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Lockdown Without Loss? A Natural Experiment of Net Payoffs from COVID-19 Lockdowns

Gerard J. Tellis, Ashish Sood, Sajeev Nair, and Nitish Sood

Abstract

Lacking a federal policy to control the spread of COVID-19, state governors ordered lockdowns and mask mandates, at different times, generating a massive natural experiment. The authors exploit this natural experiment to address four issues: (1) Were lockdowns effective in reducing infections? (2) What were the costs to consumers? (3) Did lockdowns increase (signaling effect) or reduce (substitution effect) consumers' mask adoption? (4) Did governors' decisions depend on medical science or nonmedical drivers? Analyses via difference-in-differences and generalized synthetic control methods indicate that lockdowns causally reduced infections. Although lockdowns reduced infections by 480 per million consumers per day (equivalent to a reduction of 56%), they reduced customer satisfaction by 2.2%, consumer spending by 7.5%, and gross domestic product by 5.4% and significantly increased unemployment by 2% per average state by the end of the observation period. A counterfactual analysis shows that a nationwide lockdown on March 15, 2020, would have reduced total cases by 60%, whereas the absence of any state lockdowns would have resulted in five times more cases by April 30. The average cost of reducing the number of cases by one new infection was about $28,000 in lower gross domestic product.

Keywords

lockdowns, natural experiments, difference in differences, COVID-19, disease spread, disease penetration

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The novel coronavirus (SARS-CoV-2) ravaged consumer markets worldwide in 2020. The first cases of coronavirus disease 2019 (COVID-19) were reported in Wuhan, China, in December 2019 (Zhu et al. 2020), with human-to-human transmission confirmed shortly thereafter (Wang, Horby, et al. 2020). In the absence of vaccines or a curative drug to control the spread of COVID-19, countries began implementing various nonpharmaceutical interventions (NPIs), including travel restrictions and masks. Lockdowns restricted consumers' out-of-home activities, and mask mandates required consumers to wear facial masks.

We define lockdowns as mandatory stay-at-home orders that restrict out-of-home activities to essential ones such as shopping for groceries or medications. We define a mask mandate as a consumer having to wear a protective face covering at certain designated places. In the United States, no major national interventions were ordered. Rather, governors of each state ordered lockdowns and mask mandates at varying times. By the end of June 2020, the United States had seen the highest number of confirmed cases and deaths in the world (Dong, Du, and Gardner 2020).

In the absence of federal and often state mask mandates, consumers were not obliged to change their normal behavior. Whether lockdowns or mask mandates controlled the pandemic or were complements or substitutes is hotly debated even today. This study addresses four issues: (1) Were lockdowns causally effective in reducing infections? (2) What were the costs in terms of gross domestic product (GDP), unemployment, customer satisfaction, and consumer spending? (3) Did lockdowns increase consumers' mask adoption (signaling effect) or reduce mask adoption (substitution effect)? (4) To what extent did governors' decisions depend on medical science (the spread of COVID-19 in their states) versus other nonmedical variables?

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Most prior studies have been within the context of epidemiology, where researchers use classic models that make strong assumptions (Ioannidis, Cripps, and Tanner 2020). Early predictions from such models substantially overestimated the spread of the disease and were widely criticized as unreliable or unreproducible (Chawla 2020; Ferguson et al. 2020). Most such models depend on modeling assumptions, suffer from high sensitivity of estimates, and are disconnected from real-world consumer behavior. Critics have also complained that researchers have not shown the causal impact of lockdowns through experiments. It is costly and impractical to run experiments in the area of public health because of the ethical and liberty issues involved (Holmdahl and Buckee 2020). However, governors in various states in the United States issued lockdowns at different times, creating a natural experiment. This study is the first one to exploit the ensuing natural experiment of lockdowns, thus estimating the causal impact of their costs and benefits.

Study 1 addresses whether lockdowns were causally effective in reducing infections. This study, using a difference-in-differences (DID) approach, shows that lockdowns reduced infections by 480 per million consumers per day by the end of our observation period. A counterfactual analysis shows that an early nationwide lockdown on March 15, 2020, would have reduced the total number of cases on April 30, 2020, by 60%. Conversely, had no governors issued any lockdowns until April 23, 2020, the number of cases would have been five times higher by April 30, 2020. So, consumers incurred a steep cost for delays in lockdowns in terms of higher disease incidence.

Study 2 addresses the economic and psychological costs of lockdowns in terms of customer satisfaction, consumer spending, GDP, and unemployment, exploiting a natural experiment in states' lockdown dates. It does so across six pairs of geographically neighboring and similar states in which one state issued a lockdown and the other did not. The results indicate that the states issuing lockdowns experienced a significant decline in average customer satisfaction with durable and nondurable products, utilities, retail, and services by 2.2% in the quarter following the lockdown, which is significantly larger than the "normal" change in the national quarterly American Customer Satisfaction Index (ACSI; Anderson and Fornell 2000). Moreover, in the quarter following the lockdown, these states had lower consumer spending by 7.5%, lower GDP by 5.4%, and an increase in unemployment of 2%. The estimated cost of avoiding an incremental new infection was, on average, about $28,000 in lower GDP.

Study 3 examines the impact of lockdowns on consumers' mask adoption. It uses data from self-reported mask adoption of 250,000 online consumers. The results indicate that lockdowns increased consumers' adoption of masks (signaling effect) rather than reducing it (substitution effect).

Study 4 examines the extent to which governors' decisions depended on medical science (the spread of COVID-19 in their states) versus other nonmedical variables. The results show that the spread of the disease had no significant effect on governors' decisions; instead, governors were motivated by their political affiliation, policy transfer from states affected earlier, and mini cascades from governors of the same party who acted earlier.

These results have important implications for public policy makers, managers, and consumers. To reduce mortality under such conditions, public policy makers should control pandemics on the basis of consumer health rather than political, economic, or behavioral considerations. Consumers need to observe low-cost preventive measures such as mask wearing to obviate the need for more stringent and costly lockdowns and mask mandates. The next part of the article describes these four studies. The last section discusses major implications.

Study 1: Effectiveness of Lockdowns

We first present the rationale for lockdowns and the method and results of Study 1. As the disease surged in the United States in March and April 2020, governors of states issued lockdowns and mask mandates as a last resort to control its spread. However, they did so at different times. The ensuing variance created a massive natural social experiment in controlling COVID-19 at the state level within the United States.

Theory

COVID-19 is an infectious disease (Li et al. 2020) with estimated infection fatality rates of 3.4% early on (World Health Organization 2020) and subsequently ranging from less than 1% to 2% (Fauci, Lane, and Redfield 2020; Wu et al. 2020). At the time, the scientific community believed that it spread by consumers' direct or airborne contact with droplets or other oral or nasal excretions from an infected consumer. The risk of spread is high due to the long asymptomatic incubation period of the virus (Luo et al. 2020). Two broad means of controlling the spread of the disease are pharmaceutical interventions and NPIs. The former consists of curative drugs or vaccines, which were not available in the first half of 2020 in the United States. In the absence of effective pharmaceutical interventions, NPIs become essential to control the spread of the disease (Hartley and Perencevich 2020; World Health Organization 2020). Interventions in increasing order of strictness consisted of not touching the face, washing or disinfecting hands, wearing masks, social distancing, and lockdowns. Testing, contact tracing, and selective quarantines can effectively guide the duration and intensity of these interventions (Zhang et al. 2020). The U.S. federal government announced voluntary social distancing guidelines only on March 16, letting the states adopt their own policies at their own times. Some governors ordered lockdowns; other governors issued only mask mandates.

Method

To ascertain the effect of a specific intervention in the absence of randomized controlled trials, a researcher may be able to identify natural experiments within observational data with treated states (those with lockdowns) and similar control states

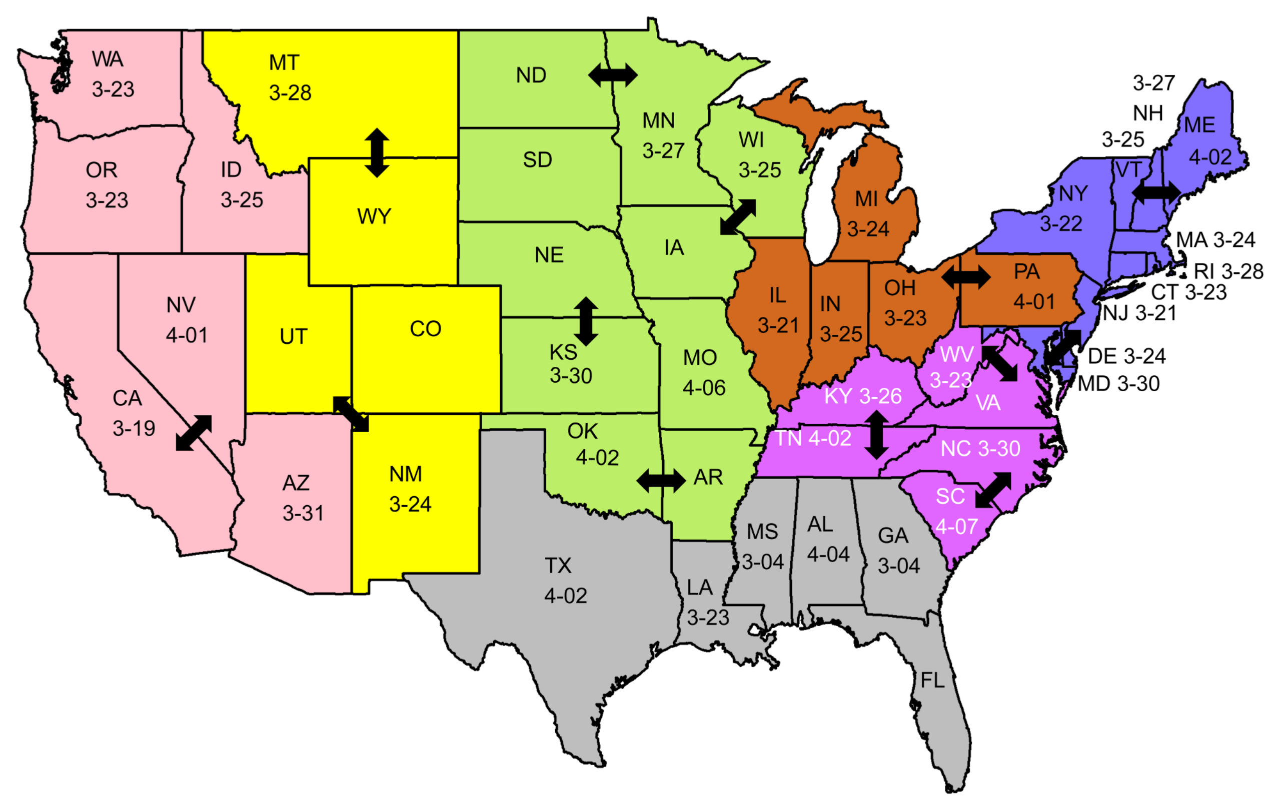

Figure 1. Identification of States for Natural Experiments.
Notes: Colors represent similar neighboring states. Arrows represent pairs of neighboring states with different lockdown dates. Dates of stay-at-home orders are included for states that issued this intervention.

(those with delayed or no lockdowns) (Tirunillai and Tellis 2017). Such a design applies to the control of COVID-19 in the United States because similar neighboring U.S. states adopted different policies at different times. Natural experiments are superior to complex mathematical and epidemiological models since the latter models are sensitive to assumptions that are not always valid in the real world (Chinazzi et al. 2020).

Identification of natural experiments in lockdowns. To test the alternate hypothesis, we identified pairs of similar neighboring states that differed only in the timing of lockdowns. Within geographic clusters, most states' lockdown dates are close to each other, implying a regional cascade. We adopted the following strategy to identify the few pairs of states within clusters that issued lockdowns at different times (Figure 1):

- Group neighboring states into geographic clusters with similar climate (temperature, humidity), population (numbers, density, urban vs. rural, biggest city in state), mobility (traffic patterns, metro traffic, vehicle miles, air travel, and tourism), economy (GDP, GDP per capita, number of businesses), and income (gross receipts, income inequality).
- Obtain lockdown dates for all states.
- Identify two similar neighboring states within these clusters that differ in lockdown dates by seven or more days.
- If three states fit these criteria, pick the two that share the widest border.
- Use a state only once for the analysis.

We identified 13 such pairs (26 states), which we call cohorts. These cohorts represent natural experiments because most other important variables (i.e., population density, climate, housing, and occupation) are similar within each. We assume residents of all states followed similar personal hygiene and social distancing guidelines as recommended by the federal government on March 16 (Harris 2020).

We obtained data on COVID-19 cases for each U.S. state from March 10 to April 30, 2020, from three main sources: Flevy, the Johns Hopkins Coronavirus Resource Center, and the coronavirus news tracking website Worldometer. Dates of statewide lockdowns were collected from the governor's offices in each state (Fullman et al. 2020). After May 1, states began to lift the lockdowns. This reopening may confound the natural experiments after April 30, 2020 (Imbens and Wooldridge 2009), so our analysis extends to April 30, 2020. We obtain monthly temperature and humidity averages from the National Oceanic and Atmospheric Administration, population density from the U.S. Census Bureau, GDP per capita from the U.S. Bureau of Economic Analysis, and mobility from the U.S. Department of Transportation.

Causal impact of the lockdown. To estimate the impact of the lockdown on the disease prevalence, we compute the difference in daily infections on the day of the first lockdown in the state versus that of its comparison state in the cohort (Difference 1) and on the last date of the observation period, April 30, 2020 (Difference 2). Difference 1 is due to differing disease penetration in the states prior to the lockdown, different disease onset times, or any remaining differences not accounted for in our search strategy. Difference 2 is due to the difference in lockdowns plus different dates of onset of the disease in the two states or any other remaining differences not accounted for in our search strategy. We then compute the difference-in-differences as Difference 2 minus Difference 1. This value estimates the pure effect of lockdowns on disease prevalence in a state relative to its comparable state. If the results of all these natural experiments are the same or at least in the same direction, that would give high confidence that lockdowns affect the disease penetration. If not, then no such conclusion can be drawn. Thus, this research design enables us to capture the causal impact of lockdowns on disease spread.

Causal impact of the timing of lockdown. To estimate the dynamic causal impact of the lockdown on the disease spread, we employ three approaches: dynamic DID regression with alternate specifications, a counterfactual analysis, and generalized synthetic control. First, we run a dynamic DID regression model (Dimick and Ryan 2014) that controls for a rich set of independent variables, including the time trend, population density, average highest temperature and humidity of the biggest city in the state, and GDP per capita (Hu, Nigmatulina, and Eckhoff 2013; Wang, Horby, et al. 2020). We pool the daily data from March 10 to April 30, 2020 (50 days), for all cohorts and estimate the following equation:

$$\begin{aligned} DP_{it} = {} & \theta_0 + \theta_1 Time_{it} + \theta_2 LDN_{it} + \theta_3 LDN_{it} \times Time_{it} \\ & + \theta_4 LDN_{it} \times Time_{it}^2 + \theta_5 EMM_{it} + \theta_6 DP_{it-1} \\ & + \theta_7 PD_i + \theta_8 TEMP_i + \theta_9 HD_i + \theta_{10} MT_i + \theta_{11} GDPPC_i \\ & + \theta_{12} II_i + \epsilon_{it}, \end{aligned} \tag{1}$$

where

DPi = disease penetration (number of total cases per million in state i);
$Time_i$ = days since lockdown in state i;
LDN_i = a dummy variable that equals 1 if the governor of a state mandated a lockdown for state i);
EMM_i = extent of mask mandate in a state (percentage of a state, by area, covered by a mask-wearing restriction for consumers);
PD_i = population density of state i;
$TEMP_i$ = average temperature in the state in the quarter under mask mandate;
HD_i = average humidity in the state in the quarter under mask mandate;
MT_i = average metro traffic in 2020 Q1 in state i;
$GDPPC_{it}$ = economic activity in the state computed as the GDP per capita in the quarter under mask mandate; and
II_i = current income inequality (Gini coefficient) in state i.

Second, we use the estimates from the dynamic DID regression model to conduct a counterfactual analysis on disease prevalence had lockdowns been issued across all 50 states on alternate dates. We first estimate the average date of the national lockdown by taking an average of each state's lockdown date, weighted by the state's population on March 28, 2020. We then run a simulation, estimating the daily total number of cases that would have occurred had there been a national lockdown on that day and comparing it with the true number of confirmed cases in the United States over the same period (March 10 to April 30). We then also estimate the daily total numbers of cases that would have occurred had a national lockdown been ordered on March 15, March 23, March 31, April 7, April 15, and April 23, 2020, respectively. Finally, we estimate a generalized synthetic control (Xu 2017) for the 13 cohorts as a robustness check. The method using this approach is explained in Web Appendix A.

Results

This subsection presents the results of the causal impact of the lockdown decisions and the causal impact of the timing of lockdown on disease prevalence using the DID analysis and the other two approaches. We ran four dynamic DID regression models with alternate specifications of variables to test sensitivity to multicollinearity, if any, and robustness of the results (Table 1).

The model-free DID graphical results suggest (Figure 2) that before the first lockdown, both states in most cohorts had similar disease prevalence. Figure 2 also shows that the two lines of the states with and without lockdowns are similar before the lockdown in one state and only diverge substantially after the implementation of a lockdown by one of the states, satisfying the parallel trend assumption (before the lockdowns occurred). After lockdowns, in 11 of the 13 cohorts, the state with a later lockdown or no lockdown has a higher disease prevalence.[1] The DID results of infection within the six pairs[2] of states, one with a lockdown and the other without, suggest an average daily difference of 480 cases per million per day on April 30, 2020 (i.e., by the last day of the observation period) in the average state (Table 2, Column E). Considering new infections on April 30, 2020, states that implemented lockdowns had 56% fewer infections compared with states that did not implement lockdowns.

[1] We also estimate the causal effect of lockdowns using a generalized synthetic control while ensuring that the treated and synthetic states had similar disease prevalence (i.e., parallel trends) before lockdowns were implemented in the treated states. (See Web Appendix A.)

[2] In the remaining seven pairs of states, both states implemented a lockdown but at different times.

Table 1. Effect of Lockdowns on Disease Prevalence (Total Cases per Million).

	26 States (13 Cohorts) Included in DID		All 50 States Included in DID	
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	1.451***	3.265***	−2.094***	−2.791***
Time trend	.127***	.132***	.135***	.138***
Lockdowns	1.003***	.997***	1.063***	1.013***
Lockdowns × time	−.044***	−.040***	−.031***	−.031***
Lockdowns × time^2	−.001***	−.001***	−.001***	−.001***
Extent of mask mandate	.003***	.000**	.002***	.003***
Lag (cases per million)	.000***	.000***	.000***	.000***
Population density (1,000/mi^2)		.256***	.201***	.129***
March temperature (°C)		−.004	−.012***	−.021***
March humidity (%)		−.009***	−.003	−.003
Reduction in mobility (%)		.003***	.002***	.000
GDP per capita		.012***	.008***	.013***
Income inequality		−.051***	.078***	.119***
Cohort 1 (Kentucky–Tennessee)				−.344***
Cohort 2 (West Virginia–Virginia)				−.739***
Cohort 3 (California–Nevada)				.111
Cohort 4 (Ohio–Pennsylvania)				−.380***
Cohort 5 (Vermont–Maine)				−.008
Cohort 6 (Maryland–Delaware)				−.052
Cohort 7 (Montana–Wyoming)				−.689***
Cohort 8 (Wisconsin–Iowa)				−.417***
Cohort 9 (Kansas–Nebraska)				−.409***
Cohort 10 (Minnesota–North Dakota)				−1.098***
Cohort 11 (Oklahoma–Arkansas)				−.352***
Cohort 12 (New Mexico–Utah)				.105
Adj. R^2	.87	.89	.87	.88
N	1,332	1,332	2,566	2,566

*$p \leq .05$, **$p \leq .01$, ***$p \leq .001$.

The dynamic DID regression models allow us to include in the analyses the remaining seven pairs of states in which both states implemented lockdowns albeit at different times. We tested all 16 variables measuring interstate differences and retained the significant ones. Models 1 and 2 include the key variables for the 26 states (lockdowns, time trend, and their interactions) without and with the control variables, respectively. Model 3 includes the key variables (lockdowns, time trend, and their interactions) and control variables and extends the analyses to all 50 states. All key and control variables are significant and in the expected direction. The results are consistent with Models 1 and 2, suggesting high generalizability. The effects of the key variables remain robust. Model 4 adds dummy variables for 12 cohorts (cohort North Carolina–South Carolina is held back as the base). The effects of the key variables remain robust. We use Model 3 for policy simulations because it is the most complete, has controls for all relevant variables, and is estimated over the entire data set.

Note that whereas the coefficient of the lockdowns by itself is positive, the coefficient of the interaction terms of lockdowns with time and time squared are both negative. Thus, the negative effect of lockdowns is realized only over time, during which it becomes increasingly important for two reasons. First, the long incubation period conceals the immediate effect of lockdowns. However, the effect builds up over time, revealed by the negative coefficient of lockdowns × time. Second, the effect compounds over time, as captured by the coefficient of lockdowns × time squared plus the coefficient of lagged cumulative cases. We call these effects the hidden benefit of lockdowns. Failure to see this benefit with the naked eye in the raw data leads to the huge public misunderstanding and criticism of lockdowns.

The results of the counterfactual analysis based on the dynamic DID regression suggests that had a lockdown been ordered on March 15, the United States would have had 60% fewer total cases by April 30 (only 1,295 estimated cases per million instead of 3,231 actual cases per million; see Figure 3). The simulations suggest that had no lockdowns been issued by April 23, the United States would have had five times its total cases by April 30 (a massive 17,183 cases per million compared with 3,231 actual cases per million).

One could argue that the effect of lockdowns could be influenced by other interventions that reduced mobility (e.g., nonessential business closures). We analyze whether nonessential business closures occurred simultaneously between each pair

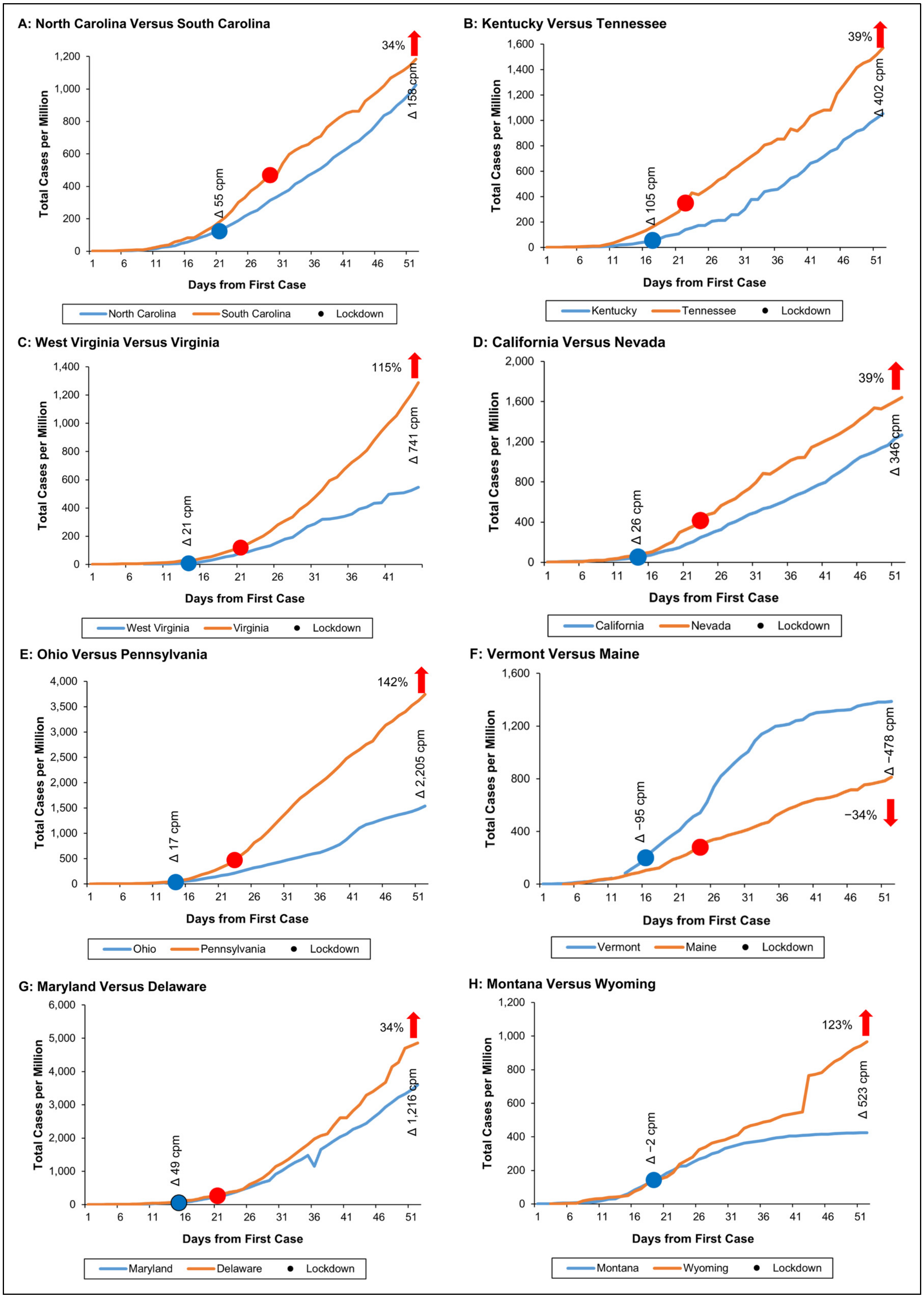

Figure 2. Disease Prevalence in Similar, Neighboring States.

Notes: Panels A through G show pairs of states differing in dates of lockdowns. Panels H through M show pairs of states in which one state had a lockdown and one did not. States where lockdowns were issued later or never are depicted in red, and states with early lockdowns are depicted in blue. The date of the lockdown, if any, is marked with a dot on the curve. cpm = cases per million. (continued)

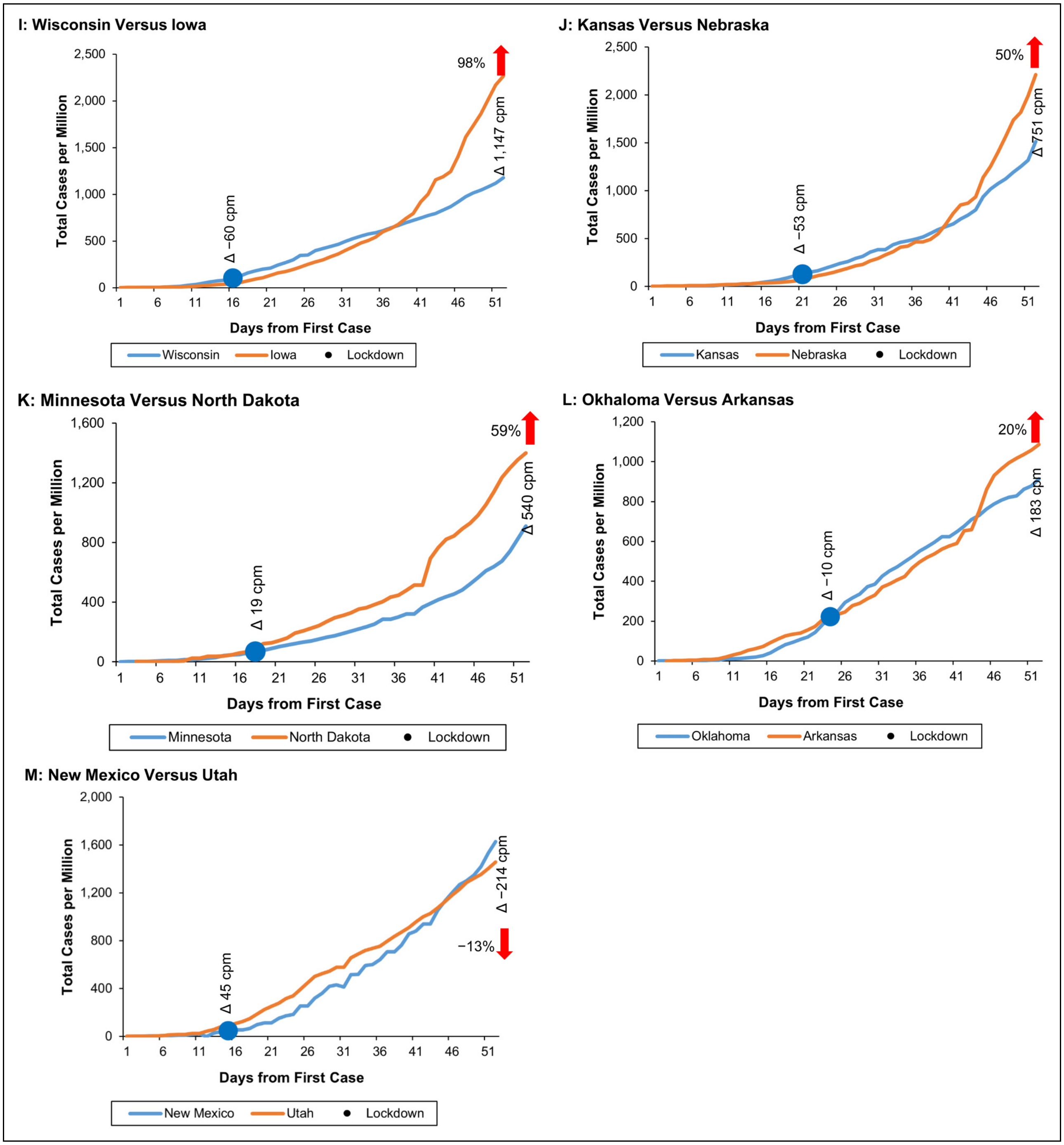

Figure 2. Continued.

of states within each cohort. We find that the time between issuance of nonessential business closure orders between the two states in each cohort is 1.0 day ($\sigma = 1.6$), which is not significantly different from zero ($p = .15$). This implies that the treatment state and the control state ordered nonessential business closures with the same lead time in advance of the lockdown. Thus, our natural experiments control for any effect from the other interventions. Finally, the results of the generalized synthetic control for the 13 cohorts as a robustness check support these findings (see Web Appendix A).

Study 2: Economic and Psychological Costs of Lockdowns to Consumers

We next examine the economic costs of lockdowns at the state and consumer level.

Theory

COVID-19 had the potential for severe economic disruption on top of high mortality if left uncontrolled. The unexpected external shock created an unprecedented shift in consumption

Table 2. DID Analyses: Economic Cost of Lockdowns in Quarterly GDP, Unemployment, Consumer Spending, Customer Satisfaction, and Disease Incidence.

Neighboring State Pair	(A) DID in Quarterly GDP	(B) DID in Monthly Unemployment (%)	(C) DID in Consumer Spending	(D) DID in Customer Satisfaction	(E) DID in Daily Cases per Million (%)	(F) Economic Cost (Per Case Avoided)
Montana–Wyoming	2.6%	−1.9%	−8.5%	−.15	−544 (−128%)	$2,247
Wisconsin–Iowa	−7.2%	−1.8%	−3.2%	−.68***	−1,148 (−98%)	−$19,773
Kansas–Nebraska	−2.2%	−3.5%	−1.7%	−.43***	−751 (−50%)	−$4,836
Minnesota–North Dakota	−9.7%	−1.4%	−12.8%	−.37***	−470 (−52%)	−$72,083
Oklahoma–Arkansas	−9.7%	−1.7%	−6.6%	−.40***	−183 (−20%)	−$91,584
New Mexico–Utah	−6.1%	−1.8%	−12.2%	.11	173 (13%)	$20,625
Mean (SD)	−5.4% (.05)	−2.02% (.01)	−7.5%	−.22***	−480 (−56%)	−$27,567

*$p < .05$.
**$p < .01$.
***$p < .001$.

Notes: Columns A through E present the impact of lockdowns computed using DID analyses for different metrics. For each metric and neighboring state pair, we first calculate Difference 1 as the difference in cases per million in the prelockdown period between the state that implemented a lockdown and the one that did not. We repeat the analyses for the period after the lockdown was issued and compute Difference 2. We then calculate the net DID as Difference 2 minus Difference 1. Column A illustrates an impact of −5.4% on quarterly GDP for 2020 Q2 versus 2019 Q4. Robustness checks for other periods (2020 Q2 vs. 2019 Q2 and 2020 Q2 vs. 2020 Q1) show similar results. Column B illustrates an impact of −2.02% on monthly unemployment for May 2020 versus March/April 2020. Column C illustrates an impact of 7.5% on consumer spending for May 2020 versus March/April 2020. Column D illustrates the impact of 2.2% on customer satisfaction for May 2020 versus March/April 2020, which is significantly larger than the "normal" change in the ACSI quarterly national index. Column E illustrates an impact of 480 on the number of daily cases for May 2020 versus March/April 2020. This translates to a reduction of 56% in the number of daily cases in the state that did not lock down at the end of the observation period. Column F illustrates the economic impact of lockdowns computed as the DID in quarterly GDP in million dollars per DID in daily cases per million. This computation suggests an estimate of $27,567 in lower GDP per case avoided.

patterns, business operations, and government regulations regarding normal business activity. Policy decisions on mandating the type, timing, and extent of NPIs had both a health benefit and an economic cost. Typically, in the first phase, governors issued an emergency declaration, perhaps because it is the least intrusive. The second phase of such interventions included restaurant and gathering restrictions, school closures, and closures of some discretionary businesses. In the third phase, governors issued closures of nonessential businesses. The fourth and most stringent measure was a stay-at-home order (hereinafter, lockdown). Lockdowns were implemented at varying times and durations from mid-March to early April 2020. Each of these lockdowns had various economic and social costs on various stakeholders and severely disrupted local and global economic and business activities.

We use four dependent measures of costs: GDP, unemployment, consumer spending, and customer satisfaction. GDP and unemployment are well-accepted indicators of total economic activity and thus the health of the economy. Consumer spending is the most important component of GDP in the United States and is 70% of the GDP (U.S. Bureau of Economic Analysis 2022). Customer satisfaction has now become a well-accepted measure of consumers' psychological evaluation of the supply of goods and services in the market (Fornell et al. 1996).

Method

Following the logic in Study 1, we use natural experiments between similar neighboring U.S. states that adopted different policies at different times to estimate the impact of lockdowns through a DID regression model. To analyze the economic and psychological impact at the state level, we select the six cohorts in which only one of the two states issued a lockdown. We collect the cost of lockdowns for two points in time: before the lockdown and after the observation period to capture the impact on economic activity.

First, we compare the GDP in the quarter before the first lockdown in the cohort, 2019 Q4, with that in the quarter of the lockdown period, 2020 Q2, for each state in the sample. Second, we compare the monthly unemployment rate in the month before the lockdown, March 2020, with the month after relaxation of the lockdown, May 2020. The data on each metric were obtained from the U.S. Bureau of Economic Analysis at the smallest unit of time available. Third, we obtained data on the percentage change in consumer spending provided by Affinity Solutions to the Opportunity Insights Economic Tracker (https://tracktherecovery.org; Chetty et al. 2020). Following the methods used in Study 1, we consider consumer spending across all industries from March 10 to April 30, 2020, in the six cohorts where only one of the two states in a cohort issued a lockdown. The data include aggregated and anonymized purchase data from consumer credit and debit card spending in

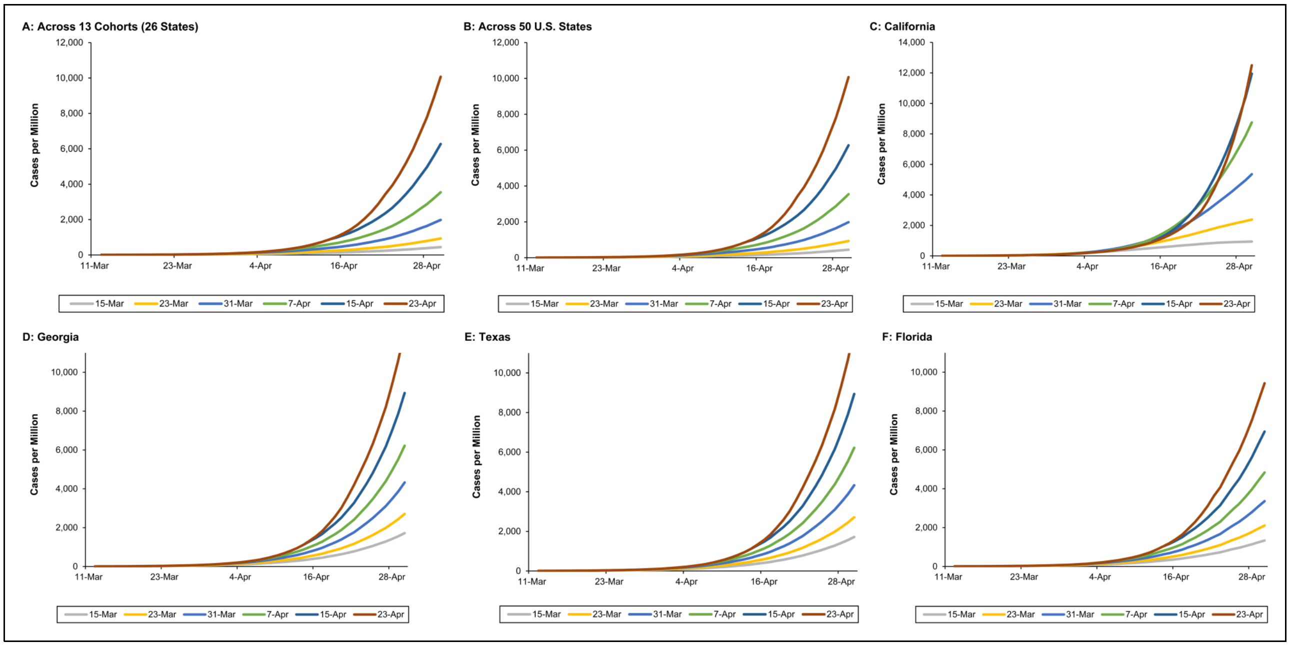

Figure 3. Counterfactual Analysis: Estimates of the Cost of Delays in Enforcing Lockdowns on Disease Penetration.

various industries, such as grocery, entertainment and recreation, health care, restaurants and hotels, retail, and transportation. The daily data are presented as a seven-day moving average and show the percentage change in spending from the index period of January 2020. Fourth, we obtain data on daily customer satisfaction from the ACSI. The ACSI measures customers' overall evaluation of the quality of goods and services, both actual and anticipated (Anderson, Fornell, and Lehmann 1994; Fornell et al. 1996; Johnson and Fornell 1991). Thus, this measure gives information on consumers' overall contentment with goods and services. Our data include daily state-level data on overall customer satisfaction with durable and nondurable products, utilities, retail, and services (1 = "Very dissatisfied," and 10 = "Very satisfied"). We compare the change in customer satisfaction in states without a lockdown with that of states with a lockdown for the period before the lockdown (January 1–February 28, 2020) and the period after the lockdown began (March 1, 2020–April 18, 2020).

Thus, Study 2 analyzes the cost of lockdowns using measures of varying granularity: state GDP is at the quarterly level, state unemployment is at the monthly level, and customer satisfaction and change in consumer spending are at the daily level. Thus, our measures of costs are quite inclusive, as three measures are objective and economic, and one is subjective and psychological.

Results

We find consistent results across pairs of states (see Table 2). First, states issuing lockdowns suffered higher GDP loss (Column A). Across all pairs of states where only one state issued a lockdown, the states with a lockdown suffered 5.4% lower quarterly GDP, on average. Second, we find consistent results with unemployment rates; the average economic cost was a higher monthly unemployment rate of 2.02% (SD = .01) (Column B). We compute the DID values for other reference periods as well. Third, states that locked down had a steeper decline in consumer spending of −7.5% points, on average, compared with those that did not have a lockdown (Column C). Fourth, a comparison of customer satisfaction in the periods before and after the lockdown using consumer-level data suggests a significant drop from 7.99 to 7.74 ($t = 5.42$; $N = 3{,}682$) in states that issued a lockdown. In contrast, we find no significant drop in states that did not issue lockdowns (from 8.00 to 7.90; $t = 1.74$; $N = 2{,}408$). The DID analyses using t-test of unequal variances suggests a difference of −.22 points ($t = -3.42$; $N = 2{,}408$; see Column D of Table 2 and Figure 4). This drop in customer satisfaction is equivalent to a decline of 2.2% in the ACSI. This is a big change relative to the quarterly change in the ACSI of .02 (Anderson and Fornell 2000). This drop probably reflects a negative halo or spillover from consumers' dissatisfaction with lockdowns to their dissatisfaction with brands (Borah and Tellis 2016; Sundar, Kardes, and Noseworthy 2014). We next divide the cost of lockdowns by the gain in reduced infections (estimated in Study 1) for each pair of states. The results are in Column F of Table 2. The estimated cost of avoiding an incremental new infection was, on average, about $28,000 in lower GDP.

Study 3: Effect of Lockdowns on Consumers' Mask Adoption

Did lockdowns encourage (signaling effect) or mitigate (substitution effect) the adoption of masks by consumers?

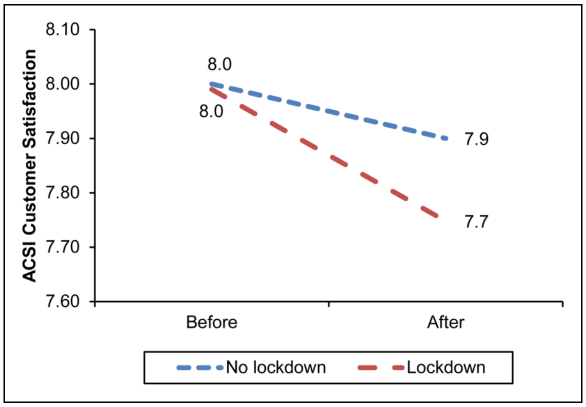

Figure 4. Impact of Lockdowns on ACSI Customer Satisfaction.

Theory

Masks mitigate the airborne spread of the coronavirus and promote public health (Maier and Brockmann 2020). Higher adoption of masks could reduce the spread of the disease, lower the demand on health care infrastructure, and lead to faster economic recovery. Lockdowns could have either of two effects on mask adoption: encourage or discourage consumers' adoption of masks. Heavier adoption of masks may be because lockdowns reinforce the severity of the disease in consumers' minds. Thus, they may be inclined to take every precaution against the disease, including social distancing, washing hands, and wearing masks if they step out for essential activities. In this context, lockdowns could signal to consumers the significant threat of infection, thereby causing them to adopt masks. This is the signaling effect. Here, lockdowns and mask mandates/adoption work as complements (Connelly et al. 2011; Fletcher-Brown, Pereira, and Nyadzayo 2018).

But lack of lockdowns may prompt lighter adoption of masks for two reasons. First, in states where lockdowns were not ordered, governors justified their actions with denial of efficacy of NPIs and antiscience rhetoric (see Study 4). Such discussions and reasoning may have led consumers to rationalize not adopting masks because of a disbelief in the effectiveness of masks, commitment to personal liberties, perceived inconvenience of masks, perceived riskiness of masks, perceived racial profiling, or simply inertia (Kahn and Money 2022; Phelan, Katz, and Gostin 2020).

However, lockdowns could have mitigated the adoption of masks because consumers go outdoors less and are less exposed to others. Thus, lockdowns could suggest to consumers that mask wearing is not important as their mobility and risk of infection is limited. This is the substitution effect, whereby lockdowns substitute for mask usage. With these rival expectations taken into account, Study 3 addresses the following question: did lockdowns increase mask adoption (signaling effect) or reduce mask adoption (substitution effect)?

Method

We use estimates from self-reported mask adoption of 250,000 online consumers between July 2 and July 14, 2020, collected by *The New York Times* and Dynata (2021). Respondents were asked the question "How often do you wear a mask in public when you expect to be within six feet of another person?" We compute the estimated share of people adhering to mask mandates in any state using the following formulation: (%Always + %Frequently) − (%Rarely + %Never). The results reveal significant differences across states regarding mask compliance. We then estimate the following equation:

$$\begin{aligned} \mathrm{MA_i} = {} & \gamma_0 + \gamma_1\mathrm{DP_i} + \gamma_2\mathrm{PP_i} + \gamma_3\mathrm{LDN_i} + \gamma_4\mathrm{EMM_i} \\ & + \gamma_5\mathrm{PD_i} + \gamma_6\mathrm{GDPPC_i} + \gamma_7\mathrm{HD_i} + \gamma_8\mathrm{TEMP_i} \\ & + \gamma_9\mathrm{MT_i} + \varepsilon_i, \end{aligned} \tag{2}$$

where $\mathrm{MA_i}$ is the average consumer mask adoption in a state, $\mathrm{PP_i}$ represents political polarization (dummy variable that equals 1 if the governor of a state is Democratic for state i), and other variables are as defined previously.

Results

Models 1 and 2 test the effects of lockdowns and mask mandates, respectively (Table 3). Each had a positive effect on consumers' mask adoption over and above the effect of disease penetration in the state. Model 3 tests the effect of both and reveals that the combination of lockdowns and mask mandates positively influenced mask adoption. Model 4 adds key control variables. Model 5 adds dummy variables as controls for each cohort pair. The results of Model 4 suggest that both information on disease penetration (8.71×10^{-6}; $t = 2.7$) and governmental interventions in the form of mask mandates (.002; $t = 2.6$) and lockdowns (.179; $t = 3.04$) drove consumer adoption of masks. Thus, lockdowns had a positive effect on consumers' mask adoption even after controlling for mask mandates. Lockdowns and mask mandates also had a bigger effect than just disease penetration. The results are consistent even with the addition of control variables (Model 5) and across 50 states (Table W2 in Web Appendix B).

Study 4: Reasons U.S. Governors Delayed Lockdowns at the Start of the Pandemic

One could also argue that governors of states that had a high number of cases knew their states would benefit from lockdowns, and so implemented lockdowns, thereby making the treatment nonrandom in our natural experiment setting. The treatment assignment (i.e., the decision to issue a lockdown) is random only if the governor ignores the potential effect of treatment. A nonrandom treatment assignment would be a case where treatment is ordered to those who would benefit the most from it, leading to a potential violation of the assumption of unconfoundedness.

Therefore, in Study 4, we examine what factors may have influenced governors' decision to implement lockdowns, to rule out the potential violation of the unconfoundedness assumption in Study 1. For example, Governor Greg Abbott of Texas questioned the need for masks by claiming that the

Table 3. Drivers of Adoption of Masks by Consumers in 26 States.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	.271**	.378***	.236**	−.351	−.055
Disease penetration	1.80×10^{-5}**	1.16×10^{-5}*	1.34×10^{-5}**	8.71×10^{-6}	2.54×10^{-6}
Political polarization	.064	.006	−.030	−.044	.025
Lockdowns	.235**		.205**	.179**	.055
Mask mandate		.003**	.002**	.002**	.001**
Population density				.006	.008**
GDP per capita				−.002	−.003
March humidity (%)				.005*	.004
Average temperature (°C)				.001	-1.61×10^{-5}
Average metro traffic				.001	.002
Cohort 1 (Kentucky–Tennessee)					−.072
Cohort 2 (West Virginia–Virginia)					.007
Cohort 3 (California–Nevada)					−.058
Cohort 4 (Ohio–Pennsylvania)					−.081
Cohort 5 (Vermont–Maine)					.150
Cohort 6 (Maryland–Delaware)					.049
Cohort 7 (Montana–Wyoming)					−.339**
Cohort 8 (Wisconsin–Iowa)					−.112
Cohort 9 (Kansas–Nebraska)					−.234**
Cohort 10 (Minnesota–North Dakota)					−.313
Cohort 11 (Oklahoma–Arkansas)					−.089
Cohort 12 (New Mexico–Utah)					−.045
Adj. R^2	.4	.64	.62	.68	.87
N	26	26	26	26	26

*$p \leq .05$, **$p \leq .01$, ***$p \leq .001$.

incidence rates dropped even after withdrawal of mask mandates in certain areas (Gillman 2021; Warth 2020). Similarly, Governor Brian Kemp of Georgia barred local county officials from mandating mask use but advocated for consumers to use masks. As early as April 2020, Dr. Fauci, the United States' top infectious disease expert, exclaimed, "I don't understand why that's not happening!" in response to a question from CNN's Anderson Cooper about why governors had not issued orders (LeBlanc 2020). Study 4 is designed to analyze to what extent governors' decisions depended on medical science (the spread of COVID-19 in their states) versus other nonmedical variables. Investigating whether medical science played a large part in governors' decisions could reveal the wisdom of relying on existing policy to combat current and future pandemics or exploring other potential policies. We next describe the theory, method, and results of this study.

Theory

In the early stages of the pandemic, with little recent experience or memory of managing pandemics in the United States, numerous agents were in conflict: governors as chief executives of their states, medical experts as advisors, and firms and consumers as both collaborators and beneficiaries of their actions and advice. Why might governors differ in their decision to control the spread of COVID-19? At least four theories from epidemiology and behavioral science suggest answers: the science of infectious disease, political affiliation, information cascades, and policy transfer.

Disease transmission. In the early days of the pandemic, when consumers' awareness of the severity of the disease and means of mitigating its spread was low (despite guidance from the Centers for Disease Control and Prevention), interventions seemed to be plausible means of controlling the spread of the disease. COVID-19 spread exponentially in most countries of the world due to a lack of pharmaceutical interventions and poor NPIs. An important indicator of how much an infectious disease has spread in a region is disease penetration, the number of cumulative cases divided by the region's population. Dr. Fauci believed, as did most medical experts, that governors' decisions would be based on medical science about the spread of the disease. We can empirically test governors' belief in the importance of disease spread versus the loss of GDP or personal liberty by examining whether governors' intervention orders relate to the penetration level of COVID-19 in their state's population.

Policy transfer. The theory of policy transfer describes the process by which policies, actions, and ideas in one political setting influence the development and implementation of such policies, actions, and ideas in another political setting exposed to the first (Dolowitz and Marsh 2000). In the present context, the theory suggests that governors in one state would have been influenced by the policies, ideas, and actions of governors of other states, who had acted earlier in responding to combat the pandemic. In the case of interventions, such policy transfer would occur if a governor observed one of two outcomes: (1) that governors who delayed intervention had unfavorable outcomes in terms of higher cases, hospitalizations, or deaths; or (2) that governors who acted early had favorable outcomes in terms of moderation or control of the spread of COVID-19, favorable press, or favorable consumer support expressed through polls, social media, or public actions. Thus, if governors whose states had a later onset of the disease took less time to adopt a NPI than those with an earlier onset of the disease, we may infer that policy transfer may have occurred from the latter to the former.

Political polarization. According to the theory of political polarization, political parties in the United States (primarily Republicans and Democrats) are polarized in their opinions about major interventions due to different values placed on outcomes of those interventions (Canen, Kendall, and Trebbi 2020; Cornelson and Miloucheva 2020; Fiorina and Abrams 2008; Hersh 2019). Republican and Democratic governors disagreed on the efficacy of various interventions to control the spread of COVID-19. Democratic governors seemed to put greater value on the health benefits of consumers (McGee 2020). In contrast, Republican governors seemed to put greater value on avoiding costs to firms and workers (Justice 2020). This political affiliation could lead to differences in the type and timing of interventions, creating policy gaps and hindering the implementation of effective NPI policy.

Information cascades. According to the theory of information cascades, when there is imperfect information and uncertainty on either attributes or outcomes of a decision, individuals tend to decide by observing the behavior of others in similar positions (Bikhchandani, Hirshleifer, and Welch 1992; Macy et al. 2019). Such information cascades are typically observed in the rush to buy a popular new product, buy stocks in a bull market, or sell stocks in a bear market (Golder and Tellis 2004; Johnson and Tellis 2005). In the case of interventions, if one governor takes the lead and issues an NPI order, others who are on the fence may also follow with the same intervention. This would result in governors issuing interventions in close sequence to each other, even though their states may be at various stages in disease penetration.

Method

We specified and ran a multivariate, time-varying hazard model to get precise estimates of the effect of our theory-based variables on the hazard rate of ordering an NPI. Since an NPI order is a time-dependent event influenced by other time-invariant and time-dependent variables, we selected variables known to affect the disease spread: population demographics (Therneau, Grambsch, and Fleming 1990), mobility (Flaxman et al. 2020; Jones et al. 2008), and economic affluence (Kraemer et al. 2020; Walker et al. 2020) as well as governors' demographics. We include interaction terms of disease penetration × each of the governors' actions. Given the temporal distribution and clustering of interventions, we include the impact of the immediate prior NPI on later interventions. We define prior intervention as the most recent intervention prior to the event under consideration. We model the hazard rate of a governor issuing an NPI thus:

$$\begin{aligned} h_{it}^{NPI} &= \psi[\chi_1 DP_{it} + \chi_2 PP_i + \chi_3 IC_{it} + \chi_4 PT_{it} + \chi_5 PNPI_i \\ &+ \chi_6 PD_i + \chi_7 MT_i + \chi_8 BA_i + \chi_9 GDPPC_i + \chi_{10} II_i + \chi_{11} GE_i \\ &+ \chi_{12} GG_i + \chi_{13} PT_i \times DP_i + \chi_{14} IC_i \times DP_i + \epsilon_{it}], \end{aligned}$$

where

IC_{it} = information cascade (number of governors issuing NPI in the previous 3 days in state i on day t);
PT_i = policy transfer (days to disease onset in state i);
$PNPI_{it}$ = prior interventions (dummy variable that equals 1 if a prior NPI has been issued in state i on day t);
BA_i = total weekly wages in 2019 Q1 in state i;
GE_i = education level of governor of state i; and
GG_i = gender of governor (dummy variable that equals 1 if the governor in state i is female).

Other variables are as defined previously. We obtained the data on daily new cases of COVID-19 for each state in the United States from Flevy, supplemented by data from the Johns Hopkins Coronavirus Resource Center and the coronavirus news tracking website Worldometer. We obtained state-level data on population density and population of the states and major cities from the U.S. Census, data on passenger miles in the biggest U.S. cities from the Federal Aviation Administration, metro traffic data from the U.S. Department of Transportation, the number of business establishments from the Bureau of Labor Statistics, income inequality data (Gini coefficient) from the U.S. Census Bureau, and GDP per capita from the U.S. Bureau of Economic Analysis. We obtained governors' education level, gender, and dates of interventions from state governments' websites (Fullman et al. 2020). These variables influence decisions of female governors, who may be more liberal on social issues than male governors (Dickes and Crouch 2015). These data were supplemented with data from online resources of the National Governors Association and the Kaiser Family Foundation. We constructed a data set in which each state has one record for every day since the first case in the state until April 30, 2020. We tested the hypotheses with this model using a pooled time series × cross-region database. We use the counting style of input (Fullman et al. 2020) to account for time-varying covariates and to prepare the data to test the hazard model.

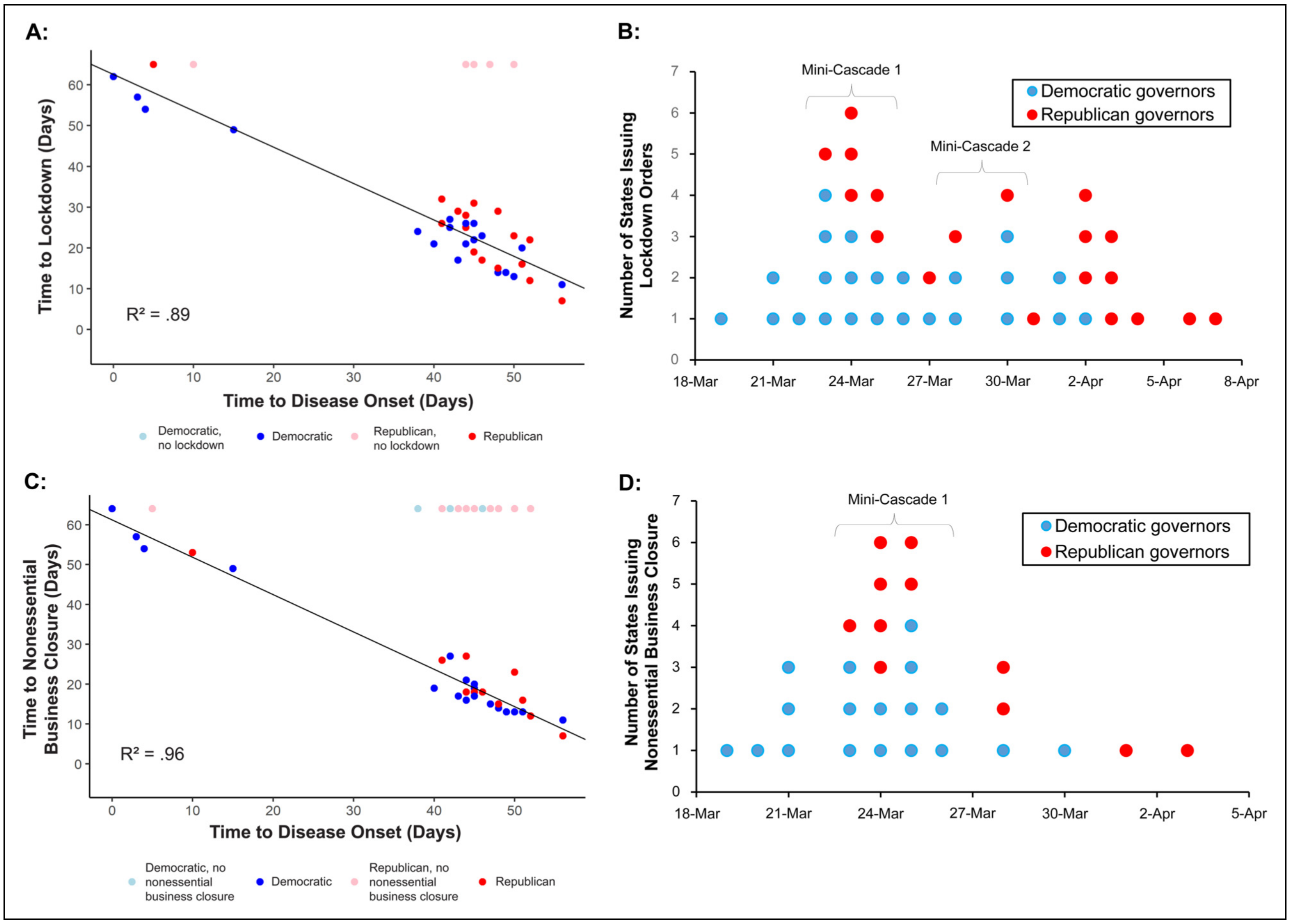

Figure 5. Model-Free Results Revealing Influence of Policy Transfer, Political Affiliation, and Information Cascades.
Notes: In Panel A, each state is plotted and colored according to the governor's political affiliation and lockdown status as of April 30, 2020. Panel B shows mini cascades in lockdown decisions. Panel C is similar to Panel A but shows the status of nonessential business closure decisions. Panel D is similar to Panel B but shows nonessential business closure decisions.

Results

This subsection presents model-free results, model results, model fit statistics, and the generalizability of results to other interventions.

We examine the time to NPI (the number of days between the first case in a state and the date of the NPI) and the drivers of governors' decisions regarding the final intervention, the lockdowns. Figure 5, Panel A, plots governors' decisions on time to disease onset versus time to lockdown. The figure provides model-free results for the effect on this NPI of three of our four theories: policy transfer, information cascades, and political affiliation. First, a strong negative correlation exists between time to disease onset and time to lockdown. This negative correlation indicates that early in the spread of the disease, governors of some states (e.g., Washington, California, Arizona) took a long time (50–60 days) to issue lockdowns. However, as the disease advanced and the costs in terms of infections, hospitalizations, and deaths became more evident, lockdowns were issued more quickly after the first case in each state (e.g., the governor of West Virginia took only seven days from disease onset to issue a lockdown). We can explain this temporal effect as policy transfer by governors about the costs of delay and the benefits to quick intervention. The explained variation (R^2) is 89%, which is quite high for cross-sectional data.

Second, more red dots (Republican governors) lie above than below the black trend line and vice versa for blue dots (Democratic governors). This pattern suggests that Republican governors acted later than Democratic governors in issuing lockdowns. Thus, political affiliation seems to account for some of the variance in the governors' decisions among those who acted. In addition, all the governors who did not act are Republicans. This result is even stronger evidence of the impact of political affiliation. Third, two clusters of states occur along the trend line, one at the top left quadrant and the other at the bottom right quadrant. After controlling for learning and political affiliation, this clustering may be due to mini cascades. To investigate this issue more deeply, we plotted a histogram of the number of states issuing interventions on a given day (Figure 5, Panel B). It provides explicit evidence of mini cascades in lockdowns. The first mini cascade seems to have started on March 19 when Governor Gavin Newsom of California imposed a lockdown (Newsom 2020), sparking

Table 4. Hazard Model Testing Four Theories to Explain Why Governors Ordered Lockdowns Against COVID-19.

	Model 1		Model 2		Model 3	
Independent Variables	**Hazard Ratio**	**Confidence Interval**	**Hazard Ratio**	**Confidence Interval**	**Hazard Ratio**	**Confidence Interval**
Theoretical variables						
Disease penetration	1.0***	[1.0, 1.0]	1.0***	[1.0, 1.0]	1.0*	[1.0, 1.0]
Political polarization	2.5***	[2.3, 2.7]	2.3***	[2.1, 2.5]	2.0***	[1.9, 2.2]
Information cascades	1.4***	[1.3, 1.4]	1.5***	[1.5, 1.5]	1.6***	[1.6, 1.7]
Policy transfer	1.1***	[1.1, 1.1]	1.1***	[1.1, 1.1]	1.1***	[1.1, 1.1]
Prior intervention: nonessential business closure	6.5***	[5.9, 7.3]	10.7***	[9.6, 12.0]	12.7***	[11.3, 14.2]
Control variables/ interactions						
Population density	—	—	1.2***	[1.1, 1.3]	1.4***	[1.3, 1.5]
Reduction in metro traffic	—	—	1.0***	[1.0, 1.0]	1.0***	[1.0, 1.0]
Business activity	—	—	1.0***	[1.0, 1.0]	1.0***	[1.0, 1.0]
Income inequality	—	—	1.5***	[1.4, 1.5]	1.4***	[1.4, 1.5]
Governor's gender	—	—	1.3***	[1.2, 1.5]	1.4***	[1.3, 1.6]
Policy transfer × disease penetration	—	—	—	—	1.0***	[1.0, 1.0]
Information cascades × disease penetration	—	—	—	—	1.0***	[1.0, 1.0]

*$p \leq .05$.
**$p \leq .01$.
***$p \leq .001$.
Notes: The hazard ratio measures the impact on the conditional probability of the event (NPI) per unit change of an independent variable. It may be interpreted as the number of times the event is more likely to occur for a unit increase in the independent variable. Political polarization is defined as the governor's political party (1 if Democratic); information cascade represents the number of states issuing an NPI in the last three days; policy transfer represents the number of days between the first case in the United States and the first case in the state; reduction in metro traffic is the percentage change in March 2020 versus March 2019; business activity is defined as the average weekly wages in 2019 Q1 from the Bureau of Labor Statistics; income inequality uses the Gini coefficient from the U.S. Census Bureau's Gini index as tabulated in the 2009 American Community Survey; prior intervention is defined as the most recent less stringent intervention imposed by the governor; and governor's gender is defined as 1 if the governor is female.

similar orders across 17 states in the next four days, mostly by Democratic governors. The second mini cascade seems to have started on March 28, sparking lockdowns in ten more states in the next three days.

To test the generalizability of these results, we repeated the model-free analyses for the next most stringent NPI, the closure of all nonessential businesses. Figure 5, Panels C and D, replicates the previous findings. An examination of other interventions also provides model-free evidence in support of the influence of policy transfer, information cascades, and political affiliation on governors' interventions (Figures W1A through W1E in Web Appendix A).

Table 4 presents the results of the hazard model. Model 1 contains only the theory-based variables plus the prior intervention. Model 2 additionally includes control variables, and Model 3 additionally includes interaction terms. Except for disease penetration, the effects of all variables hypothesized to affect the hazard rate of interventions are positive, significant, and in the expected direction. The effect of disease penetration on the hazard rate of lockdowns, whether included jointly or individually, is 1.0. This result implies that disease penetration does not affect the hazard rate of a governor issuing a lockdown. Even after controlling for other variables, the effect of disease penetration is lower than that of the other three theory-based variables (Models 2 and 3). The governor's political affiliation seems to have a large, significant effect, suggesting that political affiliation played a big role in governors' decisions. The expected hazard rate is two times higher for Democratic governors than for Republican governors. The Kaplan–Meier curves show that the curves of Democratic governors lie significantly below those of Republican governors, implying earlier intervention by the former ($p < .0001$; Figure 6). Cascades, the number of states issuing a lockdown in the prior three days, also have a large impact on the hazard rate of lockdowns. Each additional governor who announced a similar intervention in the prior days increased the hazard rate of a governor's intervention by 1.5 times. Policy transfer, captured by the number of prior governors issuing lockdowns, also has a significant impact on the type and timing of interventions. The estimated effect suggests that each day later a state had its first case relative to the first reported case in the country, the governor was about 1.1 times more likely to order a lockdown than on the previous day. This effect translates to the hazard rate of a governor ordering an NPI doubling for every week later a state had its first case relative to the first case in the country. The effects of political affiliation, cascades, and learning on governors' interventions are significant and robust across all models. In contrast to the effects of these three theory-based variables, the extent of

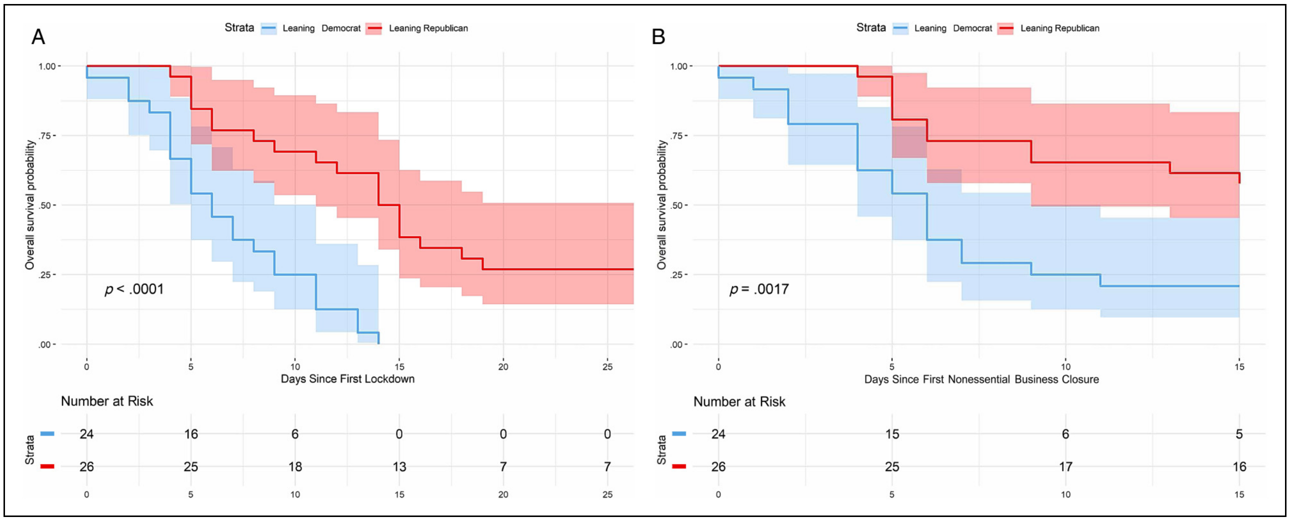

Figure 6. Kaplan–Meier Curves.
Notes: The survival curves of states with Democratic governors consistently lie below the survival curves of states with Republican governors ($p < .01$).

disease penetration in a state appears to have no effect. The hazard ratios of all control variables are also in the expected direction. None of the interaction terms of disease penetration with policy transfer or of disease penetration and information cascades, intended to ascertain whether the effect occurred indirectly, was significant, suggesting no impact of these variables on the governors' decisions (Model 3).

We test the generalizability of findings by replicating the previous analyses with the less stringent NPI measures: emergency declaration, school closure, business closure, restaurant closure, and gathering restriction, respectively (Tables W3a through W3e in Web Appendix B). All the analyses for these other interventions replicate the results obtained for lockdowns. Most importantly, the spread of the disease has a minimal effect on interventions, whereas the effect of political affiliation is consistently high and dominant. We provide additional analyses of model fit using four well-established metrics:

- Hit rates: The model's sensitivity is 80%, and its specificity is 75% (see Table W4a in Web Appendix C).
- Concordance statistic: The predictive accuracy of the hazard model can also be estimated by Harrell's concordance statistic (Gönen and Heller 2010), which estimates the agreement between observed and predicted outcomes. The results indicate excellent prediction at .92 (see Table W4b in Web Appendix C).
- Receiver operating characteristic (ROC): Figure W3a in Web Appendix C presents the ROC curves to assess the predictive power of the model. It plots the sensitivity against 1 minus the specificity for possible values of the key variable. Complete lack of prediction is indicated by the solid diagonal line from the origin to the top right. The model's best prediction is the curve that hugs the vertical left axis and the horizontal top axis. The area between these two curves reflects the predictive power of the model. The results of the proposed model show substantial prediction power even with longer times to NPI.
- Area under the ROC curve (AUC): Figure W3b in Web Appendix C presents the classification accuracy of the occurrence (vs. nonoccurrence) of the event as the AUC. An AUC of .5 indicates no discrimination between cases and controls, whereas an AUC of 1.0 indicates perfect discrimination. The figure displays the AUC curve (blue line) and the 95% confidence limits for the fitted model (blue area around the line). The results indicate high levels of discrimination over the entire range of observed days from NPI. The integrated time-dependent area under the curve, which averages all available AUC statistics over time, is .80.

Discussion

This section highlights the contributions, findings, limitations, and implications of the findings.

Contributions

This research makes the following three contributions. First, we use multiple methods to show that lockdowns causally reduced the spread of COVID-19 but at considerable cost in terms of reduced GDP, consumer spending, customer satisfaction, and increased unemployment. Second, we use a novel association of lockdowns and mask mandates to show that lockdowns increased mask adoption rather than substituting for mask wearing. Third, we also show how simple empirical models often used in marketing and validated by empirical evidence (hazard analysis and DID regression) can be used to analyze public health crises with important implications for managers and consumers. Traditional models in epidemiology suffer from too many strong assumptions about the theoretical spread of the disease.

Implications

These four studies also have critical importance for public policy makers, businesses, and consumers, as governors continue to consider their state's response to the COVID-19 pandemic or in the event of a new pandemic. First, the common assumption among laypeople and experts is that wearing masks is an alternative to lockdowns. In contrast, our study is the first to show that lockdowns increased mask adoption by consumers. The main reason may be that lockdowns heighten the urgency for consumers to adopt preventive measures. In other words, a lockdown works as a signal of the severity of the disease. However, policy makers should not issue lockdowns merely to signal the urgency of a pandemic. They should do so on the basis of a cost–benefit analysis. Our results imply that avoiding lockdowns in the belief that consumers would adopt masks may backfire.

Second, our study is the first to show the trade-off between reduction in disease from lockdowns versus their economic costs. We find that lockdowns reduced 480 infections per million consumers at the cost of 5.4% reduction in GDP and 2% increase in unemployment for the following quarter. These results give policy makers clear criteria for decision making. We were unable to compute the direct cost of GDP per death avoided because deaths in hospitals are reported by location of the hospital rather than domicile of the state of the person who died. Thus, states with large hospitals end up with a higher death rate than those with small or no hospitals. Therefore, we computed the deaths avoided indirectly using the reported COVID-19 mortality. In March 2020, the infection mortality rate, defined as the proportion of people infected with COVID-19 who died, was reported to be 3.4% (World Health Organization 2020). Combining this metric with the estimated cost of avoiding an incremental new infection of about $28,000 in lower GDP, we find that a rough estimate of the expected cost of a life saved due to lockdowns would be around $810,000. Governors can compute this value for each of their states and decide whether the improvements in health are worth the economic costs.

Third, consumers bear an enormous responsibility. They need to observe low-cost preventive measures like mask wearing, social distancing, and personal hygiene to obviate the need for lockdowns. Lockdowns have enormous economic costs. A proactive decision to minimize the disease spread would lower these negative outcomes. But if lockdowns are imperative, imposing them is preferable to avoiding them. Policy decisions that pose a minimal limitation on consumer movement can help mitigate the economic costs. Examples include whether and where to mandate the issuance and adoption of proof of vaccination, also called vaccine passports. Although such proof of vaccination has been required for many illnesses, such as tuberculosis, it is new for pandemics like the COVID-19 pandemic. These certifications can help increase health and safety for all and allow businesses to manage the perception of risk by controlling access to those who have been inoculated. These steps would hasten the return to normalcy. Industries like retail, entertainment, and travel could be among the largest beneficiaries.

Fourth, we show how tensions between medical science and behavioral theories have fundamental implications for public policy, management, and consumers. These findings show the urgent need for the federal government and public health officials to work with all governors to rely more on the science of disease spread rather than on political affiliation, policy transfer, and information cascades. Learning from the cost of delay in locking down the state would help them make informed decisions in the future.

Fifth, we show that lockdowns, by themselves, depress consumer spending and scores on customer satisfaction as measured by the ACSI. Marketing managers need to consider advertising and promotion programs to mitigate the ill effects of lockdowns. Marketers faced with a lockdown could incorporate anticipated shifts in consumer confidence and spending into their plans.

Limitations

As with other nonrandomized controlled trials, we acknowledge several limitations of this work. First, the availability of richer and more valid data, such as measures of belief in personal liberty, would allow for a better exploration of these research questions (Skiera et al. 2020; Weinberger et al. 2020). Second, we do not explicitly control for other potential drivers like geographical proximity of states to major disease epicenters, strictness of the enforcement of interventions, or cultural differences in personal hygiene. Such controls would require detailed data unavailable to us. Third, we focus on disease prevalence and not deaths. Deaths are predominantly recorded by hospitals, resulting in attribution of deaths to states with medical facilities rather than to the deceased individuals' place of residence. Fourth, we do not explicitly control for differences in the scope, type, and sample of testing across states. Future research may address these limitations.

Future Research

COVID-19 continues to exist; new variants may arise, and other pandemics may occur in the future. In each similar pandemic, governors must make critical decisions to impose NPIs in the event of a surge in cases. Our findings also raise many questions for future research on how marketing and marketers could help further address the key findings from each study.

With regard to Study 1, future research can explore how public service announcements could be created more effectively, resulting in better compliance with precautionary health care activities. Researchers can also explore the "hidden benefit" of lockdowns and the role marketers can play in educating the public about this effect, as the negatives or limitations of restrictive actions like lockdowns are immediately apparent, but the benefits become evident much later.

Future research building on Study 2 can explore the economic cost of lockdowns on additional consumer metrics including consumer savings (e.g., cash savings/retirement accounts), consumer debt, and consumer access to a suite of basic needs and services (e.g., food availability/stockouts, health care accessibility, elder care). Researchers may also explore longer-term effects on the economy, the effects on mental health of consumers, the impact of stimulus packages, and the above-average impact of lockdowns and related measures on marginalized communities. Given the high variability of the benefits and costs of lockdowns between state pairs, future research may explore other potential explanatory factors that influence the trade-offs.

Future research related to Study 3 could explore the antecedents of consumer hesitancy toward preventative health care measures like mask wearing and how that hesitancy can be addressed. Finally, with regard to Study 4, future research may explore what marketers and the marketing field could do to promote more viable and more optimal decisions at the governor level.

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