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JUE Insight: Were urban cowboys enough to control COVID-19? Local shelter-in-place orders and coronavirus case growth

Dhaval Dave a, Andrew Friedson b, Kyutarō Matsuzawa c, Joseph J. Sabia d,∗, Samuel Safford c

a Bentley University, IZA & NBER, Center for Health Economics & Policy Studies USA
b University of Colorado Denver, Center for Health Economics & Policy Studies USA
c San Diego State University, Center for Health Economics & Policy Studies USA
d San Diego State University & IZA, Center for Health Economics & Policy Studies USA

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ABSTRACT

One of the most common policy prescriptions to reduce the spread of COVID-19 has been to legally enforce social distancing through shelter-in-place orders (SIPOs). This study examines the role of localized urban SIPO policy in curbing COVID-19 cases. Specifically, we explore (i) the comparative effectiveness of county-level SIPOs in urbanized as compared to non-urbanized areas, (ii) the mechanisms through which SIPO adoption in urban counties yields COVID-related health benefits, and (iii) whether late adoption of a statewide SIPO yields health benefits beyond those achieved from early adopting counties. We exploit the unique laboratory of Texas, a state in which the early adoption of local SIPOs by densely populated counties covered almost two-thirds of the state’s population prior to adoption of a statewide SIPO on April 2, 2020. Using an event study framework, we document that countywide SIPO adoption is associated with an 8 percent increase in the percent of residents who remain at home full-time and between a 13 to 19 percent decrease in foot-traffic at venues that may contribute to the spread of COVID-19 such as restaurants, bars, hotels, and entertainment venues. These social distancing effects are largest in urbanized and densely populated counties. Then, we find that in early adopting urban counties, COVID-19 case growth fell by 21 to 26 percentage points two-and-a-half weeks following adoption of a SIPO, a result robust to controls for county-level heterogeneity in COVID-19 outbreak timing, coronavirus testing, the age distribution, and political preferences. We find that approximately 90 percent of the curbed growth in COVID-19 cases in Texas came from the early adoption of SIPOs by urbanized counties, suggesting that the later statewide shelter-in-place mandate yielded relatively few health benefits.

1. Motivation

The COVID-19 pandemic has been immensely disruptive in the United States. According to data from the New York Times, through the first eight months of 2020, over 183,000 Americans died from the illness, or one death every 1 min 58 s. The first wave of public health responses to the pandemic centered around a variety of non-pharmaceutical interventions (NPIs) such as closing schools, closing restaurants and other businesses, banning large gatherings, and shelter-in-place orders (SIPOs).

SIPOs, which require residents to remain at home for all but essential activities, have been shown to produce important benefits relative to other NPIs, both from eliciting social distancing behavior and from slowing the spread of the novel coronavirus (Cronin and Evans, 2020; Courtemanche et al. 2020a, 2020b; Friedson et al. 2020; Dave et al., 2020b; Sears et al., 2020). However, SIPOs may also limit economic activity. Studies have tied SIPOs to increased unemployment (Baek et al., 2020; Bélond et al., 2020), and to decreased economic activity (Cronin and Evans, 2020).

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While a number of prior studies have leveraged state variation in SIPOs to identify their effects on stay-at-home behavior and COVID-19 cases (Friedson et al. 2020; Dave et al., 2020b; Sears et al., 2020), more localized natural experiments are necessary to inform several unanswered questions in this literature, especially with regard to how urbanicity interacts with SIPO adoption to affect COVID-19 spread. First, evaluating sub-state variation in SIPOS is crucial to understanding mechanisms through which SIPOS may differentially affect COVID-19 infections, particularly in urban areas. Combining information on local orders with data on localized behavioral responses (i.e. social distancing behavior) is necessary to understand key channels through which SIPOS may reduce COVID-19 cases.

Second, localized data better allow for disentangling the effects of SIPOS in urbanized regions from the demographic and political characteristics of the local population, as well as ensure that estimated policy impacts are not contaminated by local pre-SIPO COVID-19 growth. Third, policy variation at the local-level permit exploration of whether there are spillovers to neighboring counties from county-level SIPO orders. This is important for assessing whether statewide orders have the advantage of reducing spillage, i.e. those constrained by their county’s SIPO may travel to neighboring counties without SIPOS, thus redistributing COVID-19 spread across counties.

Finally, local policy information allows analysis of whether COVID-19 case growth can be curbed through well-targeted local orders in urban (or densely populated) counties as opposed to a statewide SIPO. If spillovers are relatively small, targeted local SIPOS may achieve COVID-19 reduction at a lower social cost than a statewide SIPO by allowing some counties to keep non-essential businesses open.

To empirically answer these questions, it is necessary to narrow focus to a sub-state analysis, capitalizing on natural experiments occurring within states that enacted statewide SIPOS, but also had a substantial number of local orders prior to the statewide SIPO. These considerations direct our main analyses to the state of Texas, which has a number of features that make it an ideal laboratory for studying local SIPOS adopted in highly urbanized counties and comparing their effects to (i) a late-adopted statewide SIPO, and (ii) local SIPOS enacted in less urbanized areas. Texas enacted a statewide SIPO, but did so quite late relative to other states. The first statewide SIPO was enacted on March 19th (California), whereas Texas enacted its statewide SIPO on April 2nd, being the 34th state to do so. However, 85 of Texas’ 254 counties enacted their own county-level SIPOS prior to the statewide order, with 34 county orders enacted over a week prior to the statewide order, the most, by far, of any other statewide SIPO-enacting state. This time variation is essential for independently identifying the effects of these early county orders given COVID-19’s median incubation period of approximately 5 days (Lauer et al., 2020). Importantly, Texas also provides sufficient variation in both urbanicity rates and population density across the enacting counties, permitting an exploration of heterogeneity in SIPO effects by these critical characteristics.

While our focus on Texas has the advantage of a SIPO policy rollout that permits us to test our hypotheses with relatively high internal validity, this may come at the cost of external validity. For example, the population of Texas is disproportionately Hispanic, immigrant, and politically right-of-center relative to the average US state (US Census Bureau 2019a,b; Jones 2019). While we view the internal-external validity tradeoff as reasonable given the importance of the questions we seek to answer, in sensitivity checks discussed below, we explore a handful of other states that had far less local policy variation than Texas, but met some of the other criteria discussed above. The pattern of findings in these states was qualitatively similar to Texas, suggesting that our results may generalize to other jurisdictions.  

Using anonymized smartphone data collected by SafeGraph, Inc., we document that county-level enactment of a SIPO is associated with an 8.0% increase in full-time stay-at-home behavior and a 3.3% increase in median hours spent at home. Turning to foot-traffic data, SIPO adoption is associated with a 12.8 to 18.9% decline in foot-traffic to locales that could be conducive to COVID-19 spread, including restaurants, bars, non-essential retail, entertainment venues and hotels.

Furthermore, we find that the (absolute) magnitudes of SIPO-induced stay-at-home increases and foot-traffic declines were generally larger for SIPOS adopted in more urbanized and densely populated counties. For example, more urbanized areas had much larger reductions in foot-traffic at certain types of businesses, in particular hotels, which see a reduction between 3.7 and 5.8 times larger than in non-urban areas. The next largest differential in the estimated effect of a SIPO on location-specific foot-traffic (for retail establishments) is 2.1 times larger in urbanized areas. This suggests that reducing mixing due to tourism and business travel may be one important mechanism through which urban SIPOS are more effective.

Finally, using COVID-19 case data, we find that in early-adopting urban counties, COVID-19 case growth fell by 21 to 26 percentage points two-and-a-half weeks following SIPO adoption, a result robust to controls for county-level heterogeneity in COVID-19 outbreak timing, coronavirus testing, age distribution, and political leanings. Approximately 90% of the curbed growth in COVID-19 cases in Texas came from the early adoption of SIPOS by urbanized counties, suggesting that the later statewide mandate yielded relatively few health benefits.

In summary, this study is able to speak to important heterogeneity in policy effectiveness absent from existing county-level SIPO studies and improves on the extant literature by tying variation in COVID-19 policy effectiveness to plausible mechanisms, and ruling out others. Our findings also inform whether it is possible to judiciously apply local SIPOS in certain locations and still receive the majority of their public health benefits without a blanket statewide order across heterogeneously populated jurisdictions.

2. Data and methods

2.1. Social distancing data

To proxy for social distancing, we utilize data from SafeGraph, Inc. We utilize both the Social Distancing Metrics (SDM) data, following Friedson et al. (2020) and Dave et al., 2020a, 2020b, 2020c, 2020d, 2020e, as well as the Points-of-Interest (POI) data, following Cronin and Evans (2020) and Dave et al. (2020a). Both data sources are based on anonymized cellphone pings, which we aggregate to the county-day level.

In the SDM, the base unit of observation is the cellphone, with each device assigned a “home,” a 153 m by 153 m location where the cellphone pinged most frequently during the hours between 6pm and 7am. We measure the percent of cellphones within a county that spend a given day within the “home” location, as well as the median hours a cellphone spends within the “home” location. We view both of these metrics as reasonable proxies for social distancing behavior, the former capturing “full” sheltering-in-place and the latter reflecting sheltering intensity. These data are, however, limited, as they do not provide information on the type of activities avoided when individuals spend more time at home, which is why we turn to the POI.

In the POI, the base unit of observation is a point of interest, often a business. Each point of interest is flagged with both a location and type
using six-digit North American Industry Classification System industry codes), and the number of distinct cellphone pings at that point of interest are recorded each day. We then aggregate to the business type-county-day level, and calculate the count of pings in that cell. We view these variables not only as a metric for social distancing activity, but also as information on the type of activities being avoided, which may help to disentangle why different locations may have different policy responses. Specifically, we examine foot-traffic at hotels, entertainment venues, restaurants, bars, retail establishments, and business services locations.

2.2. COVID-19, policy, and other data

We draw county-level daily data on reported COVID-19 cases, compiled by the The New York Times based on reports from state and local health agencies, from March 8 through April 28, 2020 for our analyses. By April 28, there were a total of 1,012,878 confirmed reported coronavirus cases in the U.S, 26,865 (2.7%) of which were in the State of Texas.

Local policy data on SIPOs were collected by the Center for Health Economics & Policy Studies at San Diego State University, using information compiled by the National Association of Counties (2020), Mervosh et al. (2020), and searches of official county governmental websites (executive and legislative branches, including departments of health), county court records, local news agencies, and state records of gubernatorial executive orders or proclamations. Data on non-essential business closures (NEBCOs), which are subsumed within a SIPO but can be implemented without a SIPO, were also collected via searches of official county governmental websites. NEBCOs mandate the closure of all businesses not deemed to be essential for day-to-day operations. We also collected information on county emergency decrees through the same search methods. These declarations are issued by a jurisdiction’s chief public official (i.e. Mayors, County Judges or Executives, or Governors) announcing that a current or impending crisis will require additional action that exceeds a location’s standard resource response capabilities. Such proclamations typically invoke emergency powers and operations.

Information on the urbanicity (percent of county population residing within urbanized areas or urban clusters) and population density are derived from the 2010 Census. The median urbanicity rate of a Texas county was 46% and the median population density was 22 persons per square mile.

2.3. Methods

Our goal is to assess whether any public health effects accrued to local jurisdictions adopting SIPOs in advance of the statewide order, determine to what extent these effects differ based on timing and population density, and tease out any variation suggestive of plausible mechanisms.

We begin by estimating the first-order relationship between county-level SIPO adoption and social distancing through a difference-in-differences identification strategy:

\[
\text{SocDist}_{ct,t} = \gamma_0 + \gamma_1 \text{SIPO}_{ct,t} + \beta_2 (\text{SDM} - \text{POI})_{ct,t} + \alpha_c + \tau_t + \epsilon_{ct} + \epsilon_{ct,t} 
\]

\[
\text{SocDist}_{ct,t} \text{ is a proxy measure for social distancing either from the SDM or the POI, } \text{SIPO}_{ct,t} \text{ indicates whether a shelter-in-place order was in effect in county } c \text{ on day } t, \text{ and } \text{X}_{ct} \text{ is a vector of county-specific time-}\text{varying controls, including an emergency declaration, enactment of a non-essential business closure order (but not a SIPO), as well as average temperature and whether measurable precipitation fell in the county. In addition, } \alpha_c \text{ is a county fixed effect, } \tau_t \text{ is a day fixed effect, and } \alpha_c \tau_t \text{ comprise county-specific linear and quadratic time trends. All models are weighted using the county population and adjust standard errors for clustering at the county-level (Bertrand et al. 2004).}
\]

We next explore whether the social distancing effects of SIPOs differ by whether the county was highly urbanized or more densely populated. We first interact SIPO_{ct} in Eq. (1) with Urban_{ct}, which identifies mutually-exclusive indicators for whether the county urbanicity rate was greater or less than 75% in the 2010 Census. Alternatively, we replace Urban_{ct} with PopDensity_{ct}, an indicator for whether the county population density exceeded 150 persons per square mile in the 2010 Census.

Next, we examine the public health effects of local SIPO adoption by focusing on the growth in COVID-19 cases, following Courtemanche et al. (2020a,b), and estimating the following specification that accounts for (i) early SIPO adoption by counties, prior to the statewide order, and (ii) lagged effects of SIPOs:

\[
\text{COVID}_Growth_{ct,t-1} = p_0 + (S1PO_{ct,t-4} \text{ Days} \times \text{Adopt}_t) \beta_1 + (S1PO_{ct,t-3} \text{ Days} \times \text{Adopt}_t) \beta_2 + (S1PO_{ct,t-2} \text{ Days} \times \text{Adopt}_t) \beta_3 + (S1PO_{ct,t-1} \text{ Days} \times \text{Adopt}_t) \beta_4 + \text{X}_{ct} \beta_5 + \alpha_c + \tau_t + \alpha_c \tau_t + \epsilon_{ct} + \epsilon_{ct,t} 
\]

where COVID\_Growth_{ct,t-1} is the difference in the natural log of cumulative COVID-19 cases in county c between days t and t-1, thus reflecting new confirmed cases each day. S1PO\_Days denotes lagged effects of SIPOs that correspond to (i) the incubation period of COVID-19 (Lauer et al. 2020), (ii) post-treatment windows where early-adopting counties have enacted a SIPO prior to the statewide order, and (iii) longer-run post-treatment periods when prior studies have detected larger health effects of SIPOs (Courtemanche et al. 2020; Friedson et al. 2020; Dave et al., 2020b). Adopt_t is a mutually exclusive set of indicators for whether a Texas county adopted a SIPO prior to March 27, 2020 ("early adopter"), between March 27 and April 1 ("later county adopter"), or a non-adopting county bound by the statewide SIPO enacted on April 2 ("non-adopter").

Identification of our key parameters of interest, \( \gamma_1 \) (Eq. (1)) and \( p_1 \) through \( p_4 \) (Eq. (2)) comes from within-county variation in SIPO adoption. Over the analysis period, a total of 85 counties (or cities larger than 100,000 in those counties) adopted local SIPOs. Thirty-four of these counties adopted their orders between March 24 and March 26, an additional 51 counties did so between March 27 and April 1, and 169 counties were newly bound by the statewide SIPO enacted on April 2. Appendix Fig. 1 shows the geographic dispersion of these counties, reflecting that many of Texas’s most densely populated and highly urbanized counties adopted SIPOs prior to March 27, allowing for at least a week's lag before the state's adoption of a blanket SIPO on April 2.

To derive unbiased estimates of the health effects of the policy, the parallel trends assumption must be satisfied. This assumption would be visibly violated if (i) SIPOs were adopted in response to changes in COVID-19 case growth, or (ii) SIPOs serve as an observable marker for the severity of the pandemic.
for difficult-to-measure county-specific variables correlated with coronavirus growth, such as local information shocks or voluntary social distancing. Eq. (2) controls for county-specific linear and quadratic time trends to partial out unobserved factors driving the exponential growth trajectory of COVID-19 transmissions. Differential pre-existing COVID-19 growth paths may be particularly important for later-adopting counties, as the outbreak has had more time to develop. Effects in these models are identified off deviations from this trend growth, and also help account for heterogeneity across counties in the timing of coronavirus outbreak as well as heterogeneity in growth of COVID-19 testing, a point to which we return below. We further conduct event study analyses freeing the difference-in-differences estimate of a SIPO on COVID-19 case growth to differ in the periods prior to and after adoption. This allows us to test for parallel pre-treatment trends and ensure that our policy estimates are not contaminated by COVID-related health trends prior to adoption.

Drawing insights from the heterogeneity in social distancing outcomes, we further assess whether COVID-19 growth rates differ by urbanicity or population density. There is evidence that state SIPOs may be more effective in more highly urbanized or densely-populated states (Dave et al., 2020b). However, it has not been established whether such a relationship exists within-states with local SIPOs. To that end, we interact Urban, with PopDensity, with each of the lagged windows in Panel I of Table 1 shows findings from Eq. (1) using SafeGraph data on social distancing, for stay-at-home behaviors from the SDM (columns 1-2) and foot-traffic across various business types from the POI (columns 3-7). Across all outcomes, local shelter-in-place orders lead to significant increases in social distancing. Enactment of a county SIPO is associated with a 2.9% point increase (8.0% relative to the mean) in the probability of staying at home full-time and an increase in the intensity of staying at home by about 0.43 hr (3.3%). Turning to specific venues, there is a significant reduction in foot-traffic on the order of 12.8% (retail) to 18.9% (entertainment) across all these businesses and activities.13

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13 While we present and discuss estimates from saturated specifications that include predictors of social distancing and trend controls, our estimates are robust across more parsimonious specifications (Appendix Table 1), including those that exclude county-specific time trends (Panel I).
Table 1
Estimated Effect of SIPO on Stay-at-Home Behavior and Foot Traffic

| Panel I: Difference-in-Difference Estimate |  |  |  |  |  |  |  |
|------------------------------------------|---|---|---|---|---|---|---|
| SIPO                                     | % at Home | Median Hours at Home | Entertainment | Hotel | Restaurant/Bar | Retail | Business Services |
|                                          | (1)       | (2)                  | (3)          | (4)   | (5)            | (6)    | (7)               |
| SIPO                                     | 0.029***  | 0.433***             | −0.210***    | −0.146*** | −0.138***     | −0.137*** | −0.173***         |
|                                          | (0.006)   | (0.176)              | (0.026)      | (0.030) | (0.021)       | (0.021) | (0.029)           |

Panel II: Heterogeneous Treatment Effect by Urbanicity

| SIPO                                     | High Urbanicity | Low Urbanicity |
|------------------------------------------|-----------------|----------------|
|                                          | 0.034*** (0.008) | 0.016*** (0.005) |
|                                          | 0.528* (0.207)  | 0.173 (0.136)   |
|                                          | −0.233*** (0.033) | −0.145*** (0.020) |
|                                          | −0.181*** (0.041) | −0.049*** (0.031) |
|                                          | −0.152*** (0.026) | −0.097*** (0.017) |
|                                          | −0.159*** (0.026) | −0.075*** (0.017) |
|                                          | −0.190*** (0.034) | −0.127*** (0.027) |

Panel III: Heterogeneous Treatment Effect by Population Density

| SIPO                                     | High Density | Low Density |
|------------------------------------------|--------------|-------------|
|                                          | 0.034*** (0.005) | 0.017*** (0.005) |
|                                          | 0.510* (0.138)  | 0.239 (0.138)  |
|                                          | −0.235*** (0.034) | −0.147*** (0.021) |
|                                          | −0.190*** (0.044) | −0.033*** (0.026) |
|                                          | −0.149*** (0.027) | −0.108*** (0.015) |
|                                          | −0.159*** (0.027) | −0.082*** (0.016) |
|                                          | −0.194*** (0.035) | −0.119*** (0.024) |

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the county had issued a non-essential business closure order, an indicator for whether the county had issued an emergency declaration, the average temperature (in degrees Celsius) in the county, an indicator for whether measurable precipitation fell in the county, county fixed effects, day fixed effects, and a county-specific time trend. Standard errors, clustered at the county-level, are reported in parenthesis. Counties with urbanicity rate of 75% or higher is defined as High Urbanicity. Counties with urbanicity rate of lower than 75% is defined as Low Urbanicity. Counties with population density of 150 people per sq. mile or higher is defined as High Density and counties with population density of lower than 150 people per sq. mile is defined as Low Density.

* Significant at 1% level
** at 5% level
*** at 10% level

Fig. 1 visually presents the dynamics in key social distancing outcomes from an event study analysis, highlighting three main points. First, the insignificant and small lead pre-policy effects suggest that trends in social distancing between the SIPO-adopting and non-adopting counties were similar prior to enactment. In netting out the secular trend, the policy effect that we estimate captures a response above any voluntary increases in social distancing. Second, the marked increase in social distancing in the treated counties relative to the non-adopters materializes only after the implementation of the SIPO. Finally, the increase in social distancing within the treated counties remains sustained through the observed post-treatment window. These localized results are in line with previous state-level findings (Friedson et al. 2020; Dave et al., 2020b), and confirm that shelter-at-home orders proclaimed by local jurisdictions improved compliance with social distancing.

Given that social distancing inherently involves a reduced person-to-person contact for economic or non-economic reasons, we explore how these social distancing effects vary depending on the county’s urbanicity and population density, both of which are independent predictors of social interactions. Models reported in Panels II and III consistently show that, while the orders were generally effective across the board in encouraging individuals to shelter at home, the effects are significantly larger in urbanized and densely populated counties (3.4 percentage points vs. 1.6-1.7 percentage points in less urban and sparsely-populated counties). The foot-traffic analyses paint a more granular picture, pointing to differences in the impact of SIPOs based on urbanicity (and density) across different types of locations that individuals may wish to avoid or are forced to avoid because of closures. Urbanized and densely populated areas see a larger reduction in location-specific foot-traffic across the board following a SIPO, with the largest differential in foot-traffic at hotels (3.7–5.8 times larger) and in retail trade (1.9–2.1 times larger). The larger percent decreases of foot-traffic at businesses in urban areas imply less opportunity for mixing and spreading illness.

We assess this possibility next by analyzing the public health effects of the local SIPO adoption, focusing on county-level heterogeneity in the timing of the adoption and heterogeneity across urbanicity and population density. These results are presented, respectively, in Tables 2 and 3.

Turning first to the timing analyses (Table 2), we find significant reductions in the COVID-19 case growth following implementation of a local SIPO, but only for the earliest adopting counties. Growth fell by 15 percentage points within 4 days of implementation, and by 18.4 percentage points within 8 days, a time window that includes the 75th percentile of the virus’s incubation period and, importantly, which also largely precedes the implementation of the statewide SIPO (column 1). Effects accelerate as the post-policy window widens in length, with COVID-19 case growth declining on average by 25.1 percentage points following 18 days after SIPO adoption. For later-adopting counties, there are some suggestive declines in case growth, though these take a bit longer to materialize (after 5-8 days post-enactment) and are somewhat smaller relative to the gains for the early-movers. We find no beneficial effects of the statewide-SIPO for the remaining counties that had not enacted local orders. Figure 2 (Panels a and b) presents the event study analyses

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14 See Appendix Figure 2 for event study graphs for the remaining outcomes not presented in Figure 1.
15 Cronin and Evans (2020) show that NPIs in general have a modest effect on social distancing relative to private responses in the absence of policy interventions, and that SIPOs usually have the largest effect of any of the NPIs studied (in a few cases emergency declarations have similar and marginally larger effects). By netting out the secular trend prior to the policy adoption, we are differentiating out the common private response. And, any effects from national information dissemination are captured by the day fixed effects.
16 This could reflect non-essential businesses that are forced to close as well as essential businesses that are more likely to avoid due to new understanding of risks.
17 Our results and patterns remain largely similar across models with more parsimonious controls (see Appendix Table 4). Estimates are also robust to more flexibly controlling for the dynamic effects of the NERCOs and the emergency declaration orders in the same mode as we do for the SIPOs.
18 In a difference-in-differences estimator with the policy turning on at different times, as with the staggered timing of the SIPO adoption across Texas, the treatment effect is a weighted average of the many “mini” experiments comparing: (1) earlier-adopters with later-adopters as controls; and (2) non-adopting counties (bound later by the statewide order) with the earlier-adopting counties as controls (Goodman-Bacon 2018). If there are dynamic treatment effects, early-adopters may not be a good counterfactual for the non-adopters. To assess this potential bias, and more clearly identify the statewide SIPO effects for the remaining non-adopters, we introduce another set of counterfactuals – non-adopting counties in other states that were never bound by a statewide order. Appendix Table 8 presents these results, using all non-adopting states and alternatively all bordering non-adopting states, as controls. The estimates and patterns remain robust.
for the full sample and for the early-adopting counties. Differential pre-treatment trends are flat, and there is a sharp and progressively larger decline in the average growth rate in cases ensuing the adoption of the policy.

One potential concern is that estimates may be confounded by differential testing capabilities if access to testing is correlated with the timing of the localized SIPO adoption. Baseline differences in testing rates would be captured by the county fixed effects, and the county-specific trends go a long way towards addressing time-varying localized differences in testing capacity, though not fully. To account for any residual systematic variation in testing capacity, we draw on cumulative testing data from the Texas Department of State Health Services. We restrict our analysis to only those counties that had achieved a relatively high cumulative testing rate, at or above the state median, thereby ensuring a more homogeneous set of localities with respect to testing availability.

In spite of the large sample restriction, the results remain remarkably robust (column 2), with no evidence that our estimates are driven by local differences in testing.

Not all localities experienced the outbreak at the same time. To ensure comparability in the start of the outbreak cycle across counties, column (3) restricts the sample such that a county enters the analysis only after it has experienced the start of the outbreak and some level of community spread (at least two cases).

The final column accounts for any potential border spillovers by controlling for the share of population in bordering counties that are covered by a SIPO. These results continue to support the effectiveness of local SIPOs among counties that adopted these orders well in advance of the statewide order, though the effect sizes are slightly attenuated.

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19 In the presence of testing shortages, wherein tests are allocated to relatively sicker patients, confirmed counts of COVID-19 cases are more likely to reflect severe cases, which is arguably a more salient indicator of infections for studying the public health effects of a SIPO (Courtemanche et al. 2020a).

20 The earliest date these data are available at the county-level in a consistent format is April 8, which is when we calculate the median cumulative testing rate (median across

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TX counties was 10.7 per 10,000 residents and statewide mean was 24.9). Restricting the sample to counties with a cumulative testing rate at the 60th (testing rate>14.6) or the 75th percentile (testing rate>19.3), or counties with a testing rate that exceeded the state mean (>24.9) yields similar results and conclusions.

21 Estimates remain largely unchanged under alternate thresholds (counties experiencing at least 1, 3, 4, and 5 confirmed cases).

22 Results are not sensitive to alternate controlling for whether any border county is covered by a local SIPO (including SIPOs in neighboring states for those Texas counties that border other states).
Table 2
Differences-in-Differences Estimates of Effect of Shelter-in-Place Orders on COVID-19 Case Growth

| Early-Adopting SIPO Counties | (1)  | (2)  | (3)  | (4)  |
|------------------------------|------|------|------|------|
| 0-4 Days After               | −0.150*** | −0.171*** | −0.128*** | −0.118*** |
|                              | (0.043) | (0.048) | (0.052) | (0.055) |
| 5-8 Days After               | −0.184*** | −0.202*** | −0.166*** | −0.154*** |
|                              | (0.058) | (0.066) | (0.081) | (0.072) |
| 9-18 Days After              | −0.210*** | −0.220*** | −0.176**  | −0.181*** |
|                              | (0.072) | (0.080) | (0.084) | (0.083) |
| >18 Days After               | −0.251*** | −0.262*** | −0.207**  | −0.222*** |
|                              | (0.070) | (0.078) | (0.086) | (0.082) |

Late-Adopting SIPO Counties

| 0-4 Days After               | −0.031 | −0.049 | −0.069 | −0.001 |
|                              | (0.049) | (0.057) | (0.059) | (0.059) |
| 5-8 Days After               | −0.105** | −0.120** | −0.125** | −0.072 |
|                              | (0.058) | (0.066) | (0.060) | (0.069) |
| 9-18 Days After              | −0.141** | −0.155** | −0.150** | −0.108* |
|                              | (0.054) | (0.062) | (0.061) | (0.065) |
| >18 Days After               | −0.197*** | −0.211*** | −0.181*** | −0.162*** |
|                              | (0.061) | (0.067) | (0.064) | (0.068) |

Non-Adopting Counties Bound by State SIPO

| 0-4 Days After               | −0.030 | −0.039 | −0.074*  | −0.001 |
|                              | (0.044) | (0.049) | (0.043) | (0.053) |
| 5-8 Days After               | 0.020 | 0.004 | 0.059**  | 0.048 |
|                              | (0.053) | (0.060) | (0.047) | (0.059) |
| 9-18 Days After              | 0.051 | 0.049 | 0.053**  | 0.077 |
|                              | (0.072) | (0.084) | (0.061) | (0.076) |
| >18 Days After               | 0.142 | 0.152 | 0.004**  | 0.168 |
|                              | (0.105) | (0.127) | (0.086) | (0.105) |

| N                            | 12954 | 6477  | 4878    | 12954 |
| Testing Rate ≥ Median?       | No    | Yes   | No      | No    |
| Sample w/ Cases ≥ 27?        | No    | No    | Yes     | No    |
| Border Counties with SIPO?   | No    | No    | Yes     | No    |

Notes: Estimates are obtained using weighted least squares regression. The model includes the following controls: an indicator for whether the county had issued a non-essential business closure order, an indicator for whether the county had issued an emergency declaration, the average temperature (in degrees Celsius) in the county, an indicator for whether measurable precipitation fell in the county, county fixed effects, day fixed effects, and a county-specific time trend. Standard errors, clustered at the county-level, are reported in parenthesis. Counties that adopted SIPO on March 26 or before are defined as Early-Adopting SIPO Counties, and counties that adopted SIPO between March 27 and April 1 are defined as Late-Adopting SIPO Counties.

*** Significant at 1% level
** at 5% level
* at 10% level

This issue, that SIPOs may “leak,” in the absence of policy continuity across adjacent localities, can be assessed more directly with the social distancing measures (Appendix Table 7A & 7B). We find that SIPOs reduce out-of-county mobility (proxied by the number of cellphone pings, with a “home” in the SIPO county, that occur outside the SIPO county). Though, individuals are somewhat more likely to travel outside of their county (and less likely to stay at home) when a SIPO-adopting county is strictly bordered by all non-SIPO counties than when it is neighbor by at least some counties with a SIPO. On the flip-side, consistent with such county-cross mobility from SIPO to non-SIPO localities, there is some evidence of greater foot-traffic at hotels, entertainment and business venues in the non-SIPO county if it is surrounded by all SIPO counties. These spillovers, however, are generally small, not significantly different, and only evident in the parameter estimates (albeit small) for the strictest margins (i.e. a SIPO county bordered by all non-SIPO counties, or a non-SIPO county bordered by only SIPO counties). Taken together, we consider there to be weak evidence of SIPOs “leaking.” This explains why the results for COVID-19 cases are only very slightly attenuated when bordering areas do not share the same policy.

In light of our earlier evidence that the effectiveness of local SIPOs is at least partly propelled by an increase in social distancing, with stronger responses realized in urbanized and highly populated localities, next we explore whether the public health effects also line up with this pattern of spatial heterogeneity. The larger decline in foot-traffic at businesses in urban areas, could translate into lower population mixing and community spread. Urbanicity and population density may also serve as multipliers that could enhance the efficacy of a given level of social distancing.

Table 3 presents estimates which allow for heterogeneous responses by urbanicity and population density. The results show compelling evidence that virtually all of the decline in case growth accrued to urbanized counties and highly-populated counties that had adopted a local-
ized shelter-in-place order in advance of the statewide order. After 18+ days following enactment, these counties experienced significant declines in the daily growth rate of COVID-19 cases on the order of 26 percentage points. Event study analyses for these sets of early-adopting urban and populous counties, shown in panels (c) and (d) of Fig. 2, show common pre-policy trends and a significant post-policy break in the trend. In contrast, less urban and more sparsely populated counties did not reap any significant benefits from their local orders, even if these were enacted well ahead of the statewide SIPO. The results continue to show that the statewide SIPO did not have any significant impact in flattening the growth trajectory for the remaining non-adopting counties, regardless of their level of urbanization or population density.

Our finding that urban areas benefit the most from SIPOs begs the question of what is being captured by “urban” and whether the heterogeneity reflects other factors associated with urbanized areas. The findings in Table 1 point to differences in mobility and activity patterns driven by the shelter-in-place orders across these areas. However, it is possible that differential responses may be driven by variation in the local progression of the outbreak (which may drive behavioral responses including compliance with SIPOs), or the local age distribution (with urban areas reflecting a younger population share). Our pattern of results for the impact of a SIPO (and the differential between urban and non-urban counties) is not appreciably different once we net out the effect of the severity of the local outbreak and the county’s age distribution. Urban areas also tend to be more left-leaning, and political preferences have been found to correlate with social distancing orders and engagement in mitigation strategies Barrios and Hochberg (2020). In Appendix Tables 3 and 6, we stratify based on the vote share for Democratic candidate Hillary Clinton in the 2016 presidential election. While we do find some differences with regards to distancing behavior – areas with a higher voting share for Clinton did socially distance more based on our metrics, we do not find a similar separation in COVID-19 case growth. These results suggest that the urbanicity-based differentials are not due to differences based on political leaning or age or the progression of the infections.

4. Conclusions

By examining the staggered county implementations of SIPOs in Texas this study has established two important results. First, when urbanized localities mobilize early with SIPOs, the accrual of public health benefits are substantial. Second, in the presence of early urban SIPO adopters, there may be few gains from a later blanket statewide order. These findings are not surprising given the potential for exponential growth with the spread of disease. Breaking the trend in cases, by acting earlier in areas where spread has potential to be faster, has compounding effects that can greatly alter the trajectory of an outbreak.

As a result, we find that in Texas, almost all of the public health benefits from SIPO implementation came from these urban, densely populated areas. Our estimates indicate that 91.5% of the reduction in the growth in COVID-19 cases came just from the early localized adoption of SIPOs in urbanized counties alone. Very little is gained from a statewide order after this point.

These findings have large implications for the policy landscape going forward. If the benefits of SIPOs are concentrated in urban areas, then the use of these restrictive policies statewide may not be necessary when fighting outbreaks. More nuanced policy strategies that are stricter in dense urban areas and looser in other areas may yield similar health benefits without imposing the costs, both in terms of economic activity and in terms of inconvenience on part of the population.

However, targeted policies do have a drawback: individuals may find ways to avoid SIPOs when neighboring counties do not adopt such policies as well. Thus, a lack of contiguity may sap some of the benefits from better policy targeting, and will need to be traded off against. In the case of Texas, these spillovers appear to be relatively small with regard to COVID-19-related spillovers. Finally, to the extent that an important mechanism through which shelter-in-place orders exert their effect is through public appreciation of the risks, buy-in, and compliance, these channels may become less effective and enforcement more costly with greater targeting of policy to certain areas or populations.

Declaration of Competing Interest

None.

Credit Author Statement

Dhaval Dave: Conceptualization, Methodology, Visualization, Writing, Software. Andrew Friedson: Conceptualization, Methodology, Visualization, Writing, Software. Kyutaro Matsuzawa: Formal Analysis, Investigation, Software, Data Curation. Joseph Sabia: Conceptualization, Methodology, Visualization, Writing, Software, Funding Acquisition, Supervision. Samuel Safford: Formal Analysis, Investigation, Software, Data Curation.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2020.103294.

27 In supplemental analyses (Appendix Table 9), we explore other later-adopting SIPO states (PA, MO, FL, and GA) with more limited early-county SIPO adoption relative to Texas. It is validating that results from these mini-experiments in these states produced a pattern of results largely similar to Texas, suggesting that our findings are not local to Texas.

28 Much of the leftover gains accrues from the later adopting urbanized counties, who are doing so still in advance of the statewide SIPO. Appendix Table 10 provides a discussion of this calculation.

29 The semi-elasticity of COVID-19 case growth with respect to foot-traffic across all venues (as a proxy for social distancing), implied by our results, is 1.47 for an urbanized early-SIPO adopter and 0.96 for a non-urbanized early-SIPO adopter (with this latter being statistically insignificant). The differential (1.5-2 times larger) is similar for densely-populated vs. sparsely-populated early adopters (1.50 vs. 0.70), and for semi-elasticities with respect to full-time staying-at-home behaviors. Note that the semi-elasticity, as a ratio of the two reduced-form policy estimates, is akin to an imputed instrumental-variables estimate, and assumes that all of the public health benefit of the SIPO is loaded through social distancing. Clearly other compensating behaviors and mechanisms would be at play, in which case the absolute magnitude of the implied semi-elasticity is likely overstated; however, the difference in implied responsiveness (“social distancing multiplier”) across urban and non-urban counties is non-negligible. Moreover, with over-dispersion and cluster-based spread (“super-spreaders”), our measured proxies for social distancing are a crude metric to project all of the mechanisms of a SIPO, and only meant to convey that SIPOs are a policy that people are aware of and that they are impacting individuals’ behaviors.
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