Preventing COVID-19 Fatalities: State versus Federal Policies

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Abstract

Are COVID-19 fatalities large when a federal government does not impose containment policies and instead allow states to implement their own policies? We answer this question by developing a stochastic extension of a SIRD epidemiological model for a country composed of multiple states. Our model allows for interstate mobility. We consider three policies: mask mandates, stay-at-home orders, and interstate travel bans. We fit our model to daily U.S. state-level COVID-19 death counts and exploit our estimates to produce various policy counterfactuals. While the restrictions imposed by some states inhibited a significant number of virus deaths, we find that more than two-thirds of U.S. COVID-19 deaths could have been prevented by late September 2020 had the federal government imposed federal mandates as early as some of the earliest states did. Our results highlight the need for early actions by a federal government for the successful containment of a pandemic.

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NOTE: This preprint reports new research that has not been certified by peer review and should not be used to guide clinical practice.
1 Introduction

COVID-19 is a rampant disease that has affected the world population to an unprecedented scale. This experience has pushed state and federal governments to implement drastic regulatory policies to contain the spread of the disease. In many countries, such as the United States, state governments can independently implement policies while other states or the federal government do not impose any restrictions. This begets the questions: how effective are policies implemented at a local level? And what could be gained from unified containment policies at the federal level?

We answer these questions by developing an extension of the standard SIRD model of Kermack et al. (1927) that allows for travel and commuting across states within a country.¹ In our model, the government of a state can impose three types of regulations. It can impose a mask mandate that shrinks the transmission rate in the state. It can impose a stay-at-home order that shrinks the transmission rate in the state as well as the inflow of out-of-state commuters and travelers. Or it can also issue a travel ban that shrinks the inflow of out-of-state travelers. The federal government can force all states to implement the same policies or allow states to decide individually what policies to implement, if any at all. We assume that a coronavirus infection takes on average 14 days to resolve and that the fatality rate of the disease is 0.6%.² To incorporate uncertainty about the contagiousness of COVID-19, we assume that the transmission rates in individual states vary randomly over time and are not directly observable. They fluctuate around a natural mean rate but can be substantially higher or lower at times. We fit our model to data on state-level COVID-19 fatalities from the United States between February 12 and September 30, 2020. We then run counterfactual experiments using the estimated model under the assumption that states implemented policies different than the ones they adopted in reality. We measure the effectiveness of the different policies by looking at the difference between the observed and counterfactual numbers of virus deaths on September 30. All of our results are replicable by using our codes that are available on Github.

Our results show that a lack of unified policies at the federal level results in significantly elevated virus deaths nationally. We estimate that more than 136,000 deaths could have been

¹We are inspired by mean-field models that are commonly used in the financial economics literature to model credit risk contagion across financial institutions; see Cvitanic et al. (2012), Giesecke et al. (2015), Giesecke et al. (2020), and others.

²These assumptions are consistent with Fernández-Villaverde and Jones (2020), Perez-Saez et al. (2020), and Stringhini et al. (2020), and are benchmarked against alternatives in a sensitivity study.
prevented by September 30, 2020 – over two-thirds of all death cases recorded in the U.S. by that date – if the federal government had imposed federal policies that mirrored those of the earliest and strictest states. Our results also show that containment policies implemented by individual states are effective. We find that the U.S. would have recorded more than 1,000,000 additional virus deaths if states had not implemented any containment policies at all.

Our study suggests that a large number of COVID-19 deaths could have been prevented if the federal government had imposed stay-at-home orders or mask mandates that followed the leads taken by the different states. We estimate that more than 110,000 deaths could have been prevented if the federal government had imposed a federal stay-at-home order that had gone into effect on March 20, 2020, corresponding to the start of the stay-at-home order in California. Imposing a federal mask mandate as early as Connecticut did on April 17, 2020, would have prevented more than 96,000 deaths. Considering that shutting down the national economy with a federal stay-at-home order carries significant economic costs, which we do not consider in this paper, a federal mask mandate would likely be preferred over a federal stay-at-home order. Our counterfactuals suggest that between 96,000 and 183,000 virus deaths could have been prevented if the federal government had enacted a federal mask mandate sometime between March 17 and April 17, 2020, on top of the stay-at-home and travel ban policies adopted by the different states. An early federal mask mandate would have contributed to slowing down the transmission of the virus early in the Spring of 2020, when we estimate the reproduction numbers to have been the highest. While it is questionable whether an early mask mandate would have been realistic or whether there existed political or even scientific consensus for enacting such a policy, what our results indicate is that early action by the federal government that complemented the steps taken by state governments could have resulted in significantly less virus deaths. These results provide an important policy lesson for future waves of the pandemic by highlighting that early

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3By matching death counts only, we estimate that the effective reproduction numbers of the virus in the different states during the Spring of 2020 must have been up to two-times higher than prevailing estimates that are based on infection cases, which are likely under-measured due to the large number of undetected infections and asymptomatic individuals. Since our estimates depend on our modeling and parametric assumptions, we carry out several experiments that assess how sensitive our findings are to our assumed parameter values. These experiments corroborate our findings.

4During the month of March, the WHO recommended masks be reserved to medical staff and discouraged a widespread use to the general public (see WHO interim guidance of April 6, 2020). As noted by Feng et al. (2020), the rationale underlying the discouragement of mask use was to preserve the limited supplies of masks in countries were the health-care system and ICU use was under pressure.
action by a federal regulator when the reproduction rates are high is key to prevent virus deaths.

We find that interstate travel bans do not accomplish significant virus death prevention, mostly for two reasons. First, travel bans are often imposed once a regulator becomes aware of the virus, at which point the virus has already penetrated and spread in the states. The first travel ban in the U.S. went into effect in Hawaii on March 17, 2020. Our counterfactuals indicate that only around 5,100 U.S. virus deaths could have been avoided if the federal regulator had imposed a nationwide ban of interstate travel on the same day as Hawaii and maintained it through September 30. In contrast, we find that close to 6,000 deaths could have been prevented if the nationwide interstate travel ban had begun by the start of our sample on February 12. Such an early ban of interstate travel is unrealistic given that the severity of the virus was not perceived to be as serious at that point of time as to justify such a drastic policy.

Second, interstate mobility scatters virus cases across state lines and this may slow down the spread of the virus within a country. In our model, states that are net importers of individuals record higher numbers of infections than they would in the absence of interstate movement while states that are net exporters of individuals record lower number of infections. When interstate mobility is restricted, infected population that would otherwise disperse out-of-state is forced to stay in-state. The higher concentration of infected population in some states can result in accelerated virus transmission in those states and worse death outcomes at the federal level. Our counterfactuals suggest that this is only a minor effect, nonetheless. For example, we find that only around 860 of the more than 110,000 virus deaths that could have been prevented with a federal stay-at-home order on March 20 are explained by the fact that interstate commuting and traveling are discouraged when individuals are required to stay at home.

Our results suggest that policies that restrict cross-border mobility accomplish little in preventing COVID-19 deaths unless they are imposed so early and for so long that they prevent the virus from initially taking hold in a population. To the extent that our results can be extrapolated to a global setting with multiple countries, they suggest that the late banning of international travel may be an ineffective tool in combating COVID-19.

Finally, we focus on individual states and find that the states that imposed some of the strictest containment policies were able to reduce the spread of the disease. Our counterfactuals suggest that New York would have only recorded 17% fewer death cases if all states had imposed strict containment policies, while California would have recorded close to 200,000 additional deaths if the state government had not imposed any containment policies at all. These results
suggest that strict-policy states, such as New York and California, were protected by their policies even when other states implemented weaker policies. On the other end of the spectrum, we find that states that adopted weak or no containment policies could have prevented a significant number of COVID-19 deaths by adopting stricter policies. Our results suggest that over 29,000 deaths could have been prevented if Florida and Texas had adopted strict containment policies. We also find that the four states that adopted no containment policies in our sample—Iowa, Nebraska, South Dakota, and Utah—could have prevented more than 70% of their death cases by adopting early mask mandates.

Our results hinge on modeling choices and assumed parameter values. To understand how sensitive our findings are to our choices, we carry out several sensitivity analyses that assume alternative parametric values and provide a reasonable set of bounds for our results. We find, for example, that the number of preventable deaths is higher if we assume that it takes less time for a virus infection to resolve; i.e., if the virus is less severe. This is because, if a virus infection is less severe, there must have been many more infections early on in the sample to match the observed death data. Therefore, early action by the federal regulator would have been even more impactful. The sensitivity analyses highlight a key benefit of our approach. By relying on death counts only, we allow our methodology to infer how many infections there must have been to justify the death data. This enables us to make data-driven inferences on how many infections and ultimate deaths could have been prevented through regulatory actions.

Our contributions are methodological and normative. On the methodological front, we develop a novel model for infectious disease transmission within a country composed of multiple states. Our model incorporates the effects of interstate traveling and commuting, as well as uncertain transmission rates.\(^5\) It also allows for independent regulatory policies across states.\(^6\) Our methodology delivers daily estimates of the transmission rates and effective reproduction numbers (\(R_0\)); these objects are jointly estimated for 51 U.S. states based solely on death cases.\(^7\)

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\(^5\) Stochastic SIR models of COVID-19 have recently been used by Fernández-Villaverde and Jones (2020) and Hong et al. (2020). Deterministic mean-field models of infection rates have been considered by Read and Keeling (2003), Youssef and Scoglio (2011), Zhang et al. (2015), and others.

\(^6\) Brady et al. (2020) study an SIR model with spatial interaction of susceptible and infected people across neighboring states and allow for independent social distancing policies across states. This model, however, does not account for interstate travel. It also does not account for the effects of mask mandates.

\(^7\) For single-state models, a related methodology is discussed in Gouriéroux and Jasiak (2020) and implemented in Arroyo Marioli et al. (2020), Hasan et al. (2020), and Hasan and Nasution (2020) using infections data. Fernández-Villaverde and Jones (2020) develop an alternative filtering-based methodology to obtain time-varying
On the normative side, we show that early actions by a federal government that complement state-level policies result in significantly reduced virus deaths during a pandemic. Our results hint that more than 135,000 COVID-19 deaths could have been prevented if the federal government in the United States had followed the lead of some of the states that took early actions to contain the virus. We also show that early mask mandates are highly effective, while travel restrictions create distortions at the state level and have small benefits at the federal level.

While the results of this paper are compelling, it is important to keep in mind several caveats that confound our findings. First, we do not consider that changes in federal policies may have resulted in different strategies implemented in the states and different reactions by the U.S. population. This is difficult to control in counterfactual experiments. Second, we do not consider whether federal mask, stay-at-home, or travel ban policies are feasible from a legal point of view. The legality of some of these policies is beyond the scope of our paper. Finally, our results about the number of preventable deaths are based on a hindsight approach that assumes that some information about the effect of different regulatory policies may have already been known at the beginning of the pandemic. Looking forward to future pandemics, or even future waves of the current COVID-19 pandemic, our results highlight the benefits of early actions by federal and state regulators.

2 Model description

We briefly describe our model here and provide a detailed model formulation in Appendix A. We assume that a unit of time is one day and that a country is composed of several states. We model the number of people in each state that are (i) susceptible to the virus (i.e., have never been infected), (ii) infected by the virus, (iii) recovered from the virus (and immune to subsequent estimates of the $R_0$ using death counts only but it requires extensive smoothing of the data.

8Studying the economic impact of state-level stay-at-home orders, Rothert (2020) document that externalities arise if the federal government does not coordinate policies across states.

9Redlener et al. (2020) establish a similar number of preventable deaths through a comparison of international policy responses. As Shefrin (2020) argues, however, cultural and ideological differences may have prevented the U.S. government from adopting international policies. We show that a large number of COVID-19 deaths could have been prevented by following policies that were already implemented domestically in the states.

10Our results are consistent with the findings of Eikenberry et al. (2020), Ngonghala et al. (2020), and Stutt et al. (2020), who highlight the benefits of a federal mask mandate in single-state models. Other studies that consider the impact of different federal containment policies include Alfaro et al. (2020), Alvarez et al. (2020), Ferguson et al. (2020), Flaxman et al. (2020), and Fowler et al. (2020), among others.
infections), and (iv) deceased due to the virus.\textsuperscript{11} Our model explicitly takes into account the impact of different containment policies on the transmission of the disease. We consider three different types of containment policies: mask mandates, travel bans, and stay-at-home orders. Our model also accounts for the effects of traveling and commuting across state lines.

Each state is endowed with a certain number of inhabitants. On any given day in a given state, the number of people that are contaminated by an infected person is assumed to be a random draw from a Poisson distribution whose rate is the product of the policy-adjusted transmission rate in the state and the fraction of the state’s population that is susceptible to the virus. If a person is infected on any given day, that person either dies, recovers, or continues to be infected in the next day with certain probabilities. We assume that it takes on average 14 days for an infection to resolve and that the fatality rate by the end of this time period is 0.6%. All in one, on aggregate in a state, the net number of new infections in a day is Poisson distributed with rate equal to the product of the policy-adjusted transmission rate, the ratio of susceptible population, and the number of infected inhabitants of the state, after subtracting the number of infected individuals that recover or die from the disease.

We assume that the transmission rates in the different states are unobservable and evolve stochastically from day to day. They are positively correlated across states and time.

We account for interstate commuting and traveling as follows. Each day, an inhabitant of a state can commute to another state, travel to another state, or remain in the home state with given probabilities. Inhabitants that stay in their home states contribute to the disease transmission in their home states. Commuters travel during parts of the day and return to their home states at the end of a day. They contribute to the transmission of the disease in their home states and the visited states. Travelers spend several days in the visited state. They only contribute to the transmission of the disease in the state they visit.

The transmission rates in each state, as well as the travel and commuting probabilities across states, are adjusted to reflect the containment policies adopted by the different states. The effects of the different policies are modeled by shrinking the transmission rates or the inflows of travelers and commuters when the policies are active. We assume that a mask mandate in a given state shrinks the transmission rate in that state by 42% but does not affect the inflow or outflow of travelers and commuters.\textsuperscript{12} A travel ban in a given state shrinks the inflow of travelers

\textsuperscript{11}Our assumption on immunity post-infection is merely a simplification given that current evidence on re-infections from COVID-19 is thin and mixed, see, e.g., Iwasaki (2020).

\textsuperscript{12}We justify this value as follows. Based on the estimates of Fischer et al. (2020), we assume that a typical mask
by 90%, but does not affect the transmission rate or the inflow of commuters in that state.\textsuperscript{13}

Finally, a stay-at-home order shrinks both the transmission rate and the inflow of commuters and travelers in that state by 36%.\textsuperscript{14} Appendix E considers variations of these parameters and measures the sensitivity of our results to our assumptions.

We use mobility, travel, and state-level policy data from the United States to calibrate most of the parameters of our model. We develop a filtering-based maximum likelihood methodology to estimate some of the parameters governing the transmission rates of the different states. We rely on daily state-level death counts from The COVID Tracking Project since they are the least likely to be contaminated with substantial measurement issues (compared to the number of infections, for instance).\textsuperscript{15} The sample period is February 12 through September 30, 2020. Appendix B provides details of the approach we take to fit our model to the data.

Figure 5 in Appendix B shows the death counts in the data as well as the posterior mean of the death counts in our model. The figure shows that our model performs well at matching state-level and aggregate death counts. We show in Appendix B that our model implies that, in order to match the levels of fatalities we observed over the sample period in U.S. states, the effective $R_0$ of the disease in the different states must have been substantially higher than 1 through April 2020 for the majority of the states. We also show that the $R_0$ grew larger than 1 in several states over the summer. Our estimates suggest that the number of infections in the different states required to match the history of COVID-19 fatalities in the U.S. must have been substantially higher than recorded in the data. Unreported model outcomes show that the worn in the U.S. filters out particles by a median value of 85%. We assume that only half of the population wears masks as suggested by data from the Institute of Health Metrics and Evaluation, justifying a reduction factor of approximately 42%.

\textsuperscript{13}We estimate the 90% impact of travel bans as the reduction factor in the average number of daily trips of more than 100 miles that were taken in the U.S. between March 15 and April 30, 2020, compared to 2019. We assume that travel bans do not reduce the inflow of commuters into a state because travel bans were often accompanied by exemptions for commuters.

\textsuperscript{14}We estimate the impact of stay-at-home orders on transmission rates as the reduction factor in the average number of daily trips of less than 10 miles taken in 2019 versus those taken between March 15 and April 30, 2020, which is the period in which most stay-at-home orders were active in the United States. Because stay-at-home orders were often accompanied by lockdowns which closed out office buildings, we assume that stay-at-home orders also reduce the inflow of commuters into a state. Finally, because stay-at-home orders were also associated with closed out tourist attractions, we also assume that stay-at-home orders reduce the inflow of travelers into a state.

\textsuperscript{15}The fact that our estimation approach relies on death counts data only, as in Flaxman et al. (2020), is an advantage over standard approaches to estimate time-varying reproduction numbers (e.g. Bettencourt and Ribeiro (2008), Cori et al. (2013), Thompson et al. (2019)), as these approaches necessitate data on infection cases.
estimated number of infected individuals in mid March was about 50-times larger than data records show, while it was about 5-time as large as in the data by late September. Our results imply that many infected people remained undiagnosed and contributed to the spread of the disease early in the sample.

3 Results

We run counterfactual experiments in our model to study the effectiveness of the different containment policies. The underlying assumption of our counterfactuals is that states deviate from the policies they enacted in reality by imposing stricter or looser restrictions in a hypothetical world. We ask: what would have happened to the death count of a state if it had enacted a stricter containment policy than it actually did? What would have happened if it had adopted a policy that it did not enact in reality? And how would these deviations have impacted the aggregate death count in the U.S. by the end of our sample? We answer these questions for mask mandates, stay-at-home orders, and travel ban policies.

We assume that a state adopts a loose policy if it does not impose that policy at all over our sample period. In contrast, we assume that a state adopts a strict policy if it adopts that policy as early as the earliest state adopted the policy in the data, and keeps the policy active until the last state in our sample shuts off that policy. Our strict policy scenario therefore avoids forward-looking biases. Any regulator could have adopted a strict policy scenario in real life by moving along with the first state that adopted a policy and ending the policy as soon as no other state had the policy in place.16 The strict scenarios for the different policies are:

- **Stay-at-Home**: Start on March 20, 2020 (the day when California activated its stay-at-home mandate) and keep it active through September 30, 2020 (the last day in our sample in which the stay-at-home order was still active in California).

- **Travel ban**: Start on March 17, 2020 (the day the first interstate travel ban in the U.S. went into effect in Hawaii) and keep it active through September 30, 2020 (the last day in our sample in which an interstate travel ban was still active in Alaska).

- **Mask mandate**: Start on April 17, 2020 (the day the first mask mandate in the U.S. went into effect in Connecticut) and keep it active through September 30, 2020 (the last day in our sample in which several states had mask mandates in place).

16The legality of such federal mandates are outside of the scope of this paper.
We consider two variations of our counterfactual experiments. One in which only one state at a time deviates from its actual policies at a time, and another one in which all states take on the same policy jointly at the same time. With the first set of experiments we seek to answer how impactful deviations at the state level would have been. The second set of counterfactuals studies how impactful federally mandated polices would have been. To evaluate the effectiveness of the different policies, we compare the number of deaths at the state and federal levels in the different counterfactual experiments to the baseline levels in the data. Appendix C provides details of our approach to computing counterfactual results.

Table 1 shows the results of the counterfactual experiments in which we assume that all states deviate jointly. Figure 1 breaks down the number of deaths that could have been prevented through federal mandates by states and displays these in proportion to the number of death in the data of the individual states. Figure 2 shows the number of deaths that could have been prevented in the different states if individual states had deviated from their implemented policies while all other states kept their policies untouched. The time series of cumulative virus deaths in the different counterfactual scenarios are given in Figure 8 of Appendix C. We carry out several robustness checks that re-evaluate the number of preventable deaths in the different scenarios under alternative assumptions of the impact of the different policies on transmission rates and traveler and commuter flows, as well as the fatality rate of the disease and the number of days it takes for an infection to resolve. The results of these sensitivity analyses are summarized in Table 1 and further elaborated in Appendix E. The additional sensitivity analyses are consistent with our main conclusions and provide validity for our results.

3.1 Federal mandates

Table 1 suggests that 136,514 virus deaths could have been prevented if the U.S. government had mandated federal containment policies as early as the earliest state did and maintained the policies for as long as the strictest states did. Our results indicate that 110,129 deaths could have been prevented had the federal government moved along with California and mandated a federal stay-at-home order on March 20, 2020 that remained active throughout our sample. The results also indicate that 96,515 deaths could have been prevented if the federal government had issued a federal mask mandate as early as Connecticut did on April 17, 2020, and kept the mandate active through September 30. In contrast, we find that only 5,148 deaths could have been prevented had the federal government banned all interstate travel by March 17, 2020 – the
day in which Hawaii banned inbound interstate travel.

Figure 1 hints that strict federal mandates could have been highly effective at preventing death in states that adopted weak containment policies. Over 95% of all death cases in Arkansas, Florida, Iowa, South Carolina, and Texas – corresponding to close to 35,000 fatalities – could have been prevented if the federal government had imposed strict stay-at-home orders, mask mandates, and interstate travel bans. These states adopted some of the weakest containment policies during our sample period.

Although Table 1 suggests the biggest reduction of fatalities could be achieved through a federal stay-at-home mandate, this comes at the cost of shutting down the national economy. The potential substantial economic costs inherent to that policy cast doubt on whether the federal government would have been persuaded to carry out such a drastic step. Instead, imposing a federal mask mandate could have been a cost-effective option. We ask: how many deaths could have been prevented if the federal government had imposed an early federal mask mandate sometime between March 17 and April 17 that complemented the stay-at-home and interstate travel policies that were in effect in the different states? We run an additional counterfactual experiment to answer this question; Figure 3 summarizes our findings.

Our results indicate that between 96,515 and 182,710 deaths could have been prevented if a federal mask mandate that complemented the state-level stay-at-home and travel ban policies went into effect sometime between mid March and mid April. What drives our findings is that an early federal mask mandate could have provided a significant boost in reducing the potential for infections. As Figure 6 in Appendix B shows, the effective reproduction number ($R_0$) of the virus was substantially high – much higher than 1 – in all states through April 2020 even while stay-at-home orders were in place in the different states. By imposing an early mask mandate, the federal regulator could have contributed to drastically reducing the infection potential in all states early in the sample. This would have contributed to slowing down new infections over time even while some state-level policies were relaxed. Indeed, Table 1 shows that, in a counterfactual world in which a federal mask mandate had gone into effect on March 20 while no state-level policies had been enacted, only 78,136 virus deaths would have been prevented. This result suggests that the key step for the federal regulator would have been to issue an early federal mask mandate that complemented, but did not replace, the state-level stay-at-home and travel ban policies that were enacted over time.

The number of deaths that could have been prevented with early federal policies depends
on our assumptions on how fatal COVID-19 is and how long it takes for an infection to resolve. We run sensitivity analyses in Appendix E to verify that our results are robust to different calibrations. The results of Appendix E are generally consistent with Table 1 and Figures 1 through 3. They also highlight an important benefit of our methodology. Appendix E establishes that the number of preventable deaths is higher if we assume that it takes only 10 days for an infection to resolve.\textsuperscript{17} We find that this is the case because, in order to match the number of deaths observed in the data if the virus were less severe, the methodology infers that there must have been many more infected individuals early in the sample so that early federal action would have been even more impactful. We obtain these results because we rely only on death counts to make our inferences and allow the methodology to estimate how many infections there must have been to match the data. This highlights a fundamental benefit of of our approach relative to alternative approaches that rely on infection cases, which may be under-counted in the data due to the large number of asymptomatic cases or undetected infections.

Looking forward to future waves of the COVID-19 pandemic, our results suggest that early actions by the federal government when the reproduction numbers are high could have a great impact on preventing virus deaths.

3.2 State mandates

Our counterfactual experiments indicate that the actions taken by individual states benefited both the states that implemented the policies and the U.S. as a nation. We find that the U.S. would have been much worse off if no state had adopted any containment policies. In a hypothetical scenario in which no state had imposed any policies, Table 1 indicates that the U.S. would have observed 1,012,053 additional deaths due to COVID-19. Our results show that states that implemented strict containment policies were able to contain the spread of the disease. Figure 1 shows that a state like New York, which had one of the longest running stay-at-home and mask mandates, would have experienced only 17\% fewer death cases if all states had imposed all three strict policies simultaneously. Figure 2 also shows that a state like California, which imposed the strictest stay-at-home policy in the country, would have recorded around 200,000 additional COVID-19 deaths, or 13-times its end-of-September toll, if it had not imposed any containment policies at all. These results suggest that the measures adopted by individual states to contain

\textsuperscript{17}We find that the fatality rate has little impact on the number of preventable deaths, and instead mostly affects the number of deaths that would have been observed if no state adopted any policy.
the disease were highly effective and shielded states from inaction from other states.

Figure 2 also shows that states that imposed weak containment policies could have prevented a substantial number of COVID-19 fatalities by imposing stricter policies. Two states in particular stand out: Florida and Texas. These states could have prevented 13,846 deaths (95% of all death cases in Florida) and 15,250 (97% of all death cases in Texas), respectively, if they had implemented strict versions of the containment policies we consider in this paper. While it may be unrealistic to have expected most states to enact strict stay-at-home orders and interstate travel bans because these policies carry heavy economic burdens, mask mandates could have been enacted without concerns about economic consequences. We find that Texas could have prevented 81% of its COVID-19 fatalities, while Florida could have prevented 83% of its COVID-19 fatalities, if the states had enforced mask mandates as early as Connecticut did on April 17, 2020. Even some states that otherwise had strict policies in place suffered from not adopting a mask mandate early enough. Our counterfactuals suggest that California, whose mask mandate went into effect on June 19, could have prevented 10,736 virus deaths if it had adopted a mask mandate as early as Connecticut did on April 17.

We find that the four states that implemented no containment policies at all during our sample period—Iowa, Nebraska, South Dakota, and Utah—could have benefited if they had implemented mask mandates by April 17 without forcing stay-at-home orders or interstate travel bans. Figure 2 suggests that strict mask mandates could have prevented as many COVID-19 deaths as 1,011 in Iowa (75% of all COVID-19 deaths in the state), 347 in Nebraska (70%), 177 in South Dakota (75%), and 350 in Utah (75%). These results corroborate our findings on the effectiveness of mask mandates for preventing COVID-19 transmission and deaths, both at the federal and the state levels.

### 3.3 Interstate mobility

The results of Table 1 and Figures 1 and 2 suggest that interstate travel bans are not very effective in preventing COVID-19 deaths. We find that there are two reasons driving the low impact of interstate travel bans.

First, interstate travel bans were often imposed late, only once the state regulator became aware of the virus and the virus had already taken hold in the state’s population. Table 1 shows that only 5,148 deaths could have been prevented in the U.S. if all interstate travel had been banned by March 17, 2020. At that point, however, Figure 7 in Appendix B shows that most
states must have already had several infected individuals so that the virus was already spreading in the states. Banning interstate travel at that point would not have prevented the spread of the virus. It may have been different, however, if interstate travel bans were enacted earlier. Early enough that they prevented the virus from entering certain states. We run an additional counterfactual in which we ask how many virus deaths could have been prevented if the federal regulator banned all interstate travel on the first day of our sample, namely February 12. The results, summarized in Table 1, show that an additional 838 deaths could have been prevented with such an early interstate travel ban. This result indicates that travel bans are more effective if they are implemented early on.

Second, some externalities arise when individuals can move across state lines and these externalities reduce the effectiveness of travel bans. In our model, interstate travel allows for the transfer of infected population across states. Consider South Carolina, for example. On an average day, our estimates suggest that 96,242 South Carolinians travel or commute out-of-state while 83,572 out-of-state residents travel or commute into South Carolina. As a result, South Carolina is a net exporter of individuals in our model. Now, Figure 1 suggests that South Carolina would have recorded 4% more virus death cases if all interstate travel had been banned on March 17. Why is this the case? We find that this is driven by the fact that, when population is not allowed to cross state borders, infected individuals are forced to stay within the home state. The higher concentration of infected population in those state leads to an accelerated spread of the disease and therefore also to higher infections and death cases. This is showcased in Figure 9 of Appendix D, in which we plot the estimated cumulative number of infections in South Carolina both under the baseline and in the counterfactual in which a strict federal interstate travel ban is imposed.

Consider Wyoming, on the other hand. Wyoming is a net importer of travelers and commuters, receiving on an average day a net inflow of around 8,750 out-of-state individuals. Figure 1 indicates that Wyoming would have recorded 43% fewer death cases if a federal ban of interstate travel had gone into effect on March 17. Figure 9 of Appendix D suggests a similar mechanism in this case. Without a travel ban, Wyoming received infected population from other states and this resulted in a higher number of infections in the state. If the federal government had imposed a strict interstate travel ban, then the out-of-state infected population would not have easily reached Wyoming. This would have resulted in a lower number of in-state infections and ultimate virus deaths.
All in one, our experiments indicate that interstate travel makes it possible that states that are net importers of travelers record higher numbers of death cases than they would in the absence of travel, while states that are net exporters of travelers record lower number of virus fatalities. Policies that restrict interstate mobility do not resolve this externality because they only redistribute infection cases among states. Our results also suggest that late restrictions of interstate mobility can be counterproductive because they allow for the virus to spread in an accelerated fashion in some states rather than allowing for a balanced distribution of the virus across states. However, we find this is only a minor adverse consequence of policies that restrict interstate mobility. We find that interstate travel bans account only for a couple of thousand preventable deaths in our counterfactual analyses. In additional unreported experiments, we also find only 861 additional virus deaths could have been prevented through a strict federal stay-at-home order on March 20, 2020, if interstate traveling and commuting were not discouraged by the order. Putting everything together, our study shows that the ban of interstate travel can be an effective tool to prevent the spread of a virus if the ban is enacted early enough to prevent the virus from taking hold in a population.

4 Conclusion

We show that more than two-thirds of all COVID-19 death cases in the U.S. were preventable had the federal government followed the leads of several states that took early actions to contain the virus. Our results indicate that, in the absence of a unified federal approach, the policies enacted in individual states were effective and resulted in reduced virus fatalities. This benefited both the individual states and the U.S. as a whole. As a lesson for future waves of the COVID-19 pandemic, as well as future pandemics, our results highlight the need for decisive and impactful early actions by a federal regulator to complement actions taken by state regulators, especially at times when the reproduction numbers are substantially large.
A Model

A.1 Single-state model

We first introduce a single-state model to provide an overview of the assumptions underlyng the stochastic evolution of the COVID-19 disease. This provides a basis that we extend in the following section to account for a network of $N$ states.

A.1.1 From micro assumptions to aggregate dynamic equations

Consider individual $j$ that was infected on date $t-1$ (i.e., $j \in \{1, \ldots, I_{t-1}\}$). We assume that the number of people infected by this individual between dates $t-1$ and $t$ follows a Poisson distribution: $i_{j,t} \sim i.i.d. \mathcal{P}\left(\frac{S_{t-1}}{N} \beta_{t-1}\right)$. Using the fact that a sum of Poisson-distributed variables is Poisson, the total number of people infected between dates $t-1$ and $t$ is $i_t \sim i.i.d. \mathcal{P}\left(\frac{S_{t-1}}{N} I_{t-1} \beta_{t-1}\right)$.

If $j$ is infected on date $t$, then the probability that she dies between dates $t$ and $t+1$ is $\delta$ (i.i.d. Bernoulli) and, if she does not die, the probability she recovers between dates $t$ and $t+1$ is $\gamma/(1-\delta)$. (In such a way that the probability she recovers if $\gamma$.)

The cumulated number of dead people on date $t$ ($D_t$) is given by $D_t = D_{t-1} + d_t$, where $d_t$ is the number of deaths taking place on date $t$. Under the assumptions stated above, $d_t$ follows a binomial distribution: $d_t \sim \mathcal{B}(I_{t-1}, \delta)$. Moreover, the number of people who recover between dates $t-1$ and $t$ is $r_t \sim \mathcal{B}\left(I_{t-1} - d_t, \frac{\gamma}{1-\delta}\right)$.

We have $S_t = S_{t-1} - i_t$, $I_t = I_{t-1} + i_t - d_t - r_t$, and $R_t = R_{t-1} + r_t$, where $S_t$ and $R_t$ respectively denote the number of susceptible and recovered persons as of date $t$. (It is easily checked that $S_t + I_t + R_t + D_t = S_{t-1} + I_{t-1} + R_{t-1} + D_{t-1}$.)

A.1.2 Transmission rate dynamics

The transmission rate $\beta_t$ is assumed to follow a non-negative square root process whose Euler discretization reads:

$$\beta_t = E_{t-1}(\beta_t) + \sigma \sqrt{\Delta t E_{t-1}(\beta_t)} \varepsilon_{\beta,t},$$  \hspace{1cm} (1)

where $\varepsilon_{\beta,t} \sim \mathcal{N}(0, 1)$ and $E_{t-1}(\beta_t) = \beta_{t-1} + \kappa(\beta - \beta_{t-1})$. 

16
A.1.3 State-space model

Let us now write the state-space representation of the model in a context where only $D_t$ is observed. The vector of latent variables is $[\beta_t, S_t, I_t, R_t]'$.

The measurement equation is $\Delta D_t = \delta I_{t-1} + \epsilon_{D,t}$. The transition equations are:

\[
\begin{bmatrix}
S_t \\
I_t \\
R_t \\
\beta_t
\end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\
0 & 1 - \delta - \gamma & 0 & 0 \\
0 & \gamma & 1 & 0 \\
0 & 0 & 0 & 1 - \kappa
\end{bmatrix} \begin{bmatrix}
S_{t-1} \\
I_{t-1} \\
R_{t-1} \\
\beta_{t-1}
\end{bmatrix} +
\begin{bmatrix}
-\frac{S_{t-1}}{N} \beta_{t-1} I_{t-1} \\
+\frac{S_{t-1}}{N} \beta_{t-1} I_{t-1} \\
0 \\
\kappa \beta
\end{bmatrix} +
\begin{bmatrix}
\epsilon_{S,t} \\
\epsilon_{I,t} \\
\epsilon_{R,t} \\
\sigma \sqrt{\beta_{t-1} \Delta t \epsilon_{\beta,t}}
\end{bmatrix}
\]

(2)

with $\epsilon_{\beta,t} \sim i.i.d. \mathcal{N}(0, 1)$ and

\[
\begin{bmatrix}
\epsilon_{D,t} \\
\epsilon_{S,t} \\
\epsilon_{I,t} \\
\epsilon_{R,t}
\end{bmatrix} = \begin{bmatrix}
d_t - \delta I_{t-1} \\
- i_t + \frac{S_{t-1}}{N} I_{t-1} \beta_{t-1} \\
i_t - d_t - r_t - \frac{S_{t-1}}{N} I_{t-1} \beta_{t-1} + (\delta + \gamma) I_{t-1} \\
r_t - \gamma I_{t-1}
\end{bmatrix}
\]

Appendix F shows that $\text{Var}_{t-1}(\epsilon_{D,t}, \epsilon_{S,t}, \epsilon_{I,t}, \epsilon_{R,t}, \epsilon_{\beta,t})$ is equal to

\[
I_{t-1} = \begin{bmatrix}
\delta (1 - \delta) & 0 & -\delta (1 - \delta - \gamma) & -\delta \gamma & 0 \\
0 & \frac{S_{t-1}}{N} \beta_{t-1} & 0 & 0 & 0 \\
-\delta (1 - \delta - \gamma) & -\frac{S_{t-1}}{N} \beta_{t-1} & \frac{S_{t-1}}{N} \beta_{t-1} + \nu & -\gamma (1 - \gamma - \delta) & 0 \\
-\delta \gamma & 0 & -\gamma (1 - \gamma - \delta) & \gamma - \gamma^2 & 0 \\
0 & 0 & 0 & 0 & 1
\end{bmatrix},
\]

(3)

where $\nu = \frac{(1-\delta-\gamma)^2 + \gamma(1-\delta-\gamma)}{1-\delta}$.

A.2 Multi-state model

We now consider a $N$-state model. Inhabitants may travel across states for commuting or other reasons – we refer to the latter as “traveling.” In terms of notations, superscript $j$ refers to a given state. Variables without superscripts denote $N$-dimensional vectors. We denote by $p = [p_1, \ldots, p_N]'$ the vector of the state population sizes. $S_t, I_t, R_t$ and $D_t$ are $N$-dimensional vectors gathering the number of susceptible, infected, recovered, and deceased people in each state.
### A.2.1 Policy restrictions

The transmission rates $\beta_{j,t}$ and the flow probabilities are impacted by the containment policies implemented in the different states. We consider three containment policies: mask mandates, stay-at-home orders, and travel bans. The effect of each policy is captured through the binary variables $\theta^M_{j,t}$, $\theta^S_{j,t}$, and $\theta^T_{j,t}$, respectively valued in $\{\theta^\text{low}_M, 1\}$, $\{\theta^\text{low}_S, 1\}$, and $\{\theta^\text{low}_T, 1\}$. The parameters $\theta^\text{low}_M$, $\theta^\text{low}_S$, and $\theta^\text{low}_T$ are strictly lower than one; they reflect the effects of the containment policies. More precisely:

- The transmission rate $\beta_{j,t}$ is reduced when mask mandates or stay-at-home policies are implemented. Formally, it is of the form $\beta^0_{j,t}\theta^M_{j,t}\theta^S_{j,t}$, where $\beta^0_{j,t}$ is an exogenous transmission rate following the dynamics depicted by (1). Given that the $\theta$ variables are equal to one when the policies are not in place, it follows that $\beta^0_{j,t}$ coincides with the effective transmission rate ($\beta_{j,t}$) when mask mandates and stay-at-home policies are not implemented.

- The probability that a given inhabitant of State $j$ commutes to State $k$, that is $w^\text{com}_{j,k,t}$, is of the form $w^\text{com}_{j,k}\theta^\text{low}_S\theta^\text{low}_T$. Similarly, the travel probability is given by $w^\text{trav}_{j,k,t} = w^\text{trav}_{j,k}\theta^\text{low}_S\theta^\text{low}_T$. These probabilities are therefore lower when (i) stay-at-home orders are in place or (ii) when travel bans are enforced in the visited state.

### A.2.2 Traveler flows

The variables $\text{Flow}^j_{\text{trav},S,t}$, $\text{Flow}^j_{\text{trav},I,t}$, and $\text{Flow}^j_{\text{trav},R,t}$ are net travel inflows of susceptible, infected, and recovered populations, respectively.

We denote by $w^j_{\text{trav},t}$ the average fractions of the date-$t$ population of State $k$ that travels to State $j$; $e_j$ is the $j^{th}$ column of the $N \times N$ identity matrix; $1$ is a $N \times 1$ vector of ones; $w^j\cdot\cdot_{\text{trav},t}$ and $w\cdot^j_{\text{trav},t}$ respectively denote the $j^{th}$ row vector and column vector of $W_{\text{trav},t}$. Consistent with the assumptions made in A.2.1, we have:

$$W_{\text{trav},t} = \tau_{\text{trav}} w_{\text{trav}}(\theta_{S,t}) d(\theta_{S,t}).$$

(4)

Here, $\tau_{\text{trav}}$ measures the average number of days that a traveler spends in the visited states. Using the Poisson approximation of the binomial distribution, we consider that the number of outward travelers is drawn from Poisson distributions. For example, the number of susceptible individuals traveling from State $k$ to State $j$ between dates $t$ and $t + 1$ is:

$$\text{Flow}^{k,j}_{\text{trav},S,t} \sim \text{i.i.d.} \mathcal{P}(w^k_{\text{trav},t}\theta^j_{S,t}).$$

(5)
This implies in particular that the net number of inhabitants traveling into State \( j \) between dates \( t \) and \( t+1 \) (denoted by \( \text{Flow}_{trav,S,t}^j \)) is such that:

\[
\phi_{trav,S,t}^j := \mathbb{E}(\text{Flow}_{trav,S,t}^j | S_t) = \left( \sum_{k \neq j} w_{trav,t}^{k,j} S_t^k \right) - \left( \sum_{j \neq k} w_{trav,t}^{j,k} S_t^j \right) S_t^j \\
= \left( w_{trav,t}^{\cdot,j} - (w_{trav,t}^{\cdot,1}) e_j \right)' S_t.
\]

Using the convention \( w_{trav,t}^{j,j} = 0 \), it follows that the \( N \)-dimensional vector \( \phi_{trav,S,t} \) is given by

\[
\phi_{trav,S,t} = \Omega_{trav,t} S_t, \quad \text{where} \quad \Omega_{trav,t} = W_{trav,t}' - d(W_{trav,t} 1).
\]

By the same token, and with obvious notations for \( \phi_{trav,I,t} \) and \( \phi_{trav,R,t} \): \( \phi_{trav,I,t} = \Omega_{trav,t} I_t \) and \( \phi_{trav,R,t} = \Omega_{trav,t} R_t \).

### A.2.3 Commuter flows

Interstate commuters are people who spend a fraction \( \tau \) of each day in another state. Consider the infected inhabitants of State \( k \) working in State \( j \). They contaminate less people in State \( k \) because they spend less time in that state. But they may also contaminate people in State \( j \) because they spend some time in that state while commuting. We respectively denote by \( \text{Flow}_{com,S,t}^{j \rightarrow com} \), \( \text{Flow}_{com,I,t}^{j \rightarrow com} \) and \( \text{Flow}_{com,R,t}^{j \rightarrow com} \) the commuting inflows of susceptible, infected and recovered people in State \( j \). Outflows are given by \( \text{Flow}_{com,S,t}^{j \rightarrow com} \), \( \text{Flow}_{com,I,t}^{j \rightarrow com} \) and \( \text{Flow}_{com,R,t}^{j \rightarrow com} \).

Let us denote by \( W_{com,t} \) the “commute” matrix; that is, the matrix whose component \((i,j)\), denoted by \( w_{com,t}^{i,j} \), is the fraction of the date-\( t \) population of State \( k \) that commutes to State \( j \).

On date \( t \), the number of susceptible people commuting from State \( k \) to State \( j \) is:

\[
\text{Flow}_{com,S,t}^{k,j} \sim i.i.d. \mathcal{P}(w_{com,t}^{k,j} S_t^k).
\]

This implies in particular, with obvious vectorial notations, that:

\[
\phi_{com,S,t}^{k,j} := \mathbb{E}(\text{Flow}_{com,S,t}^{k,j} | S_t) = W_{com,t}' S_t,
\]

with (consistently with the assumptions made in A.2.1):

\[
W_{com,t} = W_{com} d(\theta_{S,t}).
\]

where \( W_{com} \) is the commute matrix that would prevail under no containment policies.
By the same token:

\[ φ_{\text{com},S,t} := \mathbb{E}(\text{Flow}_{\text{com},S,t} | S_t) = d(W_{\text{com},t} 1) S_t. \]  (10)

All in all, if we denote by \( \text{Flow}_{\text{com},S,t} \) the vector of time-weighted commuters net inflows, we have:

\[ \mathbb{E}(\text{Flow}_{\text{com},S,t} | S_t) = Ω_{\text{com},t} S_t, \]  (11)

with

\[ Ω_{\text{com},t} = τ_{\text{com}} W_{\text{com},t} - τ_{\text{com}} d(W_{\text{com},t} 1). \]  (12)

A.2.4 Transmission rate dynamics

Each state \( j \) features an autonomous \( β_{j,t}^0 \) process (see A.2.1). These variables, gathered in vector \( β_0^t \), follow non-negative square-root processes whose dynamics is approximated by:

\[ β_{j,t}^0 \approx β_{j,t-1}^0 + κ(β - β_{j,t-1}^0) \Delta t + σ \sqrt{Δt} β_{j,t-1}^0 ε_t, \]

with \( ε_t \sim i.i.d. N(0, Σ) \), where the diagonal elements of Σ are ones and the extra-diagonal entries are set to \( ρ \).

A.2.5 State-space model

The state-space model is characterized by

\[
\mathbb{E}_{t-1} \left( \begin{array}{c}
D_t \\
S_t \\
I_t \\
R_t \\
β_0^t
\end{array} \right) \quad \text{and} \quad \mathbb{V}_{t-1} \left( \begin{array}{c}
D_t \\
S_t \\
I_t \\
R_t \\
β_0^t
\end{array} \right). 
\]

We have:

\[
\mathbb{E}_{t-1} = \begin{pmatrix}
D_t \\
S_t \\
I_t \\
R_t \\
β_0^t
\end{pmatrix} = \begin{pmatrix}
0 & \text{Id} & 0 & δ\text{Id} & 0 & 0 \\
0 & \text{Id} & 0 & 0 & 0 \\
0 & 0 & (1 - δ - γ)\text{Id} & 0 & 0 \\
0 & 0 & γ\text{Id} & \text{Id} & 0 \\
κβ_1 & 0 & 0 & 0 & (1 - κ)\text{Id}
\end{pmatrix} \mathbb{E}_{t-1} + 
\begin{pmatrix}
D_{t-1} \\
S_{t-1} \\
I_{t-1} \\
R_{t-1} \\
β_{t-1}^0
\end{pmatrix}.
\]
\[
\begin{bmatrix}
0 \\
0 \\
-\text{Id} \\
+\text{Id} \\
0 \\
0
\end{bmatrix}
\left(\theta_{S,t-1} \odot \theta_{M,t-1} \odot \beta_{t-1}^0 \odot \frac{1}{P} \odot ([\text{Id} + \Omega_{t-1} I_t] \odot ([\text{Id} + \Omega_{t-1} S_t])\right), \quad (13)
\]

where \(\Omega_{t-1} = \Omega_{\text{com},t-1} + \Omega_{\text{trav},t-1}\), where the latter two matrices are respectively defined in equations (6) and (12). Notice that the state-space ends up being of size \(5 \times N\), where \(N\) is the number of states, so 255 in our application.

Appendix G details the computation of the conditional variance of \([D_t, S_t, I_t, R_t, \beta_0^t]\) (see equation 28 in G.4).

The previous equations constitute the set of transition equations of the state-space. We complete the formulation with the measurement equations being only the (seasonally adjusted) time series of fatalities per day, for each state, which we denote by \(D_t^{\text{obs}}\). We assume that the number of deaths per day is measured nearly perfectly, such that:

\[
D_t^{\text{obs}} = D_t + \eta_t, \quad \text{where} \quad \eta_t \sim \mathcal{N}(0, 0.001^2\text{Id}). \quad (14)
\]

Since the state-space is non-linear, we resort to the extended Kalman filter for estimation. This requires the computation of the Jacobian matrix of \(E_{t-1}[D_t, S_t, I_t, R_t, \beta_0^t]\) with respect to \([D_{t-1}, S_{t-1}, I_{t-1}, R_{t-1}, \beta_0^{t-1}]\), which is closed-form and detailed in Appendix H. We then apply a fixed-interval Rauch-Tung-Striebel smoother (backward filter) with the estimated trajectories produced by the filter.

### B Data & estimates

Our model features several parameters that we need to fix: The death rate \(\delta\), the recovery rate \(\gamma\), the parameters \(\beta, \kappa, \sigma\), and \(\rho\) governing the dynamics of transmission rates in the states, the effects \(\theta_M^\text{low}, \theta_S^\text{low},\) and \(\theta_T^\text{low}\) of the different containment policies, and the average traveling and commuting flows across states. We proceed as follows to select parameter values. We summarize our parameter estimates in Table 2.

We follow Fernández-Villaverde and Jones (2020), Perez-Saez et al. (2020), and Stringhini et al. (2020) and assume that it takes on average 14 days for an infection to resolve. We assume that after this period, an infected person either recovers and becomes immune, or dies with a probability of 0.6%. These assumptions imply that \(\gamma = \frac{1}{14}\) and \(\delta = \frac{0.06\%}{14} = 0.0004\).
We estimate average interstate travel flows from travel and mobility data in the United States. We collect data on interstate travels from the Traveler Analysis Framework published by the Federal Highway Administration (https://www.fhwa.dot.gov/policyinformation/analysisframework/01.cfm). We also collect data on state-level mobility and staying-at-home from the Trips by Distance database of the Bureau of Transportation Statistics (https://www.bts.gov/distribution-trips-distance-national-state-and-county-level). We combine these two databases to compute the percentage of a state’s population that stays home before and during the pandemic, as well as the percentage of a state’s population that traveled across state boundaries before and during the pandemic. We use these data to determine the travel matrix $W_{trav}$ of Appendix A.2.2. We illustrate the estimated interstate travel network in Figure 4(a). The size of a node is proportional to the percentage of a state’s population that travels outwards and the width of a link is proportional to the percentage of a state’s population that travel to the linked state. We assume that an average traveler spends 4 days on vacation. This implies that $\tau_{trav} = 4$.

We measure commuting flows from the 2011-2015 5-Year ACS Commuting Flows table of the U.S. Census (https://www.census.gov/data/tables/2015/demo/metro-micro/commuting-flows-2015.html). We use these data to estimate the commuter matrix $W_{com}$ of Appendix A.2.3. Figure 4(b) shows the implied commuting travel network. In this figure, however, the size of a node is proportional to the logarithm of the percentage of a state’s population that commutes outwards. We assume that out-of-state commuters spend 8 hours each business day and no time during a weekend in the visited state. We also assume that commuters sleep 8 hours a day and during that time infections are not possible. As a result, we set $\tau_{trav} = 0$.

We calibrate the parameters $\theta_{low}^M$, $\theta_{low}^S$, and $\theta_{low}^T$ to match mobility and mask usage data from the United States. We collect data on when the different policies were active in the different states from the National Academy for State Health Policy (https://www.nashp.org/governors-prioritize-health-for-all/) and the Steptoe COVID-19 State Regulatory Tracker (https://www.steptoe.com/en/news-publications/covid-19-state-regulatory-tracker.html). Figure 6 showcases the time periods in which policies were active in the different states. We also collect data on average mask adoption across U.S. states from the Institute of Health Metrics and Evaluation (https://covid19.healthdata.org/united-states-of-america). We assume that a stay-at-home policy is in place for the time period that covers any order for staying at home, sheltering at home, or being safer at home issued by a state.
governor. We neglect any stay-at-home advisories that are not strictly enforced by law officials. We estimate $\theta_{S}^{low} = 0.64$ as the reduction factor in the number of short trips taken during the pandemic versus before the pandemic.\(^{18}\) We consider a travel ban to be active when a state requires inbound travelers to self-quarantine for an extended period of time. Travel bans are active in our model only if they apply for all states. That is, we neglect any travel ban that only applies for travelers from selected states. We estimate $\theta_{T}^{low} = 0.10$ as the reduction factor in the number of long trips taken during the pandemic versus before the pandemic.\(^{19}\) Finally, we assume that a mask mandate is active if a state requires the use of masks indoors in public places. We do not consider mask mandates to be active if mask wearing is only recommended or only required outdoors. We estimate $\theta_{M}^{low} = 0.58$ by assuming that only half of the population adopts mask usage (as suggested by the Institute of Health Metrics and Evaluation) and that an average mask used in the U.S. reduces COVID-19 transmission by 85\% (as suggested by Fischer et al. (2020)).

We develop a quasi maximum likelihood methodology to estimate the parameters governing the dynamics of the transmission rates $\beta_{j,t}$ from daily data on state-level deaths in the United States for the time period between February 12 through September 30, 2020. We remove weekly seasonality patterns observed in COVID-19 fatality records using an STL approach. Our methodology assumes that daily death counts at the state-level are measures with small measurement errors. We take into account all state-level containment policies that were observed over the sample period. We write a non-linear state-space representation of the model, gathering $S_{j,t}^j$, $I_{j,t}^j$, $R_{j,t}^j$, $D_{j,t}^j$, and $\beta_{j,t}$ for all states simultaneously (255 variables). Filtering is easily performed through the first order extended Kalman filter algorithm. While we could estimate the speed of reversion $\kappa$ with our methodology, we find that the data prefers to set $\kappa$ arbitrarily close to zero, implying an extremely high persistence for the $\beta_{j,t}$. This results in numerical instabilities. To avoid these issues, we fix $\kappa = 0.001$ so that the first-order autocorrelation of the $\beta_{j,t}$ is 0.999. We then estimate the remaining parameters $\beta$, $\sigma$, and $\rho$ using our quasi maximum likelihood methodology. The estimates are provided in Table 2. We find that our parameter estimates are

\(^{18}\)More precisely, for each state we evaluate the average number of daily trips of less than 10 miles taken in 2019 and compare that number to the average number of daily trips of less than 10 miles taken during the time frame March 15 through April 30, 2020. We compute $\theta_{S}^{low}$ as the average reduction factor across states.

\(^{19}\)We evaluate the average number of daily trips of more than 100 miles taken in 2019 and compare that number to the average number of daily trips of more than 100 miles taken during the time frame March 15 through April 30, 2020. We compute $\theta_{T}^{low}$ as the average reduction factor across states.
not very sensitive to alternative choices for the value of $\kappa$.

Figure 5 shows the data-implied death counts in each state as well as the smoothed model-implied death counts. We see that our model performs well at fitting the state-level data. The estimated measurement errors are fairly small. Figures 6 and 7 show the smoothed model-implied effective $R_0$ and cumulated infections for each state. The data pushes our model to showcase high $R_0$ in the different states. The highest $R_0$ were observed in New Jersey, New York, and Washington in February and March, reaching levels of more than 8. Indeed, we find that the state-level $R_0$ must have been substantially higher than 1 for most states through April 2020. Several states, like Delaware, Hawaii, Idaho, Montana, Oklahoma, South Carolina, Texas, and West Virginia, experienced significant upticks in their Coronavirus $R_0$ in the summer. There have also been upticks in the $R_0$ in September in states like Arkansas, Florida, Kansas, Michigan, Missouri, North Dakota, Rhode Island, South Dakota, and Virginia. Some states have been successful at maintaining their $R_0$ values consistently at or below 1. The list of states that have accomplished this task include California, D. C., Illinois, Indiana, Maine, Maryland, Massachusetts, Minnesota, New Hampshire, New Mexico, New York, Oregon, and Vermont.

Overall, our findings suggest that the virus spread drastically in the U.S. through the Fall of 2020. In fitting the data, our model estimates that the number of infections in the different states must have been significantly higher than recorded in the data. These observations suggest that there must have been many undiagnosed infections that facilitated the spread of the disease throughout our sample period. Note that we never use infections data for the estimation or calibration of our model parameters.

C Counterfactual experiments

This section details how our counterfactual experiments are conducted.

---

20The $R_0$ of State $j$ in our model is given by $\theta_{t,M}^j, \theta_{t,S}^j, \beta_{t,H}^j, (\delta + \gamma)$.

21Our estimates of the effective reproduction numbers are one-and-a-half to two-times larger than prevailing estimates in Fernández-Villaverde and Jones (2020). We find that this is driven by a key difference in our models. Fernández-Villaverde and Jones (2020) assume that, while it take two weeks for an infection to resolve, an infected individual is only contagious for the first 5 days of an infection. We, instead, assume that an infected individual is contagious during the whole infection period. We run several experiments in Appendix E in which we study whether are results are sensitive to this assumption, and we find that this is not the case.
C.1 Baseline scenario

The estimated dynamics constitutes our baseline scenario. All of our results are presented as a difference with respect to this baseline scenario. We compare the outcomes in terms of fatalities.

C.2 “Strict” and “loose” counterfactuals

We consider two types of experiments, which we call strict and loose, respectively:

- In the strict scenario, we assume that the states start adopting the same policy as that implemented by the earliest state during the sample period and relax it when the latest state does so. The scenarios are as follows:
  
  - **Stay-at-Home**: Start on March 20, 2020 (the day when California activated its stay-at-home mandate) and keep it active through September 30, 2020 (the last day in our sample in which the stay-at-home order was still active in California).
  
  - **Travel ban**: Start on March 17, 2020 (the day the first interstate travel ban in the U.S. went into effect in Hawaii) and keep it active through September 30, 2020 (the last day in our sample in which an interstate travel ban was still active in Alaska).
  
  - **Mask mandate**: Start on April 17, 2020 (the day the first mask mandate in the U.S. went into effect in Connecticut) and keep it active through September 30, 2020 (the last day in our sample in which several states had mask mandates in place).

- For the loose scenario, we assume that states do not implement a specific policy at all. We then re-propagate the model with these counterfactual policies according to the methodology described below.

We conduct these two types of experiments one policy at a time, and one last time all together.

C.3 Joint and state-by-state counterfactuals

Our analysis is split into joint and state-by-state experiments. For the former, we assume that the federal government imposes on all states the counterfactual policy (strict federal mandate), i.e. to be as strict as the strictest or to do nothing (loose federal mandate). For the latter, we take each state one at a time and assume that only this state follows the strict or loose scenario and compute the counterfactual outcomes one state at a time.
C.4 Computation of counterfactual scenarios

Recall that the model parameters and the latent variables ($S_t$, $I_t$, $R_t$ and $\beta_t^{0}$) are estimated by employing the extended Kalman filter. The observed variables are the numbers of deaths $D_t^{obs.}$, as well as the observed implemented policies $\theta_{obs.}$.

In order to derive our counterfactual outcomes, we also extend our filtering approach. The broad idea is the following: We augment the state vector used at the estimation step – i.e. $X_t = [D_t, S_t, I_t, R_t, \beta^0_t]$ – with a similar state vector for a fictitious country ($fict.$), with the same number of states, where the counterfactual policies would be implemented. Critically, we assume that the basic, standardized, shocks affecting the two countries are almost perfectly correlated, implying in particular that the $\beta^0_t$’s are the same for the baseline and fictitious countries.

Specifically, let us denote by $X^*_t$ the state vector corresponding to the fictitious country. The transition equation of the augmented state-space model are:

$$
\begin{bmatrix}
    X_t \\
    X^*_t
\end{bmatrix} = 
\begin{bmatrix}
    \mathcal{E}(X_{t-1}, \theta_{obs.}) & \mathcal{E}(X^*_{t-1}, \theta_{fict.}) \\
    \mathcal{E}(X_{t-1}, \theta_{obs.}) & \mathcal{E}(X^*_{t-1}, \theta_{fict.})
\end{bmatrix}
\begin{bmatrix}
    \mathcal{E}(X_{t-1}, \theta_{obs.}) & \mathcal{E}(X^*_{t-1}, \theta_{fict.}) \\
    \mathcal{E}(X_{t-1}, \theta_{obs.}) & \mathcal{E}(X^*_{t-1}, \theta_{fict.})
\end{bmatrix}^{-1}
\begin{bmatrix}
    \mathcal{V}^{1/2}(S_{t-1}, I_{t-1}, \theta_{obs.})\varepsilon_{true,t} \\
    \mathcal{V}^{1/2}(S^*_{t-1}, I^*_{t-1}, \theta_{fict.})\varepsilon_{fict.,t}
\end{bmatrix},
$$

where $\theta_{obs.}$ and $\theta_{fict.}$ contain the full trajectories of observed and fictitious policies, respectively; where $\varepsilon_{true,t}$ and $\varepsilon_{fict.,t}$ denote differences of martingale sequence; and where $\mathcal{V}^{1/2}(S, I, \theta)$ is such that $(\mathcal{V}^{1/2}(S, I, \theta))(\mathcal{V}^{1/2}(S, I, \theta))' = \mathcal{V}(S, I, \theta)$, with the function $\mathcal{V}$ defined in (28). To capture the idea that the two countries are affected by very similar standardized shocks, which are the $\varepsilon_{true,t}$’s and the $\varepsilon_{fict.,t}$’s, we further assume that:

$$\mathbb{V}ar\left(\begin{bmatrix}
    \varepsilon_{true,t} \\
    \varepsilon_{fict.,t}
\end{bmatrix}\right) \approx \begin{bmatrix}
    \text{Id} & \text{Id} \\
    \text{Id} & \text{Id}
\end{bmatrix}.$$

On top of the transition equation (15), the state-space model comprehends the following measurement equation:

$$D_t^{obs.} = D_t,$$

where $D_t^{obs.}$ is the observed vector of numbers of deaths (in the “observed” country). By construction, the filtered variables $X_t$ resulting from this augmented state-space framework are exactly equal the the ones of the regular state-space. Indeed, it produces the moment $\mathbb{E}(X_t|D_t^{obs.}, D_{t-1}^{obs.}, \ldots)$, which is the same in both state-space models. However, $X^*_t$ will be different from $X^*_t$ since the implemented policies are different, and their impacts are non-trivial since they are non-linearly propagated in the state-space.
As a last step, we provide backward path estimates using the Bryson-Frazier smoother and compare the paths of $D_t$ and $D^*_t$ produced by the smoother. We used Bryson-Frazier rather than Rauch-Tung-Striebel because the latter requires to invert the conditional variance-covariance matrices of the transition equations, which are of size $(9N \times 9N)$. In our empirical application (51 states), this results in matrices of size $(459 \times 459)$ that have to be inverted for each day of data. This results in a large numerical instability. Instead, the Bryson-Frasier smoother only requires the inversion of the variance-covariance matrix of the observables, that is of matrices of size $(N \times N)$. The time series dynamics of the federal counterfactuals are presented on Figure 8.

D Infected populations in travel ban counterfactual

Figure 9 showcases the posterior (smoothed) mean of the cumulative number of infected individuals in the baseline scenario for some select states. The figure also shows the smoothed mean of the cumulative number of infected individuals in the counterfactual in which a federal interstate travel ban goes into effect on March 17, 2020.

E Sensitivity analysis

We run several analyses to understand how sensitive our results are with respect to changes in our parameter values. Table 1 shows confidence bands that are derived from re-estimating the number of preventable deaths if the policy that deviated from the data was either twice or half as impactful. What we mean in precise terms by this is that if, for example, we assume that a counterfactual is carried out with respect to changes in a mask mandate, we would evaluate the number of preventable deaths by assuming that $\theta^\text{low}M$ is either half or twice as large as indicated in Table 2. This sensitivity analysis provides confidence bands for our estimates of the number of deaths that could have been prevented by adopting policies different than the ones that were adopted in reality by considering that the policies may have a different impact on reducing transmission rates and traveler and commuter inflows than what we assume in our study.

We also carry out additional sensitivity analyses with respect to two key parameters in our model: the number of days that it takes for an infection to resolve, and the fatality rate of the disease. Tables 3 through 6 repeat the experiments of Table 1 by assuming that it either takes 10 or 20 days for an infection to resolve, or that the fatality rate of the disease is 0.4% or 1%. 

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To obtain the results, we re-estimate the parameters $\beta$, $\sigma$, and $\rho$ that would be necessary under the new assumptions for the fatality rate or the number of days for infection resolution. The sensitivity analyses are carried out one-by-one.

We find that adopting early federal containment policies would have been less impactful and prevented less deaths if an infection took longer time to resolve. Vice versa, we find that early federal action would have been more impactful if an infection took less time to resolve. This is primarily because, if the disease were less severe than we assumed and it took less time to resolve an infection, then the methodology estimates that there must have been many more infections early on in the sample to match the number of deaths observed throughout the sample. That means that early action would have been more impactful if the disease is less severe than we assumed. Note that this is always a conclusion based on matching the amount of death cases that we observe in the data. If the disease were less severe and we still observed as many deaths as in the data, then the only possible explanation is that there must have been more infections early on in the sample. As a result, early action would have been the more impactful.

We find that the number of preventable deaths would not be much different if the virus were less lethal. However, we find that the costs of inaction at the state level would be much higher if the virus were more lethal. We find that close to 2,000,000 additional deaths would have been observed if no state enacted any policy and if the lethality rate of the virus were 1%. These observations further corroborate our findings of the success of the policies enacted by the individual states to prevent COVID-19 deaths both at the state and federal levels.

F Conditional covariances for the single-state model

We have:

$$
\mathbb{E}_{t-1}(r_t + d_t) = \mathbb{E}_{t-1}(d_t + \mathbb{E}_{t-1}(r_t|d_t)) - (\gamma + \delta)I_{t-1}
$$

(17)

$$
\text{Var}_{t-1}(r_t + d_t) = \text{Var}_{t-1}(d_t + \mathbb{E}_{t-1}(r_t|d_t)) + \mathbb{E}_{t-1}(\text{Var}_{t-1}(d_t + r_t|d_t))
$$

$$
= \text{Var}_{t-1}\left(\frac{1 - \delta - \gamma}{1 - \delta}d_t\right) + \mathbb{E}_{t-1}\left((I_{t-1} - d_t)\frac{\gamma(1 - \delta - \gamma)}{(1 - \delta)^2}\right)
$$

$$
= \left(\frac{1 - \delta - \gamma}{1 - \delta}\right)^2 I_{t-1}(1 - \delta) + \mathbb{E}_{t-1}\left((I_{t-1} - d_t)\frac{\gamma(1 - \delta - \gamma)}{(1 - \delta)^2}\right)
$$

$$
= \frac{(1 - \delta - \gamma)^2 \delta + \gamma(1 - \delta - \gamma)}{1 - \delta} I_{t-1}. \quad (18)
$$
Because $d_t + r_t$, on the one hand, and $i_t$, on the other hand, are independent conditional on the information available on date $t - 1$, it follows that:

$$\mathbb{E}_{t-1}(\Delta I_t) = \frac{S_{t-1}}{N} I_{t-1} \beta_{t-1} - (\gamma + \delta) I_{t-1}$$

(19)

$$\text{Var}_{t-1}(\Delta I_t) = \frac{S_{t-1}}{N} I_{t-1} \beta_{t-1} + \nu I_{t-1}.$$  

(20)

**Remark:** Let us introduce $Z_t \equiv \Delta I_t - \mathbb{E}_{t-1}(\Delta I_t)$. By construction, $\mathbb{E}_{t-1}(Z_t) = 0$. It can be seen that $Z_t$ is the sum of $I_{t-1}$ i.i.d. random variables. Hence, if $I_{t-1}$ is large, we approximately have:

$$Z_t \sim \mathcal{N}\left(0, \frac{S_{t-1}}{N} I_{t-1} \beta_{t-1} + \nu I_{t-1}\right),$$

conditional on the information available on $t - 1$. This is also true for $i_t$, $r_t$ and $d_t + r_t$. Because the conditional variances of these variables are in $I_{t-1}$ (and not in $I_{t-1}^2$), it follows that, when $I_{t-1}$ is large, the deterministic version of the SIR model provides a good approximation of the dynamics of $(S, I, R, D)$ – at least up to potential stochastic variation of $\beta_t$.

In the remaining of this appendix, we detail the computation of some of the covariances appearing in equation (3)

$$\text{Cov}_{t-1}(\varepsilon_{D,t}, \varepsilon_{R,t}) = \text{Cov}_{t-1}(r_t, d_t) = \text{Cov}_{t-1}(\mathbb{E}_{t-1}(r_t | d_t), d_t)$$

$$= \text{Cov}_{t-1}\left(\frac{(I_{t-1} - d_t) \gamma}{1 - \delta}, d_t\right)$$

$$= -\frac{\gamma}{1 - \delta} \text{Var}_{t-1}(d_t) = -\gamma \delta I_{t-1}. $$

$$\text{Cov}_{t-1}(\varepsilon_{D,t}, \varepsilon_{I,t}) = -\text{Cov}_{t-1}(d_t, d_t + r_t) = -\left(\mathbb{E}_{t-1}(d_t (d_t + r_t)) - \mathbb{E}_{t-1}(d_t) \mathbb{E}_{t-1}(d_t + r_t)\right)$$

$$= -\text{Var}_{t-1}(d_t) - \text{Cov}_{t-1}(r_t, d_t)$$

$$= -\delta(1 - \delta) I_{t-1} + \gamma \delta I_{t-1}$$

$$= -\delta(1 - \delta - \gamma) I_{t-1}.$$ 

$$\text{Var}_{t-1}(r_t) = \text{Var}_{t-1}(\mathbb{E}_{t-1}(r_t | d_t)) + \mathbb{E}_{t-1}(\text{Var}_{t-1}(r_t | d_t))$$

$$= \text{Var}_{t-1}\left(\frac{(I_{t-1} - d_t) \gamma}{1 - \delta}\right) + \mathbb{E}_{t-1}\left(\frac{(I_{t-1} - d_t) \gamma(1 - \delta - \gamma)}{(1 - \delta)^2}\right).$$

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\[ \frac{\gamma^2 \delta}{1 - \delta} I_{t-1} + \frac{\gamma (1 - \delta - \gamma)}{1 - \delta} I_{t-1} = (\gamma - \gamma^2) I_{t-1}. \]

\[ \text{Cov}_{t-1}(r_t, d_t) = -\text{Cov}_{t-1}(r_t, r_t) = - (\mathbb{E}_{t-1}(r_t(d_t + r_t)) - \mathbb{E}_{t-1}(r_t)\mathbb{E}_{t-1}(d_t + r_t)) \]

\[ = -\text{Var}_{t-1}(r_t) - \text{Cov}_{t-1}(r_t, d_t) \]

\[ = -(\gamma - \gamma^2) I_{t-1} + \gamma \delta I_{t-1} \]

\[ = -\gamma (1 - \gamma - \delta) I_{t-1}. \]

### G Conditional means and variances in the multi-state model

#### G.1 Conditional variance of commute and travel flows

Let us denote by \( \text{Flow}_{\text{com}, I, t} \) the vector whose \( i \)th component is the time-weighted net inflow of infected commuters in state \( i \). (Remember that \( \tau \) is the fraction of time spent by commuters in the state where they work.) We have:

\[ \text{Flow}_{\text{com}, I, t} = \tau \text{Flow}_{\text{com}, I, t-1} - \tau \text{Flow}_{\text{com}, I, t-1}. \]

Using equations (8) to (12), we have, in particular:

\[ \mathbb{E}(\text{Flow}_{\text{com}, I, t} | I_t) = \tau \phi_{\text{com}, I, t} - \tau \phi_{\text{com}, I, t} = \Omega_{\text{com}, t} I_t. \]

We also have

\[ \text{Cov}(\text{Flow}_{\text{com}, I, k, t}, \text{Flow}_{\text{com}, I, j, t} | I_t) = \left\{ \begin{array}{ll}
-\tau^2 w_{\text{com}, k}^{\text{com}, j} I_k^j - \tau^2 w_{\text{com}, j}^{\text{com}, k} I_l^j & \text{if } j \neq k \\
\tau^2 \left( \sum_{k \neq j} w_{\text{com}, k}^{\text{com}, j} I_k^j \right) + \tau^2 \left( \sum_{j \neq k} w_{\text{com}, j}^{\text{com}, k} I_l^j \right) & \text{if } j = k,
\end{array} \right. \]

that is, in vectorial form:

\[ \text{Var}(\text{Flow}_{\text{com}, I, t} | I_t) = -\tau^2 W_{\text{com}, t} \odot (I_t 1') - \tau^2 W_{\text{com}, t}' \odot (1' I_t') + \mathbf{d}(\tau^2 W_{\text{com}, t}' I_t + \tau^2 (W_{\text{com}, t} 1) \odot I_t), \]

which we denote by

\[ \text{Var}(\text{Flow}_{\text{com}, I, t} | I_t) = C(W_{\text{com}, t}, I_t, \tau), \quad (21) \]

where function \( C \) is defined by

\[ C(W, Z, \tau) = \tau^2 \left\{ -W \odot (Z 1') - W' \odot (1' Z') + \mathbf{d}(W' Z + (W 1) \odot Z) \right\}. \quad (22) \]
The same type of computation leads to

\[ \text{Var}(\text{Flow}_{\text{com},t}|S_t) = C(W_{\text{com},t}, S_t, \tau) \]  
\[ \text{Var}(\text{Flow}_{\text{trav},t}|I_t) = C(W_{\text{trav},t}, I_t, 1) \]  
\[ \text{Var}(\text{Flow}_{\text{trav},t}|S_t) = C(W_{\text{trav},t}, S_t, 1). \]  

\[ \text{(23)} \text{Var}(\text{Flow}_{\text{com},t}, S_t, I, \tau) \]
\[ \text{(24)} \text{Var}(\text{Flow}_{\text{trav},t}, I_t, I, \tau) \]
\[ \text{(25)} \text{Var}(\text{Flow}_{\text{trav},t}, S_t, I, \tau) \]

G.2 Conditional variance of new infections

For any pair of independent random vectors \( X \) and \( Y \), we have

\[ \text{Var}(X \odot Y) = E(XX') \odot E(YY') - E(X)E(X)' \odot E(Y)E(Y)' \]
\[ = \text{Var}(X) \odot \text{Var}(Y) + \text{Var}(X) \odot E(Y)E(Y)' + \text{Var}(Y) \odot E(X)E(X)'. \]

Therefore:

\[ \text{Var}
\[ \left( I_{t-1} + \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \mid S_{t-1} + \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \right| I_{t-1}, S_{t-1} \right) \]
\[ = \text{Var}
\[ \left( \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \mid I_{t-1} \right) \odot \text{Var}
\[ \left( \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \mid S_{t-1} \right) + \text{Var}
\[ \left( \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \mid I_{t-1} \right) \odot \left( (\text{Id} + \Omega_{t-1}) S_{t-1} S_{t-1}' (\text{Id} + \Omega_{t-1})' \right) + \text{Var}
\[ \left( \text{Flow}_{\text{com},t-1} + \text{Flow}_{\text{trav},t-1} \mid S_{t-1} \right) \odot \left( (\text{Id} + \Omega_{t-1}) I_{t-1} I_{t-1}' (\text{Id} + \Omega_{t-1})' \right) \]
\[ = \left( C(W_{\text{com},t-1}, I_{t-1}, \tau) + C(W_{\text{trav},t-1}, I_{t-1}, 1) \right) \odot \left( C(W_{\text{com},t-1}, S_{t-1}, \tau) + C(W_{\text{trav},t-1}, S_{t-1}, 1) \right) + \left( C(W_{\text{com},t-1}, I_{t-1}, \tau) + C(W_{\text{trav},t-1}, I_{t-1}, 1) \right) \odot \left( (\text{Id} + \Omega_{t-1}) S_{t-1} S_{t-1}' (\text{Id} + \Omega_{t-1})' \right) + \left( C(W_{\text{com},t-1}, S_{t-1}, \tau) + C(W_{\text{trav},t-1}, S_{t-1}, 1) \right) \odot \left( (\text{Id} + \Omega_{t-1}) I_{t-1} I_{t-1}' (\text{Id} + \Omega_{t-1})' \right) \]
\[ = D(W_{\text{com},t-1}, W_{\text{trav},t-1}, S_{t-1}, I_{t-1}, \tau, \Omega_{t-1}), \]

where \( \Omega_{t-1} = \Omega_{\text{trav},t-1} + \Omega_{\text{com},t-1} \) and where

\[ D(W_1, W_2, S, I, \tau, \Omega) = \left( C(W_1, I, \tau) + C(W_2, I, 1) \right) \odot \left( C(W_1, S, \tau) + C(W_2, S, 1) \right) + \left( C(W_1, I, \tau) + C(W_2, I, 1) \right) \odot \left( (\text{Id} + \Omega) SS' (\text{Id} + \Omega)' \right) + \left( C(W_1, S, \tau) + C(W_2, S, 1) \right) \odot \left( (\text{Id} + \Omega) II' (\text{Id} + \Omega)' \right), \]

function \( C \) being defined in \( (22) \).
G.3 Conditional variance of susceptibles

Let us use the notation:

\[ I^*_{t} = I_t + \text{Flow}_{com,I,t} + \text{Flow}_{trav,I,t} \quad \text{and} \quad S^*_{t} = S_t + \text{Flow}_{com,S,t} + \text{Flow}_{trav,S,t}. \]

Using the law of total variance:

\[
\begin{align*}
\text{Var}_{t-1}(S_t) &= \text{Var}_{t-1}(E_{t-1}(S_t|I_{t-1}, S_{t-1}, \text{Flow}_{com,I,t-1}, \text{Flow}_{com,S,t-1}, \text{Flow}_{trav,I,t-1}, \text{Flow}_{trav,S,t-1})) + \\
&\quad E_{t-1}(\text{Var}_{t-1}(S_t|I_{t-1}, S_{t-1}, \text{Flow}_{com,I,t-1}, \text{Flow}_{com,S,t-1}, \text{Flow}_{trav,I,t-1}, \text{Flow}_{trav,S,t-1})) \\
&= \text{Var}_{t-1}\left(\theta_{t-1} \circ \beta_{t-1} \circ \frac{1}{p} \circ I^*_{t-1} \circ S^*_{t-1}\right) + E_{t-1}\left(d\left(\theta_{t-1} \circ \beta_{t-1} \circ \frac{1}{p} \circ I^*_{t-1} \circ S^*_{t-1}\right)\right)
\end{align*}
\]

Let’s denote the previous conditional variance by \( \Theta_{t-1} \). We have:

\[
\Theta_{t-1} = \text{Var}_{t-1}(S_t)
\]

\[
:= \left[\left(\theta_{t-1} \circ \beta_{t-1} \circ \frac{1}{p}\right) \circ \left(\theta_{t-1} \circ \beta_{t-1} \circ \frac{1}{p}\right)^T\right] \circ D(W_{com,t-1}, W_{trav,t-1}, S_{t-1}, I_{t-1}, \tau, \Omega_{t-1}) + \\
\quad d\left(\theta_{t-1} \circ \beta_{t-1} \circ \frac{1}{p} \circ [(\text{Id} + \Omega_{t-1})I_{t-1}] \circ [(\text{Id} + \Omega_{t-1})S_{t-1}]\right),
\]

(27)

where \( \Omega_{t-1} = \Omega_{\text{com},t-1} + \Omega_{\text{trav},t-1} \) and function \( D \) is defined by (26).

G.4 Conditional variance of the state vector

What precedes implies that:

\[
\mathcal{V}(S_{t-1}, I_{t-1}) := \text{Var}_{t-1}\begin{pmatrix}
D_t \\
S_t \\
I_t \\
R_t \\
\beta_t
\end{pmatrix} =
\]

(28)
\[
\begin{bmatrix}
\delta(1-\delta)d(I_{t-1}) & 0 & -\delta(1-\delta-\gamma)d(I_{t-1}) & -\delta\gamma d(I_{t-1}) & 0 \\
0 & \Theta_{t-1} & 0 & 0 & 0 \\
-\delta(1-\delta-\gamma)d(I_{t-1}) & -\Theta_{t-1} - \nu d(I_{t-1}) & -\gamma(1-\gamma-\delta)d(I_{t-1}) & 0 & 0 \\
-\delta\gamma d(I_{t-1}) & 0 & -\gamma(1-\gamma-\delta)d(I_{t-1}) & (\gamma-\gamma^2)d(I_{t-1}) & 0 \\
0 & 0 & 0 & 0 & \Omega_{\beta,t-1}
\end{bmatrix}
\]

with

\[
\Omega_{\beta,t-1} = \sigma^2 \Delta t d(\sqrt{\beta_{t-1}^-}) \cdot \Sigma \cdot d(\sqrt{\beta_{t-1}^-}),
\]

and where \(\Theta_t\) is defined by equations (27), and \(\nu\) is defined in equation (18).

**H Jacobian matrix for extended Kalman filter implementation**

We hereby provide the formulas for the Jacobian computation in the extended Kalman filter recursions. Denoting by \(J = \partial E_t \partial \mathbf{t}^{-1} [D_t, S_t, I_t, R_t, \beta_0^t] / \partial \mathbf{t}^{-1} \), we have:

\[
J = \begin{bmatrix}
\mathbf{Id} & 0 & \delta \mathbf{Id} & 0 & 0 \\
0 & \mathbf{Id} & 0 & 0 & 0 \\
0 & 0 & (1-\delta-\gamma) \mathbf{Id} & 0 & 0 \\
0 & 0 & \gamma \mathbf{Id} & \mathbf{Id} & 0 \\
0 & 0 & 0 & 0 & (1-\kappa) \mathbf{Id}
\end{bmatrix}
\]

\[
\frac{\partial \left( \theta_{S,t-1} \circ \theta_{M,t-1} \circ \beta_{t-1}^0 \circ \frac{1}{\mathbf{P}} \circ ([\mathbf{Id} + \Omega_{t-1}]I_{t-1}) \circ ([\mathbf{Id} + \Omega_{t-1}]S_{t-1}) \right)}{\partial [D_{t-1}, S_{t-1}, I_{t-1}, R_{t-1}, \beta_{t-1}^0]} (29)
\]

The matrix of partial derivatives is given by:

\[
\frac{\partial \left( \theta_{S,t-1} \circ \theta_{M,t-1} \circ \beta_{t-1}^0 \circ \frac{1}{\mathbf{P}} \circ ([\mathbf{Id} + \Omega_{t-1}]I_{t-1}) \circ ([\mathbf{Id} + \Omega_{t-1}]S_{t-1}) \right)}{\partial [D_{t-1}, S_{t-1}, I_{t-1}, R_{t-1}, \beta_{t-1}^0]} (29)
\]
$$\begin{bmatrix}
0 \\
(Id + \Omega_{t-1}) \times d \left( \theta_{S,t-1} \odot \theta_{M,t-1} \odot \beta_{t-1}^{0} \odot \frac{1}{p} \odot ([Id + \Omega_{t-1}]I_{t-1}) \right) \\
(Id + \Omega_{t-1}) \times d \left( \theta_{S,t-1} \odot \theta_{M,t-1} \odot \beta_{t-1}^{0} \odot \frac{1}{p} \odot ([Id + \Omega_{t-1}]S_{t-1}) \right) \\
d \left( \theta_{S,t-1} \odot \theta_{M,t-1} \odot \frac{1}{p} \odot ([Id + \Omega_{t-1}]I_{t-1}) \odot ([Id + \Omega_{t-1}]S_{t-1}) \right)
\end{bmatrix}.$$  \hspace{1cm} \text{(30)}$$

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| Counterfactual assumption                                                                 | Federal mandate active on: | Deaths in excess of baseline |
|-----------------------------------------------------------------------------------------|----------------------------|------------------------------|
| Strict stay-at-home orders, mask mandates, and travel bans for all states.               | 3/20 4/17 3/17             | -136,514 [-162,029; -105,168] |
| Strict stay-at-home orders in all states, and all other state-level policies remain as in the data. | 3/20 4/17                  | -110,129 [-136,201; 78,960]  |
| Strict mask mandates in all states, and all other state-level policies remain as in the data. | 4/17 3/17                  | -96,515 [-116,362; -67,520]  |
| Strict travel bans in all states, and all other state-level policies remain as in the data. |                            | -5,148 [-5,435; -2,557]      |
| No stay-at-home order, mask mandate, or travel ban in any state.                          |                            | +1,012,053 [+379,784; +1,600,955] |
| No stay-at-home order in any state, but all other policies remain as in the data.         |                            | +657,949 +[253,519; +1,483,567] |
| No mask mandate in any states, but all other policies remain as in the data.              |                            | +439,193 [+78,136; +1,290,944] |
| No travel ban in any states, but all other policies remain as in the data.                |                            | +2,286 [+1,061; +2,433]       |
| Mask mandate in all states on March 20, 2020, while no state adopts any state-level policies. | 3/20 4/17                  | -78,136 [-188,723; 181,526]   |
| Strict travel bans in all states by February 12, 2020, while all other state-level policies remain as in the data. | 2/12 3/17                  | -5,986 [-6,265; -2,983]       |

Table 1: Results of the counterfactual experiments in which we assume that all states jointly deviate from their enacted policies and adopt either strict or loose versions of the policies instead. The reported values are excess deaths relative to the number of U.S. deaths recorded in our data on September 30, 2020. In the counterfactuals, we compute the trajectories of death counts per state under the alternative policy scenarios that are consistent with the susceptible, infected, recovered, and dead populations as well as the transmission rates filtered from the observed data. The values in brackets give confidence bounds based on a sensitivity analysis of the estimates of the impact of the different policies on transmission rates and traveler and commuter inflow. The lower bounds assume that any policy that deviates from what it was in the data is half as impactful, while the upper bound assumes that any policy that deviates is twice as impactful. Table 2 in Appendix E provides the parameter values used for the sensitivity analyses. In the sensitivity analysis, we proceed in a similar way as for the counterfactuals and first compute posterior means of the state-level transmission rates that would explain the observed death counts under the assumption of alternative effectiveness for the different policies. We then compute the number of death that would have been observed if the policies had changed while keeping the recomputed trajectories of the transmission rates fixed.
### Table 2: Parameter values.
The values in brackets give alternative parametrizations used for a sensitivity analysis of our results in Appendix E.

| Parameter | Value  | Alternative Values |
|-----------|--------|--------------------|
| $\gamma$  | 0.07   | [0.05, 0.1]        |
| $\delta$  | 0.0004 | [0.0003, 0.0007]   |
| $\kappa$  | 0.001  |                    |
| $\beta$   | 0.16   |                    |
| $\sigma$  | 0.05   |                    |
| $\rho$    | 0.49   |                    |
| $\theta_{low}^S$ | 0.64 | [0.32, 0.82]          |
| $\theta_{low}^T$ | 0.10 | [0.05, 0.55]          |
| $\theta_{low}^M$ | 0.58 | [0.29, 0.79]          |
| $\tau_{com}$ | 0.36 |                    |
| $\tau_{trav}$ | 4.00 |                    |
Table 3: Results of the counterfactual experiments in which we assume that all states jointly deviate from their enacted policies and adopt either strict or loose versions of the policies instead. Here, we assume that it takes on average 10 days for an infection to resolve, while keeping the fatality rate of the disease fixed at 0.6%. The reported values are excess deaths relative to the number of U.S. deaths recorded in our data on September 30, 2020. In the counterfactuals, we compute the trajectories of death counts per state under the alternative policy scenarios that are consistent with the susceptible, infected, recovered, and dead populations as well as the transmission rates filtered from the observed data. The values in brackets give confidence bounds based on a sensitivity analysis of the estimates of the impact of the different policies on transmission rates and traveler and commuter inflow. The lower bounds assume that any policy that deviates from what it was in the data is half as impactful, while the upper bound assumes that any policy that deviates is twice as impactful. Table 2 in Appendix E provides the parameter values used for the sensitivity analyses. In the sensitivity analysis, we proceed in a similar way as for the counterfactuals and first compute posterior means of the state-level transmission rates that would explain the observed death counts under the assumption of alternative effectiveness for the different policies. We then compute the number of death that would have been observed if the policies had changed while keeping the recomputed trajectories of the transmission rates fixed.

| Counterfactual assumption (γ = 0.1)                                                                 | Federal mandate active on: Stay-at-home | Mask | Travel ban | Deaths in excess of baseline |
|--------------------------------------------------------------------------------------------------|----------------------------------------|------|------------|------------------------------|
| Strict stay-at-home orders, mask mandates, and travel bans for all states.                       | 3/20                                   | 4/17 | 3/17       | -145,158                     |
| Strict stay-at-home orders in all states, and all other state-level policies remain as in the data.| 3/20                                   |      |            | -115,868                     |
| Strict mask mandates in all states, and all other state-level policies remain as in the data.     | 4/17                                   |      |            | -109,675                     |
| Strict travel bans in all states, and all other state-level policies remain as in the data.      | 3/17                                   |      |            | -5,447                       |
| No stay-at-home order, mask mandate, or travel ban in any state.                                 |                                        |      |            | +1,055,371                   |
| No stay-at-home order in any state, but all other policies remain as in the data.                |                                        |      |            | +711,567                     |
| No mask mandate in any states, but all other policies remain as in the data.                     |                                        |      |            | +687,774                     |
| No travel ban in any states, but all other policies remain as in the data.                       |                                        |      |            | +2,501                       |
| Mask mandate in all states on March 20, 2020, and all other state-level policies remain as in the data. | 3/20                                   |      |            | -185,023                     |
| Mask mandate in all states on March 20, 2020, while no state adopts any state-level policies.   | 3/20                                   |      |            | -39,228                      |
| Strict travel bans in all states by February 12, 2020, while all other state-level policies remain as in the data. | 2/12                                   |      |            | -6,063                       |
| Counterfactual assumption (γ = 0.05)                                                                 | Federal mandate active on: | Deaths in excess of baseline |
|--------------------------------------------------------------------------------------------------|---------------------------|-------------------------------|
| Strict stay-at-home orders, mask mandates, and travel bans for all states.                       |                           | -126,471                      |
| Strict stay-at-home orders in all states, and all other state-level policies remain as in the data.|                           | -103,321                      |
| Strict mask mandates in all states, and all other state-level policies remain as in the data.      | 4/17                      | -81,338                       |
| Strict travel bans in all states, and all other state-level policies remain as in the data.        | 3/17                      | -4,785                        |
| No stay-at-home order, mask mandate, or travel ban in any state.                                 |                           | +910,918                      |
| No stay-at-home order in any state, but all other policies remain as in the data.                 |                           | +592,475                      |
| No mask mandate in any states, but all other policies remain as in the data.                      |                           | +249,573                      |
| No travel ban in any states, but all other policies remain as in the data.                        |                           | +2,052                        |
| Mask mandate in all states on March 20, 2020, and all other state-level policies remain as in the data. |                           | -173,620                      |
| Mask mandate in all states on March 20, 2020, while no state adopts any state-level policies.    | 3/20                      | -97,146                       |
| Strict travel bans in all states by February 12, 2020, while all other state-level policies remain as in the data. | 2/12                      | -5,385                        |

Table 4: Results of the counterfactual experiments in which we assume that all states jointly deviate from their enacted policies and adopt either strict or loose versions of the policies instead. Here, we assume that it takes on average 20 days for an infection to resolve, while keeping the fatality rate of the disease fixed at 0.6%. The reported values are excess deaths relative to the number of U.S. deaths recorded in our data on September 30, 2020. In the counterfactuals, we compute the trajectories of death counts per state under the alternative policy scenarios that are consistent with the susceptible, infected, recovered, and dead populations as well as the transmission rates filtered from the observed data. The values in brackets give confidence bounds based on a sensitivity analysis of the estimates of the impact of the different policies on transmission rates and traveler and commuter inflow. The lower bounds assume that any policy that deviates from what it was in the data is half as impactful, while the upper bound assumes that any policy that deviates is twice as impactful. Table 2 in Appendix E provides the parameter values used for the sensitivity analyses. In the sensitivity analysis, we proceed in a similar way as for the counterfactuals and first compute posterior means of the state-level transmission rates that would explain the observed death counts under the assumption of alternative effectiveness for the different policies. We then compute the number of death that would have been observed if the policies had changed while keeping the recomputed trajectories of the transmission rates fixed.
| Counterfactual assumption ($\delta = 0.0003$) | Federal mandate active on: | Deaths in excess of baseline |
|---------------------------------------------|-----------------------------|------------------------------|
| Strict stay-at-home orders, mask mandates, and travel bans for all states. | 3/20 4/17 3/17 | -135,805 |
| Strict stay-at-home orders in all states, and all other state-level policies remain as in the data. | 3/20 | -109,118 |
| Strict mask mandates in all states, and all other state-level policies remain as in the data. | 4/17 | -95,703 |
| Strict travel bans in all states, and all other state-level policies remain as in the data. | 3/17 | -5,965 |
| No stay-at-home order, mask mandate, or travel ban in any state. | | +673,173 |
| No stay-at-home order in any state, but all other policies remain as in the data. | | +463,490 |
| No mask mandate in any states, but all other policies remain as in the data. | | +338,903 |
| No travel ban in any states, but all other policies remain as in the data. | | +2,002 |
| Mask mandate in all states on March 20, 2020, and all other state-level policies remain as in the data. | 3/20 | -178,419 |
| Mask mandate in all states on March 20, 2020, while no state adopts any state-level policies. | 3/20 | -78,541 |
| Strict travel bans in all states by February 12, 2020, while all other state-level policies remain as in the data. | 2/12 | -3,719 |

Table 5: Results of the counterfactual experiments in which we assume that all states jointly deviate from their enacted policies and adopt either strict or loose versions of the policies instead. Here, we assume that the fatality rate of the disease is 0.4% instead of 0.6%, and keep the number of days that it take for an infection to resolve at 14 days. The reported values are excess deaths relative to the number of U.S. deaths recorded in our data on September 30, 2020. In the counterfactuals, we compute the trajectories of death counts per state under the alternative policy scenarios that are consistent with the susceptible, infected, recovered, and dead populations as well as the transmission rates filtered from the observed data. The values in brackets give confidence bounds based on a sensitivity analysis of the estimates of the impact of the different policies on transmission rates and traveler and commuter inflow. The lower bounds assume that any policy that deviates from what it was in the data is half as impactful, while the upper bound assumes that any policy that deviates is twice as impactful. Table 2 in Appendix E provides the parameter values used for the sensitivity analyses. In the sensitivity analysis, we proceed in a similar way as for the counterfactuals and first compute posterior means of the state-level transmission rates that would explain the observed death counts under the assumption of alternative effectiveness for the different policies. We then compute the number of death that would have been observed if the policies had changed while keeping the recomputed trajectories of the transmission rates fixed.
| Counterfactual assumption (δ = 0.0007) | Federal mandate active on: | Deaths in excess of baseline |
|----------------------------------------|---------------------------|-------------------------------|
|                                        | Stay-at-home | Mask | Travel ban |                          |
| Strict stay-at-home orders, mask mandates, and travel bans for all states. | 3/20  | 4/17 | 3/17 | -137,349 |
| Strict stay-at-home orders in all states, and all other state-level policies remain as in the data. | 3/20 | | | -111,536 |
| Strict mask mandates in all states, and all other state-level policies remain as in the data. | | 4/17 | | -95,924 |
| Strict travel bans in all states, and all other state-level policies remain as in the data. | | | 3/17 | -5,152 |
| No stay-at-home order, mask mandate, or travel ban in any state. | | | | +1,660,900 |
| No stay-at-home order in any state, but all other policies remain as in the data. | | | | +1,009,853 |
| No mask mandate in any states, but all other policies remain as in the data. | | | | +572,851 |
| No travel ban in any states, but all other policies remain as in the data. | | | | +2,524 |
| Mask mandate in all states on March 20, 2020, and all other state-level policies remain as in the data. | 3/20 | | | -180,651 |
| Mask mandate in all states on March 20, 2020, while no state adopts any state-level policies. | 3/20 | | | -77,375 |
| Strict travel bans in all states by February 12, 2020, while all other state-level policies remain as in the data. | 2/12 | | | -6,017 |

Table 6: Results of the counterfactual experiments in which we assume that all states jointly deviate from their enacted policies and adopt either strict or loose versions of the policies instead. Here, we assume that the fatality rate of the disease is 1% instead of 0.6%, and keep the number of days that it take for an infection to resolve at 14 days. The reported values are excess deaths relative to the number of U.S. deaths recorded in our data on September 30, 2020. In the counterfactuals, we compute the trajectories of death counts per state under the alternative policy scenarios that are consistent with the susceptible, infected, recovered, and dead populations as well as the transmission rates filtered from the observed data. The values in brackets give confidence bounds based on a sensitivity analysis of the estimates of the impact of the different policies on transmission rates and traveler and commuter inflow. The lower bounds assume that any policy that deviates from what it was in the data is half as impactful, while the upper bound assumes that any policy that deviates is twice as impactful. Table 2 in Appendix E provides the parameter values used for the sensitivity analyses. In the sensitivity analysis, we proceed in a similar way as for the counterfactuals and first compute posterior means of the state-level transmission rates that would explain the observed death counts under the assumption of alternative effectiveness for the different policies. We then compute the number of death that would have been observed if the policies had changed while keeping the recomputed trajectories of the transmission rates fixed.
All states adopt the three policies simultaneously

(a) All states impose strict or loose policies.

(b) All states impose strict or loose stay-at-home orders.

(c) All states impose strict or loose mask mandates.

(d) All states impose strict or loose interstate travel bans.

Figure 1: State-by-state breakdown of excess deaths relative to the baseline in the different counterfactual scenarios in which all states jointly deviate from their implemented policies. The excess death values are measured as proportions of the death cases in the data for each state. Policies are divided into stay-at-home order (b), mask mandates (c), travel bans (d), and all three policies together (a). Counterfactual policies are divided into a strict scenario in which all states implement a policy as long as at least one state decides to do so, and a loose scenario in which no state implements a particular policy. Counterfactual death counts are computed through the methodology detailed in Appendix C.
Figure 2: State-by-state breakdown of excess deaths relative to the baseline in the data in the different counterfactual scenarios in which states deviate individually from their implemented policies. Policies are divided into stay-at-home order (b), mask mandates (c), travel bans (d), and all three policies together (a). Counterfactual policies are divided into a strict scenario in which a particular state implements a policy as long as at least one state decides to do so, and a loose scenario in which a state does not implement a particular policy. Counterfactual death counts are computed through the methodology detailed in Appendix C.
Figure 3: Number of deaths that could have been prevented through an early federal mask mandate. The $x$-axis indicates the date in which we assume a federal mask mandate had gone into effect, while the $y$-axis gives the number of deaths that could have been prevented had a federal mask mandate gone into effect on that date. We assume that state-level stay-at-home and travel ban policies remain as in the data, and that a federal mask mandate supersedes the state-level mask policies.
Figure 4: Estimated interstate travel and commuting flows. For both networks, the width of a link is proportional to the percentage of a state’s travel or commuting that takes place between the linked states.

(a) Interstate travel network. The size of a node is proportional to the percentage of a state that commutes out-of-state.

(b) Interstate commuting network. The size of a node is proportional to the logarithm of the percentage of a state that commutes out-of-state.
Figure 5: Data and model-implied death counts across states. The model-implied death counts correspond to the number of fatalities that needed to have been recorded in our model to match the total number of deaths in a state at the end of the sample period (i.e., the smoother). Estimation is performed through forward-backward extended Kalman filtering, using the time series of death counts per state from February 12 to September 30, 2020. Our estimation methodology is detailed in Appendix B.
Figure 6: Smoothed means of the model-implied effective $R_0$ of COVID-19 in U.S. states. The shaded red areas denote 2-standard-deviation confidence bands. Estimation is performed through forward/backward extended Kalman filtering, using the time series of death counts per state from February 12 to September 30, 2020. Our estimation methodology is detailed in Appendix B. The $R_0$ estimates correspond to the ratio of estimated daily $\gamma + \delta$ multiplied by the policy dummies and divided by the sum of the daily fatality and recovery rates ($\gamma + \delta$). The figure also shows the periods of time in which the different containment policies were active. Green shaded areas correspond to active stay-at-home policies, purple shaded areas to active mask mandates, and yellow areas to active travel bans. Horizontal lines correspond to the standard value of $R_0 = 1$, below which the virus does not reproduce itself indefinitely.
Figure 7: Smoothed means of the model-implied cumulative number of COVID-19 infections in U.S. states. The figures also show the number of infections that are recorded in state-level data from JHU. We obtain the cumulative number of infections by summing all populations per state except the susceptible. Estimation is performed through forward/backward extended Kalman filtering, using the time series of death counts per state from February 12 to September 30, 2020. Our estimation methodology is detailed in Appendix B.
Figure 8: Time series of counterfactual death counts in which the federal government imposes strict joint mandates (left axis), along with the number of states that adopted stay-at-home or mask mandates in the data (right axis). The black solid line provides the death count obtained from the original data. The grey, red, and beige solid lines provide the time series of deaths that would have been observed if the federal government had imposed strict stay-at-home, masks, and all policies together on all states, respectively. The strict mandates start as early as the earliest state in the sample, that is March 20, 2020 for stay-at-home, and April 17, 2020 for mask mandates. The red dashed line presents a counterfactual scenario where masks are imposed as early as March 17, 2020. Green and purple-shaded areas provide the number of states that implemented stay-at-home policies and mask mandates in the data, with respect to time. Their units are presented on the right axis.
Figure 9: Time series of estimated number of infected individuals in select states. The grey line marks the posterior (smoothed) mean of the cumulative number of infections in the baseline. The red line denotes the posterior (smoothed) mean of the cumulative number of infections in the counterfactual in which a federal interstate travel ban goes into effect on March 17, 2020. Estimation is performed through forward/backward extended Kalman filtering, using the time series of death counts per state from February 12 to September 30, 2020. Our estimation methodology is detailed in Appendix B.