. Even if such data were available, there are concerns about the possibility of manipulation and over-reporting (Martinez, 2022; Angrist et al., 2021). To obtain a consistent measure of local economic activity across China, we utilize visible lights emitted from the Earth's surface at night as a proxy — night lights (nighttime light) data have already been recognized to be capable of accurately capturing changes in local economic activity (Hodler and Raschky, 2014).[16]

We obtain the night lights data from the Visible Infrared Imaging Radiometer Suite (VIIRS) on a monthly basis,[17] covering the period from 2019 to September 2022. To filter out noise from sources such as aurora, fires, and other temporary lights, we employ a threshold of 0 and $1.5(\mu+3\sigma)$, following Li et al. (2020); Gibson (2021).[18] The spatial resolution of VIIRS image data is 413m, the absolute radiation values in the unit of $Watts/cm^2/sr$ (Chen et al., 2022b). We use the same *Raptor Join* method describe in the PM 2.5 section to aggregate the grids at county level by month.

2.6 Weather Data

We obtain the weather data including precipitation and temperature from Global Historical

[13] see Fu et al. (2021); Chen et al. (2022c); Sager and Singer (2022).

[14] If we do not upsample, there will be missing values for some counties that are smaller than 50km $\times$ 60km in size.

[15] To account for the daily air pollution's high volatility, we follow He et al. (2020) and aggregate the PM 2.5 at the weekly level.

[16] Also see Harari (2020); Storeygard (2016); Henderson et al. (2018) and Donaldson and Storeygard (2016) for a comprehensive review of economic literature using night lights as proxy for economic actives.

[17] See Elvidge et al. (2017). The raw data from VIIRS is at monthly basis.

[18] See Figure A3, an example of filtered data of Night Lights in March 2022 obtained from VIIRS, combine with the shapefile of China's county boundary.

Climatology Network form the National Oceanic and Atmospheric Adminictration (NOAA).[19] We use the inverse distance weights to calculate the daily prefecture-level weather data.

2.7 Daily Confirmed COVID-19 Cases

We gather the daily confirmed COVID-19 cases provided by the *Dingxiangyuan* website, which compiles official daily COVID-19 cases at the prefecture level.

3 Identification

Our empirical analysis relies on two sets of difference-in-differences (DiD) models to identify the impact of the zero-COVID policy on the pandemic's dynamics during local outbreaks and its subsequent influence on various measures of economic activity, including traffic mobility, air pollution, and night lights. We employ a DiD specification as our baseline regression to estimate the relative change in the outcome variable between the treated and control groups. The model is specified as follows:

$$Y_{it} = \beta D_{it} + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \varepsilon_{it}$$

where Y_{it} represents the outcome variable of interest in region (prefecture or county) i during period (day, week or month) t. D_{it} is a dummy variable indicating the treatment status in region i at time t, where it equals 1 if any community within this region is classified as a *Risk* area and 0 otherwise. Regions with *Risk* areas would be subject to the enforcement of zero-COVID policies. $\mathbf{X}_{it}$ are the control variables. μ_i represents prefecture (county) fixed effects, which control for time-invariant prefecture (county)-level factors, and θ_t represents time fixed effects, which control for shocks that are common to all regions during a given time period.

The underlying assumption for the DiD estimator is that the zero-COVID policy implementation is not driven by unobserved factors that could also systematically influence the differences in outcome variable between regions with *Risk* areas and regions without *Risk* areas. This assumption is unverifiable as it requires knowledge of the counterfactual scenario, but we can investigate

[19]See Menne et al. (2012)

whether the parallel trends assumption is satisfied before the date when any areas within these regions were classified as Risk areas. To do so, we performed an event study approach to estimate the dynamic effect of the treatment. Moreover, we can understand how long the treatment effect persists. Our model is as follows:

$$Y_{it} = \sum_{k \neq -1} \beta_k D_{it}^k + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \varepsilon_{it}$$

where D_{it}^k represents the indicator for i's treatment status at k periods relative to period t. It takes a value of 1 if region i has any areas classified as *Risk* was k periods relative to period t and 0 otherwise. We exclude $k = -1$ so that the dynamic effect is compared to the period immediately before initial treatment. The parameter of interest β_k estimates the effect of zero-COVID policy k periods after/before the implementation. We expect the pre-trends to be parallel, as β_k would not be significantly different from zero for $k \leq -2$. Intuitively, economic activities were restricted by the zero-COVID policy in the enforced regions and slowly recovered after the implementation was over, thus we expect β_k to be negative for $k \geq 0$ and converge to zero as k increases.

To investigate the heterogeneity of the effect of the Lockdown and zero-COVID policy over time, we perform separate DiD regressions and event studies for the years 2020, 2021, and 2022. As in some regions the zero-COVID policies were triggered multiple times across 2021 and 2022, we exclude the regions that have already been classified as *Risk* during 2021 from our subsample used in the analysis for year 2022.[20] As the risk level data is unavailable for 2020, we use the lockdown data from He et al. (2020) to generate the treatment status for year 2020. In the following sections, we present our empirical results for different outcome variables and provide more details on the regression specifications used for our analysis.

[20] We did not exclude regions that have experienced lockdown in 2020 in any of these regressions, because, in fact, almost all prefectures in China implemented some level of restriction in mobility during the initial outbreak of the pandemic. On the other hand, the share of regions that were at *Risk* during 2021 is relatively small so the subsample after excluding these regions could still be representative.

4 Results

4.1 COVID-19 Cases

Before we examine the economic consequences of zero-COVID policies, we apply an event study approach to examine the dynamic effects of the risk level on COVID-19 cases in China, with the goal of examining the trends in COVID-19 cases before and after the implementation of the zero-COVID policy and estimating the average time it took from the launch of zero-COVID policy to when the outbreak was under control. To achieve this, we estimate the following model:

$$Case_{it} = \sum_{k=-30}^{-2} \beta_k D_{it}^k + \sum_{k=0}^{50} \beta_k D_{it}^k + \mu_i + \theta_t + \varepsilon_{it}$$

where $Case_{it}$ represents confirmed COVID-19 cases in prefecture i at date t. D_{it}^k represents the indicator for prefecture i's treatment status at k periods relative to date t. Given the potential reverse causality between COVID-19 cases and risk level status and potential anticipation[21], we are not estimating a causal impact, but examining the correlation. The coefficient of interest β_k estimates the correlation between the status of *Risk* or non-risk k periods after/before the risk level classification and the daily confirmed COVID-19 cases. The dynamic effect results are displayed in Figure 3.

We begin by presenting the dynamic effect of the 2020 lockdown implementation in Figure 3a. Prior to the lockdown, the dynamic effect is negative. Subsequently, the effect remains positive for approximately 50 days after the initial lockdown, and reaches its peak at 40 around 21 days later, before starting to decline towards 0. It is unsurprising to observe a surge in daily confirmed cases following a lockdown, as extensive COVID-19 testing is likely to start after the lockdown is imposed when the virus has already spread for some time. As a result, the daily confirmed cases during the weeks following the lockdown tend to be higher on average than before it. Additionally, the extensive variation in the estimated dynamic effect and the predominantly insignificant estimators

[21] See Goodman-Bacon and Marcus (2020) for a review of challenges of causality identification in COVID-19 research.

suggest that some prefectures prefectures may have implemented precautionary policies before potential increases in cases.

In Figure 3b and 3c, we present the results of our event study analysis for the years 2021 and 2022, respectively. Our findings suggest that the dynamic effect of zero-COVID policy on COVID-19 cases differs over the two years. Specifically, in 2021, the dynamic effect increases from day 0 to day 7 and then gradually declines, becoming negligible after day 21. In contrast, in 2022, the dynamic effect remains high for a more extended period, it takes around 25 days to control the size of the pandemic to about 5 cases, and around 50 days to decrease the magnitude close to 0. The peak of the curve is also much higher than in 2021, with an average of more than 10. Additionally, the variation of the dynamic effect in 2022 is much larger than in 2021. These findings suggest that while some prefectures were able to reduce COVID-19 cases quickly by implementing stringent measures immediately after they were classified as *Risk* regions, others found it more challenging to contain the spread of the virus effectively in 2022.

Overall, these findings suggest that the risk level policy in China has been effective in controlling the spread of COVID-19 in 2021, with the number of cases peaking shortly after the initial intervention and declining afterwards. However, in 2022, the emergence of new virus variants, such as the Omicron, poses challenges to the effectiveness of the policy, as it took much longer to control the pandemic in 2022 compared to 2021.

Additionally, these results highlight the considerable variation in the implementation of the zero-COVID policy across different regions in China, with some prefectures experiencing a rapid decline in cases immediately after being classified as *Risk* regions, while others had a slower decline or even an increase in cases before a decline.

4.2 Traffic Mobility

Next, we investigate the effect of the zero-COVID policy on mobility. Our models are as follow:

$$Mobility_{it} = \beta D_{it} + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \varepsilon_{it}$$

$$Mobility_{it} = \sum_{k=-30}^{-2} \beta_k D_{it}^k + \sum_{k=0}^{50} \beta_k D_{it}^k + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \varepsilon_{it}$$

where the dependent variable $Mobility_{it}$ has two measures: inflow and outflow traffic mobility index at prefecture i on date t, taking the natural log. For the sample period of 2020, D_{it} is an indicator variable for lockdown or not.[22] For the sample period of 2021 or 2022, D_{it} is a binary variable equal to 1 if any community within this prefecture i at date t is classified as a *Risk* area and 0 otherwise. We control prefecture fixed effects by μ_i and date fixed effects by θ_t. It should be noted that the timing of the risk level classification and the adoption of corresponding zero-COVID policies may be correlated with the severity of COVID-19. We therefore include daily confirmed COVID-19 cases in the matrix of prefecture-day level controls $\mathbf{X}_{it}$. We also include weather factors in $\mathbf{X}_{it}$. The standard errors are clustered at the prefecture level. We estimate the effect of the zero-COVID policy on mobility separately for year 2020, 2021, and 2022.

The DiD regression results in Table 2 show that the impacts of the zero-COVID policy on inflow and outflow mobility in 2021 and 2022 are significantly negative. However, the impact of lockdown on mobility in 2020 is negligible. In columns (3) and (4), the coefficients for both inflow and outflow traffic mobility during 2021 and 2022 are approximately -0.3, indicating a 30% decrease in traffic flow between a prefecture and other prefectures after it is listed as *Risk* region. This result is significant at the 1% level. In columns (1) and (2), the magnitude of the coefficient is only around -0.02, suggesting only a 2% change in traffic mobility, which is not significant. The R-squared for all regression specifications indicate that the models explain a considerable proportion of the variance, lending credibility to our estimation.

We present the dynamic effects of the lockdown and zero-COVID policy implementation on inflow and outflow traffic mobility in Figure 4 and 5, respectively. The patterns are similar for the two sets of figures within the same year. Figures 4a and 5a display the dynamic effect of lockdown on inflow and outflow mobility in 2020. There is no significant trend in the pre-treatment periods, indicating that the treatment does not affect mobility before the launch of the lockdown. Both mobility measures experienced a significantly negative effect immediately after the lockdown and stopped the decreasing trend within one week. There are sharp increases in mobility that happened

[22] For the sample period of 2020, we use similar setting with He et al. (2020)

during the third week after the lockdown, which may be due to the fact that the lockdown duration in 2020 was clustered around 20 days, and the mobility increase reflected the lifting of restrictions. This pattern help us to explain the insignificant lockdown effect in Table 2, On average, a significant positive rebound in traffic flow during the third week offsets the negative effects observed in the first two weeks.

In Figure 4b and 5b, we present the effect of zero-COVID on inflow and outflow mobility in 2021. The figures show a significantly negative effect that occurs immediately after the prefectures were classified as a *Risk* region, remains at a large effect size for around 15 days, and gradually returns to null around 30 days after the initial treatment. Regarding the impact of zero-COVID policy on mobility in 2022, as displayed in Figure 4c and 5c, we observe almost an identical pattern as in 2021, while the magnitude of the dynamic effects in 2022 was larger than in 2021 at its peak.

There are two possible reasons to explain this phenomenon. Firstly, it could be due to the more stringent implementation of the zero-COVID policy, which led to greater restrictions on mobility. Secondly, the release of the Travel Codes Tracker system could have also contributed to this effect by limiting travel and mobility across regions. In early 2020, despite the virus being more lethal, only individuals traveling from Wuhan were required to undergo quarantine [23]. However, in 2021 and 2022, anyone with a travel history to medium- or high-risk areas within 14 to 21 days were required to undergo mandatory quarantine at their own expense. Individuals would be tracked by the combination of Travel Code and the risk level system [24]. With the higher expected cost for traveling, it is reasonable to observe larger negative effect on the inter-prefecture traffic flow in 2021 and 2022, as compared to 2020.

In all event studies in 2021 and 2022, we observe that the pre-trend has a dip around 3 days before the enforcement of the zero-COVID policy. This suggests that people observed the COVID-19 cases and voluntarily avoided entering and leaving the region. Nevertheless, we believe that this will not harm the credibility of our DiD estimation as the scale of the pre-treatment change due to anticipation is relatively small compared to the post-treatment changes in inter-prefecture

[23] See Prevention Guidance for Novel Coronavirus Pneumonia (version 4): http://www.nhc.gov.cn/xcs/zhengcwj/202002/573340613ab243b3a7f61df260551dd4/files/c791e5a7ea5149f680fdcb34dac0f54e.pdf

[24] See the reports on China's truck drivers stuck in the quarantine rules and QR trackers:https://www.reuters.com/world/china/china-truckers-use-fake-travel-records-clean-drivers-dodge-covid-rules-2022-03-30/

traffic mobility.

It is important to note that the impact of zero-COVID policy on traffic mobility may vary across regions, depending on the severity of the pandemic and the specific measures taken to restrict mobility. Nonetheless, our results suggest that the zero-COVID policy has been effective in restricting inter-prefecture mobility, which could contribute to controlling the spread of the virus, while also negatively impacting the transportation industry and other related sectors. It should be emphasized that the measured effect is a combination of the traffic restriction effect and the "voluntary" precaution effect of the Travel Code tracker system. Furthermore, since the outcome variables are inter-prefecture traffic flows, the effect could not be attributed to within-prefecture traffic.

4.3 Pollution

We proceed by examining the influence associated with the zero-COVID policy on PM2.5 concentration levels in China from 2020 to 2022. Specifically, we fitted the following equations:

$$Pollution_{it} = \beta D_{it} + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \pi_{it,jm} + \varepsilon_{it}$$

$$Pollution_{it} = \sum_{k=-5}^{-2} \beta_k D_{it}^k + \sum_{k=0}^{5} \beta_k D_{it}^k + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \pi_{it,jm} + \varepsilon_{it}$$

where $Pollution_{it}$ represents the average PM2.5 concentration level at county i during week t, taking natural log. Here, we aggregate the hourly PM2.5 data into week level to average out the high volatility of the daily air pollution, following He et al. (2020). For the sample period of 2020, D_{it} is a indicator for lockdown launched in county i during week t or not. For the sample period of 2021 or 2022, D_{it} is a binary variable equals 1 if any community within county i during week t is classified as a *Risk* area and 0 otherwise. We control county fixed effects μ_i and week fixed effects θ_t. $\mathbf{X}_{it}$ include daily confirmed COVID-19 cases and weather factors such as temperature and precipitation. $\pi_{it,jm}$ denotes prefecture by month fixed effects, taking value of 1 for any county i within prefecture j during month m including week t and 0 otherwise. We control prefecture by month fixed effects to account for time-variant regional conditions shared by counties within the same prefecture in a given month. The standard errors are clustered at the county level.

Table 3 reports our DiD regression results. In column (1), we replicate the estimations used in He et al. (2020) and estimate the impact of lockdown on PM2.5 pollution levels in 2020. Our result is similar to theirs. In columns (2) - (5), we estimate the influence of implementing the zero-COVID policy on PM2.5 pollution levels in 2021 and 2022 and our results show an ambiguous policy effect.

Different from the lockdown effects found in column (1) of Table 3 in 2020, our findings suggest that the zero-COVID policy may not significantly reduce pollution levels in 2021. Column (2) shows a significantly positive correlation between the implementation of zero-COVID policy and PM2.5 concentration in the baseline regression. We further control for prefecture by month fixed effects in column (3), and the coefficient remains significantly positive but with a smaller magnitude. This suggests that potential time-variant prefecture-level factors that are positively correlated with the risk level status may contribute to the positive change in PM2.5 pollution level. Moreover, some time varying county-level factors might be correlated with both the probability of being classified as *Risk* region and pollution concentrations. For example, Urban counties may have a higher chance of being classified as *Risk* regions and may also experience faster increases in PM2.5 pollution levels than their rural counterparts due to their larger number of manufacturers and motor vehicles that elevate PM2.5 pollution. Overall, in 2021, county-specific growth trend of pollution appears to outweigh the influence of the zero-COVID policy.

In columns (4) and (5), we find that the policy effects become significantly negative in 2022. The zero-COVID policy reduces the PM2.5 concentration by 1.2% to 3.5%. This is expected because the zero-COVID policy imposes more stringent restrictions on economic activities in 2022. As a result, similar to the scenario in 2020, counties with *Risk* areas experienced a significant reduction in PM2.5.

To further explore the influence of zero-COVID policy on pollution levels, we present our event study analysis in Figure 6. We first replicate the model of He et al. (2020) in Figure 6a for the dynamic effect of lockdown policy on pollution levels in 2020. Then we perform event studies for 2021 and 2022. Figure 6b illustrates the dynamic effect of zero-COVID on PM2.5 concentration in

2021, showing a slightly decreasing trend after the counties were classified as *Risk* areas, but with an increasing trend starting from week 3, and a positive and significant effect in weeks 4 and 5. In contrast, Figure 6c shows that in 2022, the treatment effects is negative in the first three weeks after the counties are categorized as *Risk* region. In both figures, the pre-trends are consistent with the parallel trends assumption as the coefficients prior to the treatment are all close to zero and statistically insignificant. Combining the results from our baseline DiD regression, we find that the zero-COVID policy in 2021, unlike the strict lockdown implementation in 2020, does not bring substantial improvement to air pollution levels as the restriction imposed by zero-COVID policy is limited within a county rather than the entire prefecture. However, the change in PM2.5 concentration becomes larger and more significant when counties are categorized as *Risk* regions with more stringent zero-COVID policy, as seen in 2022.

As discussed in Sun and Abraham (2021), the event study approach requires relatively strong assumptions on the homogeneity of treatment effect, especially over time and across individuals, to deliver consistent estimates. These assumptions are likely to be violated in our context of zero-COVID policy, as the treatments are implemented across multiple time periods and local government could endogenously choose the stringency of their policy implementation and result in heterogeneous treatment effects. In order to overcome this potential identification issue and allow for heterogeneity in treatment effects, we apply the method proposed by Sun and Abraham (2021) and present the robust estimators in our figures. In Figure 6, it can be observed that the robust estimators follow a similar pattern to the regular dynamic effect estimators and our results are robust to the potential heterogeneous treatment effects.

In conclusion, our findings reveal ambiguous effects of the zero-COVID policy on PM2.5 concentration level in 2021 and 2022. In 2021, when the zero-COVID policy was less stringent, the county-specific growth trend of pollution appears to outweigh the influence of the zero-COVID policy. In 2022, with the more stringent implementation of the zero-COVID policy, it took an average of three weeks for PM2.5 concentration to return to its original level. This suggests a corresponding three-week decrease in industrial production and traffic flow within the county. It is worth noting that during 2021 and 2022, COVID-19 containment was prioritized over environmental protection. As a result, when counties were categorized as *Risk* regions, local governments may have relaxed environmental restrictions, leading to increased pollution. This could potentially lead us to overestimate the change in pollution level associated with the implementation of the zero-COVID policy.

4.4 Night Lights

Finally, we present empirical evidences related to night lights (nighttime light). We use the following models:

$$NightLight_{it} = \beta D_{it} + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \pi_{it,j} + \varepsilon_{it}$$

$$NightLight_{it} = \sum_{k=-5}^{-2} \beta_k D_{it}^k + \sum_{k=0}^{5} \beta_k D_{it}^k + \mathbf{X}_{it} \times \boldsymbol{\alpha} + \mu_i + \theta_t + \pi_{it,j} + \varepsilon_{it}$$

where $NightLight_{it}$ represents the night lights level at county i during month t, taking natural log. For the sample period of 2020, D_{it} is an indicator for lockdown launched in county i during month t or not. For the sample period of 2021 or 2022, D_{it} is a binary variable equal to 1 if any community within county i during month t is classified as a *Risk* area and 0 otherwise. We control county fixed effects μ_i and month fixed effects θ_t. $\mathbf{X}_{it}$ include daily confirmed COVID-19 cases and weather factors. We also include prefecture by month fixed effects for robustness, where $\pi_{it,j}$ denotes prefecture by month fixed effects, taking a value of 1 for any county i within prefecture j during month t and 0 otherwise.

Similar to the effects on PM2.5, we found divergent effects of the zero-COVID policy on night lights over the sample periods, which are presented in Table 4. In column (1), we find the lockdown implementation has a significantly negative coefficient at -0.0391, which implies counties that underwent lockdowns in 2020 had a 4% decrease in night lights compared to counties that did not implement lockdowns. In columns (2) and (4), we report the estimations for the zero-COVID policy in 2021 and 2022. In 2021, we observed a positive correlation between the implementation of the zero-COVID policy and the changes in night lights, while in 2022, the zero-COVID policy reduced 14% economic activities proxied by night lights. In 2021, compared to the county-specific economic growth trend, the change in night lights associated with the less stringent zero-COVID policy in 2021 was negligible, as it only imposed restrictions in a limited number of communities within the county. However, in 2022, with the emergence of the highly contagious Omicron variant, the zero-COVID policy became stricter and seriously disrupted economic activities. We show the robustness of our results in columns (3) and (5) by controlling for prefecture by month fixed effects, and find that the coefficients remain statistically significant at the 1% level.

The dynamic effect results in Figure 7 provide further support for our argument. To allow for heterogeneity in the treatment effect over time and across treated units, we include the robust estimators of Sun and Abraham (2021) in the figures. In 2020, lockdowns occurred mostly during the early phase of the pandemic, severely affecting the economic environment and consumer confidence. As shown in Figure 7a, the negative impact of lockdown on the night lights was significant and persistent, lasting more than five months after the event date, with no signs of recovery. In 2021, shown in Figure 7b, a slight increasing trend of night lights is associated with the probability that a county is categorized as a *Risk* region. A possible explanation is that counties that had more active economic performance were more likely to be classified as *Risk* regions while also experiencing faster economic recovery. However, in 2022, as shown in Figure 7c, the decreasing trend was evident, with all treatment effects negative and significant after the implementation of the zero-COVID policy. The magnitude of the negative impact continued to expand until four months after the county was categorized as a *Risk* region, with no complete recovery observed. This implies that the zero-COVID policy in 2022 brought persistent negative impacts to local economies, which may have contributed to the end of the era of zero-COVID policy and the reopening in December 2022.

It should be noted that, in Figure 7b, we observe positive pre-trend and post-trend that are significantly away from zero. This indicates that, compared to the difference in night lights between the treated and control groups in the baseline period $t = -1$, these differences in night lights are larger between two groups in periods at least two months before or after the implementation of the zero-COVID policy. As the zero-COVID policy is unlikely to bring more economic opportunities to the region due to its nature of suppressing human activities, this result could be explained by the positive correlation between the likelihood that a county will be classified as a *Risk* region and its county-specific economic growth trend in 2021. As shown in Figure A2a, only a small proportion of regions in China experienced the zero-COVID policy in 2021. It is plausible that a county in a more economically developed prefecture could enjoy a stronger recovery from the pandemic shock in 2020 and display a higher economic growth rate in 2021. Meanwhile, such prefectures were more likely to experience a pandemic outbreak in 2021. As shown in previous Section 4.1 as well as in Figure 2, the COVID-19 outbreaks in 2021 were usually on small scales and the zero-COVID policy in 2021 lasted for relatively short periods. Therefore, the persistent impact of the zero-COVID policy could be very limited in 2021. As a result, these counties could pick up the economic growth trend from the disruption of the zero-COVID policy quickly and continue with strong economic performance even after the zero-COVID policy. This potentially explains the positive estimated influence of the zero-COVID policy on night lights in 2021, as shown in columns (4)-(5) of Table 4, as well as the upward trend of dynamic effects after the treatment of zero-COVID in Figure 7b.

We provide back-of-the-envelope calculations of the GDP loss caused by the zero-COVID policy in 2022. We replicate the original dataset used in Martinez (2022) and calculate the elasticity between GDP and night light. The calculation shows that a 1% change in night lights corresponds to a 0.858% change in China's GDP. Then, as shown in Panel B of Table 1, by the end of December 2022, zero-COVID policies had been implemented in 1700 out of 2853 counties in China. Finally, based on our calculation, the economic loss can be estimated as $0.077 * 0.858 * 1700/2853 = 0.039$,[25] suggesting that the zero-COVID policy resulted in a reduction in China's GDP of approximately 3.9%. Interpreting the results from this back-of-the-envelope calculation should be approached with caution due to two major limitations: (1) the estimated policy effects derived from the DiD setting may be subject to bias due to spillover effects; (2) the elasticity estimated from the data of Martinez (2022) does not consider the regional heterogeneity within China. In the presence of heterogeneity between counties affected by the zero-COVID policy and counties not affected, this calculation could be inaccurate.

[25]We choose policy effect as .077, from Column 5 of Table 4

4.5 Spillover Effect Results

When two adjacent regions exhibit a close economic linkage, the implementation of human activity restrictions, such as a zero-COVID policy, in one region could exert an impact on activities in the other. This spatial correlation poses a potential bias in our difference-in-difference estimation. To isolate the spillover effects of zero-COVID policy in neighboring regions, we introduce a control variable for adjacent treated areas, following the spirit of literature on spillover effects in difference-in-difference settings (Clarke, 2017), as well as on peer effects (Goldsmith-Pinkham and Imbens, 2013). Specifically, we define a control variable termed "Neighbors Risk" as follows:

$$Neighbors\ Risk_{it} = \frac{\sum_{j \in I \setminus i} D_{jt} R_{ij}}{\sum_{j \in I \setminus i} R_{ij}}$$

where for any two regions $i, j \in I$ at any period t, D_{jt} is a dummy variable for whether j is under the zero-COVID policy at t, R_{ij} is a dummy variable for whether a pair of prefectures i, j is neighboring. Consequently, $Neighbors\ Risk_{it}$ calculates the proportion of neighboring regions implementing a zero-COVID policy relative to all adjacent regions for a given region i at time t.

We incorporate this constructed "Neighbors Risk" variable, along with its lagged terms, into the primary regression models presented in prior sections. Note that to fully capture the potential spatial correlation, a spatial econometric model, such as Spatial Durbin model (SDM) is desired. Our approach only accounts for the proximate (lagged) spillover effects from zero-COVID policies in neighboring regions during 2021 and 2022. The resulting regression results for mobility, pollution, and night lights are presented in Table 5, Table 6, and Table 7, respectively.

In columns (1), (3), (5), and (7) of Table 5, we present the baseline estimates initially showcased in Table 2. Correspondingly, columns (2), (4), (6), and (8) offer estimates of local policy effects on traffic mobility that are robust to spillover influences. Across all these specifications, the local estimates exhibit only negligible variations when compared to the original findings. There is no statistically significant negative spillover effect from adjacent zero-COVID policies in 2021. However, a notable negative impact emerges in 2022, consistent with our earlier results that the stringent zero-COVID measures in 2022 exerted a more pronounced adverse effect on economic activities than those in 2021.

In columns (1) and (3) of Table 6, we offer the baseline estimates for pollution outcomes from Table 3, while columns (2) and (4) include regression results accounting for spillover effects. No substantive changes are observed compared to the original estimations, and negative, statistically significant spillover effects are found for both 2021 and 2022. Given that PM2.5 concentration data are extracted from satellite image and aggregated at the county level, it is plausible that the implementation of a zero-COVID policy in a neighboring county could reduce pollution levels in adjacent areas due to restricted traffic mobility and manufacturing.

In columns (1) and (3) of Table 7, we present the baseline estimates for night light data from Table 4 and include spillover-adjusted regression results in columns (2) and (4). Again, the estimates remain substantively unchanged compared to the original findings, and no statistically significant spillover effects on night lights are observed for either 2021 or 2022. This suggests that long-term economic activities, as reflected by night light data, are unlikely to be influenced by zero-COVID policies in nearby regions.

4.6 Synthetic Diff-in-Diff Results

As mentioned in Section 4.4, potential selection bias may exist within the treated sample. Specifically, regions with greater economic development could be more susceptible to experiencing COVID-19 outbreaks, thereby making it more likely for them to implement the zero-COVID policy and consequently be included in the treatment group. In estimating the impact of zero-COVID policy implementation on economic outcomes like pollution and night lights, uncontrolled county-level time-varying trends could raise concerns regarding the validity of our estimated results.

To enhance the comparability between the treatment and control groups in our empirical examination of pollution and night lights, we conduct several auxiliary regressions employing the Synthetic Difference-in-Differences (SDID) method, a fusion of the Difference-in-Differences and Synthetic Control methodologies (Arkhangelsky et al., 2021). The SDID approach assigns weights to individual fixed effects and time fixed effects to approximate the pretrends between the treatment and control groups, thereby mitigating the reliance on the parallel trends assumption and generating more stable and robust estimates. It is noteworthy that, to comply with the SDID framework, we keep a balanced sample, resulting in a reduced sample size. We also disclose the outcomes of our primary regressions utilizing the balanced sample in Table A1 and Table A2 for reference.

We present our SDID estimations for pollution and night lights in Table 8 and Table 9, respectively. In column (1) of Table 8, the impact of lockdowns on PM2.5 concentration remains significantly negative. In column (2) of Table 8, the estimated changes in PM2.5 following the initiation of zero-COVID policy retain the same sign as the original estimate. In column (3), the estimated coefficient shifts from negative to positive, though with a relatively small magnitude. These outcomes align with our prior findings presented in the dynamic effect results of Figure 6. Specifically, local pollution showed a marked decline post-lockdown in 2020; its trend began to rise a few weeks following the implementation of the zero-COVID policy in 2021; and in 2022, the pollution exhibited a short-lived dip but did not sustain it.

In Table 9, we observe similar results for changes in night lights correlated with zero-COVID policy, compared with the original estimates in Table 4. The estimated coefficient for 2020 remains negative, though its statistical significance diminishes, while the results for 2021 and 2022 retain their original signs and are statistically significant. In summary, despite potential confounding factors involving the relationship between the implementation of zero-COVID policy and pre-treatment economic trends, our SDID estimations reaffirm the robustness of our primary regression outcomes and are consistent with our other findings.

5 Conclusions

In this paper, we provide evidence on the economic impacts of the zero-COVID policy implemented by the Chinese government as a pilot experiment in using big data for country management from 2020 to 2022. We employ a difference-in-differences specification with a novel dataset of China's COVID-19 risk level system. First, we find that the zero-COVID policy in China effectively contained COVID-19 transmission within a 21-day window in 2021. However, controlling virus transmission took twice as long with the emergence of the Omicron variant in 2022. Second, the zero-COVID policy led to a 30% reduction in inflow and outflow mobility, indicating a potential negative impact on the transportation industry and related sectors. Third, our study indicates that the zero-COVID policy had a negligible effect on pollution levels in 2021. Nevertheless, it led to a decrease in PM2.5 concentration in the estimated range of 1.17% to 3.47% in 2022. Lastly, the evidence reveals that the zero-COVID policy had trivial impacts on night lights in 2021, which was overshadowed by the strong economic performance due to the recovery effect. However, we discover a significant reduction in economic activities proxied by night lights, ranging from 7.7% to 14%, as a result of the implementation of the zero-COVID policy in 2022. We calculate that the zero-COVID policy resulted in a reduction of approximately 3.9% in GDP.

Several other countries pursued an elimination strategy like China, with strict border controls and lockdowns to keep the virus at bay, for example, New Zealand, Australia, Singapore, Vietnam, and Thailand. Studies generally show that COVID-19 has had a negative impact on these economies, especially for the countries that rely heavily on tourism and international trade (Dang et al., 2023; Bui et al., 2022; Fouda et al., 2020; O'Sullivan et al., 2020). Most countries experienced an economic contraction during the initial stage of the pandemic, but were able to have a quick rebound since their proactive response to the pandemic had effectively minimized cases infected. An exact comparison of economic impacts between China and these countries, however, is not feasible because the strictness of containment policies enforced by different countries varies, and some countries shift their strategies in response to changing circumstances at different times.

Overall, our findings offer important insights into the effectiveness and limitations of the zero-COVID policy in controlling the spread of COVID-19, as well as its impact on various aspects of the economy and society. These insights can inform the design and implementation of big data-driven public health policies that aim to reduce the impact of public health crises and minimize economic costs in China.

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6 Figures and Tables

6.1 Figures

Figure 1: Daily Confirmed Cases v.s. Number of Counties with *Risk* (excluding Shanghai)

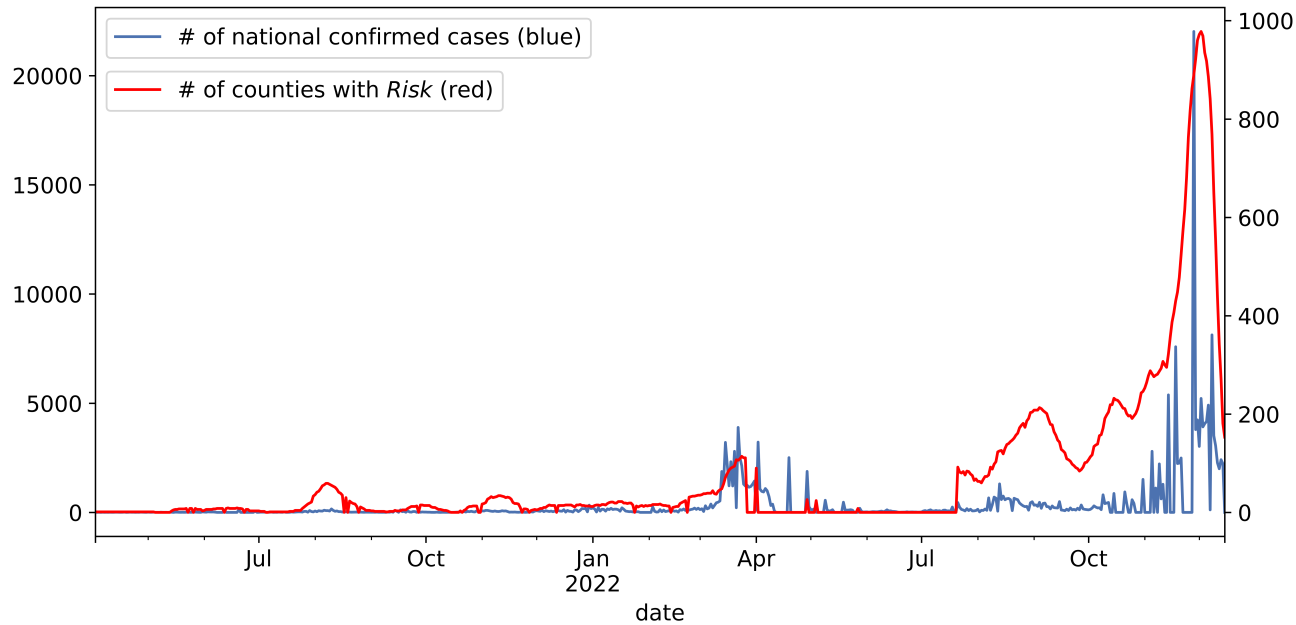


Figure 2: Distribution of *Risk* Duration per County

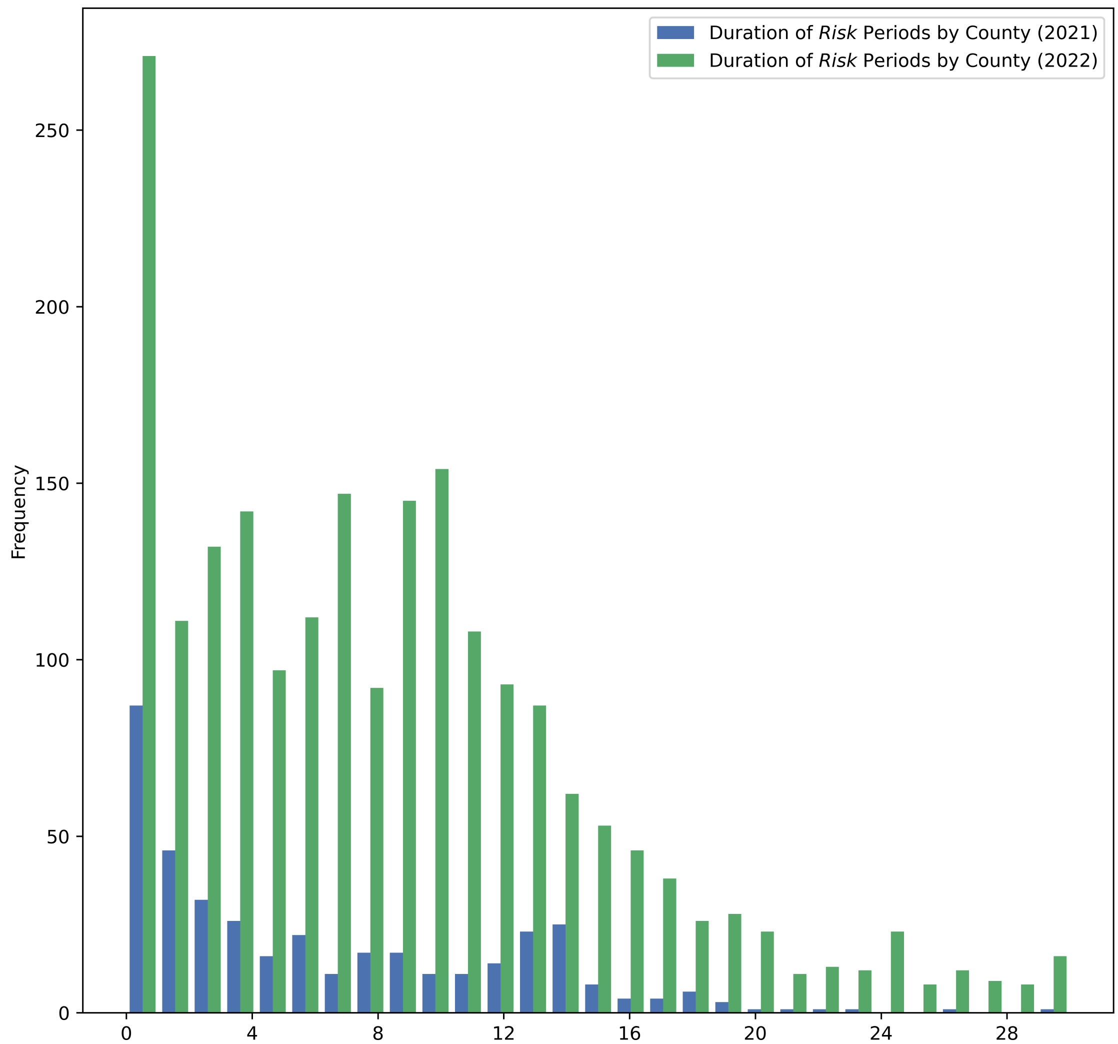
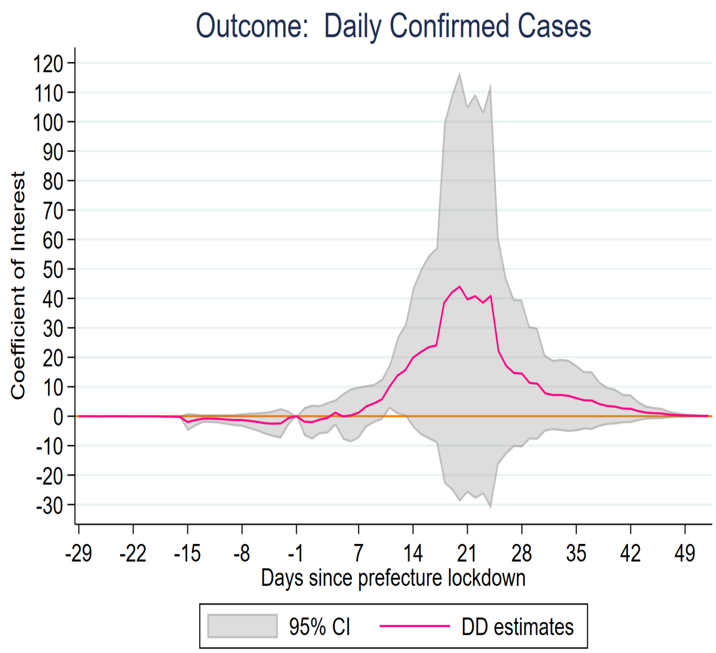
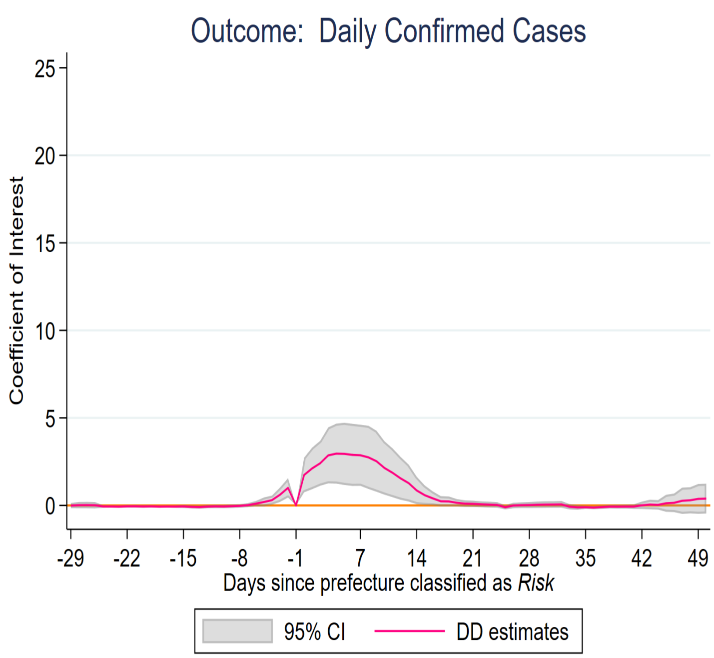


Figure 3: Event Study: Daily Confirmed Cases

(a) Lockdown 2020



(b) *Risk* 2021



(c) *Risk* 2022

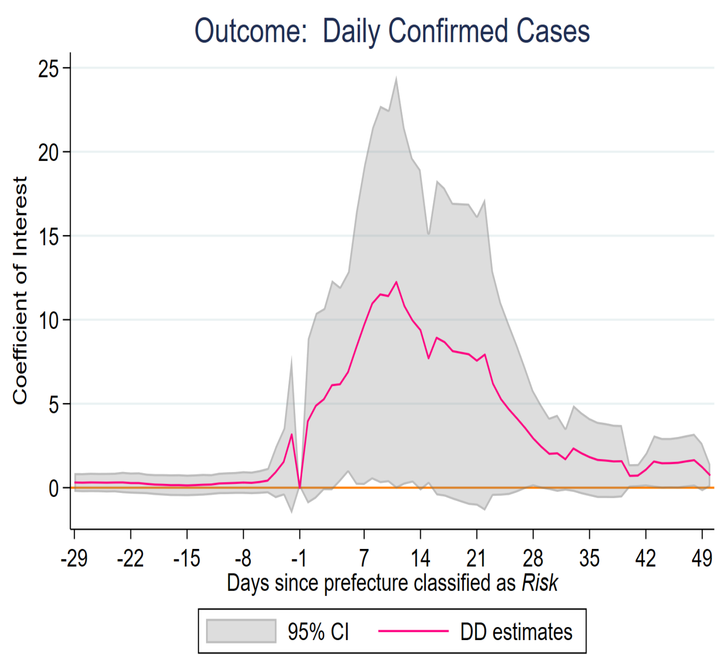
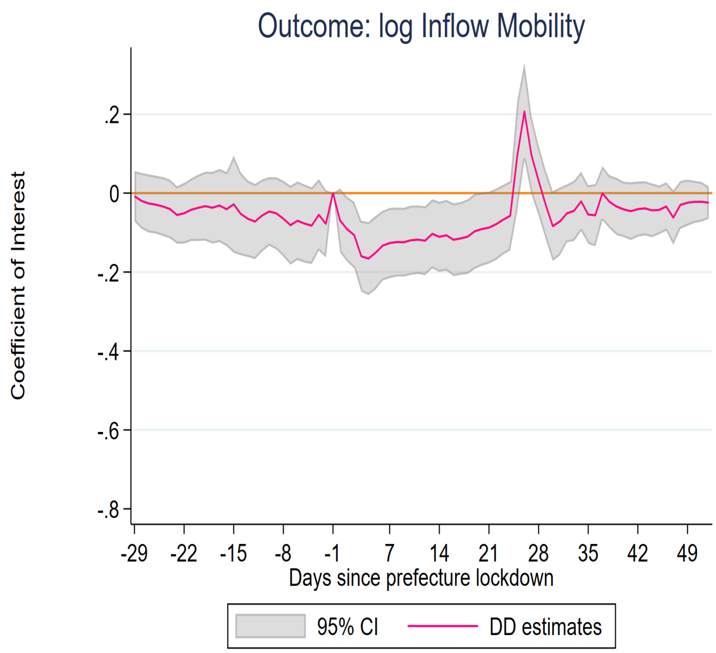
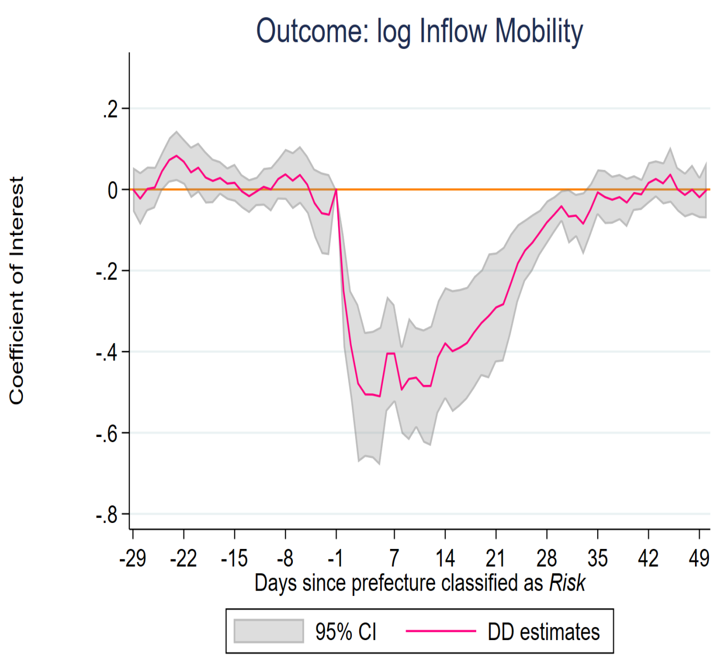


Figure 4: Event Study: Inflow Mobility

(a) Lockdown 2020



(b) *Risk* 2021



(c) *Risk* 2022

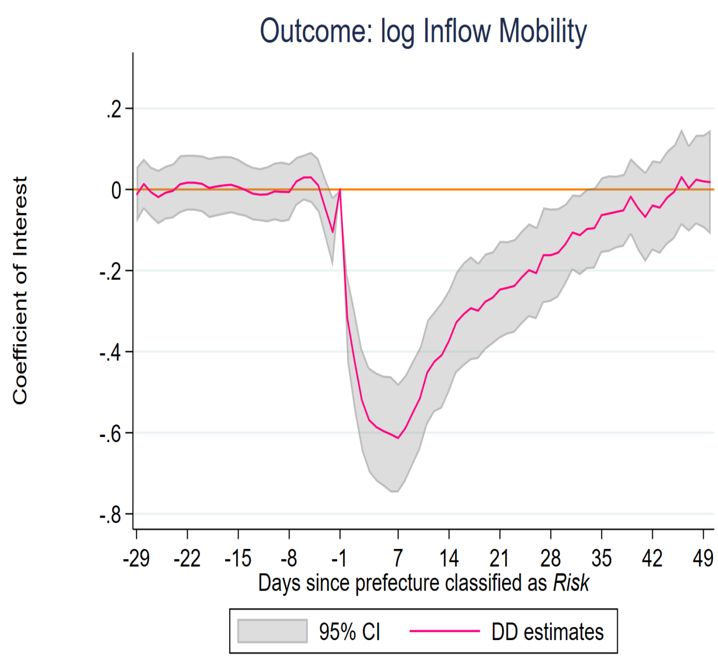
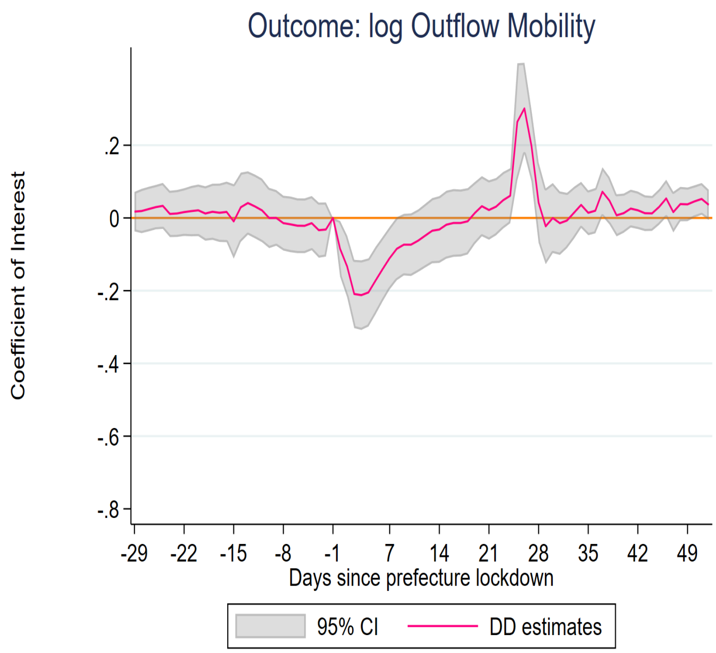
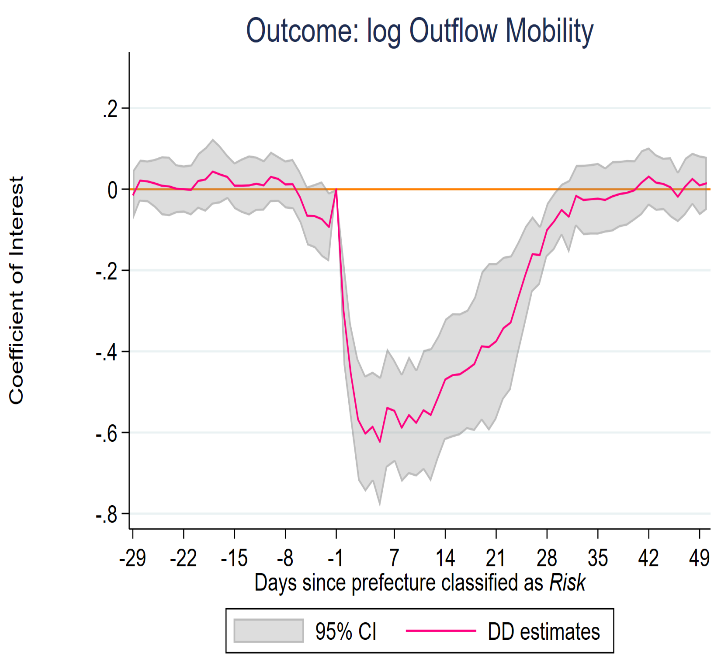


Figure 5: Event Study: Outflow Mobility

(a) Lockdown 2020



(b) *Risk* 2021



(c) *Risk* 2022

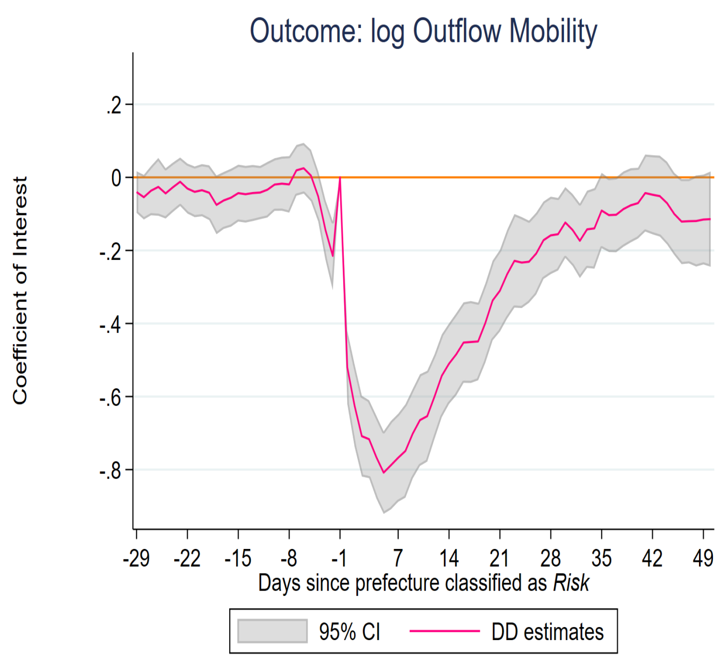
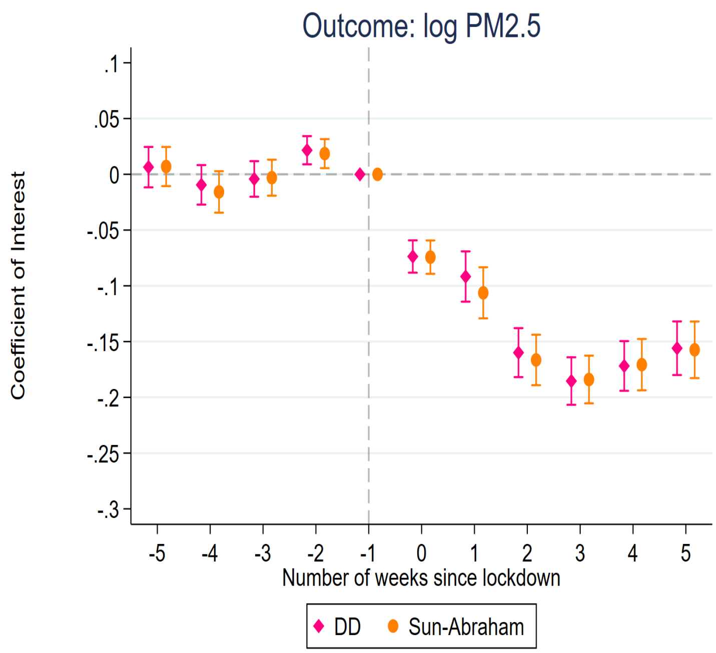
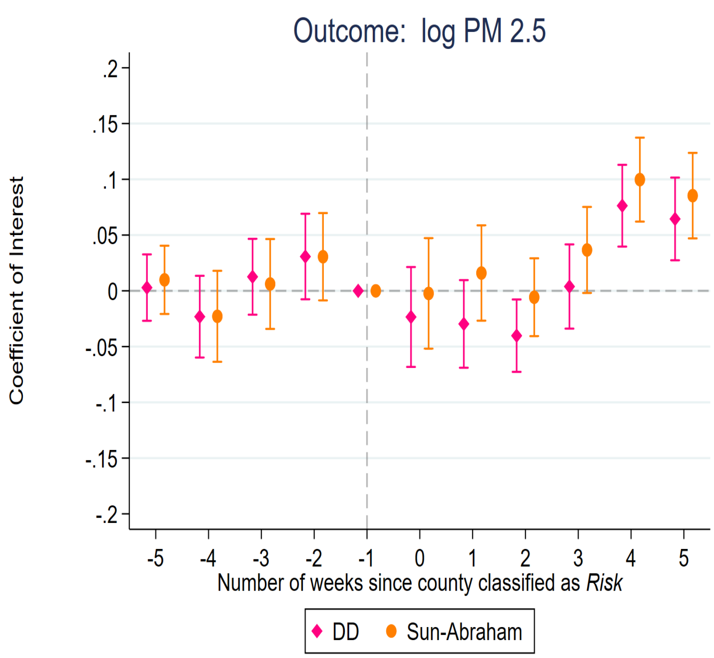


Figure 6: Event Study: PM2.5

(a) Lockdown 2020



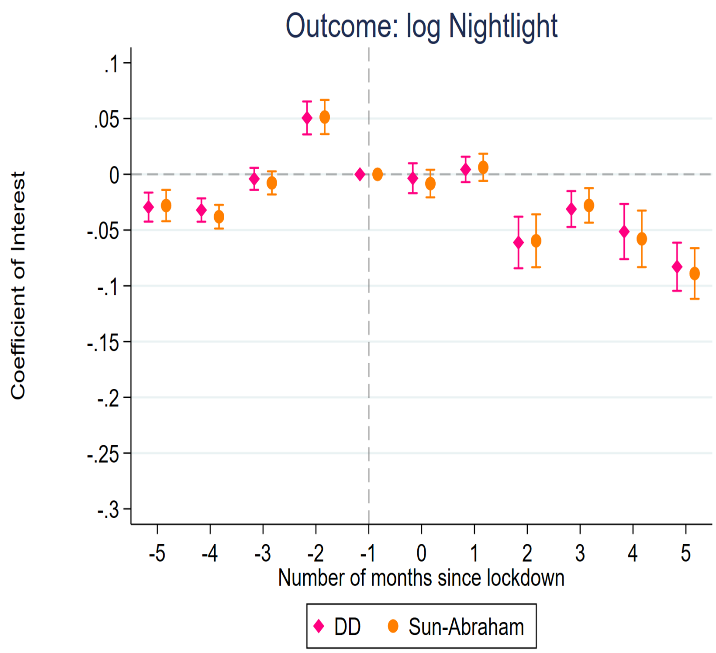
(b) *Risk* 2021



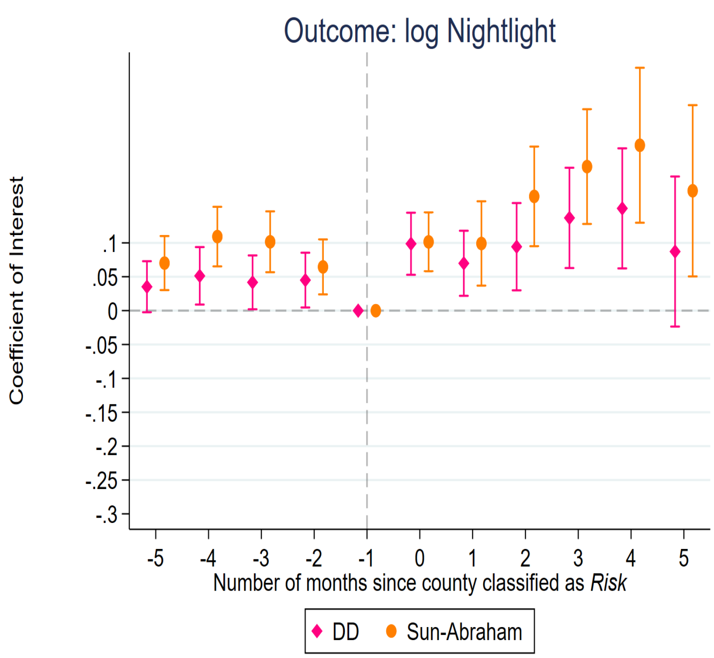
(c) *Risk* 2022

Figure 7: Event Study: Night Light

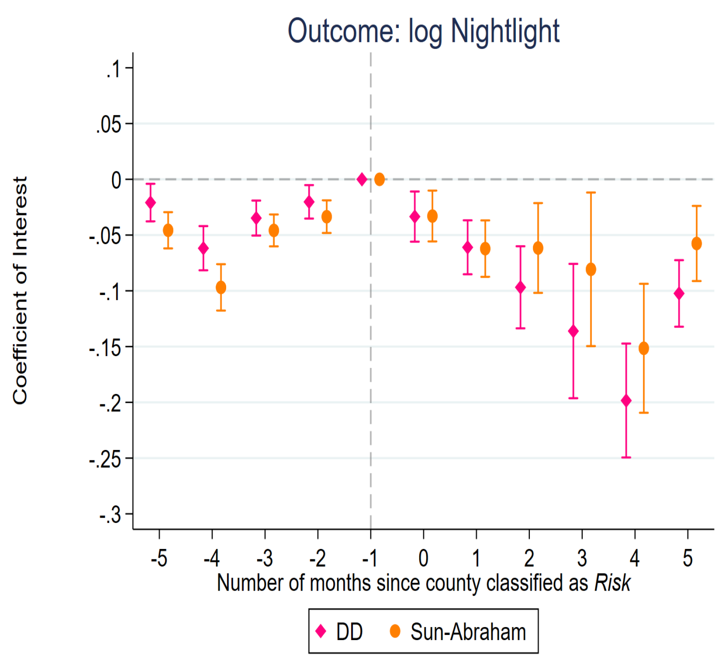
(a) Lockdown 2020



(b) *Risk* 2021



(c) *Risk* 2022



6.2 Tables

	Obs	Mean	Std.Dev	Min	Max
Panel A: County Panel	ref.				
Classified as *Risk* (County)	1777419	0.026	0.159	0.0	1
Night Lights (monthly) ($Watts/cm^2/sr$)	45350	2.420	4.457	0.1	53
PM2.5 (weekly) (μ/m^3)	253352	26.665	15.070	0.4	394
Panel B: County by Dec15,2022	ref.				
Cumulative Days Classified as *Risk* (County)	2853	16.095	23.231	0.0	243
Cumulative Days Classified as *Risk* (Exclude Never Treated)	1700	27.011	24.716	1.0	243
Panel C: Prefecture Panel	ref.				
Classified as *Risk* (Pref)	229264	0.074	0.262	0.0	1
Share of counties Classified as risk (Pref)	229264	0.025	0.117	0.0	1
Num of Counties Classified as *Risk* (Pref)	229264	0.200	1.025	0.0	35
Daily Confirmed COVID Cases	657218	0.545	47.862	0.0	23718
Inflow Mobility	179041	0.281	0.313	0.0	4.039
Outflow Mobility	175695	0.281	0.321	0.0	4.671
Panel D: Prefecture by Dec15,2022	ref.				
Cumulative Days Classified as *Risk* (pref)	368	46.220	41.815	0.0	250
Cumulative Confirmed COVID Cases	356	1001.298	5239.218	1.0	64978

Table 1: Statistical Summary

Table 2: Mobility Regression Results

	2020		2021		2022	
	(1) log Mobility Inflow	(2) log Mobility Outflow	(3) log Mobility Inflow	(4) log Mobility Outflow	(5) log Mobility Inflow	(6) log Mobility Outflow
Lockdown	-0.0137	-0.0283				
	(0.0442)	(0.0366)				
Risk			-0.287***	-0.350***	-0.292***	-0.323***
			(0.0344)	(0.0431)	(0.0385)	(0.0383)
R-squared	0.835	0.849	0.968	0.963	0.888	0.883
Observations	23231	23234	30060	30060	38352	38352
Mean of Mobility	0.277	0.277	0.284	0.284	0.234	0.235
Controls	✓	✓	✓	✓	✓	✓
Prefecture FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Pollution Regression Results

	(1) log PM2.5 2020	(2) log PM2.5 2021	(3) log PM2.5 2021	(4) log PM2.5 2022	(5) log PM2.5 2022
Lockdown	-0.162***				
	(0.00956)				
Risk		0.0842***	0.0159***	-0.0347***	-0.0117***
		(0.0153)	(0.00576)	(0.0100)	(0.00320)
R-squared	0.870	0.773	0.873	0.749	0.882
Observations	42750	99750	99050	145944	144864
Mean of PM2.5 (Weekly Average)	31.52	25.83	25.83	26.94	26.94
Controls	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓
Prefecture × Month FE			✓		✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Night Lights Regression Results

	(1) log Night Lights 2020	(2) log Night Lights 2021	(3) log Night Lights 2021	(4) log Night Lights 2022	(5) log Night Lights 2022
Lockdown	-0.0391***				
	(0.00643)				
Risk		0.0812***	0.219***	-0.139***	-0.0771***
		(0.0229)	(0.0241)	(0.0135)	(0.0129)
R-squared	0.969	0.980	0.965	0.962	0.980
Observations	40103	19598	19991	23838	23341
Mean of Nightlight (Monthly)	2.614	2.268	2.268	2.354	2.354
Controls	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Month FE	✓	✓		✓	
Prefecture × Month FE			✓		✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Mobility Spillover Results

	2021				2022			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log Mobility Inflow	log Mobility Inflow	log Mobility Outflow	log Mobility Outflow	log Mobility Inflow	log Mobility Inflow	log Mobility Outflow	log Mobility Outflow
Risk	-0.287***	-0.286***	-0.350***	-0.349***	-0.292***	-0.295***	-0.322***	-0.321***
	(0.0344)	(0.0354)	(0.0431)	(0.0446)	(0.0385)	(0.0394)	(0.0384)	(0.0398)
Neighbors Risk		-0.0309		-0.0620		-0.0849*		-0.195***
		(0.0345)		(0.0500)		(0.0495)		(0.0429)
R-squared	0.968	0.969	0.963	0.963	0.888	0.885	0.883	0.880
Observations	30060	29970	30060	29970	38352	36585	38352	36585
Mean of Mobility	0.284	0.284	0.284	0.284	0.234	0.234	0.235	0.235
Neighbors Risk Lag 7 days		✓		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Prefecture FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Pollution Spillover Results

	(1) log PM2.5 2021	(2) log PM2.5 2021	(3) log PM2.5 2022	(4) log PM2.5 2022
Risk	0.0159***	0.0161***	-0.0117***	-0.00917***
	(0.00576)	(0.00624)	(0.00320)	(0.00326)
Neighbors Risk		-0.0982***		-0.0464***
		(0.0306)		(0.00868)
R-squared	0.873	0.878	0.882	0.880
Observations	99050	93060	144864	139072
Mean of PM2.5 (Weekly Average)	25.83	25.59	26.94	26.72
Neighbors Risk Lag 2 weeks		✓		✓
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Week FE	✓	✓	✓	✓
Prefecture × Month FE	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Night Lights Spillover Results

	(1) log NightLight 2021	(2) log NightLight 2021	(3) log NightLight 2022	(4) log NightLight 2022
Risk	0.0812***	0.0997***	-0.0771***	-0.0703***
	(0.0229)	(0.0247)	(0.0129)	(0.0129)
Neighbors Risk		-0.0386		0.00277
		(0.0393)		(0.0178)
R-squared	0.980	0.979	0.980	0.979
Observations	19598	17196	23341	20626
Mean of Nightlight (Monthly)	2.268	2.317	2.354	2.254
Neighbors Risk Lag 1 month		✓		✓
Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Prefecture × Month FE	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Pollution SDID Results

	(1) log PM2.5 2020	(2) log PM2.5 2021	(3) log PM2.5 2022
Lockdown	-0.115***		
	(0.00839)		
Risk		0.0314	0.00537
		(0.0312)	(0.00541)
Observations	42750	99750	145584
Mean of PM2.5 (Weekly Average)	31.52	25.83	26.93
Controls	✓	✓	✓
County FE	✓	✓	✓
Week FE	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Night Lights SDID Results

	(1) log NightLight 2020	(2) log NightLight 2021	(3) log NightLight 2022
Lockdown	-0.00401		
	(0.00465)		
Risk		0.108***	-0.124***
		(0.0226)	(0.0245)
Observations	23790	12976	11000
Mean of Nightlight (Monthly)	2.385	2.083	1.844
Controls	✓	✓	✓
County FE	✓	✓	✓
Month FE	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Appendix

7.1 Appendix A: China's COVID Risk Level Database

In order to comply with the Prevention Guidance for Novel Coronavirus Pneumonia (version 5),[26] starting from March 2020, the State Council of China began to release a national COVID risk level system on a regular basis through their website. This system categorizes communities within the 2853 counties into high, medium, or low-risk groups on a daily basis. In specific, the risk level is reported by local governments and compiled by National Health Commission of China.

This website had two access interfaces. Interface A on the left column of Figure A1 is a search engine that allows users to obtain communities' risk level results for a specific county by entering its name. Interface B, located in the right column, displays all counties that have communities classified as *Risk* along with their corresponding community names. Counties that do not appear on this list are considered non-risk areas.[27]

We started risk level data collection through interface B since April 02, 2021 and ended by Dec 15, 2022.[28] [29] The China COVID Risk Level Database contains daily risk level information for 2853 counties from April 02, 2021 to December 15, 2022. This database is the most systematic compilation of China's risk level classification during 2021 and 2022.

7.2 Appendix B: Figures

[26] Prevention Guidance for Novel Coronavirus Pneumonia (version 5): http://www.nhc.gov.cn/jkj/s3577/202002/a5d6f7b8c48c451c87dba14889b30147.shtml and a follow up guidance: http://www.gov.cn/zhengce/zhengceku/2020-04/16/content_5503261.htm

[27] The web links for both pages have already expired. Interface A: bmfw.www.gov.cn/yqfxdjcx/index.html and Interface B: bmfw.www.gov.cn/yqfxdjcx/risk.html

[28] The weblink of interface B expired on Dec 15, 2022. But the weblink of interface A was still active until Dec 25, 2022, we collected the data between Dec 15 to Dec 25 through a third party website, http://bj.bendibao.com/ but did not integrate the last 10 days data into our dataset yet.

[29] We thank open-source projects *BeautifulSoup* and *Selenium*.

Figure A1: Demo of State Council's website for the Risk Level System.

(a) Interface A

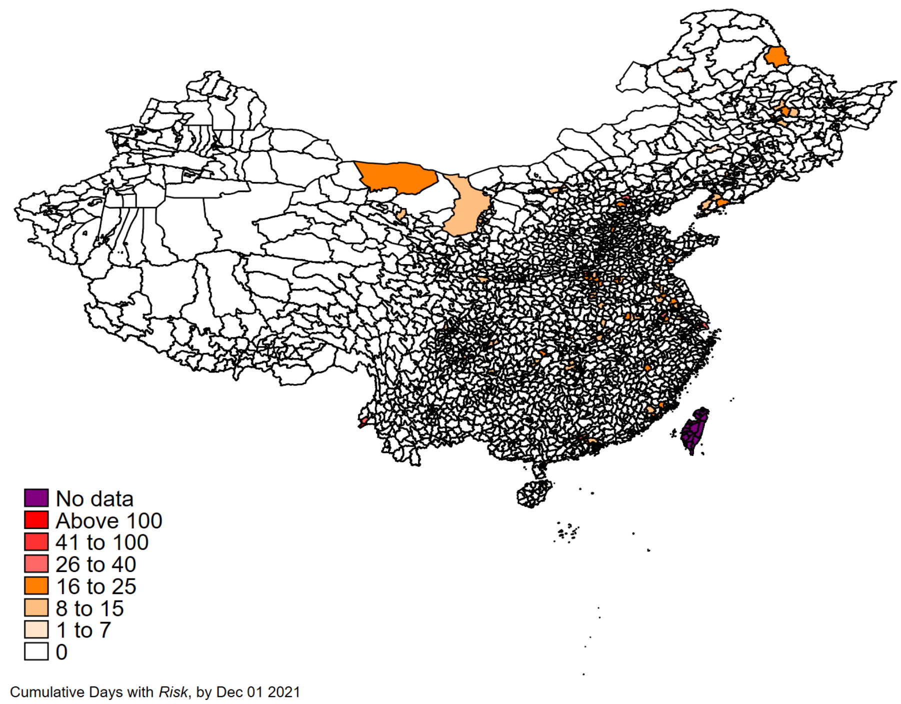
(b) Interface B

Figure A1:

Notes: The web links for both pages have already expired.
Interface A: bmfw.www.gov.cn/yqfxdjcx/index.html
and Interface B: bmfw.www.gov.cn/yqfxdjcx/risk.html

Figure A2: Geographical Distribution of counties with *Risk*

(a) *Risk* 2021



(b) *Risk* 2022

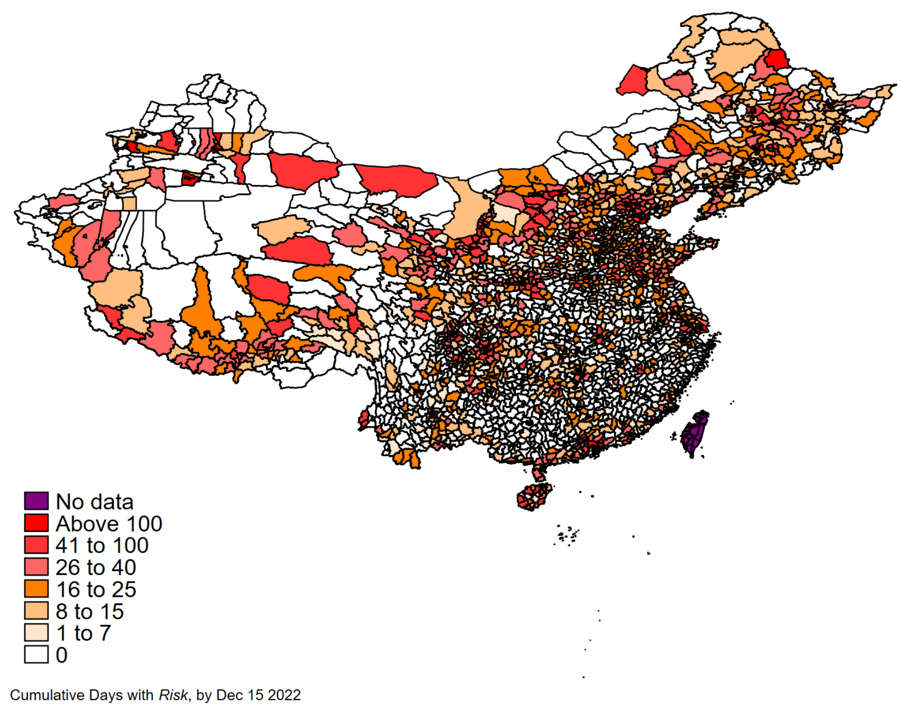


Figure A3: Night Lights in March 2022

Figure A3:

Note: This is the filtered data of Night Lights in March 2022 obtained from VIIRS, combine with the shapefile of China's county boundary.

7.3 Appendix C: Tables

Table A1: Pollution Balanced Sample Regression Results

	(1) log PM2.5 2020	(2) log PM2.5 2021	(3) log PM2.5 2022
Lockdown	-0.162***		
	(0.00956)		
Risk		0.0842***	-0.0344***
		(0.0153)	(0.0101)
R-squared	0.870	0.773	0.749
Observations	42750	99750	145584
Mean of PM2.5 (Weekly Average)	31.52	25.83	26.93
Controls	✓	✓	✓
County FE	✓	✓	✓
Week FE	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Night Lights Balanced Sample Regressions Results

	(1) log NightLight 2020	(2) log NightLight 2021	(3) log NightLight 2022
Lockdown	-0.0669***		
	(0.00951)		
Risk		0.0777***	-0.137***
		(0.0249)	(0.0261)
R-squared	0.966	0.981	0.953
Observations	23790	12648	11000
Mean of Nightlight (Monthly)	2.385	2.083	1.844
Controls	✓	✓	✓
County FE	✓	✓	✓
Month FE	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$