北京大学中国经济研究中心
China Center for Economic Research
讨论稿系列
Working Paper Series

E2020012 2020-11-30

Do Lockdowns Bring about Additional Mortality Benefits or Costs? Evidence based on Death Records from 300 Million Chinese People

Authors: Jinlei Qi[1*], Dandan Zhang[2*], Xiang Zhang[2], Peng Yin[1], Jiangmei Liu[1], Yuhang Pan[3], Tanakao Takana[4], Peiyu Xie[2], Zhaoguang Wang[2], Shuocen Liu[5], George F. Gao[6†], Guojun He[3,4,7†], Maigeng Zhou[1†]

*These authors contributed equally to this work. † These authors are co-correspondence.

Affiliations:

1 National Center for Chronic and Noncommunicable Disease Control and Prevention, Chinese Center for Disease Control and Prevention, 27 Nanwei Road, Xicheng District, 100050 Beijing, China (J Qi PhD, P Yin PhD, J Liu MPH, M Zhou PhD)

2 National School of Development, Peking University, 5 Yiheyuan Road, Haidian District, 100871 Beijing, China (D Zhang PhD, X Zhang BA, P Xie MA, Z Wang MA)

3 Division of Environment and Sustainability, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, China (Y Pan MPhil, G He PhD)

4 Division of Social Science, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, China (T Takana MPhil, G He PhD)

5 Peking University HSBC Business School, Peking University, University Town, Nanshan District, 518055 Shenzhen, Guangdong Province, China (S. Liu MA)

6 Chinese Center for Disease Control and Prevention, 155 Changbai Road, Changping District, 102206 Beijing, China (George Gao DPhil)

7 Department of Economics, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, China (G He PhD)**Address for correspondence**:

Dr. Maigeng Zhou, National Center for Chronic Noncommunicable Disease Control and Prevention, Chinese Center for Disease Control and Prevention, Beijing 100050, China (zhoumaigeng@ncncd.chinacdc.cn), or Dr. Guojun He, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong SAR, China (gjhe@ust.hk),

or Dr. George F. Gao, Chinese Center for Disease Control and Prevention, Beijing 102206, China (gaofu@chinacdc.cn),

Abstract

Objectives To estimate the short-term effect of stringent lockdown policies on non-COVID-19 deaths, and explore the heterogeneity of lockdowns on mortality in China after the COVID-19 outbreak.

Design Employing a difference-in-differences method.

Setting Using comprehensive death records covering around 300 million Chinese people, we estimate the impacts of city and community lockdowns on non-COVID-19 mortality outside of Wuhan.

Participants 44,548 deaths recorded in 602 counties or districts by the Disease Surveillance Point System of the Chinese Center for Disease Control and Prevention from 1 January 2020 to14 March 2020.

Results We find that lockdowns reduced the number of non-COVID-19 deaths by 4.9% (cardiovascular deaths by 6.2%, injuries by 9.2%, and non-COVID-19 pneumonia deaths by 14.3%). A back-of-the-envelope calculation shows that more than 32,000 lives could have been saved from non-COVID-19 diseases/causes during the 40 days of the lockdown on which we focus.

Main outcome measures Weekly numbers of deaths from all causes without COVID-19, cardiovascular diseases, injuries, pneumonia, neoplasms, chronic respiratory diseases, and other causes were used to estimate the associations between lockdown policies and mortality.

Conclusions The results suggest that the rapid and strict virus countermeasures not only effectively controlled the spread of COVID-19 but also brought about massive unintended public health benefits. The health benefits are likely driven by significant reductions in air pollution, traffic, and human interactions. These findings can help better inform policymakers around the

world about the benefits and costs of city and community lockdowns policies in dealing with the COVID-19 pandemic.

Keyword: Lockdown; Anti-contagion policy; COVID-19; China

Introduction

By the end of October 2020, COVID-19 had affected more than 219 countries and caused more than 45,940,000 deaths worldwide.[1] Facing this unprecedented crisis, different countries adopted various measures to mitigate its impacts, ranging from one extreme, where governments imposed draconian measures to restrict human mobility immediately after the outbreak, to the other extreme, where governments were reluctant to adopt any serious disease preventive measures and explicitly resorted to herd immunity. Effective policies not only depend on the social preferences of people and the capacity of government but also depend on our accurate understanding of the costs and benefits of different counter-COVID-19 measures. However, relatively little is known about the broader impacts of these policies.

A key component when evaluating the welfare implications of the anti-contagion policies is their overall public health consequences. Multiple studies have shown that strict social distancing and human mobility restrictions can effectively control the spread of COVID-19 and thus save lives from the virus.[2-6] However, it remains unknown to researchers and policymakers how such interventions affect disease patterns and deaths from other causes. On the one hand, hospitals may decline nonurgent service requests (especially when the system is overburdened by COVID-19)[7] and the fear of getting infected by COVID-19 may make patients reluctant to visit hospitals. This could impact the quality of health services and delay medical treatment, which would negatively impact the population health. Additionally, in many countries, the strict virus containment policies led to sudden and sharp economic disruption, causing massive layoffs.[8] As documented in the previous literature, such economic downturns and high unemployment could also damage population healtht.[9-15] All these factors would increase the mortality when strict counter-virus measures were enforced. On the other hand, because the virus containment policies significantly improved air quality, restricted human-to-human interactions, and reduced traffic volume, it is also possible that a large number of people could be saved from dying from air pollution, other types of communicable diseases, and traffic accidents.[17-19] Therefore, it is of great scientific and policy relevance to assess whether the counter-virus measures bring about additional public health gains or additional public health losses.

Using data from China, we examine how city and community lockdown policies affect non-COVID-19 mortality. We focus on China because the country mandated strict social distancing and lockdown policies to control the virus. Within a few weeks after the COVID-19 outbreak in Wuhan, a large number of cities enforced strict quarantines, traced close contacts, prohibited public gatherings, mandated social distancing, and limited human mobility. A large number of cities were locked down even though they had less than 100 confirmed cases (Figure SM1 and Figure SM2). Exploiting the staggered introduction of city and community lockdowns in different cities of China, we estimate the impacts of lockdowns on the number of deaths from various causes and explore the channels through which these impacts are manifested. These results will help policymakers around the world design effective measures to mitigate the damages from the pandemic.

The core of our empirical analysis uses the comprehensive deaths record from China's Disease Surveillance Points (DSPs) system, covering more than 324 million people in 605 DSP's districts/counties in 321 cities, which accounts for 24.3% of the country's population.[20, 21] This dataset includes cause-specific deaths, which allows us to examine the mechanism of lockdowns' impacts on non-COVID-19 mortality. Each city's lockdown information is collected from news media and government announcements. During the end of January and the mid of February, a large number of Chinese cities have implemented the lockdown policies (Figure 1). There are two types of lockdowns: city lockdown and community lockdown. The former is defined as mobility being restricted across different cities, and the latter is defined as restriction of mobility within a city. Matching these datasets, we construct a daily DSP site-level panel dataset from January 1 to March 14, 2020, which is the period largely overlapping with the coronavirus outbreak in China. Our dataset includes 393,133 death records that were reported to the DSPs system by May 15, 2020 (Table SM1). Note that we exclude 3 DSPs in Wuhan from the baseline analysis because the city is the epicenter of the outbreak in China, and we are concerned that its death reporting process could have been affected during the study period.[22]

To quantify the impacts of lockdowns on mortality, we employ a difference-in-differences (DiD) approach, which is an econometric approach and is widely used to infer causal impacts of various policies and events using observational data[23]. An advantage of this approach is that it compares the policy effects relative to the plausible counterfactuals. While the results from a before-and-after comparison could be driven by different mortality trends or other unobserved confounders, DiD compares the changes in mortality between the locked-down DSPs (treatment group) and the non-locked-down DSPs (control group) before and after the enforcement of lockdown policies. In other words, the control group can serve as a counterfactual, mimicking what would have happened in locked down DSPs in the absence of the lockdown, which essentially allows us to compare the policy effects relative to business as usual. Note that a key assumption of the DiD is that the treatment and the control group follow parallel trends in the number of deaths in the absence of the lockdown policies. We examine whether this assumption is likely to hold using an event-study test. We describe the model in more detail in the Materials and Methods.

Methods

Materials

Study area: We collected data from 605 Disease Surveillance Point (DSPs) districts/counties from January 1 to March 14, 2020, which include 393,133 death records that were reported to the DSPs system by May 15, 2020. In our baseline analysis, we exclude three points (districts) in Wuhan due to concerns that the data might be unrepresentative because the pandemic started there.

Mortality Data: Weekly mortality data are provided (See supplementary material). The causes of death are coded in accordance with the International Classification of Diseases-10th revision (ICD-10). We classified the main underlying causes of deaths into 6 categories: I00-I99 for cardiovascular diseases (CVD), V01-Y89 for injuries, J12-J15, J18.9 and J98.4 for pneumonia (excluding COVID-19), C00-C97 for neoplasms, J30-J98 for chronic respiratory diseases, and other causes (remaining ICD-10 codes for all other causes). We further disaggregate cardiovascular diseases, injuries, and pneumonia deaths into specific diseases/causes. Cardiovascular diseases include stroke (I60-I62, I67, and I69), myocardial infarction (I20-I25), and other cardiovascular diseases. Injuries include traffic accidents (V01-V04, V06, V09, V87, V89, and V99), suicide (X60-X84 and Y87), and other injuries. Pneumonia includes mycoplasma pneumonia (J18.9), viral and bacterial pneumonia (J12-J15), and pulmonary infection (J98.4). We also divide the daily number of deaths into three age groups (0-15, 15-64, and ≥65). All death data are analyzed at the aggregated level.

Lockdown Data: We collected local governments' lockdown information city by city from news media and government announcements. Most of the cities' lockdown policies were directly issued by the city-level governments, while a few were promulgated by the provincial governments. There are two types of lockdowns: city lockdown and community lockdown. The former is defined as human mobility being restricted across different cities, and the latter is defined as mobility being restricted within a city. At the early stage of the outbreak, to prevent the virus from spreading outside Hubei province, city lockdowns were adopted in Wuhan and its neighboring cities. The purpose of city lockdowns was to restrict people in the epicenter of coronavirus from traveling to other cities. Later, as more cases were identified in other cities, community lockdowns were implemented to further control the spread of the coronavirus within cities. The time lag between city lockdowns and community lockdowns was typically one to two weeks. The evolution of different DSPs' lockdown status is presented in Figure SM1 and Figure SM2. In Table SM11, we further provide a complete list of cities that adopted different lockdown policies at different times. The lockdowns gradually spread to different surveillance districts/counties between January 23 and February 20. By the end of February, 486 out of 602 surveillance points had lockdown policies.

Weather Data: Weather variables include daily temperature, atmospheric pressure, relative humidity, wind speed, and precipitation. The data are obtained from the China Meteorology Administration (CMA). We aggregate station-level air pollution data to city-level data using the inverse squared distance (to city centers) as the weights. Stations closer to the population center are given higher weights so that city-level weather data can be representative of people dwelling in the city.

Air Pollution Data: We obtain air pollution data from the Ministry of Ecology and Environment. The original dataset includes hourly air quality readings from over 2,000 monitoring stations covering 338 prefectural cities in China. We follow the same procedure to aggregate station level air pollution data to the city level. As an omnibus measure of the overall air quality, we use $PM_{2.5}$ concentration in our regressions. Our results are quantitatively unchanged if we use the Air Quality Index or PM_{10}.

Socio-Economic Conditions: We assemble the socio-economic data at the city or county level from the 2018 China City Statistical Yearbook and 2018 China County Statistical Yearbook, including GDP, population, and the number of hospital beds per 1,000 people. We also obtain data on the employment share of the manufacturing and service industries using the 10% sample of the 2015 1% Population Sampling Survey in China.

Summary Statistics: We report the summary statistics of mortality, lockdown status, and other covariates for 602 DSP counties in Table SM1. In Panel A, we report the summary statistics of the DSPs data. The average daily total number of deaths at the county level is 8.7, with a standard deviation of 0.025. The leading cause of death during this period is cardiovascular diseases, which account for 49.7% of all deaths. The second leading cause of death is neoplasms (22.3%), followed by chronic respiratory diseases (8.7%), and injuries (5.5%). In Panel B, we report the summary statistics of several other variables. The $PM_{2.5}$ concentration during our study period is 50 μg/m^3, five times higher than the WHO standard (10 μg/m^3 for annual mean, and 25 μg/m^3 for a daily mean). The average share of employment in the manufacturing industries was 24.2% as of 2015.

Statistical Analysis

We use a generalized Difference-in-Differences (DiD) model to identify the impact of counter-COVID-19 measures on mortality. First, in our baseline regression, we estimate the relative change in the number of deaths between the treated and control DSPs using the following model:

$$D_{ijt} = \alpha + \beta \cdot lockdown_{jt} + \lambda_i + \pi_t + \varepsilon_{ijt} \qquad (A1)$$

where D_{ijt} denotes the daily number of deaths in DSP *i* in city *j* on date *t*, and $lockdown_{jt}$ is a dummy variable indicating whether a city/community lockdown is in place in city *j* on date *t*. The lockdown dummy takes the value one if either city lockdown or community lockdown was implemented, and zero otherwise. Thus, the coefficient β measures the average effect of three types of lockdown policies: mobility restrictions across cities (city lockdown), mobility restrictions within a city (community lockdown), and both restrictions (city lockdown + community lockdown). To understand how the city and community lockdowns affect health outcomes differently, we separately estimate these effects (Table SM5). λ_i are DSP-fixed effects and π_t indicate date fixed effects. ε_{ijt} is the error term.

The county fixed effects, λ_i, which are a set of DSP-specific dummy variables, can control for time-invariant confounders specific to each DSP. For example, the DSP's geographical conditions, short-term industrial and economic structure, income, and natural endowment can be controlled by introducing the DSP fixed effects. The date fixed effects, π_t, are a set of dummy variables that account for shocks that are common to all DSPs in a given day, such as the nationwide holiday policies, macroeconomic conditions, and the national time trend for mortality. As both location and time fixed effects are included in the regression, the coefficient β estimates the difference in the number of deaths between the treated (locked down) and the control cities before and after the enforcement of the lockdown policy. We also add a set of control variables in the regressions to check the robustness of the results (Figure SM3).

The underlying assumption for the DiD estimator is that lockdown and control cities would have parallel trends in the number of deaths in the absence of the event. Even if the results show that mortality declines in the treatment counties after the lockdown, the results may not be driven by the lockdown policy, but by systematic differences in treatment and control cities. This assumption is untestable because we cannot observe the counterfactual: what would happen to the mortality levels in the locked-down counties if such policies were not enforced. Nevertheless, we can still examine the trends in mortality for both groups before the lockdown and investigate whether the two groups are indeed comparable. To do so, we conduct the event study and fit the following equation:

$$D_{ijt} = \alpha + \sum_{m=k,m\neq -1}^{M} \beta^k \cdot lockdown_{ijt,k} + \lambda_i + \pi_t + \mathcal{E}_{ijt} \qquad (A2)$$

where $lockdown_{jt,k}$ are a set of dummy variables indicating the treatment status at different periods. Here, we put 7 days (one week) into one bin ($bin\ \ m \in M$), so that the trend test is not affected by the high volatility of the daily number of deaths.

The dummy for $m = -1$ is omitted in Equation (A2) so that the post-lockdown effects are relative to the period one week before the launch of the policy. The parameter of interest β^k estimates the effect of lockdown m weeks after the implementation. We include leads of the treatment dummy in the equation, testing whether the treatment affects the air pollution levels before the launch of the policy. Intuitively, the coefficient β^k measures the difference in the number of deaths between cities under lockdown and otherwise in period k relative to the difference two weeks before the lockdown. If lockdown reduces mortality, β^k would be negative when $k \geq -1$. If the pre-treatment trends are parallel, β^k would be close to zero when $k \leq -2$.

We feel confident in using the estimates from our main results to calculate the averted deaths in the entire country, because our dataset includes around one-quarter of the Chinese population and are representative. To do so, we predict the number of deaths in two scenarios: with/without lockdown policies. Taking the difference between these two predicted deaths, we can calculate the number of saved lives from the lockdown policies. To do so, we first predict the number of deaths with lockdown policies in each DSP county/district in each day by fitting the following model:

$$\widehat{D}_{ijt} = \hat{\alpha} + \hat{\beta} \cdot lockdown_{jt} + \hat{\lambda}_{\mathrm{i}} + \hat{\pi}_t \qquad (A3)$$

where $\widehat{D}_{ijt}$ denotes the predicted deaths with lockdown policies in each DSP county/district i in city j. $\hat{\alpha}$, $\hat{\beta}$, $\hat{\lambda}_{\text{i}}$, and $\hat{\pi}_t$ are the fitted values from Equation (A1). In this function, predicted deaths in each DSP, denoted by $\widehat{D}_{ijt}$, can be affected by the lockdown status (represented by $lockdown_{jt}$).

We then predict the counterfactual, i.e., the number of deaths that would have occurred without lockdowns in any DSP, by fitting the following equation:

$$\widehat{D}_{ijt}(0) = \hat{\alpha} + \hat{\beta} \cdot lockdown_{jt}(0) + \hat{\lambda}_{\text{i}} + \hat{\pi}_t \qquad (A4)$$

where $\widehat{D}_{ijt}(0)$ denotes the predicted averted deaths without any lockdown policies. $lockdown_{jt}(0)$ always takes a value of zero so that this function is not affected by the policies. Taking the differences between $\widehat{D}_{ijt}$ and $\widehat{D}_{ijt}(0)$, we can calculate how many non-COVID-19 deaths are saved from the lockdown policies in each DSP in each day.

Because lockdowns were implemented for 38.5 days on average, we estimate the following model to obtain the averted deaths in the whole country during our study period:

$$\widehat{D}_{all} = \frac{Chpop^{LD}}{DSPpop^{LD}} * \sum_{i \epsilon I} \widehat{D}_{ijt} - \widehat{D}_{ijt}(0) \qquad (A5)$$

where $\widehat{D}_{all}$ denotes the averted deaths in the entire county during our study period, $Chpop^{LD}$ denotes the total Chinese population in locked-down cities (around 1,161 million), and $DSPpop^{LD}$ represents the total population in locked-down DSPs counties/districts in our dataset (around 291 million in 486 DSPs). The difference between the scenarios with and without lockdowns, denoted by $\widehat{D}_{ijt} - \widehat{D}_{ijt}(0)$, is totaled from January 1 to March 14, which is our study period ($i \ \epsilon \ I$). Note that, in our main text, we repeat these steps to estimate the averted deaths from each cause and disease to understand how many averted deaths can be attributed to different diseases/causes.

Ethical Approval

The ethics committee from the National Center for Chronic Non-Communicable Disease Control and Prevention (NCNCD) of the Chinese Center for Disease Control and Prevention approved the study. No individual consent was required as all the data were analyzed at aggregated level, and no patients were involved in setting the research question or the outcome measures, nor were they involved in developing plans for recruitment, design, or implementation of the study.

Results

Impacts of City and Community Lockdowns on Non-COVID-19 Deaths

Figure 2 summarizes the baseline regression results by fitting the DiD model (Equation A1; full results are in Table SM2). Panel A reports the effects on the number of deaths, while Panel B reports the percentage change. In row (1), we find that lockdowns overall have a negative impact on non-COVID-19 mortality. After human mobility is restricted, the DSP-level daily number of deaths decreased by 0.429 (or 4.92%), as compared to the control group.

In rows (2) to (7), motivated by several factors that could potentially affect population health during the lockdown period, we separately examine the effects on different causes of death. We are especially interested in the following three outcome variables: cardiovascular diseases (CVD), injuries, and (non-COVID-19) pneumonia deaths. Existing literature on the acute effects of air pollution suggests that elevated air pollution levels can significantly increase deaths from strokes, myocardial infarction, and other types of cardiovascular diseases.[24-25] We thus expect the number of deaths from CVDs may decrease due to the improved air quality.[27] As shown in row (2) of Figure 2, we find that cardiovascular deaths were reduced by 6.2% (0.27 in levels) after lockdown. Relatedly, as the lockdown policies restrict production, social activities, and traffic, we expect the number of deaths from injuries (which include workplace injuries, traffic accidents, etc.) to also drop. The result in row (3) of Figure 2 confirms this conjecture; we observe that the number of deaths caused by injuries decreased by 9.2% (0.044 in levels). In addition, as human mobility is greatly restricted during the lockdown period, this should reduce the likelihood of people getting infected by and dying from other types of bacteria and viruses that cause pneumonia. The result in column (4) shows that deaths from non-COVID pneumonia were reduced by a large margin of 14.7% (0.022 in levels) during the lockdown period.

In rows (5) to (7), we report the findings on several other causes of death that are less likely to be affected by short-term restrictions on human activities. They include deaths from neoplasms, chronic respiratory diseases, and other diseases. While the coefficients for these causes of death are also negative, they are all not statistically significant. We thus conclude the temporary human mobility restrictions during China's lockdowns primarily reduce the deaths caused by acute diseases and accidents and have a weaker impact on people with chronic diseases and cancers.

Some additional analyses complement our main findings. A key assumption of the DiD is that the treatment and the control group follow parallel trends in the number of deaths in the absence of the lockdown policies. Using an event-study approach, we show that this assumption is likely to be held (Figure 3 and Supplementary Note 1 and Table SM3). Also, we find that our results are robust to the inclusion of additional controls, adoption of different weighting, and sampling (Supplementary Note 2, Table SM5, and Figure SM3). Finally, we further disaggregate the data into more specific causes/diseases (Table SM4). For example, in the cardiovascular disease category, we observe that deaths from myocardial infarction, strokes, and other types of cardiovascular diseases all significantly decreased after the lockdown.

Heterogeneity

In Figure 4, we examine the heterogeneous impacts of lockdowns on mortality. Here we report our findings on the total number of non-COVID-19 deaths and explore the following dimensions: baseline income (measured by per capita GDP in 2018), healthcare resources (measured by hospital beds per thousand people in 2018), air pollution levels (measured by average $PM_{2.5}$ concentrations in 2019), industrial structure (measured by the share of employment in manufacturing industries in 2015), and initial health status (measured by mortality rate in 2019).

To do so, we interact the lockdown indicator separately with each of the heterogeneity dimensions in the regression (Table SM6), and then plot the predicted impacts and their 95% confidence intervals in Figure 4. We observe significant heterogeneities with respect to the air pollution level, the employment shares in the manufacturing industries, and the baseline mortality level. Specifically, the health benefit of lockdowns on mortality is greater when a DSP is more polluted and more industrialized, and when the initial health status is worse.

We also repeat this exercise separately for deaths from specific causes: cardiovascular diseases, injuries, and non-COVID-19 pneumonia (Figure SM4). Several patterns stand out: (1) for cardiovascular diseases, there exist significant heterogeneities for air pollution and industrial structure, with more polluted and more industrialized cities seeing fewer deaths from cardiovascular diseases during lockdowns relative to other cities (Panel a); (2) for injuries, the more industrialized the DSP, the higher its initial injury mortality, and, as expected, the greater the impact of the lockdown (Panel b); (3) for pneumonia, we only observe significant heterogeneity with respect to initial mortality rate, *i.e.*, cities with a higher initial pneumonia mortality rate are more strongly affected by lockdowns (Panel c). Across all the causes of death, per capita GDP and availability of healthcare resources do not seem to play an important role in terms of magnitude, although occasionally they are statistically significant. The corresponding regression results are reported in Tables SM7-9. As a side note, we also examined many other dimensions of heterogeneity, including the severity of the COVID-19 outbreak, alternative measures of health care resources, other measures of economic structure, etc. However, we do not observe strong heterogeneities along these dimensions and thus do not report them in the paper.

Finally, we investigate which age group(s) are driving the overall reduction in mortality. We expect older people and younger people to be sensitive to the overall lockdown policies, while we expect adults to be vulnerable to injuries and accidents. Figure SM5 summarizes the results. We find that children (-10.6% in row 1) and the elderly (-5.5% in row 5) are indeed more likely than adults (-2.5% in row 2) to be saved by the lockdown policies. If we further examine different causes of death, we find that the elderly is saved both from air pollution-related disease (-6.6% in row 6) and infectious disease (-17.0% in row 8), and younger adults are protected from injuries (-14.7% in row 4). These results are generally consistent with our understanding of the threats of various diseases to different age groups. More detailed results are represented in Table SM10.

Back-of-the-envelope calculation

In Figure 5, using the estimates in our analyses, we calculate the averted non-COVID-19 deaths in the whole nation due to the lockdown policies during our study period. In Panel a, we plot the predicted average daily deaths. The red and blue lines respectively represent the predicted deaths with and without lockdown policies. Therefore, the differences between these lines can be regarded as the lockdown effects. We see that these two lines start to diverge as more cities implement lockdown policies, and the difference remains stable throughout mid-March.

Because our dataset includes around a quarter of the Chinese population, we apply our estimates to the entire Chinese population, in Panel b. During our study period, 486 DSPs (80.7%) eventually implemented lockdowns, with an average of 38.5 days. We apply our estimates to all the cities that implemented the lockdown policies and calculate the number of averted deaths during our study period. We find that the lockdown policies brought about considerable health benefits: as many as 32,023 lives may have been saved. If we look at the cause-specific effects, we find that cardiovascular diseases account for 62.9% (20,129) of overall averted deaths. Deaths from injury also declined by 10.2% (3,261), pneumonia by 5.0% (1,607), respiratory by 7.4% (2,373), and cancer by 8.5% (2,726).

Discussion

When COVID-19 spread across the globe, we observed a large variation in the public responses in mitigating its impacts: some countries immediately adopted harsh counter-virus measures while others delayed the launch of the policies. As an example of prompt and stringent responses to the COVID-19 outbreak, we investigate the mortality consequences of community and city lockdowns using data from China (excluding Wuhan) during the pandemic period. Here, we discuss several important implications of our findings.

First and foremost, our findings demonstrate that the China's unprecedented lockdowns not only effectively controlled the spread of COVID-19, but also brought about substantial unintended benefits to population health during this period. We find that such policies reduced non-COVID-19 deaths by 4.92%, which corresponds to 32,000 averted deaths in the nation during 40 days of lockdown. Given the increasingly heated cost-benefit debates regarding different counter-COVID-

19 policy choices across the world, our results provide a benchmark to understand the health consequences of the lockdown policies. Besides China, several other countries have managed to take the COVID-19 threat under control after one to two months' strict social distancing, largely because they dealt with the COVID-19 seriously and decisively. We believe these stringent measures should also be better appreciated by policymakers around the world, particularly in countries where the COVID-19 is out of control.

Second, our research points out the directions to improve population health after the pandemic. In particular, we observe a significant reduction in the number of cardiovascular deaths during the lockdown periods, and the effect is larger in cities with higher levels of initial air pollution. Since the lockdown is negatively associated with air pollution which have been pointed out by previous studies,[17-18] the reduction in air pollution due to the lockdown can attribute to averted deaths of cardiovascular. A back-of-the-envelope calculation suggests that the total number of averted premature deaths from cardiovascular diseases in the locked-down DSPs alone has far exceeded the total number of deaths caused by COVID-19 in China. This result suggests that air pollution imposed a significant health risk to the Chinese population and it is critically important for the government to continue to improve the environmental quality even when the lockdown is lifted.[28, 29] Besides, the finding on pneumonia mortality confirms that reducing human contacts and raising awareness of preventive measures (such as wearing masks) not only helps control the spread of COVID-19, but also other infectious diseases. These measures should be more appreciated by both public health practitioners and governments.

Third, our results also serve as corroborating evidence that China's data on the number of COVID-19 deaths are largely reliable, especially those outside of Wuhan. The logic is the following: if the deaths from COVID-19 were intentionally classified as other causes, such as pneumonia or other unclassified diseases, we might observe an unexplainable hike in those causes of death in the locked-down cities (presumably, there were few cases of COVID-19 in the control group). Our results suggest this is not the case; we find that the lockdown reduces all these causes of death in the locked-down cities (using data outside Wuhan), suggesting that COVID-19 deaths are unlikely to be misreported in a substantial way. For Wuhan, however, we do have suggestive evidence of potential misclassification of COVID-19 deaths, as including Wuhan in the regression reverses the sign for deaths from non-COVID-19 pneumonia.

Finally, while the literature has emphasized that economic downturns are usually associated with increased mortality (particularly in less affluent countries), our analyses show that the negative health effects of income shocks during China's lockdowns were offset by unintended benefits to population health, at least in the short run. While economic collapse is likely to seriously harm public health in the long run, we believe that countries currently affected by COVID-19 can maintain overall population health for a short time by containing the virus as quickly as possible through strict social distancing/mobility restrictions. Future research is needed to understand the long-term welfare implications of different ways to handle the COVID-19 pandemic.

Figure legends

Figure 1. Lockdown status of the DSPs from January to February 2020. The figure shows the map of DSPs in the different periods indicating their lockdown status. The numbers of locked-down DSPs in the four panels are respectively 26, 160, 460, and 486.

Figure 2. The impacts of city/community lockdowns on deaths from different causes. Each row in the figure represents a separate DiD regression (Equation (A1)). The number of observations for each regression is 44,548 covering 602 DSPs except for 3 DSPs in Wuhan. The outcome variable is the daily number of non-COVID-19 deaths. We use mortality data from January 1 to March 14, 2020. The explanatory variable is a dummy indicating whether the DSP site is locked down on a particular date. In Panel A, we report the results on the lockdown's impacts on number of deaths (except for deaths from COVID-19). DSP fixed effect and date fixed effect are included in each regression, and the standard errors are clustered at DSP level. The red dots and the lines refer to the point estimates and their 95% confidence intervals. Panel B presents the lockdown's impacts on percentage changes for different causes of death. The blue dots and lines refer to the point estimates and their 95% confidence intervals, respectively. We compute the numbers in Panel B by combining the estimates from Panel A and the mean values for each cause of death; for example, the number -4.92% in the first row of Panel B is computed by -0.429/8.721*100%.

Figure 3. Tests for parallel trends assumption. This figure summarizes the results using the event-study approach (SM: Equation A2). We include leads and lags of the start of the lockdown dummy in the regressions. The dummy variable indicating one week before the lockdown policies is omitted from the regressions. The estimated coefficients and their 95% confidence intervals are plotted. The vertical lines refer to the reference week.

Figure 4. The heterogeneous impacts of city/community lockdowns on deaths. Each row in the figure represents the predicted impacts of lockdown at different baseline socio-economic conditions, and their 95% confidence intervals. The heterogeneous dimension is shown in two scenarios: one standard deviation larger (+SD) / smaller (-SD) than mean. The prediction is based on the estimates from Table SM5. The top blue dot and line represent the baseline point estimates and 95% confidence interval, respectively.

Figure 5. Estimated averted covid-19 unrelated deaths from lockdown policies. This figure summarizes how lockdown policies affect the number of deaths relative to the counterfactual (without lockdown policies). In Panel A, the red line and blue line represent the predicted average deaths per DSP per day with and without lockdown policies. The difference between these two lines is regarded as the effects of lockdown policies. The red circle is observed deaths and the gray bar is the cumulative percentage of DSPs with lockdown policies in each day. In Panel B, using the entire nation's population in the locked-down cities, we estimate how many lives are saved due to lockdown policies from each disease in all of China.

Contributors

M.Z., G.H. and G.G. are joint senior authors. M.Z., G.H., D.Z. and J.Q. designed the project. J.Q., D.Z., X.Z., P.X., Z.W., and S.L. curated data. D.Z., J.Q., X.Z., P.Y., J.L, and T. T., analyzed the data. M.Z., G.H, D.Z. and J.Q. interpreted the results. G.H., D.Z., J.Q, and T.T. wrote the manuscript. G.H., G.G., J.Q., D.Z., and P.Y. edited the manuscript.

Acknowledgments

We thank all the staff who work in the primary health facilities, hospitals, and Center for Disease Control and Prevention for death reporting at county/district, city, province, and national levels. We also thank Yun Qiu for sharing the community lockdown data with us. Wei Wang and Yaxuan Liu provided for research assistance.

Data and materials availability

The DSPs data are proprietary data owned by the Chinese CDC. They can be accessed through application to the National Center for Chronic and Noncommunicable Disease Control and Prevention (a subsidiary of the Chinese CDC). The codes necessary to re-produce all the tables in the paper are ready to submit to the journal as supplementary materials or to post on a public repository.

Funding

The project is funded by Nationl Natural Science Foundation of China (82073675), Peking University Research Grant (7100602966) and HKUST School-Based Initiative (SBI17HS02).

Declaration of interests

The authors have declared that no competing interests exist.

References

1. World Health Organization, *WHO Coronavirus Disease (COVID-19) Dashboard*. https://www.who.int/emergencies/diseases/novel-coronavirus-2019 (accessed November 2, 2020)

2. Tian H, Liu Y, Li Y, et al. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science* 2020; **368**: 638-42.

3. Qiu Y, Chen X, Shi W. Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *J Popul Econ* 2020: 1-46.

4. Chinazzi M, Davis JT, Ajelli M, et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* 2020; **368**: 395-400.

5. Hsiang S, Allen D, Annan-Phan S, et al. The effect of large-scale anti-contagion policies on the COVID-19 pandemic [published online ahead of print, 2020 Jun 8]. *Nature* 2020.

6. Lai S, Ruktanonchai NW, Zhou L, et al. Effect of non-pharmaceutical interventions to contain COVID-19 in China [published online ahead of print, 2020 May 4]. *Nature* 2020.

7. Coibion, Gorodnichenko, Yuriy O, Webe M. Labor Markets During the Covid-19 Crisis: A preliminary view. National Bureau of Economic Research 2020.

8. Gordon SH, Sommers BD. Recessions, Poverty, and Mortality in the United States: 1993-2012. *Am J Health Econ* 2016; **3**: 489-510.

9. Baird S, Friedman J, Schady N. Aggregate Income Shocks and Infant Mortality in the Developing World. *Rev Econ Stat* 2011; **3**: 847-56.

10. Jérôme A, Von Gaudecker H, Bank J. The Impact of Income Shocks on Health: Evidence

from Cohort Data. *J Eur Econ Assoc* 2009;**6**: 1361-99.

11. Snyder SE, Evans WN. The effect of income on mortality: evidence from the social security notch. *Rev Econ Stat* 2006; **3**: 482-95.

12. Cutler DM, Knaul F, Lozano R, Zurita OMAB. Financial crisis, health outcomes and ageing: Mexico in the 1980s and 1990s. *J Public Econ* 2002;(NO.2): 279-303.

13. Vlachadis N, Vrachnis N, Ktenas E, Vlachadi M, Kornarou E. Mortality and the economic crisis in Greece. *Lancet* 2014; **383**: 691.

14. Falagas ME, Vouloumanou EK, Mavros MN, Karageorgopoulos DE. Economic crises and mortality: a review of the literature. *Int J Clin Pract* 2009; **63**: 1128-35.

15. Lundin A, Lundberg I, Hallsten L, Ottosson J, Hemmingsson T. Unemployment and mortality--a longitudinal prospective study on selection and causation in 49321 Swedish middle-aged men. *J Epidemiol Community Health* 2010; **64**: 22-8.

16. World Health Organization, *COVID-19 significantly impacts health services for noncommunicable diseases*. https://www.who.int/news-room/detail/01-06-2020-covid-19-significantly-impacts-health-services-for-noncommunicable-diseases(accessed July 5,2020).

17. He, G. Pan, Y. & Tanaka, T., The short-term impacts of COVID-19 lockdown on urban air pollution in China. *Nature Sustainability*. https://doi.org/10.1038/s41893-020-0581-y

18. Chen K, Wang M, Huang C, Kinney PL, Anastas PT. Air pollution reduction and mortality benefit during the COVID-19 outbreak in China. *Lancet Planet Health*. 2020;**4**:e210-e212.

19. Shilling F, Waetjen D. "Special Report (Update): Impact of COVID19 Mitigation on Numbers and Costs of California Traffic Crashes". Road Ecology Center 2020 (accessed June 14, 2020).

20. Liu S, Wu X, Lopez AD, et al. An integrated national mortality surveillance system for death registration and mortality surveillance, China. *Bull World Health Organ* 2016; **94**: 46-57.

21. Yang G, Hu J, Rao KQ, Ma J, Rao C, Lopez AD. Mortality registration and surveillance in China: History, current situation and challenges. *Popul Health Metr* 2005; **3**: 3.

22. The Wall Street Journal, Wuhan's Coronavirus Death Toll Surges by 50% After China Revision. https://www.wsj.com/articles/wuhans-coronavirus-death-toll-surges-by-50-after-china-reviews-data-11587110435 (accessed June 14, 2020).

23. Angrist JD, Pischke J. Mostly harmless econometrics: An empiricist's companion. Princeton university, 2008.

24. Chen R, Yin P, Meng X, et al. Fine Particulate Air Pollution and Daily Mortality. A Nationwide Analysis in 272 Chinese Cities. *Am J Respir Crit Care Med* 2017; **196**: 73-81.

25. Shah AS, Lee KK, McAllister DA, et al. Short term exposure to air pollution and stroke: systematic review and meta-analysis. *BMJ* 2015; **350**: h1295.

26. Mustafic H, Jabre P, Caussin C, et al. Main air pollutants and myocardial infarction: a systematic review and meta-analysis. *JAMA* 2012; **307**: 713-21.

27. Yin P, He G, Fan M, et al. Particulate air pollution and mortality in 38 of China's largest cities: time series analysis. *BMJ* 2017; **356**: j667.

28. He G, Fan M, Zhou M. The effect of air pollution on mortality in China: Evidence from the 2008 Beijing Olympic Games. *Journal of Environmental Economics & Management* 2016: 18-39.

29. Ebenstein A, Fan M, Greenstone M, He G, Zhou M. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proc*

Natl Acad Sci U S A 2017; **114**: 10384-9.

Figures

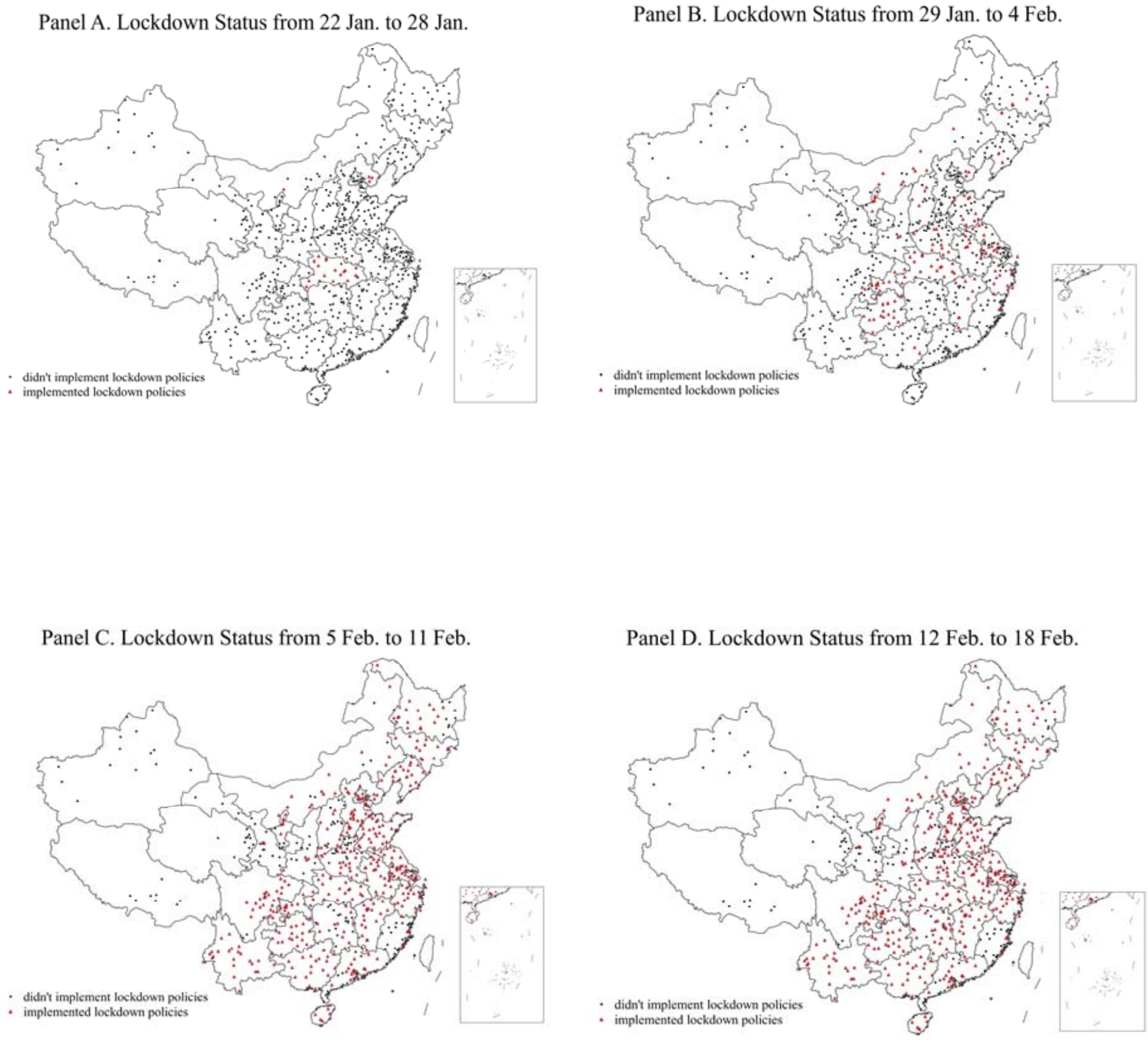

Figure 1. Lockdown status of the DSPs from January to February 2020.

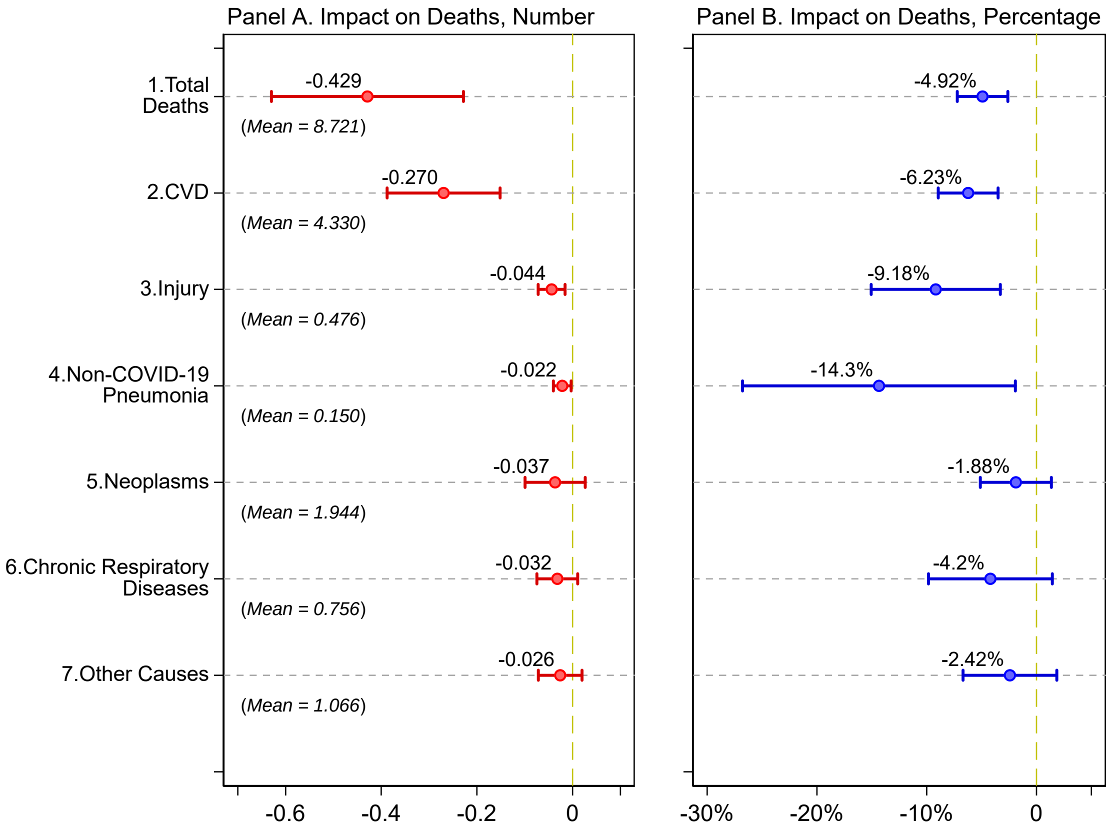

Figure 2. The impacts of city/community lockdowns on deaths from different causes.

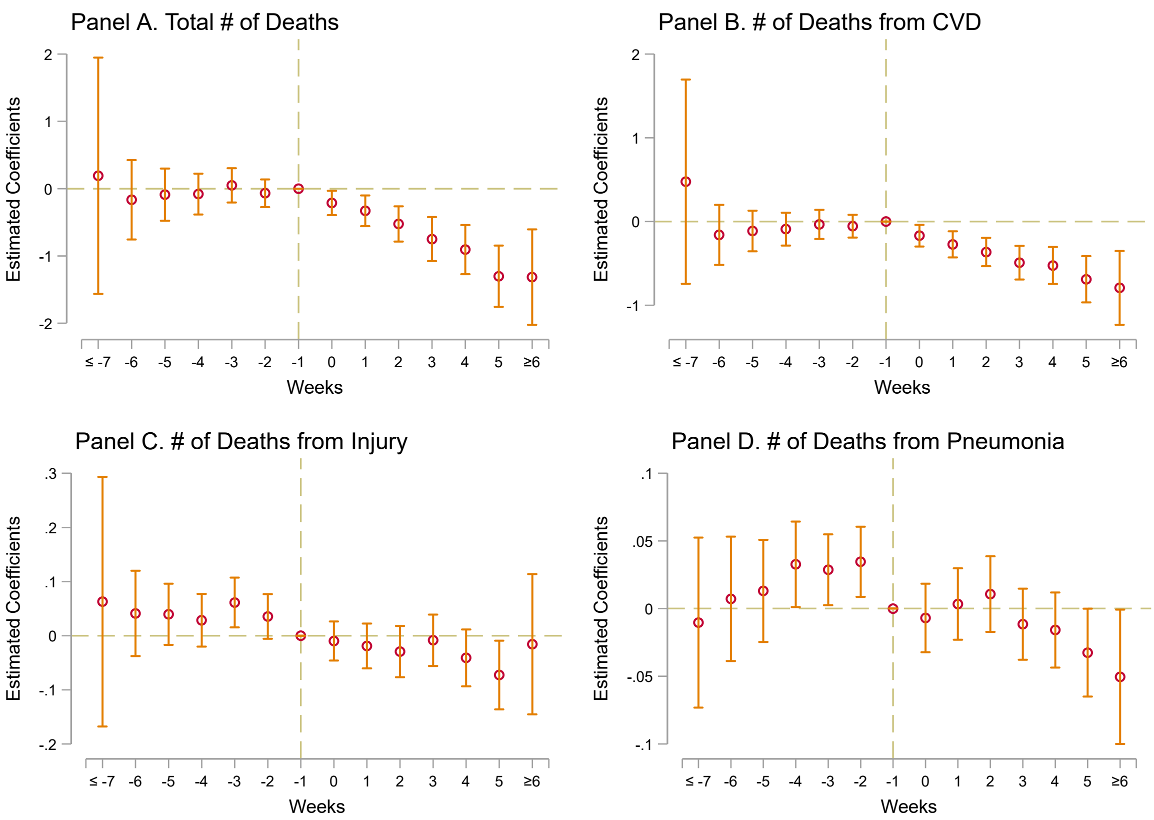

Figure 3. Tests for parallel trends assumption.

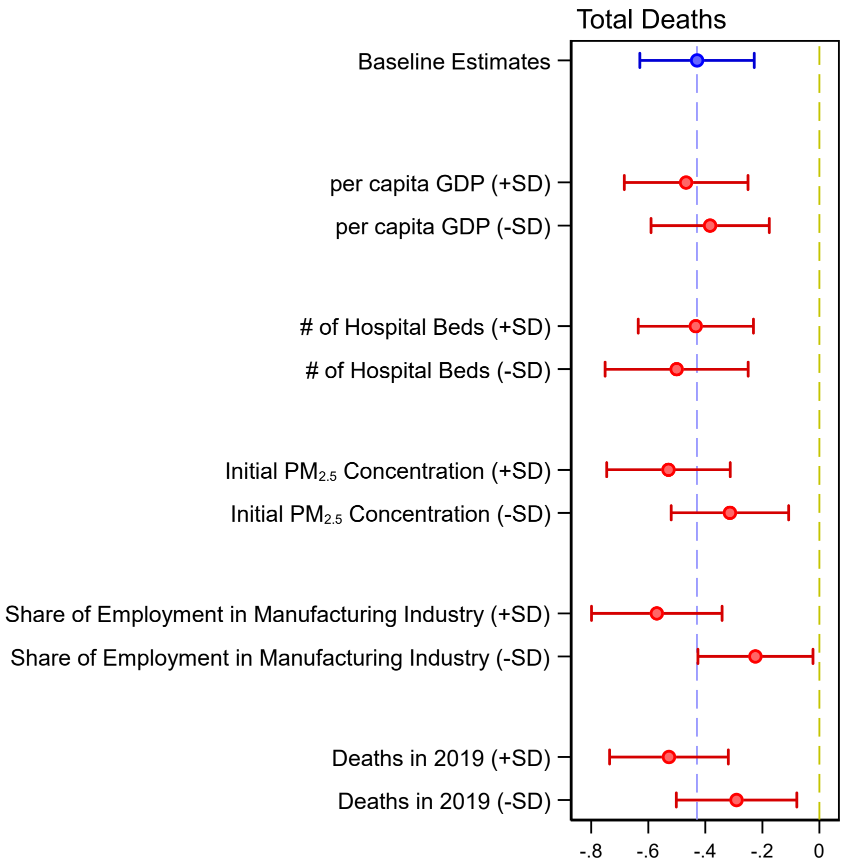

Figure 4. The heterogeneous impacts of city/community lockdowns on deaths.

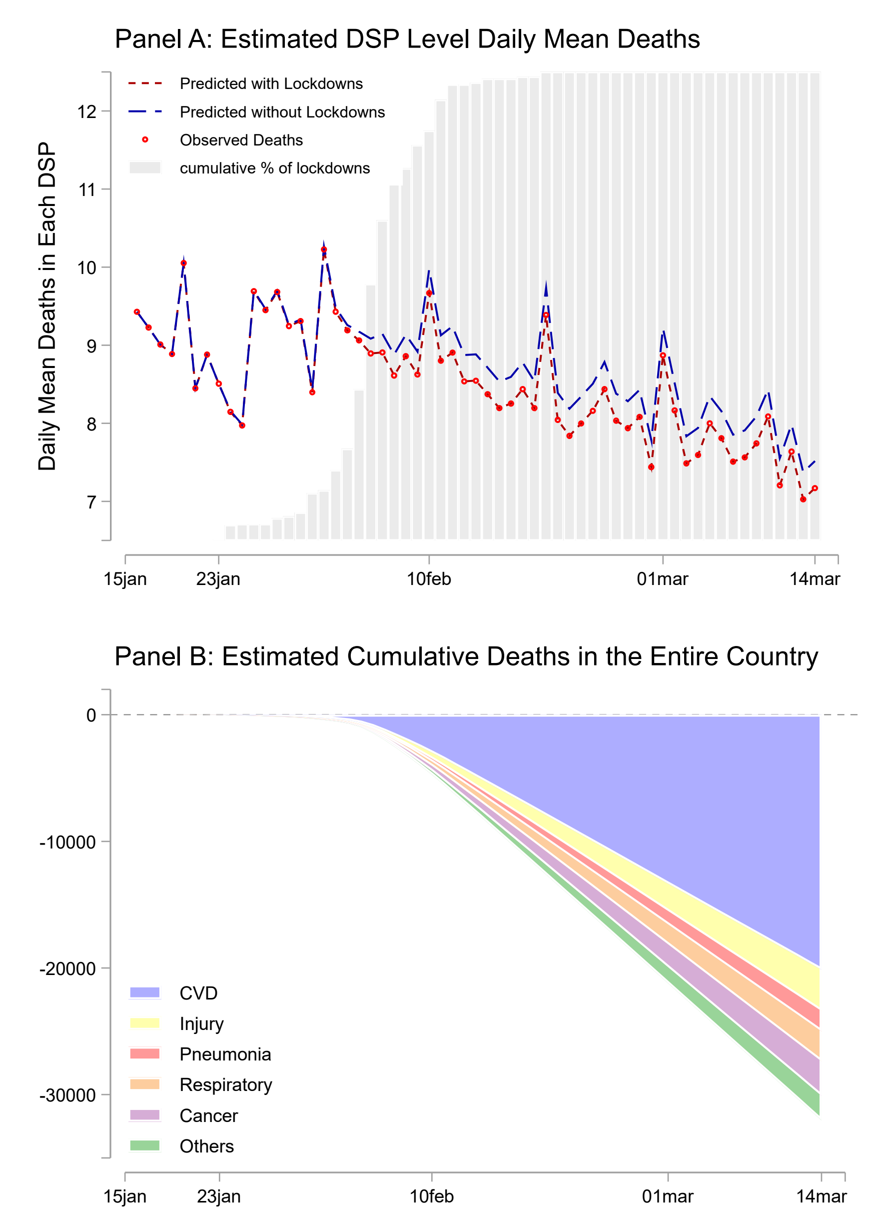

Figure 5. Estimated averted covid-19 unrelated deaths from lockdown policies.