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Compact living or policy inaction? Effects of urban density and lockdown on the COVID-19 outbreak in the US

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Abstract

The coronavirus pandemic has reignited the debate over urban density. Popular media has been quick to blame density as a key contributor to rapid disease transmission, questioning whether compact cities are still a desirable planning goal. Past research on the density–pandemic connection have produced mixed results. This article offers a critical perspective on this debate by unpacking the effects of alternative measures of urban density, and examining the impacts of mandatory lockdowns and the stringency of other government restrictions on cumulative Covid-19 infection and mortality rates during the early phase of the pandemic in the US. Our results show a consistent positive effect of density on Covid-19 outcomes across urban areas during the first six months of the outbreak. However, we find modest variations in the density–pandemic relationship depending on how densities are measured. We also find relatively longer duration mandatory lockdowns to be associated with lower infection and mortality rates, and lockdown duration's effect to be relatively more pronounced in high-density urban areas. Moreover, we find that the timing of lockdown imposition and the stringency of the government's response additionally influence Covid-19 outcomes, and that the effects vary by urban density. We argue that the adverse impact of density on pandemics could be mitigated by adopting strict lockdowns and other stringent human mobility and interaction restriction policies in a spatially targeted manner. Our study helps to inform current and future government policies to contain the virus, and to make our cities more resilient against future shocks and threats.

Keywords

built environment, Covid-19, density, health, lockdown, planning, policy

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摘要
新冠疫情重新激起了关于城市密度的争论。大众媒体马上将矛头指向了城市密度，认为其是疾病快速传播的关键因素，对紧凑型城市是否仍然是理想的规划目标提出了质疑。之前关于城市密度与疫情之间关系的研究得出的结论不一。本文针对这场争论提供了一个批判性的视角，分析了城市密度替代措施的影响，并研究了强制封锁和其他政府限制措施的严格度对美国新冠肺炎疫情早期累积感染率和死亡率的影响。我们的结果表明，在疫情爆发的前六个月，城市密度与整个城市地区的新冠肺炎感染结果呈一致的正相关。然而，我们发现，不同的城市密度测量方式得出的城市密度与疫情的关系存在适度差异。我们还发现，相对较长的强制封锁时间与较低的感染率和死亡率有关，而在高密度城市地区，封锁时间的影响相对更为明显。此外，我们发现实施封锁的时机和政府应对措施的严格程度还影响新冠肺炎的传播结果，并且影响因城市密度而异。我们认为，针对特定空间，通过采取严格的封锁以及其他严格的人员流动和交往限制政策，可以减轻因为密度而造成的流行病传播的不利影响。我们的研究有助于为政府当前和未来遏制病毒的政策提供参考，并使我们的城市在面对未来的冲击和威胁时更具有复原力。

关键词
建筑环境、新冠肺炎、密度、健康、封锁、 规划、 政策

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Introduction

The Covid-19 pandemic has reignited the debate about whether compact cities are still a desirable planning goal. The opponents of urban density claim that densely populated and crowded places can catalyse the spread of infectious diseases (e.g. Cox, 2020). Density, according to them, is more of a liability than an asset during infectious disease outbreaks. Others, however, argue that urban density does not necessarily exacerbate the outbreak, citing several examples of high-density Asian cities that have been relatively successful in containing the virus (e.g. Hamidi et al., 2020). Given the benefits of density in terms of public service provision in response to Covid-19 (e.g. sanitation and health care) and the role of density in achieving larger sustainability goals, some others have argued that it is more important to pay attention to prudent pandemic management in high-density places, rather than call for de-densification of cities (Angel et al., 2020).

In urban studies, density is a contestable concept, with multiple definitions and measures – capturing various dimensions of the built environment and human activities or interactions within cities (Boyko and Cooper, 2011; McFarlane, 2016). For example, the measure of urban density is typically defined as the ratio of urban population to total land area within the metropolitan boundary. However, urban population is not uniformly distributed within a city's administrative boundaries, giving an incomplete picture of urban density. Alternatively, urban density can be measured as a population-weighted density that takes into account the proportion of sub-regional population (e.g. number of people in census tracts) to total metropolitan population as weights, giving a more accurate representation of urban density as experienced by the average person (Rappaport, 2008). Moreover, density can be defined as representing not only the degree of population concentration but also levels of job or building concentration. Yet, existing studies evaluating density impacts on the pandemic seldom recognise this heterogeneity in the conceptualisation of urban density. Consequently, we do not know whether different types of density can have different impacts on the pandemic.

Furthermore, even if density contributes to virus transmission, the outcome of the pandemic hinges on the effectiveness of government policies to contain the virus. Lockdowns (i.e. mandatory stay-at-home orders and closure of economic activities, implemented at varying levels of geography, lengths of time and severity) are a common type of policy response globally and in the US. The effects of lockdowns on economic performance and public health have been examined extensively (Flaxman et al., 2020; Olney et al., 2021; Perra, 2021). We extend that literature by analysing the effectiveness of lockdowns (or mandatory stay-at-home orders, measured in terms of duration and start timing) and other government responses (i.e. closures, restrictions and controls related to economic activities and human mobility) in managing the pandemic, on average and across different levels of urban density.

In this article, we primarily investigate the effects of various measures of urban density and lockdown duration on Covid-19 infection and mortality rates during the early phase of the pandemic in the US. Specifically, we estimate and compare the effects of different density measures and governmental lockdown duration on Covid-19 cases and deaths per 100,000 people across US urban areas over the first six months since the onset of the disease (January to June 2020). We explore whether the estimated lockdown effect varies by level of urban density. We also examine the effects of lockdown start time (early versus late in terms of pandemic severity) and governmental response stringency on Covid-19 infection and mortality rates, on average and across different density levels.

Among novel findings, we show that the density–pandemic relationship depends on how densities are measured. Most importantly, while density seems to be a disadvantage during pandemics, we find evidence that strategic governmental action can help effectively combat pandemics in cities. Specifically, we find that longer duration mandatory lockdowns are associated with lower infection and mortality rates, and that longer lockdowns are most effective in high-density urban areas. Moreover, we find that the timing of lockdown imposition and the stringency of the government's response additionally influence Covid-19 infection and death rates. All else equal, early lockdowns (when cumulative cases per capita are relatively low) and stringent responses seem to help manage virus transmission more effectively in relatively low-density urban areas, and to help manage mortality rates in relatively high-density urban areas.

This article makes significant and timely contributions by critically examining the role of urban density, lockdown and other governmental policy responses in the context of the pandemic crisis. Our findings will help inform current and future government policies to contain the virus and to build pandemic-resilient cities.

Literature review

Since the onset of the Covid-19 pandemic, popular media (e.g. Kling, 2020) and scholars (e.g. Hamidi et al., 2020) have explored the impacts of urban population and job density on disease transmission and mortality. This is not surprising given the common sense regarding the density–pandemic relationship. More people living or working per unit area, all else equal, can indeed increase the likelihood of close encounters and face-to-face interactions, and potentially facilitate human-to-human virus transmission. While this density pathology dominated in the early phase of the pandemic, the relationship between density and pandemic is not straightforward. On the one hand, we know that population density and economic performance reinforce each other (see e.g. Becker et al., 1999). Therefore, more intra-city human mobility and higher in- and out-migration rates in denser, more economically active cities can accelerate virus transmission, particularly during the early stages of an outbreak. On the other hand, higher population density is commonly associated with stronger social networks that can promote pro-social and personal protective behaviours, thereby slowing down virus transmission and containing an outbreak. Density can additionally help in the efficient delivery of health care and social services during pandemics.

The impact of population density on infectious diseases has been the subject of ongoing debate. Research has shown that crowding and mass gatherings associated with high density can increase the frequency of human-to-human contact and facilitate virus transmission (Hu et al., 2013). Sy et al. (2021) find a positive association between population density and the basic reproductive number (R_0) of the SARS-CoV-2 virus in the US, indicating that density has contributed to virus transmission. Kadi and Khelfaoui (2020) find a positive correlation between population density and Covid-19 cases in Algeria. You et al. (2020) find higher population density to be associated with a higher Covid-19 morbidity rate in Wuhan, China. Bhadra et al. (2021) report a similar finding from India. A study by Carozzi et al. (2020) finds that in the US, higher urban population density is associated with earlier arrival of the Covid-19 disease but not with faster post-arrival transmission rates, and that density is positively associated with social distancing policy compliance.

However, empirical evidence on the impact of population density on virus transmission rates and mortality is mixed and inconclusive. In the US, Hamidi et al. (2020) find that population and job densities are not significantly associated with infection rate (i.e. per capita cases), and are, in fact, negatively related to Covid-19 mortality rate. The authors suspect greater adherence to social distancing guidelines and better health care systems in dense metropolitan areas to have influenced their findings. Liu et al. (2020) also report a negative association between urban population density and Covid-19 cases in China at the early stages of the pandemic, largely due to the migration of workers from larger cities to smaller towns and rural areas during the festival period in spring. The mixed results are likely due to differences in research approaches, virus and disease characteristics and geographic contexts, and to the presence of a large number of confounding variables (e.g. sociodemographic factors, public health parameters and public policies) that render investigation of the density–disease relationship challenging. Moreover, different arguments around the density–pandemic relationship have emerged, giving a more nuanced understanding of density as both a static and a dynamic concept as well as a highly politicised space (McFarlane, 2021).

In addition to the debates around urban density, there is a separate stream of research underscoring the importance of urban public policies that impose or promote social distancing and lockdown orders at certain places and times to contain virus transmission and consequently reduce mortality (Flaxman et al., 2020; Olney et al., 2021; Perra, 2021). Past research involving the influenza virus suggests that quarantining, travel restrictions and the closure of economic activities can, in certain situations, effectively contain virus transmission (Ferguson et al., 2005, 2006). Specifically, studies show that it is useful not only to rapidly identify and isolate infected persons, but also to contain the movement of individuals, particularly at early stages of the outbreak of new viruses with potentially high human-to-human transmissibility (Bonardi et al., 2020; Haug et al., 2020). Quarantine and lockdowns, however, are not easy tasks for governments; and not all governments prefer such strategies. Policy formulation and implementation depend on various factors such as political ideologies and priorities (e.g. Tellis et al., 2020), and organisational capacity and resources of various levels of the government (e.g. Katz et al., 2019).

To summarise, the extant literature does not help develop a clear and consistent understanding of the causal impact of urban density on the infection and mortality rates of Covid-19. It is unclear whether different conceptualisations of density that capture various aspects of urban form and life can have different impacts. It is also unknown whether spatially and temporally targeted lockdowns can be effective in managing pandemics in cities, and whether they can provide important insights into our understanding of the density–pandemic relationship. There is also little evidence on the role of lockdown start timing and the stringency of the government's restrictive response policies on pandemic impacts in urban areas. Our study addresses these gaps.

Methods

Objectives

Our principal objective is to analyse the impacts of density (different measures, weighted and unweighted as applicable, discussed later in the article) and lockdown (mandatory stay-at-home order) duration on Covid-19 cases and deaths per 100,000 people over our study period (January to June 2020) across US urban areas. We also examine whether the estimated lockdown effects vary by different density types and levels. We additionally test whether lockdown start time (early versus late in terms of cumulative cases at the time of lockdown imposition) and the stringency of the government's response (definition given later in the article) over the study period affected Covid-19 infection and death rates across urban areas. Lastly, we examine whether estimated effects of lockdown timing and policy stringency vary by the level of population density.

Study area

Our study area comprises all urbanised counties in the contiguous US as of 1 January 2019 (Figure 1(a)). We define an urbanised county as any county that overlaps with one or more Census-designated urbanised areas (UZAs). We only focus on urbanised counties (2440 total) because of our interest in examining the determinants of Covid-19 infection and death rates in urban areas.

Main outcome variables

Our main outcome variables are total confirmed Covid-19 cases and deaths per 100,000 people (ACS 2014–2018 five-year estimates) from 1 January to 30 June 2020 (our study period) in urbanised counties. We obtained the data from the Center for Systems Science and Engineering at the Johns Hopkins University, which provides daily updates based on reports from state, local and territorial health departments (Dong et al., 2020).

We strategically chose our study period from 1 January to 30 June 2020. Our primary interest is in exploring density and early lockdown effects on Covid-19 infection

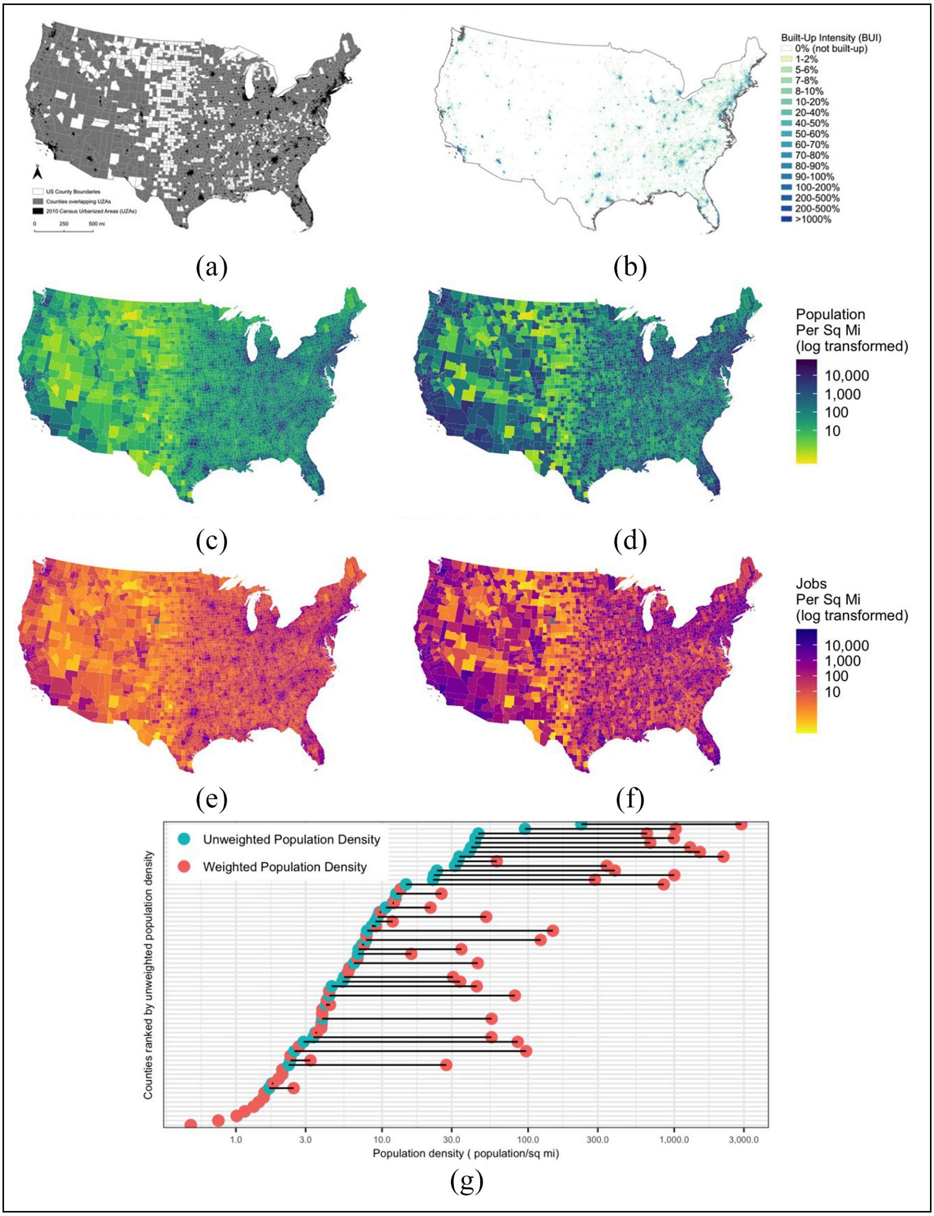

Figure 1. Study area and comparison of different density measures in the US. (a) Counties overlapping 2010 Census-designated urbanised areas (UZAs). (b) Spatial representation of urban built-up intensity. (c) Unweighted population density. (d) Weighted population density. (e) Unweighted job density. (f) Weighted job density. (g) Example of unweighted and weighted population densities of all counties in Washington State.

and mortality rates during the initial waves of the pandemic, when policies and practices to effectively combat the disease were still emerging. Moreover, except for California, all states ended their stay-at-home/shelter-in-place orders (our definition of lockdown) by the end of June 2020 (Raifman et al., 2020). We did, however, consider shorter and longer study periods in our robustness checks.

We include both estimated cases and deaths over the study period, expressed as proportions of county population, in our analysis. Confirmed Covid-19 cases per 100,000 people capture a county's cumulative Covid-19 infection rate over the study period. This helps analyse the determinants of the variation in infection rates across counties. We speculate that the Covid-19 infection rate in a given county could depend on the number of tests conducted per capita, over the study period. We therefore control for state-level testing rates by including the total number of tests over the study period in the constituent state (based on data from the Covid Tracking Project, https://covidtracking.com) and state population (ACS 2014–2018 five-year estimates) as control variables in our regression models. We also control for county population, as population size is hypothesised to determine the cumulative infection rate, all else equal.

In addition to confirmed cases, we use total Covid-19 deaths per 100,000 people at the county level over the study period as a more robust measure of Covid-19 impact. Confirmed cases of Covid-19 include false positives, and asymptomatic cases often go unreported. This may lead to estimation errors, and the total number of actual infections may remain unknown. In contrast, all Covid-19 deaths must be certified by physicians, unless the death occurs outside of the hospital, in which case a medical examiner or a coroner would investigate each case. Therefore, Covid-19 death rates suffer less from measurement errors. In general, the number of deaths as a proportion of total population in a given county over the study period captures the county's average (crude) disease mortality rate, which is an important metric to analyse.

Independent variables

Urban density measures. We use different indicators of urban density in three domains: population, employment and building. These domains capture different dimensions of urban density, representing concentrations of functions (people and jobs) and structures (gross floor area). Population density indicators are computed based on total population counts from the 2018 American Community Survey (ACS) five-year estimates. Job density indicators are calculated based on the total number of jobs from the 2016 LEHD Origin-Destination Employment Statistics (LODES) from the US Bureau of Labor Statistics. Building density is based on the built-up intensity database which contains the sum of indoor floor areas of all buildings at 250 m spatial resolution across the entire US (Leyk and Uhl, 2018).

For population and job densities, we calculated both unweighted and weighted densities. For example, unweighted population density is computed by dividing the population by the total area of land enclosed, which is formally expressed as:

$$\text{Unweighted population density} = \frac{P_0}{A_0} = \sum_{k=1}^{N} \frac{P_k}{A_k} \cdot \frac{A_k}{A_0} \quad (1)$$

P_0 is population at the county level and A_0 is county area in hectares. P_k is population at the tract level and A_k is tract area in hectares.

We also calculated weighted population density as the weighted sum, where each tract-level population density is multiplied by the tract's share of the county-level population. This can be formalised as:

$$\text{Weighted population density} = \sum_{k=1}^{N} \frac{P_k}{A_k} \cdot \frac{P_k}{P_0} \quad (2)$$

Unweighted population density can be understood as 'area-weighted density', where each tract-level density is weighted by the tract's share of the county area (equation (1)). Similarly, weighted density can be understood as 'population-weighted density', where each tract-level density is weighted by the tract's share of the county population (equation (2)). The weighted measures are aggregated from the tract-level density, and therefore are more accurate than the unweighted measures, which do not account for density variations at the tract level. The US Census recognises the difference between weighted and unweighted measures, and began to use weighted population density as a more precise measure of density (Wilson et al., 2012).

For job density, we used the same approach as the population density but replaced population with jobs. Note that the building density was calculated without any weighting mechanism. As shown in Figure 1(c) to (f), weighted density tends to give more weight to counties with a larger population size. Figure 1(g) shows the difference between weighted versus unweighted population density for Washington State as an example.

Measures of government response policy. *Lockdown duration*: Our key variable capturing government response policy is the duration of lockdown or the number of days lockdown was in effect during the study period. These data were derived from the Covid-19 US State Policy (CUSP) database (Raifman et al., 2020). In the wake of the Covid-19 outbreak around late February 2020, each state responded to the outbreak differently, creating variation in lockdown policy implementation across states. To minimise ambiguity in determining the effect of various lockdown measures, we focus on the most stringent policies that include state-wide mandates to stay at home, not advisory orders that recommended people remain at home. We are not trivialising the role of other social distancing measures, but for the purpose of this study, we focus on examining the effectiveness of mandatory stay-at-home policy and urban density. Since this is a state-level measure, all study counties in a given state get the same lockdown duration value.

Lockdown start time: As an indicator of early versus late lockdown imposition, we consider the cumulative number of confirmed Covid-19 cases per 100,000 people at the county level on the date when the above-mentioned state-wide lockdown (i.e. stay-at-home order) was imposed. Counties where such lockdowns were not imposed are excluded from analyses involving this variable. A relatively lower value indicates relatively early (in terms of cumulative infection rate) lockdown in a given county. Lockdown start time enters our regression models as a dummy (0/1) variable called 'late lockdown' that takes the value 1 if confirmed Covid-19 cases per 100,000 people are more than five (i.e. above the median) on the lockdown start date.

Stringency of government's Covid-19 response: We include the 'Covid-19 Government Response Stringency Index' from the Oxford Covid-19 Government Response Tracker (OxCGRT) project (Hale et al., 2021), averaged over the study period at the state level. The stringency index is a composite measure of nine response metrics involving closures, restrictions and controls (see Roser, 2021). A relatively higher stringency index value for a given state, and hence for all its constituent counties, indicates that relatively stricter governmental restrictions were imposed there, on average, over the study period.

Other covariates and controls. Our analysis includes a number of county-level covariates that are expected, based on the literature, to

influence Covid-19 outcomes across study counties over the study period. We include demographic characteristics, such as the proportion of older adults aged 65 or more, sex, race/ethnicity and college education. We also include median household income, and income inequality, which is defined as the ratio of household income at the 80th percentile to that at the 20th percentile. All these data were obtained from the 2018 ACS five-year estimates. Moreover, we test the influence of social capital measures, specifically, the numbers of establishments in civic and social associations (NAICS 813410), and religious organisations (NAICS 813110). These data are derived from the 2014 social capital dataset from the Northeast Regional Center for Rural Development (Rupasingha et al., 2006). In addition, we also analyse the effects of health factors on the Covid-19 death rate. We include the percentage of adults with diagnosed diabetes, and the cardiovascular disease mortality rate (per 100,000), as health variables. Diabetes prevalence data are based on the 2016 CDC Diabetes Atlas (https://gis.cdc.gov/grasp/diabetes/diabetesatlas.html), and the cardiovascular disease (CVD) mortality data are based on the CDC's Interactive Atlas of Heart Disease and Stroke (2014–2016) (https://nccd.cdc.gov/DHDSPAtlas).
County population, state population and state-level number of Covid-19 tests performed are used as control variables. Rationale is given in the discussion on main outcome variables.

Analytical approach

Effects of density and lockdown duration. First, we estimate the effects of density and lockdown duration on Covid-19 infection and mortality rates at the study county level over the study period. One can argue that states' decisions regarding complete lockdowns were based, in part, on the severity of the pandemic at the county level, or on assessments of the impacts of lockdown imposition on Covid-19 trends across counties. We therefore adopt a two-stage least squares (2SLS) regression modelling approach (i.e. instrumental variables approach) to address the possible endogeneity between lockdown duration and the Covid-19 outcomes. The five density measures are included individually, in separate regressions.

Ignoring the endogeneity issue potentially renders the lockdown duration estimate associative rather than causal. To address this, we identified an appropriate instrumental variable that is expected to be correlated with (and to influence) the lockdown duration variable, but is uncorrelated (i.e. no causal connection, in theory) with the error term. Based on literature review and our expert judgement, we identified an instrument – party of state Governor (Republican versus not Republican dummy variable) during the study period – which captures political support for (or lack thereof) using lockdowns as tools for controlling the pandemic. The instrument helps address the reverse causality problem linking higher cases/deaths to the imposition of longer lockdowns. Out of 2440 study counties, 1737 counties (71.19%) are located in Republican party-governed states. The data source is MIT's Election Data and Science Lab (MIT Election Data and Science Lab, 2018). The instrument choice can be justified both theoretically and empirically. Emerging anecdotal evidence and early findings suggest that political beliefs are associated with support for social distancing orders or other restrictions to reduce virus transmission (Painter and Qiu, 2021; Pinsker, 2020). These findings help understand the differences, primarily along political party lines, in state government support for imposition of lockdown across states. President Donald Trump had repeatedly dismissed concerns about the coronavirus pandemic and publicly expressed his opposition to lockdown measures, and Republican Governors and local leaders have been relatively reluctant in imposing social distancing or lockdown policies.

The 2SLS regression model is estimated in two stages. In the first stage, the lockdown duration variable is modelled as a function of the instrumental variable, holding all other independent variables constant, to obtain predicted values of lockdown duration. In the second stage, we regress the outcome variables on the predicted values of lockdown duration from the first stage, along with other independent variables. We use a set of tests to determine if the 2SLS approach provides a more robust and unbiased estimate of the lockdown duration variable.

We also stratify study counties into three density levels (low, medium and high) for select density measures (weighted population and job densities, and building density), and re-estimate the 2SLS models, to analyse whether the estimated lockdown effects on the outcome variables differ by density levels, determined based on 25th and 75th percentile cut-offs.

Effects of lockdown start time and stringency of government's response. To test the effects of lockdown start time (early/late, in terms of cumulative infection rate on the lockdown start date in a given county) and the stringency of the government's response on Covid-19 outcomes, we use ordinary least squares (OLS) regression models. We add the usual control variables (as described earlier in the article) in the regression models, including weighted population density (as the only density variable) and lockdown duration. Since lockdown duration is included as a control in these models (i.e. causal connection is not analysed for the lockdown duration variable), we do not use the 2SLS approach. We additionally control for lockdown start date as a variable that takes integer values ranging from 1 to 20, since lockdowns across all our study areas started within a 20-day window from 19 March 2020 to 7 April 2020. All else equal, we expect lockdown start date – a variable that accounts for the nationwide pandemic severity effect at the time of lockdown imposition – to have a separate influence on Covid-19 impacts in our study counties over the study period. We also analyse whether the estimated effects of lockdown start time and stringency on the outcome variables differ by weighted population density levels (above/below median). All statistical analyses were performed in Stata version 14.2. The maps and plots were produced using R version 1.1.456 and QGIS version 3.14.

Results

Descriptive statistics

Descriptive statistics of the variables used in our regression models are given in Table 1. The average Covid-19 infection rate is about 548. On average, about 19 Covid-19 death rates have been recorded across the study counties. The number of days for which state-level lockdowns were in effect ranges from zero to 103 days, with an average of 39 days.

Regression analysis

Density effects. The results of two-stage least square (2SLS) regression models are summarised in Tables 2 and 3. The five density measures are tested individually in separate models, and the results are presented in columns (1) to (5). In general, all five density measures have statistically significant positive associations with both infection and mortality rates.

Comparison of standardised (beta) coefficients (not shown in the table) of variables in the 2SLS model in Table 2 indicates that the magnitude of influence of population

Table 1. Descriptive statistics of variables used in regression analysis.

Variable	*N*	Mean	Std dev.	Min.	Max.
Confirmed cases (January–June 2020)	2440	1057.52	5942.86	0	215,179
Deaths (January–June 2020)	2440	51.36	507.72	0	23,096
Cumulative infection rate (January–June 2020) (per 100,000 people)	2440	548.19	752.15	0	13,181.11
Mortality rate (January–June 2020) (per 100,000 people)	2440	19.43	44.44	0	1414.78
Confirmed cases per 100,000 (on lockdown start date)	1836	16.70	36.40	0	615.05
Stringency index (January–June 2020 average)	2440	34.78	5.29	17.52	46.17
Lockdown duration (January–June 2020)	2440	38.59	28.78	0	103
Population density, unweighted (per sq. mi.)	2440	344.01	2040.76	0.11	72,052.96
Population density, weighted (per sq. mi.)	2439	1136.55	3484.03	1.05	106,427.60
Job density, unweighted) (per sq. mi.)	2423	176.45	2148.86	0.12	101,698.80
Job density, weighted (per sq. mi.)	2422	1648.83	10,568.66	0.12	415,174.70
Building density (built-up intensity, indoor building area in % pixel area)	2422	6314.59	49,241.64	0	2,092,758
% Age 65 or more	2440	0.18	0.04	0.05	0.57
% Female	2440	0.50	0.02	0.34	0.57
% Black or African-American	2440	0.10	0.14	0.00	0.82
% Asian	2440	0.02	0.03	0.00	0.43
% Hispanic	2440	0.10	0.14	0.01	0.96
% White	2440	0.75	0.20	0.03	0.98
% Mixed race	2440	0.03	0.07	0.00	0.91
% College educated	2440	0.58	0.11	0.19	0.90
Median income (US$)	2440	52,430.52	14,047.40	24,783	136,191
Income inequality	2440	4.53	0.72	2.67	9.15
Diabetes rate (per 100 people)	2440	12.12	3.92	1.90	34.10
Cardiovascular disease (CVD) death rate (per 100,000 people)	2439	186.03	44.36	56.30	603.00
Religious establishment	2439	73.21	138.84	0	3275
Civic establishment	2439	10.52	23.19	0	546
County population (in ‘00,000s)	2440	1.30	3.70	0.02	100.98
State Covid-19 tests (January–June 2020) (in ‘00,000s)	2440	8.66	8.81	0.34	41.67
State population (in ‘00,000s)	2440	94.24	84.98	5.82	391.49

Note: Unit of observation is US county (urbanised counties only).

density on the outcome variable (cases/100,000 people) is higher if the weighted measure is used rather than the unweighted measure (β = 0.178 for weighted versus 0.173 for unweighted). The pattern is opposite for job density (β = 0.213 for weighted versus 0.241 for unweighted). Comparison of beta coefficients of the 2SLS model in Table 3 shows similar patterns. This suggests that the effect of

Table 2. Two-stage least square (2SLS) regression models of Covid-19 infection rate (confirmed cases per 100,000 people) from January to June 2020.

Variable	(1) Unweighted population density	(2) Weighted population density	(3) Unweighted job density	(4) Weighted job density	(5) Building density
First stage (dependent variable = Lockdown duration)					
Republican Governor (dummy)	−19.536***	−19.576***	−19.369***	−19.329***	−19.403***
Other covariates[a]	Y	Y	Y	Y	Y
N	2439	2438	2423	2422	2422
Adj. *R*-squared	0.453	0.452	0.453	0.453	0.454
Second stage (dependent variable = Covid-19 cases / 100,000 population)					
Lockdown duration	−4.820**	−5.071**	−4.328**	−4.285**	−4.651**
Density measure	0.075***	0.045***	0.100***	0.018***	0.004***
% Age 65 or more	−459.567	−291.238	−536.266	−474.518	−824.787*
% Female	−403.692	−464.546	−600.812	−394.559	−594.826
% Black	1648.793***	1665.307***	1673.709***	1681.087***	1633.852***
% Asian	853.092	486.883	2427.991***	2228.906**	2431.687***
% Hispanic	1511.350***	1451.377***	1486.801***	1507.503***	1470.741***
% Mixed race	−108.022	−91.938	425.433 +	430.855 +	396.597
% College	−1684.698***	−1764.862***	−1738.363***	−1799.552***	−1738.849***
Median income	0.012***	0.012***	0.011***	0.012***	0.011***
Income inequality	23.539	24.907	3.488	3.401	9.067
Religious establishment	0.064	0.174	0.385	0.219	0.173
Civic establishment	9.133***	9.046***	5.212***	5.146***	7.152***
County population (in ‘00,000s)	−50.734***	−57.599***	−42.348***	−44.094***	−46.299***
State Covid-19 tests (in ‘00,000s)	35.063***	34.904***	32.965***	34.108***	34.349***
State population (in ‘00,000s)	−4.888***	−4.883***	−4.810***	−4.901***	−4.926***
Constant	1055.692**	1063.648**	1290.245***	1168.292***	1346.802***
N	2439	2438	2423	2422	2422
Adj. *R*-squared	0.286	0.279	0.333	0.309	0.312
Statistics for tests of endogeneity					
Durbin chi^2	4.244*	4.506*	3.884*	3.349 +	4.561*
Wu-Hausman F	4.220*	4.481*	3.862*	3.329 +	4.536*
Statistic for test of instrument strength					
F-statistic	374.275***	374.266***	364.088***	361.749***	365.732***

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
[a]All covariates of the second-stage model including the constant term. Unit of observation is US county (urbanised counties only).

Table 3. Two-stage least square (2SLS) regression models of Covid-19 mortality rate (deaths per 100,000 people) from January to June 2020.

Variable	(1) Unweighted population density	(2) Weighted population density	(3) Unweighted job density	(4) Weighted job density	(5) Building density
First stage (dependent variable = Lockdown duration)					
Republican Governor (dummy)	−18.551***	−18.572***	−18.393***	−18.348***	−18.432***
Other covariates[a]	Y	Y	Y	Y	Y
N	2439	2438	2423	2422	2422
Adj. *R*-squared	0.465	0.464	0.465	0.465	0.466
Second stage (dependent variable = Covid-19 deaths / 100,000 population)					
Lockdown duration	−0.313***	−0.353***	−0.218**	−0.206*	−0.260**
Density measure	0.010***	0.006***	0.012***	0.002***	0.000***
% Age 65 or more	87.199***	108.331***	72.609***	80.701***	35.863
% Female	129.334**	120.811**	133.401***	153.784***	134.274***
% Black	76.845***	78.743***	79.336***	79.796***	74.270***
% Asian	−97.076**	−142.069***	−44.267	−69.184^{+}	−46.217
% Hispanic	23.899***	16.877*	23.859***	27.569***	21.199**
% Mixed race	19.803	21.198^{+}	34.872**	35.452**	31.225*
% College	−69.406***	−79.050***	−67.350***	−72.298***	−68.015***
Median income	0.001***	0.001***	0.001***	0.001***	0.001***
Income inequality	5.751***	6.134***	4.917***	4.821***	5.508***
Diabetes rate	0.002	0.076	−0.110	−0.027	−0.069
CVD death rate	−0.022	−0.023	−0.013	−0.005	−0.020
Religious establishment	−0.035^{+}	−0.025	−0.001	−0.02	−0.025
Civic establishment	0.796***	0.813***	0.340***	0.326***	0.560***
County population (in '00,000s)	−2.951***	−3.831***	−1.510*	−1.703**	−1.973**
State Covid-19 tests (in '00,000s)	1.895***	1.905***	1.661***	1.773***	1.831***
State population (in '00,000s)	−0.202***	−0.205***	−0.189***	−0.198***	−0.202***
Constant	−85.826***	−86.469***	−83.531***	−100.316***	−74.195***

(continued)

Table 3. Continued

Variable	(1) Unweighted population density	(2) Weighted population density	(3) Unweighted job density	(4) Weighted job density	(5) Building density
N	2439	2438	2423	2422	2422
Adj. *R*-squared	0.363	0.336	0.497	0.404	0.423
Statistics for tests of endogeneity					
Durbin chi^2	15.455***	16.715***	13.252***	9.288**	14.979***
Wu-Hausman F	15.426***	16.693***	13.215***	9.246**	14.948***
Statistic for test of instrument strength					
F-statistic	388.184***	337.465***	328.883***	326.494***	330.466***

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
[a]All covariates of the second-stage model including the constant term. Unit of observation is US county (urbanised counties only).

density on Covid-19 infection and mortality rates depends on the type of density used and the measurement approach.

Lockdown duration effects. Tables 2 and 3 show that the Republican Governor variable is highly correlated (significantly negatively associated) with lockdown duration (refer to first-stage model results). The model results show that once the endogeneity issue is addressed, lockdown duration has a statistically significant negative effect on both Covid-19 infection and mortality rates. Recall that in the first stage of 2SLS, we used political party of the state Governor (Republican or not) as the instrumental variable to model lockdown duration. As explained in the methodology section, the 'Republican Governor' dummy variable is not expected to directly influence our outcome variables of interest, and is therefore theoretically a valid instrument. The Durbin and Wu–Hausman test statistics are statistically significant at the $p < 0.05$ level (or better) for nine out of 10 models (note: significant at the 90% confidence level for one model), indicating that the null hypothesis of exogeneity of the lockdown duration variable can be rejected. The *F*-statistic of the test for joint significance of instruments is statistically significant at the $p < 0.001$ level and >10 for all 10 models, indicating that the instrument is sufficiently strong.

Lockdown duration effects stratified by density levels. Figure 2 shows the effect of lockdown duration stratified by different density levels (low, medium and high density). For this analysis, we only consider weighted population and job density measures, and building density. Low-, medium- and high-density bands are based on 25th and 75th percentile cut-offs of the distributions of the chosen density measures. The

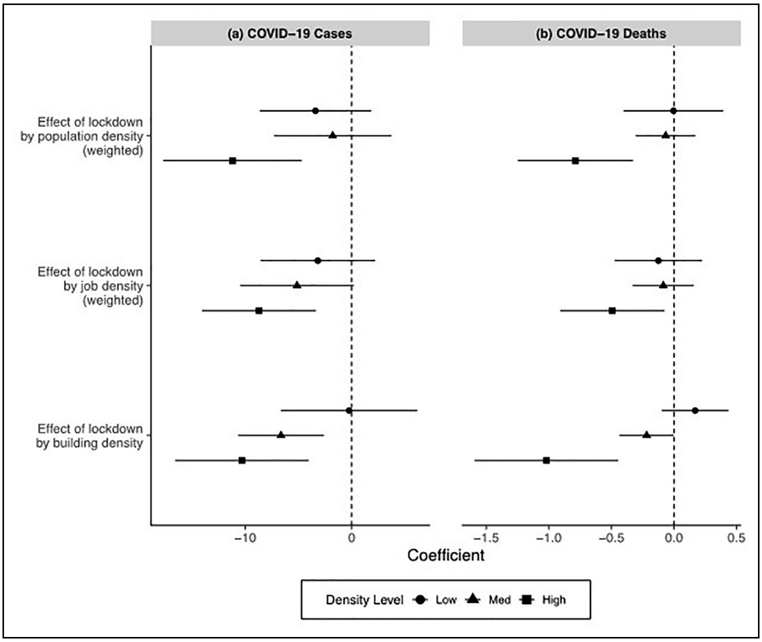

Figure 2. Effects of lockdown by different density types and levels.

strength of the association between lockdown duration and Covid-19 outcomes shows a dose–response relationship across density level, with the largest effect in high-density contexts.

Effects of lockdown start time and government's response stringency. Table 4 (columns 1 and 4) shows that, on average and all else equal, a late lockdown start (i.e. at a time when the number of confirmed cumulative Covid-19 cases per 100,000 people is relatively high in a given county) is associated with relatively higher cases and deaths per 100,000 people over the study period. Conversely, the stringency of the government's response is negatively associated with both cases and deaths per 100,000 people. When counties are stratified by weighted population density level (i.e. above/below median), we find that the effects of lockdown start time and stringency on cases are more prominent in low-density counties, while their effects on deaths are more prominent in high-density counties (see Table 4 columns 2, 3, 5 and 6).

Effects of other covariates. We find anticipated signs and consistent results for all covariates in our models (both 2SLS and OLS models). Income level and number of civic establishments have statistically significant positive associations with Covid-19 outcomes. The proportion of older persons is positively associated with the mortality rate, but negatively associated with the infection. The proportion of college-educated persons is negatively associated with both outcomes. The ethnic/racial composition of counties seems to determine both outcomes. The rates of diabetes- and heart disease-related deaths do not have statistically significant associations with

Table 4. OLS regression models of Covid-19 infection rate and mortality rate from January to June 2020: effects of lockdown start time (early versus late) and stringency of government's response.

Variable	Dep. Var. = Cases per 100,000 people			Dep. Var. = Deaths per 100,000 people		
	(1) All obs.	(2) Low wt. pop. density (below median)	(3) High wt. pop. density (above median)	(4) All obs.	(5) Low wt. pop. density (below median)	(6) High wt. pop. density (above median)
Late lockdown (dummy; 1 = late, 0 = early)	93.185**	109.999**	95.964 $^{+}$	8.348***	8.132**	10.938**
Stringency index (January–June 2020 average)	−10.801*	−11.798*	−5.492	−1.097***	−0.591	−1.219*
Controls						
Weighted population density	*Yes*	*No*	*No*	*Yes*	*No*	*No*
Lockdown start date	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Lockdown duration	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Other controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	1835	863	973	863	1835	973
Adj. *R*-squared	0.367	0.387	0.341	0.248	0.404	0.308

Notes: $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Unit of observation is US county (urbanised counties only). Late lockdown = 1 when confirmed Covid-19 cases per 10,000 people is more than five (i.e. above the median) on the lockdown start date. Refer to the analytical approach section for a description of control variables.

the mortality rate once age and other sociodemographic factors are controlled for.

Robustness checks. In order to assess the robustness of the estimated effects of the principal independent variables of interest – lockdown duration and density (different measures) – we re-estimate the set of 10 2SLS regression models of county-level Covid-19 outcomes using three alternative approaches (regression results are available upon request).

First, we consider all study counties minus New York City (comprising five counties: New York County, Kings County, Bronx County, Richmond County and Queens County). New York City, as an urban area, is an outlier in terms of population, jobs and the intensity of Covid-19 pandemic impact. Dropping the city, all else equal, helps test the extent to which estimated effects of the principal independent variables are driven by New York City. This approach results in a reduction in the estimated magnitude of the impact of lockdown duration on Covid-19 outcomes. Density effects on both outcomes are also smaller in models without New York City compared to corresponding models with New York City. This suggests that New York City influences our nationwide average estimates of the principal independent variables, but the estimated effects are valid for the rest of urban US.

Second, we shorten the study period to 1 January to 31 May 2020. This conservative approach drops the period of protests following the George Floyd incident (see Reuters, 2020). Specifically, the wave of nationwide protests triggered by George Floyd's death in late May 2020 that extended to June 2020 could potentially confound the relationship between the lockdown duration and Covid-19 infection and mortality rates. Mass gatherings as part of the protests could have increased the risk of infection spread and hence mortality, and governments could have extended lockdown orders as a reaction to the protests and their likely implications during the pandemic. This approach largely preserves the effects of lockdown duration and density on Covid-19 outcomes. Lockdown duration, however, is not statistically significant at the $p < 0.05$ level in three out of 10 models.

Lastly, we extend the study period to 1 January to 15 September 2020. This covers two full waves of the pandemic in the US. This extension, all else equal, helps test whether the estimated effects of the principal independent variables could be different at different stages of the pandemic. Using this approach, the statistically significant lockdown duration effect on the outcomes of interest is observed across all models. None of the density variables, however, are statistically significant in the infection models. Two out of five density measures are not statistically significant at the $p < 0.05$ level in the mortality models.

Discussion

Our results suggest that the density effects are more nuanced, especially when we compare weighted versus unweighted measures. Comparison of standardised (beta) coefficients (for the models presented in Tables 2 and 3) shows that compared to the crude unweighted measures, the effect of weighted measures is smaller for population density and larger for job density. The magnitudes of estimation differences, however, are relatively modest. Unweighted density measures do not accurately represent the actual perceived density (Rappaport, 2008), and thus may not actually capture the essence of what we want to measure – that is, the concentrations of people and the potential pathogen. Weighted density, we argue, captures more realistic density perceived by the average person, and is therefore considered an improvement over the crude unweighted density measure (Eidlin, 2010). The estimated effect of density, therefore, depends on how density is conceptualised and measured, which could explain the conflicting findings in the literature (Hamidi et al., 2020; Rocklöv and Sjödin, 2020).

While the incongruent findings may stem from the use of different density measures, recent research provides important insights, suggesting that crowding may be more important than density itself (Hamidi and Hamidi, 2021). This implies that static density measures would be insufficient to capture the complex dynamics of disease transmission (McFarlane, 2021). Our results are in line with this recent finding that there are varied meanings and interpretations of density, and that density alone cannot fully explain the spread of Covid-19 (McFarlane, 2021). Future studies, therefore, should take into account the heterogeneity in conceptualising and measuring urban density, as well as exploring a more precise measure of density that can effectively capture human crowding and interactions that contribute to disease transmission. This may require moving beyond traditional measures of density, and leveraging new data sources and computational techniques (e.g. Hong et al., 2021) to provide a more accurate assessment of the density–pandemic relationship.

The magnitude of the density effect varies by the type of density we use in our analysis. For example, considering standardised (beta) coefficients of the 2SLS model in Table 2 (cases/100,000 people), job density has a larger effect size than population and building densities (β = 0.213 for weighted job density; β = 0.178 for weighted population density; β = 0.204 for building density). The effect differences, however, seem to be modest in terms of magnitude. One possible explanation for this finding is that a higher concentration of jobs would occur in places where most economic activities take place, such as central business districts and commercial districts. This suggests that capturing the functional aspect of urban density, rather than a simple measure of population concentration, is more useful because certain kinds of human interactions can potentially facilitate virus spread more efficiently, for example indoor dining. From the perspective of urban planners and decision makers, it would be critical to identify the types of urban forms and associated human activities that could increase the risk of disease transmission and develop effective mitigation strategies.

We find lockdown duration to have had a statistically significant and sizeable effect in reducing infection and mortality rates across US urban areas. We also find evidence that early lockdowns and more stringent government responses, all else equal, were associated with fewer Covid-19 infection and mortality rates across urban areas over the study period. These findings are generally consistent with previous research which examined different types of government responses to Covid-19 (e.g. Flaxman et al., 2020). Compared to less stringent measures, such as educational campaigns, research has shown that stay-at-home orders were most effective in 'flattening the curve' (Fowler et al., 2021; Saez et al., 2020). Our finding provides further evidence that it is not only different types of government response that matter but also the duration of such measures.

Our results suggest that the effect of lockdown duration was most potent in urbanised counties that have the highest levels of density in terms of population, jobs and buildings. When it comes to lockdown start timing and the stringency of the government's response policy, evidence is mixed. Relatively lower-density urban areas seem to have benefitted more from early lockdown impositions and stringent response policies in terms of total Covid-19 infections per capita over the study period, in the early phase of the pandemic. Higher-density urban areas benefitted more in terms of total deaths per capita over the study period from early lockdowns and stringent responses.

We know that densely populated and well-connected metropolitan areas (e.g. New York) had the most severe cases in the beginning, but there was a lot of uncertainty and lack of guidance, leading to haphazard government responses (Abutaleb et al., 2020). Our study shows that early lockdown (when per capita cases are low) helped cities keep the virus under control. Urban areas that prolonged lockdowns or imposed more stringent restrictions performed better in terms of containing virus transmission and mortality. Similar results of greater lockdown effects in urban areas were found in the Netherlands, as the author notes that the potential to reduce virus transmission was much greater in urban areas than in low-density provinces (Boterman, 2022). While urban densities create more opportunities for interactions and thus virus transmission, our results suggest that the disadvantage of urban density can be counteracted with more proactive policy response. While prudent policy action clearly benefits high-density urban areas, we also find, for the first time in the literature to our knowledge, that early lockdown imposition is critical for containing virus spread in low-density areas. Future research on land use and human behaviour interactions during pandemics should explore why late lockdowns in low-density areas can potentially lead to rapid virus transmission.

This study has some limitations. First, we focus on the initial phase of the coronavirus outbreak in the US. Our estimated density and lockdown effects are therefore valid for the pandemic onset period only. It is possible that the effects vary across different stages of the pandemic. Second, we are not sure about the extent to which our findings are transferable to other geographic contexts beyond the US because US urban areas are unique in terms of their urban forms, population characteristics and governance styles. Finally, we use a simple definition of lockdown (mandatory stay-at-home order) in our analysis. It is possible that different types of mobility restrictions, and the closures of different types of activities (economic, social, recreational, religious, cultural establishments) will have different effects on virus transmission and mortality.

Conclusion

Our results suggest that density worsens pandemic impacts, but that the effect of density likely depends on how we define and measure urban density. Even if density contributes to virus transmission and mortality, we find that the adverse impact can be mitigated by adopting strict lockdown measures, especially in highly urbanised areas in the early phase of an outbreak. Early rather than late lockdowns, longer rather than shorter lockdowns and more- rather than less-stringent government response in the form of restrictions on economic activities and mobility seem to help, although their efficacy levels vary by urban density.

We are, however, mindful of the side effects of lockdowns. Lockdowns can have a disproportionate impact on the most disadvantaged and marginalised groups. Research has shown that people living in wealthier neighbourhoods were more likely to reduce mobility significantly more than those in poorer neighbourhoods (Weill et al., 2020). Better-educated and higher-earning employees were more likely to work from home than low-wage earners (Bloom, 2020). To make matters worse, lower-income communities have higher disease burdens due to higher levels of pre-existing health conditions and lower levels of health care access (Adhikari et al., 2020). Combined with the disproportionate impact of Covid-19, low-income and minority groups have to bear the brunt of strict lockdown measures.

As evidenced in the 2020 US Presidential election, the argument over lockdown is often dichotomised as the 'health versus economy' rhetoric. This is unfortunate. On the one hand, the side effects of unplanned, prolonged lockdowns can deeply hurt economies, and exacerbate health problems of vulnerable populations who experience unequal burdens. On the other hand, the protection of health and life from the onslaught of Covid-19 or other pandemics through social distancing and lockdown measures is often a prerequisite for rebuilding the economy. Policymakers need to consider these costs and benefits, and make careful decisions. There is increasing evidence suggesting that aggressive and early control strategies work best when the situation calls for drastic interventions to contain a virus (e.g. during periodic infection or mortality rate spikes in specific hotspots), or in order to break the virus transmission chain early on during an outbreak (Gibney, 2020). Our study shows that spatially targeted lockdowns can be highly effective. Context-sensitive approaches to post-pandemic recovery will be necessary to not only overcome the current pandemic crisis more effectively, but also rebuild our cities and economies to be more equitable, inclusive and resilient against future shocks.

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