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Abstract

In the absence of a vaccine or more effective treatment options, containing the spread of novel coronavirus disease 2019 (COVID-19) must rely on non-pharmaceutical interventions. All U.S. states adopted social-distancing measures in March and April of 2020, though they varied in both timing and scope. Kentucky began by closing public schools and restaurant dining rooms on March 16th before progressing to closing other non-essential businesses and eventually issuing a “Healthy at Home” order with restrictions similar to the shelter-in-place (SIPO) orders adopted by other states. We aim to quantify the impact of these measures on COVID-19 case growth in the state. An event-study model allows us to link adoption of social distancing measures across the Midwest and South to the growth rate of cases, allowing for effects to emerge gradually to account for the lag between infection and positive test result. We then use the results to predict how the number of cases would have evolved in Kentucky in the absence of these policy measures – in other words, if the state had relied on voluntary social distancing alone. We estimate that, by April 25, Kentucky would have had 44,482 confirmed COVID-19 cases without social distancing restrictions, as opposed to the 3,857 actually observed.

Keywords: Kentucky, COVID-19, Coronavirus, Social Distancing, Event Study, Non-Pharmaceutical Interventions

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I. Introduction

The COVID-19 pandemic has quickly become not only the defining public health challenge of our time but also the greatest economic threat since the Great Recession. As cases began to emerge in the United States in March of 2020, states and localities implemented social distancing restrictions that varied in timing and scope. In Kentucky, the first major interventions took effect on March 16, when Governor Andy Beshear closed public schools and the dining-in sections of restaurants and bars (Beshear, 2020). Governor Beshear soon closed other non-essential businesses, banned large gatherings, and ultimately declared that the state's "Healthy at Home" directive was functionally equivalent to the shelter-in-place orders (SIPOs) enacted in most states (Baker, 2020; Aulbach, 2020). These suppression measures are recommended as a necessary step in a recent road map by American Enterprise Institute to reopening the economy (Gottlieb et al., 2020).

The "Opening Up America Again" guidelines issued by the Trump administration identify conditions when a state can safely proceed to a gradual reopening. These include a downward trajectory of documented cases within a 14-day period (or positive tests as a percent of total tests), sufficient health care capacity such that hospitals can safely able to treat all patients without crisis care, and a robust testing program in place for at-risk healthcare workers, including emerging antibody testing (The White House, 2020). With states beginning to gradually reopen parts of their economies as part of this phase, evidence to help policymakers strike the best balance between protecting public health and avoiding continued economic collapse is urgently needed. If less invasive restrictions such as school closures and large event bans can achieve nearly the same reduction in COVID-19 case growth as more comprehensive measures such as SIPOs, then extreme restrictions are likely not necessary moving forward. In

contrast, if strong measures are the only way to achieve substantial mitigation, then the benefits of lengthy SIPOs could outweigh their substantial costs.

Theoretically, the extent to which SIPOs flatten the curve once closures of schools and many types of businesses are already in place is unclear. On one hand, SIPOs may be largely redundant if the main sources of community spread have already been eliminated. SIPOs are also difficult to enforce and many (including Kentucky's) do not specify formal penalties for violations (Mazziotta, 2020). SIPOs may therefore be best characterized as a “nudge” with social pressure being the main channel through which they could work (Thaler and Sunstein, 2009). On the other hand, SIPOs might be necessary if closing gathering places like schools and restaurants simply redirects social activities towards other settings, such as parks or houses. Explicitly prohibiting such gatherings in all settings, including informal ones, may be necessary to substantially slow the spread.

Epidemiological models link the frequency and nature of social interactions to case growth but tend to simply assume that particular government restrictions can reduce these interactions to a given level. For instance, Thunstrom et al. (forthcoming) rely on measures from the 1918 influenza pandemic to assume that social-distancing measures will reduce the average contact rate by 38 percent. The well-known Imperial College London and University of Washington models project case trajectories with social distancing versus no social distancing, but they are agnostic about how the specified level of social distancing will be achieved (Ferguson et al., 2020; The Institute for Health Metrics and Evaluation, 2020). Economists' policy evaluation toolkit can therefore help fill a critical void in the literature.

Accordingly, recent studies provide evidence on the effectiveness of these social-distancing measures in the U.S., but their relevance for Kentucky is unclear. Abouk and Heydari

(2020), Andersen (2020), Engle, Stromme and Zhou (2020), Gubta et al. (2020), Painter and Qiu (2020), Siedner et al. (2020) and Tucker and Yu (2020) all use publicly available aggregated mobility data obtained from cell phones to document the extent to which social distancing restrictions influence movement. Friedson et al. (2020) find that California's SIPO reduced COVID-19 case growth in the first three weeks following its implementation, while Dave et al. (2020) find evidence that SIPOs are most effective in early adopting states and those with high population densities. Siedner et al. (2020) find that early social distancing restrictions of any type, but not later SIPOs, decreased states' COVID-19 growth rates. In cross-sectional state-level analyses, Orazem (2020) and Reilly (2020) do not find evidence that SIPOs inhibit COVID-19 caseload growth. Courtemanche et al. (2020) estimate an event-study model with all U.S. counties and show that SIPOs strongly reduced the growth rate of COVID-19 cases, while closing entertainment-related businesses had a moderate effect. However, they find no evidence that closing public schools or banning large gatherings reduced case growth without a broader SIPO also being in place.

We conduct a similar analysis to Courtemanche et al. (2020) but with a unique focus on Kentucky – a state whose early, aggressive actions to curb the spread of coronavirus, particularly relative to the slower response by its neighbor Tennessee – received international attention (Lenthang, 2020; National Public Radio, 2020). First, rather than estimating the model for the entire U.S., we limit the sample to counties in the states in the South and Midwest Census Regions, which are more comparable to Kentucky than the Northeast and West Census Regions that we leave out (U.S. Census Bureau). We then use the results to estimate how the COVID-19 curve could have evolved in Kentucky without government-imposed social distancing restrictions – i.e. relying only on voluntary social-distancing measures taken by individuals and

businesses. In effect, the model leverages the fact that other states and counties in the South and Midwest implemented different social distancing restrictions than Kentucky, or implemented the same restrictions at different times, to make counterfactual predictions about what would have happened in Kentucky under different policy choices.

Similarly to the Courtemanche et al. (2020) results for the entire U.S., we find that SIPOs were the most effective policy in slowing the spread of COVID-19 in the Midwest and South; closing entertainment-related facilities such as restaurants, bars, gyms, and entertainment centers was the second most effective; and closing schools and banning large events in the absence of a SIPO had no statistically or economically significant effect. The combined impact of all of these measures in Kentucky was to limit the number of confirmed COVID-19 cases to 3,857 by April 25, compared to the 44,482 that our model predicts would have occurred in their absence.

II. Data

Our dataset includes daily official case counts from each of the 2,477 counties (or equivalents such as parishes and independent cities) in the South and Midwest. Following Courtemanche et al. (2020), our sample period starts on March 5, 2020, the day the U.S. reached 100 total cases (and the starting point on many graphs in the popular press of COVID-19 case growth). This was also the day before Kentucky's first official case. Our sample period ends on April 25. The resulting sample size is 128,804 county-by-day observations. In all analyses, each county observation is weighted by population using 2018 estimates (United States Department of Agriculture, 2019).

Our COVID-19 case data come from the Johns Hopkins Center for Systems Science and Engineering's 2019 Novel Coronavirus COVID-19 Data Repository, which includes information from an array of sources such as government and independent health institutions (Johns Hopkins

University & Medicine, 2020). We use these data to compute each county's daily exponential growth rate in confirmed COVID-19 cases, which is equal to the natural log of daily COVID-19 cases minus the log of daily COVID-19 cases on the prior day, multiplied by 100 to be interpretable as percent. Following Bursztyn et al. (2020), we add one to the case totals to prevent the log of cases from being undefined when there are no cases in a county on a given day. The sample mean is 507 cases, so adding one is only a small distortion that does not materially impact the results. The growth rate was multiplied by 100 and can be read as percentage point changes.

Our information on state and local government social-distancing interventions comes from Killeen et al. (2020). As explained in Courtemanche et al. (2020), we corrected a few errors in the dates, and our final lists of state- and county-level policies are shown in that study. The majority of the policy variation, including all variation in Kentucky, is at the state level, but a number of counties implemented restrictions prior to the state, and our use of county-level data allows these restrictions to be incorporated.

As in Courtemanche et al. (2020), we study four separate interventions. One is whether public schools were closed, with the closure coded as taking effect on the first cancelled school day. This was March 16 in Kentucky. Another is whether there was a closure of at least some entertainment-related businesses. Formally, this is an indicator for either restaurant dining areas (including bars) or gyms/entertainment centers being closed. In practice, the two types of closures were almost always enacted at either the same time or close to it. In Kentucky, restaurants were closed on March 16 and gyms, entertainment centers, and other businesses that involve gathering were closed just two days later; this variable is therefore set to one starting on March 16. The third intervention is a ban on large gatherings that is at least as restrictive as 500

or more people. Most such bans, including Kentucky's (which took effect on March 20), applied to gatherings of 50 or more people. Finally, the strongest restriction is the SIPO. Killeen et al. (2020) code Kentucky's SIPO as starting on March 26. While Governor Beshear has not officially used the term SIPO, March 26 is the date he closed all non-life-sustaining business, which made Kentucky's "Healthy at Home" initiative functionally equivalent to the SIPOs in place in other states.

Our sample period begins on March 5, 2020, which is the day before Kentucky reported its first case. The number of COVID-19 cases in Kentucky grew to 3,857 by April 25, the last day in our sample. Figure 1 illustrates the reach of social-distancing policies on the population in the Midwest and South over time relative to the timing of Kentucky in implementing these measures (indicated by the vertical red lines). 22 percent of the population in the South and Midwest lived in counties where schools were already closed when Kentucky's closure took effect. 41 percent of the population in these regions lived in counties with restaurant or entertainment center closures when Kentucky did so. When Kentucky officially banned large gatherings, similar orders already affected 73 percent of people in these regions. About 46 percent of the population in these regions was covered by a SIPO at the time of Kentucky's equivalent measure. On balance, then, Kentucky was implemented social-distancing restrictions somewhat earlier than other Midwestern and Southern states but was not an outlier.

III. Econometric Model

Our econometric model is an event-study-style generalization of the standard difference-in-differences framework. Whereas difference-in-differences models include the interaction of indicators for treatment group and whether the time is post-treatment, an event-study model allows for more flexible timing of impacts by interacting treatment with *several* indicators of

time relative to treatment. Differentiating between the effects of treatments that just occurred versus those that occurred a longer time ago may be particularly valuable in the case of COVID-19, where the effects of social-distancing restrictions are likely to be gradual due to incubation periods, delays seeking medical care after the onset of symptoms, delays obtaining COVID-19 tests after seeking care, and waits for test results (Lauer et al., 2020). Additionally, event study models include indicators reflecting time *before* treatment, allowing for an evaluation of pre-treatment trends. If divergence between the trends of the treatment and control groups emerges *prior* to treatment, then the observed relationships reflect unobserved confounders or reverse causality rather than the causal effect of the intervention on the outcome.

Following Courtemanche et al. (2020), our event-study model contains six variables for each of the four types of social-distancing policies: whether it was implemented

- 1-5 days ago,
- 6-10 days ago,
- 11-15 days ago,
- 16 or more days ago,
- -5 to -9 days ago (i.e. will be implemented 5-9 days from now), or
- <-9 days ago (i.e. will be implemented 10 or more days from now).

Implementation in the next five days (0 to -4 days ago) is the omitted reference group to which the coefficients for the other time periods are compared. For instance, the coefficient on the variable for “SIPO was implemented 11-15 days ago” measures the effect of starting a SIPO 11-15 days ago instead of in the next five days.¹

¹ The Supplemental Appendix to Courtemanche et al. (2020) provides formal notation for our event-study model.

Since we include four different types of policies together in the same model, their coefficients represent partial effects, holding all other types of policies constant. While the sequence in which the restrictions on schools, businesses, and events took effect varied across states and counties, SIPOs were almost always implemented after at least one other restriction was in place – usually all three. The estimated effects of SIPOs therefore represent their *additional* impacts above and beyond prior closures. The “full” impact of issuing a SIPO – which, by definition, encompasses the other smaller restrictions – without any prior restrictions is better measured as the linear combination of the coefficients of all four policy variables in the specified time frame.

Other covariates in our model are county and day fixed effects; i.e. dummy variables for each county and each day in the sample. The county fixed effects capture determinants of counties’ COVID-19 case growth rates that do not appreciably change throughout the sample period, such as population density, demographic characteristics of the population, and political orientation (Wright et al., 2020; Painter and Qiu, 2020). The day fixed effects capture common shocks to case growth rates shared by all counties in the U.S., such as voluntary social distancing in response to CDC guidance and other nationwide sources of information, international travel bans, and national trends in testing access. Therefore, the ability to interpret our results as causal effects of the policies rests on the assumption that these unmeasured factors do not change differentially across counties over time in a way that is correlated with the timing of the policies’ implementation.

Courtemanche et al. (2020) report results from numerous robustness checks designed to rule out threats to the validity of this model. Their first few checks show that their statistically insignificant results for school closures and event bans are *not* due to insufficient identifying

variation independent from the other policies. Their other checks provide evidence that their main conclusions are not sensitive to excluding unique early outbreak states, constructing the policy variables in other defensible ways, imputing or excluding certain questionable observations in the case data, starting the sample at a different time, controlling for number of tests performed in the state, and controlling for county-specific pre-treatment trends in case growth rate. In unreported regressions (results available upon request), we have verified that the results are similarly robust to these checks in our dataset, which differs from theirs only in that we include nine additional days of data and exclude the West and Northeast Census Regions.

IV. Results

The coefficients and their 95% confidence intervals for the four social-distancing policies obtained from the event-study are displayed in Figure 2. The confidence intervals are based on standard errors that are robust to heteroskedasticity and clustering by state. A variable is statistically significant at the 5% level if its coefficient's confidence interval does not include zero.

The upper left panel of Figure 2 shows that SIPOs led to a gradual but substantial reduction in the growth rate of COVID-19 cases. In the first time period after the implementation (1-5 days), the growth rate fell by a statistically insignificant 2.4 percentage points relative to the reference period of the five days before implementation. The effect became statistically significant in each subsequent period, growing to 3.9 percentage points after 6-10 days, 5.3 percentage points after 11-15 days, and 8 percentage points after 16 or more days.

The restrictions on restaurants and entertainment centers had a relatively steady effect on the growth rate of COVID-19 cases once in place. Closing either restaurant dining areas or gyms/entertainment centers (usually both) lowered the growth rate by 5 percentage points in the

first five days after taking effect, with the impact rising only slightly – to 6.2 percentage points – after 16 days. In contrast, however, we found no evidence that bans on large social gatherings or school closures reduced growth rates after any length of time, holding the other types of policies constant. The estimated effect of event bans is nearly zero and statistically insignificant, while the effect of closing schools is consistently positive (faster case growth), though never significant.

For all four types of policies, we observe no “placebo” effect on the pre-enactment growth rate. All coefficient estimates representing “impacts” of future implementation are small and statistically insignificant. In other words, we find no evidence of bias from reverse causality (case growth driving policy implementation) or unobserved confounders.

As discussed previously, the combined effects of all four policies is the best estimate of the overall impact of government-imposed social distancing restrictions. This combined effect was 5.4 percentage points in the first five days, 6.8 percentage points after 6-10 days, 7.1 percentage points after 11-15 days, and 9.1 percentage points after 16 or more days. Only the second and fourth of these estimates is statistically significant at the 5% level, with the first and third having p-values of 0.16 and 0.12, respectively. These estimates are relatively similar to those for SIPOs alone, as the positive (though insignificant) effect of closing schools on case growth was roughly offset by the reduction from restaurant/gym/entertainment center closures. In other words, on average, states’ and counties’ early social distancing efforts made little difference in slowing the spread of COVID-19, but stronger measures implemented later were more successful.

V. COVID-19 Case Growth Rate in Kentucky without Social-Distancing Policies

We next use these regression results to simulate a counterfactual scenario in which no jurisdiction in Kentucky ever implemented any social distancing restriction. To calculate the number of counterfactual cases, we first predict the counterfactual growth rate from the regression estimates discussed above by setting all of the post-implementation policy variables equal to zero. We do not also subtract out the “placebo” effects of the future policy implementation variables, since those are intended to capture unobserved confounders rather than part of the causal effect of the policies. The number of predicted cases on a given day is easily calculated from cases on the previous day and the predicted growth rate.² Once the number of cases in each county and day is predicted under the given counterfactual, we can sum them by day to create state-by-day predicted cases. Those predicted counterfactual totals are estimates of how many cases the state would have if no social distancing policies had been implemented.

Figure 3 compares the reported number of observed COVID-19 cases in Kentucky over time to the number of cases predicted by our event-study regression estimates under the aforementioned counterfactual scenario of no social distancing policies. The graph in the left panel uses the natural logarithm of Kentucky cases (or predicted cases) for the y-axis scale, but with corresponding numbers (in thousands) labeled on the y-axis instead of logs. The graph in the right panel shows presents the same numbers on a linear scale.

Both counterfactual and observed cases increase roughly linearly on the log scale, as expected under exponential growth, until the beginning of April – approximately two weeks after the first restrictions and one week after the first SIPO. The actual path of observed cases on the log scale then begins to flatten substantially, while cases predicted under the counterfactual

² The details of this calculation, which uses the fact that the exponential function is the inverse of the natural logarithm, can be found in Courtemanche et al. (2020).

scenario deviate very little from their existing path. The exponential growth rate of cases under the counterfactual is especially striking on the linear scale in the right panel. By April 25, the observed number of cases reached 3,857. If no social-distancing measures had been implemented, our estimates predict the number of cases would have been 44,482.

VI. Conclusion

The finding on reduced growth in confirmed COVID-19 cases from our regional model that includes Kentucky finds strong agreement with other recent, credible studies on the impact of social distancing measures in California (Friedson et al., 2020) and across the U.S. as a whole (Courtemanche et al., 2020; Dave et al., 2020). Our results are also consistent with evidence that SIPOs and closures of restaurants/entertainment facilities reduce cell-phone-tracked measures of mobility, while school closures and bans on medium-sized events do not (Abouk and Heydari, 2020; Andersen, 2020). Although the confirmed case counts that we use to create growth rates understate true prevalence (Hortaçsu, Liu and Schwieg, 2020; Bendavid et al., 2020), they are a critical metric in the Trump administration’s “Opening Up America Again” plan (The White House, 2020). The plan proposes either a “downward trajectory of documented cases within a 14-day period” or “downward trajectory of positive tests as a percent of total tests within a 14-day period (flat or increasing volume of tests)” as criteria to loosening social distancing measures.

Many SIPOs are set to expire in the near future, and some of Kentucky’s neighbors are reopening (Mervosh and Lee 2020). Georgia, which has had a SIPO in place since April 3, allowed gyms, hair and nail salons, bowling alleys and tattoo parlors to reopen on April 24, and restaurants, movie theaters, and other entertainment to reopen on April 27. Oklahoma did not have a SIPO, but lifted restrictions on salons, barbers and pet groomers on April 24, and

scheduled restaurant dining, movie theaters, gyms, houses of worship and sporting venues to reopen on May 1. South Carolina's SIPO has been in effect since April 7, and began reopening on April 20 with retail stores, operating at reduced capacity. Tennessee's SIPO is set to expire April 30, although restaurants will reopen starting April 27, with retail stores to follow, both operating at reduced capacity.

The Institute for Health Metrics and Evaluation (2020) projects June 14 as the day Kentucky can consider relaxing social distancing measures with a containment strategy. Some of the other states that are currently relaxing social distancing measures – Georgia, Oklahoma, South Carolina, and Tennessee – have projections of June 22, June 17, June 8, and May 20, respectively. According to these projections, few states are currently positioned to reopen in the very near future, even with a containment strategy (Huth and Wu, 2020).

Weighing health benefits against economic harms – and the debate about appropriate timing for reopening – will continue. Some recent analyses either deny the existence of health benefits or argue that such concerns are only important for hot spots such as New York City, but are irrelevant elsewhere (Reilly, 2020; Rodgers, 2020). Their conclusions are based on poorly specified empirical models that do not produce appropriate counterfactual findings.³ Our event-study model – focused on the Midwest and South – strongly rebuts the idea that social distancing policies are ineffective or irrelevant. In Kentucky, our forecasts find that confirmed COVID-19 cases would be ten times higher without government-imposed social distancing restrictions. Kentucky's fatality rate for confirmed cases is approximately 5 percent. Under the assumption

³ In particular, cross-sectional analyses like those of Reilly (2020) and Rodgers (2020) cannot separate the causal effect of social distancing policies on the severity of the COVID-19 outbreak from the reverse-causal effect of outbreak severity influencing timing of adoption. This leads to bias in the direction of underestimating the effectiveness of the restrictions.

that individuals who did not become confirmed cases as a result of these restrictions would have died at the same rate, our results suggest that they have prevented more than 2,000 fatalities.⁴

Our model's estimates also suggest that returning to partial measures – as some neighboring states are – would be insufficient to curb the spread of the virus. Specifically, we find no evidence that school closures and bans of moderate-sized events have *any effect at all* on the growth rate of COVID-19 cases unless accompanied by broader shelter-in-place directives such as Kentucky's "Healthy at Home" initiative. While such findings may appear paradoxical, they are consistent with the economic concept of substitution. Certainly COVID-19 can spread at schools and group events, but that does *not* imply that closing/banning them slows the spread. The effect depends on what individuals do in the absence of these activities. Kids who are out of school may simply end up in different social settings such as day care or gatherings at houses. Those whose youth baseball seasons are postponed may still congregate at the local park for pick-up games. Adults who can no longer go to concerts may attend house parties instead. Strong stay-at-home directives shut down these alternate routes of socialization and transmission.

Of course, the practicality of lengthy SIPOs is another matter. Although a large majority of Americans currently believe social distancing efforts should be the top priority right now, viewpoints are highly partisan (CBS/YouGov, 2020). Many states – including Kentucky – have witnessed small but vocal protests against SIPOs and other restrictions based on frustration about economic security and individual liberty (Bogel-Burroughs and Peters, 2020). Recent calculations find that the approximately 90 percent health-related benefits of the lockdown

⁴ There is currently considerable debate over the true *infection* fatality rate, which is much lower than the *case* fatality rate because of asymptomatic or mild infections going untreated and limitations in testing access. However, that debate is irrelevant here: because we measure effects on *confirmed* cases, the case fatality rate is the appropriate one to use. In other words, if we were able to examine infections rather than cases, the fatality rate would be lower, but the number of infections averted would be higher by the same proportion.

accrue to individuals aged 50 and over, while the job losses and economic harm accrue more to younger and healthier individuals – particularly those in relatively low-wage professions whose work cannot easily move online (Greenstone and Vishan, 2020). Therefore, social distancing shutdowns essentially represent a regressive transfer, and compliance among those bearing more of the costs but receiving less of the benefits is likely to erode without sufficient measures to mitigate those costs. Economists often argue against comprehensive social safety net programs on the grounds that they discourage work, but this argument is irrelevant when the job losses are involuntary, unrelated to performance, and (hopefully) temporary. All levels of government should deliver economic aid with the same sense of urgency with which they adopted public health measures. Moving forward, it is likely that the effectiveness of the latter will be proportional to the effectiveness of the former.

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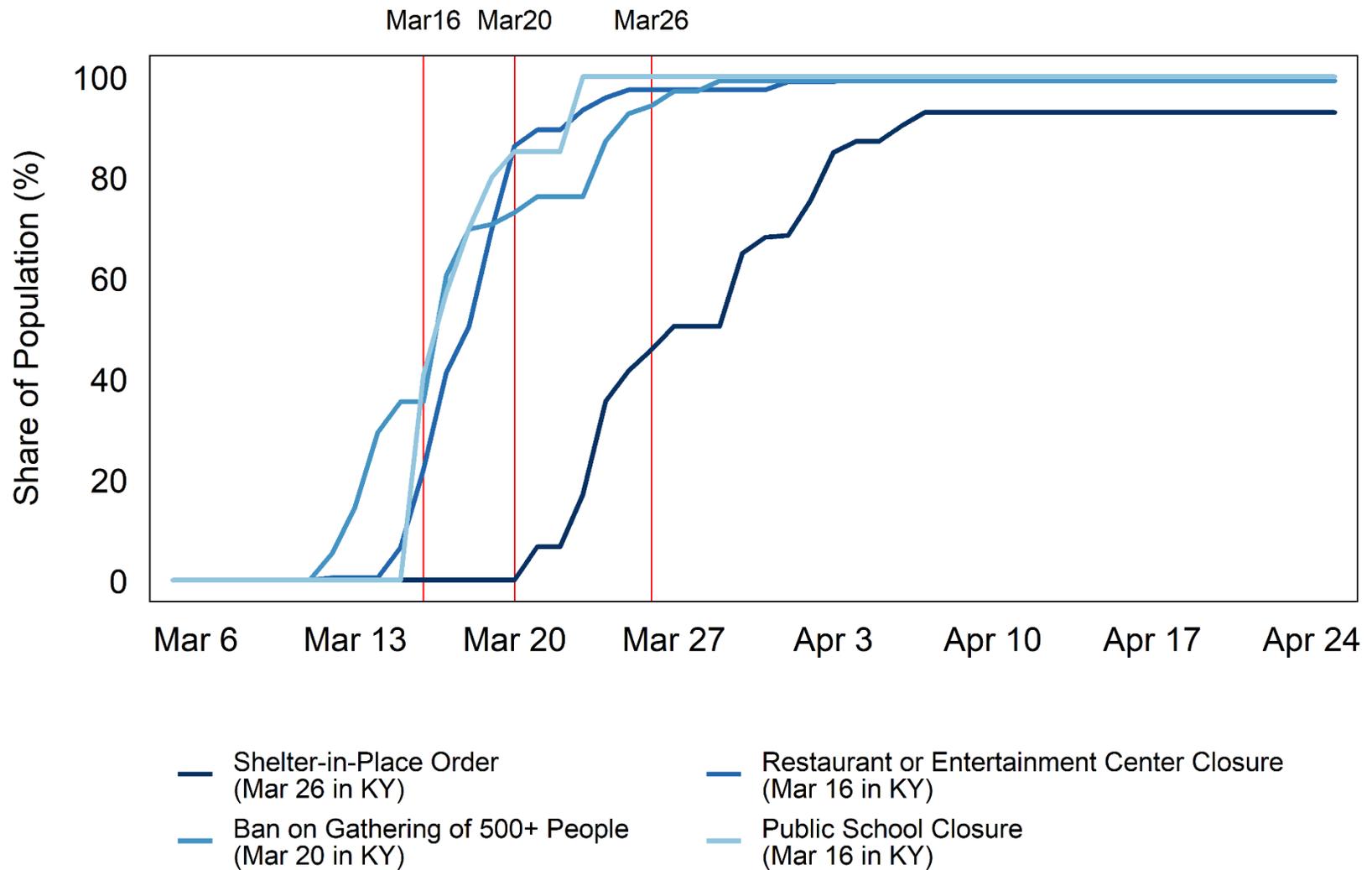
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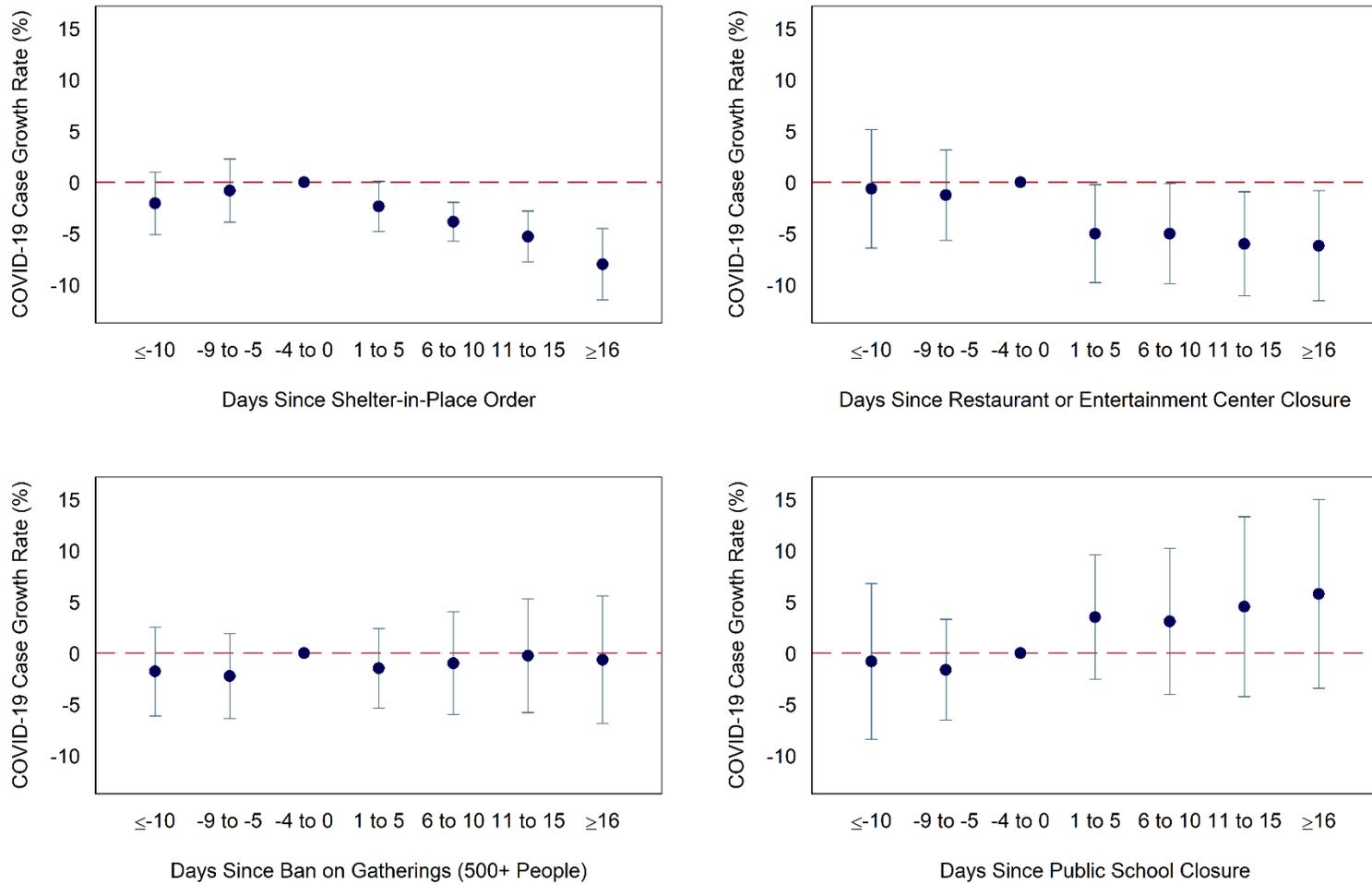
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Figure 1: Fraction of Population in Southern and Midwestern States Covered by Social-Distancing Measures



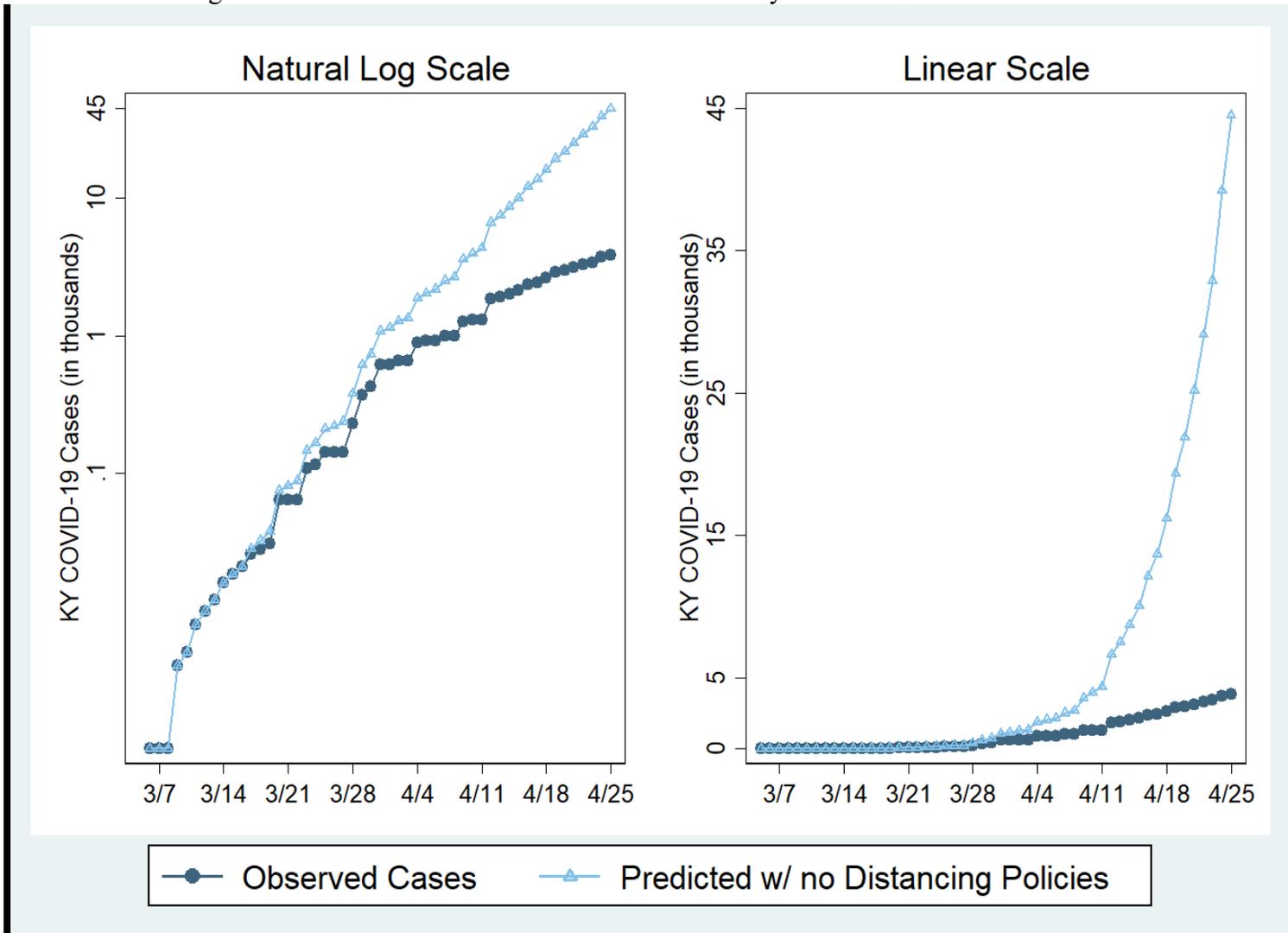
Notes: Authors' calculations from population-weighted county data. The red lines indicate Kentucky's adoption dates.

Figure 2: Estimated Impacts of Social-Distancing Measures over Time from Event-Study Model



Notes: Coefficients and 95% confidence intervals were derived from authors' event-study regression using daily county-level data from March 5-April 25 from the South and Midwest Census Regions, weighted by population. Day and county fixed effects were included. Standard errors were heteroskedasticity-robust and clustered by state.

Figure 3: Social-Distancing Policies Flatten the Curve of Confirmed Kentucky COVID-19 Cases



Notes: Predicted cumulative cases each day in Kentucky with distancing policy variables set to 0 are derived from authors' event-study regression using daily county-level data from March 5-April 25 from the South and Midwest Census Regions, weighted by population.