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MANDATED AND VOLUNTARY SOCIAL DISTANCING DURING THE COVID-19 EPIDEMIC: A REVIEW

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Mandated and Voluntary Social Distancing During The COVID-19 Epidemic: A Review
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ABSTRACT

For much of 2020, the COVID-19 epidemic upended social and economic life globally. In an effort to reduce COVID-19 risks in the U.S., state and local governments issued many recommendations and regulations to induce social distancing, adding to voluntary reductions in interpersonal contact. The responses to the epidemic helped contain spread, but also lead to high unintended societal costs. In the summer months, states took steps to revive the economy and lift social distancing regulations. However, as many epidemiologists expected, the scale of the epidemic has expanded very rapidly in the fall. In the week of October 14, the US generated around 57,000 new COVID-19 cases and 700 deaths each day. By November 15, the country was generating about 151,000 new cases and 1,200 deaths per day. These rapid increases in cases and deaths raise concerns about the capacity of local healthcare systems around the country. State governments are once again facing difficult choices about whether and how to use policies to address the spread of the virus. The incoming Biden-Harris administration faces an important challenge in trying to manage the epidemic as well as a large scale vaccination campaign. Although the epidemic is less than a year old, it has generated a huge volume of research by economists, epidemiologists, and others. This body of work may help inform policy decisions facing society in the coming months.

In this paper, we make five broad contributions. First, we provide a concise review of economic and social science research on mobility patterns, labor market outcomes, consumer behavior, and population health during the first phase of the epidemic. Second, we sketch a simple microeconomic model that may be useful considering the determinants of social distancing and the role of different policy instruments in promoting distancing. Third, we present a simple typology of the policies that were used at the state and county levels during the closure and re-opening phases of the epidemic in the U.S.. Fourth, we review a collection of new data sources that have played an important role in monitoring and analyzing population behavior this year. Fifth, we present results from event study regressions that try to disentangle private vs. policy-induced changes in mobility patterns during the early part of the epidemic.

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1 Introduction

During the first half of 2020, social distancing became the primary strategy for reducing the spread of SARS-COV-2, which is the virus that causes COVID-19. Basic information about the threat posed by the epidemic started to become clear when early cases and deaths occurred in January and February. In March, the level of human physical mobility fell substantially across the country. Mobility started to recover somewhat in May and June as initial fears regarding hospital capacity surges diminished (Kowalczyk, 2020), and scientific knowledge regarding lower-risk ways of interacting emerged (CDC, 2020). Although people started to resume some aspects of regular life over the summer months, mobility remained far below its pre-epidemic levels.

As many epidemiologists expected, the scale of the epidemic has expanded very rapidly in the fall. In the week surrounding October 14, the US population was generating around 57,000 new confirmed cases and 700 COVID-19 deaths each day. By November 15, the country was generating about 151,000 new cases and 1200 deaths per day. Just as they did in the early spring, these rapid increases in cases and deaths raise concerns about the capacity of local healthcare systems around the country. Preliminary results from clinical trials suggest that the Pfizer-BioNTech vaccine could be more than 90% effective at preventing COVID-19 cases, and the company reports that up to 50 million doses could be available by the end of 2020 and more than 1.3 billion doses could be produced in 2021.

The rapidly rising COVID-19 counts means that state governments around the country are once again facing difficult choices about whether and how to use government policies to control the spread of the virus. The incoming Biden-Harris administration faces an important challenge in trying to manage the epidemic as well as a large scale vaccination campaign.

Although the epidemic is less than a year old, it has generated a huge volume of research by economists, epidemiologists, and other social scientists. This body of work may help inform thinking about the policy options facing us in the coming months. In this paper, we make five broad contributions that we hope will be useful to researchers and practitioners alike. First, we provide a concise review of economic and social science research on mobility patterns, labor market outcomes, consumer behavior, and population health during the first phase of the epidemic. While we searched widely when conducting this review, we do not intend this to be a formal literature search for papers with specific key words, which we think is not feasible given the very actively evolving nature of this work. Second, we sketch a simple microeconomic model that may be useful for thinking about the determinants of social distancing and the role of different policy instruments in promoting distancing. Third, we present a simple typology of the kinds of policies that were used at the state and county level during the shut down and re-opening phase of the epidemic in the United States. Fourth, we review a collection of new data sources that have played an important role in monitoring and analyzing population behavior during the epidemic. Fifth, we present results from event study regressions that try to disentangle private vs policy-induced changes in mobility patterns during the early part of the epidemic.

The prevailing level of mobility is generated in part by the private decisions people make in response to the health threat posed by the epidemic. But state and local governments have also adopted a variety of mandates and regulations to reduce mobility even further. The production of higher levels of social distance and lower levels of physical mobility is not a typical goal for democratic governments. Normally, governments act to encourage and protect freedom of mobility and assembly. During the epidemic, social distancing is valuable because it helps control the epidemic. Unfortunately, the pre-COVID academic literature provides little guidance on which policy levers governments can use to produce the most social distance at the lowest economic cost. And existing economic and public health data systems do not provide much information on patterns of physical mobility and contact, which makes it hard to optimize social distancing policies in an iterative fashion. There may be substantial value in research that identifies principles that can guide policy and perhaps support the development of better targeted social distancing strategies.

In a series of research papers, we have measured levels of physical mobility using high frequency data, and we have used the data to assess the role of state and local public policies in shaping levels of social distancing. Our over arching goal is to develop knowledge on the underlying factors that make some distancing policies more effective than others (Gupta et al., 2020; Nguyen et al., 2020; Montenovo et al., 2020; Rojas et al., 2020; Bento et al., 2020; Gupta et al., 2020). In this paper, we provide an overview of social distancing policies, provide a comprehensive literature review of what is known to date of their effects on key outcomes, explain a collection of new data sources that can be used to track levels of mobility, and present a core set of empirical results from the shutdown and reopening phases of the epidemic.

The paper is in eight parts. Section 2 discusses the literature on social distancing and physical mobility in the context of the COVID-19 epidemic. Most of the literature is very recent and we attempt to summarize the key questions, empirical strategies, and conclusions that have emerged so far. In section 3, we sketch a microeconomic model of household production and choice that incorporates physical contact and infection risk into the agent's decision process. The model is very simple and abstracts from many features of the real world. However, it helps clarify the incentives and constraints that affect decisions to engage in physical contact with others, and it suggests broad principles that might be used to guide the design of social distancing policies. Section 4 reviews the long list of public policies that state and local governments have actually adopted during the epidemic, and explains how we organized and grouped these policies to facilitate empirical analysis. Section 5 provides an overview of the cell signal based data sources that we are using to measure mobility patterns across states and over time.

These mobility data are not perfect measures of the underlying behavior of interest. We look at several different measures from several sources. But at their core, all of the measures are constructed by tracking (anonymously) the physical location of smart devices. They proxy human mobility under the assumption that smart devices change locations because people carry them from one place to the next. But mobility measures generally do not reveal whether a person who changes locations remains six feet away from other people during the trip. They also don't indicate whether the person wore a mask or how often they washed their hands. Despite their limitations, cell-phone-based mobility data are probably the best proxy measure of social distancing currently available. One of the main advantages of our line of research is the use of multiple measures from multiple data systems. This provides some ability to assess the robustness of our results.[1] Section 6 lays out the event study framework we use in much of our empirical work. We present results in section 7 and offer conclusions in section 8.

2 Related Research

In the four months since the start of the epidemic in the U.S., the social science literature on the epidemic and the policy response has grown very rapidly. The papers in the emerging literature are organized around a collection of broad research questions:

1. How has the epidemic affected the way people interact with each other and with physical spaces?
2. How has the response to the epidemic affected the level of economic activity?
3. How much of the changes in mobility and economic activity are generated by private responses to the health and safety threat from the virus, and how much of these changes have been induced by public policies themselves?
4. How have various public policies and private responses affected the downstream severity of the epidemic?

The first two questions are essentially descriptive. They have been answered using a combination of existing and new data sources. Research on questions about physical mobility and person-to-person contact have a long history in the literature on infectious disease epidemiology. But the conventional methods in that literature are not well-suited to monitoring population behaviors in real time. The COVID-19 epidemic has led to heavier reliance on data harvested from smart devices, mapping applications, and financial transactions. These data sources have expanded the set of concepts that can be brought into the surveillance system, but it is still not clear how different types of information are useful for public health decision making. Understanding the strengths and

[1] It is possible that future researchers will have access to richer data on how person-to-person contact is changing. For example, it is conceivable that data harvested from video recordings might provide information on often people touch each other to shake hands, hug, exchange objects, etc. Data like this could provide important insight into behavior during the epidemic.

weaknesses of new data sources is one of the key challenges in the literature. Balancing the value of high frequency and low frequency measures for monitoring the state of the epidemic is another overarching concern.

The third and fourth questions are concerned with the causal effects of public policies adopted during the epidemic, and to some extent with the causal effect of changes in knowledge about the state of the epidemic. One line of work, the mobility literature, is concerned with the "first stage" effects of policy on transmission related behaviors. Another line of work is essentially about the possible unintended consequences of the same policies. Research on the effects of distancing policies on labor market outcomes and consumer behavior falls into this category. A third line of work is concerned with the way that different policy responses have shaped the course of the epidemic as measured by COVID-19 case loads and deaths. In all three streams of work, event studies and generalized difference in difference designs have emerged as the main strategy for trying to isolate the causal effects of policy changes. These designs are natural given the setting and available data. However, they rely on strong assumptions that may fail in some circumstances and not others.

In the appendix to the paper, we include two tables that summarize key pieces of information from a large set of working papers and recently published articles. Appendix table A1 lists papers that provide estimates of the effects of one or more COVID-19 shutdown policies. To the extent possible, we report the main quantitative effect estimate provided in each paper. But we caution the reader that these "treatment effect" estimates do not correspond to a common structural parameter. We should not expect the magnitude of the policy effects to be the same across studies based on different outcome measures, different policy definitions, and different time horizons. Not all of the studies we examined offer estimates of the effects of COVID-19 policies. Appendix table A2 gives a summary of these papers; they do not include a specific quantitative effect size column, but these papers provide useful context are organized by the same sub topics as the first table.

2.1 Pre-COVID Epidemiological Research On Mobility

Prior to the COVID-19 epidemic, the economic and public health data systems in the U.S. were not set up to measure close physical interactions at a level of frequency and detail necessary to provide near real-time information about human movement and mixing (Buckee et al., 2020) during an epidemic. However, infectious disease researchers have made heavy use of information from *social contact surveys*. These are point-in-time (cross-sectional) household or individual surveys that collect detailed information on each respondent's daily contacts with other people who have specific age and gender attributes (Mossong et al., 2008; Bento and Rohani, 2016; Prem et al., 2017). Static contact surveys have proven to be useful for studying endemic diseases and seasonal diseases that occur fairly reliably in a population because sudden disruptions of behavior are not expected.

Contact surveys are most often used to estimate age-specific contact matrices, which are a way to describe the frequency of contact between people from different age-strata in a given population

(Mossong et al., 2008; Prem et al., 2017). Survey-based estimates of contact matrices are used to build more sophisticated models of the spread of infectious diseases within and between populations with different demographic and geographic structures (Mossong et al., 2008; Rohani et al., 2010; Bento and Rohani, 2016; Prem et al., 2017). Incorporating information on the contact structure of a population produces structural models that more successfully explain shifts in disease prevalence over time and across age groups. Models that ignore the contact structure in a population may misinterpret the epidemiological processes that determine the spread of the disease. Although contact surveys provide useful information about the average contact patterns in a population, they are costly, slow, and may suffer from recall bias and coverage gaps (Mossong et al., 2008; Prem et al., 2017). Thus, researchers generally do not use contact surveys to empirically track behavioral changes during an epidemic. Likewise, we are not aware of any studies that use repeated waves of a contact survey to estimate the effects of social distancing policies on contact patterns. That said, things may be different during the COVID-19 epidemic. For example, in recent work on COVID-19 Jarvis et al. (2020) fielded longitudinal contact survey that collected data on the same people each week for 16 weeks. They compare their COVID era contact data with data from an earlier cross-sectional contact survey collected in 2006 and find substantial changes in the contact patterns since 2006.

Although contact surveys may still play an important role, they are a cumbersome way to monitor the population in real time during an epidemic. In a major outbreak, it is critical to assess the effects of public policies and informational events on the individual behaviors that shape contact patterns. One alternative to surveys that has proven valuable is aggregate mobility data, such as the smart device data we use in this paper. Wesolowski et al. (2012) pioneered the use of cell phone records to understand the role of human travel patterns on the spread of malaria in Kenya. They found that human travel facilitates malaria parasites to spread much farther than possible through mosquito dispersal alone. Information about the importance of specific travel routes in spreading the epidemic provides a guide for policy efforts to reduce transmission. More recently, Wesolowski et al. (2015a) used cell phone data to study the role of travel patterns on the spread of Dengue virus during an epidemic in Pakistan in 2013. They found that previous model-based descriptions of human mobility did not perform well in describing the travel patterns captured by the cell phone data, and that incorporating the cell phone travel data led to epidemiological models that were more accurate in explaining the spread of the epidemic over time and across locations. Wesolowski et al. (2016) offer a review of the emerging role of cell phone data in the study of infectious diseases and epidemics.

Aggregate mobility data provide a way to measure the intensity of movement within and between specific geographic locations. However, the underlying data are harvested from convenience sources, like cell phone records, which may not be representative of the population in the way that a formal survey sample might be. The mobility measures that can be constructed from aggregate data also lack the careful attention to construct validity that is a feature of the measures available in well-designed contact surveys. Despite these limitations, the aggregate data allow researchers to measure mobility using a daily time series available at various geographic levels of detail. These time series data can be compared with pre-epidemic baselines and can be used as a foundation for policy analysis based on interrupted time series and difference in difference research designs. They offer nearly real time insight into the extent to which people are complying with various kinds of social distancing initiatives (Wesolowski et al., 2015b). Although aggregate data are still relatively new, previous work shows that they can be integrated with other epidemiological data, and has explored methods that account for spatial and temporal dependence to support accurate inferences regarding dynamics on scales appropriate to pathogens and their human hosts (Keeling and Rohani, 2011) .

The pre-COVID literature provides clear empirical evidence that human movement shapes transmission dynamics Bharti et al. (2015). The details depend on the pathogen, of course. But research suggests that travel and mobility related behaviors are important in both introducing novel pathogens into susceptible populations, and in determining how easily the pathogen spreads by altering the frequency of contact between infected and susceptible individuals (Wesolowski et al., 2016). For example, Mari et al. (2012) examine the role of travel patterns and waterways on spread of Cholera. And Gog et al. (2014) study spread the 2009 influenza epidemic in the U.S. They find that models that account for both spatial diffusion and local school opening dates fit the data the best. There is also evidence from the pre-COVID data driven studies, that social distancing policies can reduce the magnitude of an epidemic (Bootsma and Ferguson, 2007; Hatchett et al., 2007). In addition, Ferguson et al. (2005) use a simulation model to assess alternative strategies for containing an influenza epidemic in Asia. They find – for specific disease parameters – that strategies that combine anti-viral medication with social distancing interventions are most successful.

2.2 Mobility Patterns and Social Distancing Related Behaviors

One of the most active strands of social science research on the COVID-19 epidemic is concerned with how mobility patterns have changed in response to the risk of infection, and in response to state and local social distancing policies. The literature has come to a consensus that human mobility dropped precipitously in mid March, very early in the shut down sequence and around the time of the March 13th National Emergency proclamation. The mid-March decline is large and quite sudden. Most studies have used high frequency data sources derived from smart device apps. These data sources do not have a long history of use in economics. As we mentioned in the discussion of pre-COVID research, epidemiologists have been using similar data to study epidemics since at least Wesolowski et al. (2012). So far, the emerging economics literature on mobility and social distancing has focused on simple descriptive time-series work, and on quasi-experimental estimates of the effects of state and local policies on mobility patterns. Although there is overlap between the methods used in the economics and epidemiology literature, it is probably fair to say that the epidemiological literature focuses less on the determinants of mobility, and more on the role that prevailing mobility patterns in the dynamics of a given epidemic. They use cell phone data to build better structural models of the epidemic across time and space. Economists have focused somewhat more on the idea that mobility patterns are an outcome that public policies are trying to change in the population.

One concern in the literature on mobility is that the smart device users underlying the mobility measures are unlikely to be a representative sample from the population. However, the sample size underlying the data are at least 10% of the U.S. population, and the timing and size of the fall in mobility seems to be similar regardless of the mobility data and concept used in individual studies. That is, the basic time series is similar for measures of staying at home, going in to work, average distance travelled, percent of individuals who travel out of state or out of county, indices of how much foot traffic occurs in certain types of establishments, etc.

Some studies – such as our own – estimate how much of the change is attributable to various state and local social distancing policies. The literature has devoted the most attention to the effects of stay-at-home (SAH) mandates, which occurred later in the shutdown sequence implemented in most states. Although there are a few outlier results, most of studies find that SAH policies reduced measured mobility by about 5-10% within the first week after the policy was implemented (Abouk and Heydari, 2020; Alexander and Karger, 2020; Andersen, 2020; Chen et al., 2020b; Cicala et al., 2020; Cronin and Evans, 2020; Dave et al., 2020; Elenev et al., 2020; Engle et al., 2020; Goolsbee and Syverson, 2020; Lin and Meissner, 2020; Painter and Qiu, 2020; Gupta et al., 2020).

The outsize attention to SAH mandates makes sense since they have proven to be the most controversial laws and they seem to be nominally the most restrictive. However, some studies have also examined the effects of other policies, like school closures, which happened often sooner. But it maybe hard to reliably separate the effects as multiple policies implemented so tightly together.

2.3 Labor Market Outcomes

The losses of employment since the start of the COVID-19 epidemic are massive. There were with 20.5 million job losses in in April alone and rapid increases in unemployment insurance applications (Rojas et al., 2020; Montenovo et al., 2020). The unemployment rate rose to from 4.5 percent in March to 14.7 percent in April. Many people may also have dropped out of the labor market (Coibion et al., 2020b) and would not be captured in unemployment statistics. The unprecedented increase in initial UI claims in the early part of the pandemic was largely across-the-board and occurred in all states, suggesting that the economic disruption was driven by both the health shock itself and the state policies to induce social distancing (Lozano Rojas et al., 2020; Gupta et al., 2020). On average, the literature notes a modest 2-8% increase in UI claims due to state policies, with business closures having a larger effect than stay-at-home orders (Kahn et al., 2020; Kong and Prinz, 2020; Lozano Rojas et al., 2020).

The timeline and nature of job losses is noteworthy. Relative to the timing of the human mobility reduction, job market losses occurred later.

It is possible that labor market responses were delayed partly because of increases in the number of workers who reported that they were "employed but absent" in the monthly Current Population Surveys (CPS). That is, people may have been temporarily unemployed but expecting to be recalled to the same jobs. This could have led to an undercount of point-in-time unemployment levels. Surprisingly, research suggests that workers who remained employed during the early epidemic did not experience much change in hours worked or earnings Cheng et al. (2020); Gupta et al. (2020). During the shutdown period employment declines were steeper for Hispanics, workers aged 20 to 24, and those with high school degrees and some college. Pre-epidemic sorting into occupations with more potential for remote work and industries that were deemed essential explain a large share of gaps in recent unemployment for key racial, ethnic, age, and education sub-populations (Montenovo et al., 2020).

Since April, there have been reductions in the number of new unemployment claims and signs of improved labor market performance. Studies note that the official state reopenings have contributed a modest 0-4% increase in employment; decreases in job loss among those employed were smaller (Cheng et al., 2020; Chetty et al., 2020). Moreover, majority of those who were reemployed appear to have returned to their previous employment, with the rate of reemployment decreasing with time since job loss. Lastly, the groups that had the highest unemployment rates in April - Hispanic and Black workers, youngest and oldest workers, and women - have had the lowest reemployment rates (Cheng et al., 2020). These racial and ethnic labor market disparities are important because they add to already existing disparities in the extent of the health tolls of COVID-19 Benitez et al. (2020); McLaren (2020); Hooper et al. (2020).

2.4 Consumer Spending

Research to date consistently finds that consumer spending also fell by approximately 35% in mid-March. The decline in spending occurred despite close to $2 trillion in additional federal spending thus far for COVID-19 economic support. Rates of food insecurity have also climbed substantiallyBitler and Schanzenbach (2020). Consumer spending may have fallen in part because people reduced their demand for consumption goods that require high levels of social interaction. That is, efforts to avoid transmitting and contracting the virus is probably part of the story. However, spending may also have been affected by the timing of federal stimulus payments, enhanced unemployment benefits, and the consequences of state shutdown and reopening policies.

Research documents that in addition to spending having declined immediately and dramatically, there are important shifts in the composition of people's consumption bundles. Consumer spending at small businesses and large retail outlets has fallen. But spending on orders of food has been rising (Alexander and Karger, 2020)). The decline in consumer spending happened across the country

(Alexander and Karger, 2020; Baker et al., 2020; Chetty et al., 2020) and is highly correlated with a self-reported measure of whether a person was under a "lockdown" (Coibion et al., 2020a).

Despite declines in spending and high rates of food insecurity, federal stimulus spending appears to have ensured an actual fall in the poverty rate after the start of the pandemic, relative to pre-pandemic levels (Han et al., 2020). This is noteworthy as the start of the pandemic occurred after a strong growing economy, thus it will be important to monitor consumer spending rebounds, and implications for financial health.

2.5 Health Outcomes

The foremost objective of the collection of state social distancing policies has been to mitigate the spread of SARS-CoV2. A major concern is that if the virus is allowed to spread too quickly, local health care systems could be overwhelmed. Even a slower spread of the virus could lead to tremendous loss of life.

Overall, the emerging literature seems to agree that the intense social distancing that occurred between mid March and mid April did indeed "flatten the curve" during the early months of the epidemic. The estimated effect of state policies on case and death rates vary somewhat depending on the specific policy measure examined in the study and also on the time frame of the study. However, most studies estimate a 20-60% reduction in cases and deaths (Chernozhukov et al., 2020; Dave et al., 2020; Friedson et al., 2020; Jinjarak et al., 2020) and a 2-9% reduction in daily growth rates of cases and deaths (Courtemanche et al., 2020; Lyu and Wehby, 2020; Wang et al., 2020; Yehya et al., 2020) as a result of mandatory policies and informational events.

2.6 Research Related to Reopening

Declining case and death rates have been critical to determine when states can safely reopen - the CDC recommended 3 weeks of steady decline in cases and deaths prior to lifting any social distancing mandates. Our work finds that human mobility, although still below the pre-COVID19 level, started to recover somewhat prior to official state reopenings, and then increased by a further 1-8% in response to official state reopenings (Nguyen et al., 2020). Again, both voluntary behavior and mandates appear to guide behavior. The relatively modest increase in mobility following reopenings is not surprising since the risk of infection has not changed. Moreover, state reopenings cannot be viewed as the reversal of state closures.[2]Although states varied in the exact timing of their closure mandates, once implemented, school closures or stay-at-home orders were relatively homogeneous across the states. In contrast, state reopenings have varied a great deal in nature - immediate vs phased reopenings, sectors/industries that initially reopened and capacity limits on businesses.

[2]In only 3 states - FL, ID, MO - official state reopenings coincided with the lifting of stay-at-home orders. In most cases stay-at-home orders/ school closures expired after date of initial reopenings.

Despite a slow and partial return to economic activity recent reports note a surge in cases and deaths following reopenings (New York Times, 2020; The Washington Post, 2020).

If rates of cases and deaths continue to grow, states will be faced with the difficult decision to implement second rounds of shutdowns, which research finds can been effective in curbing the spread, but are also economically very costly. At present, states appear to be pursuing a more nuanced policy stance based on adaptive behaviors like mask wearing, maintaining 6 feet distance from others, capacity limits, and implementing designated business hours for at-risk population to minimize interaction with others. Since significant voluntary social distancing occurred in response to information of COVID-19 in mid march, we would expect that individuals would voluntarily adopt these practices as well to lower their risk of infection. However, the large voluntary increases in social distancing in the early days of the epidemic hides considerable heterogeneity in behavioral response to the threat of infection along lines of political affiliation, race and other socioeconomic and demographic characteristics (Aksoy et al., 2020; Allcott et al., 2020; Huang et al., 2020; Mongey and Weinberg, 2020).

3 Theoretical Framework

In epidemiology, the dominant paradigm for analyzing an infectious disease outbreak is the susceptible-infected-recovered (SIR) model (Kermack and McKendrick, 1927), which examines dynamics of an epidemic that arise as a population moves through disease relevant states. These models do not provide much insight into the way that an epidemic might alter the behavior of people in a population. The economic epidemiology literature nests a micro level model of individual behavior inside the SIR framework to try to model the role of endogenous self-protection behaviors might alter the dynamics of an epidemic (Philipson, 1996; Kremer, 1996; Geoffard and Philipson, 1996; Philipson, 2000). A much larger literature in economics explores individual choices and investments that affect health (Grossman, 1972, 2000). This literature allows health to affect the utility function directly, and also indirectly as an input into many other activities that people value. A key point is that health is not the only thing that people value, and it is common for people to make trade-offs between health and other objectives. Indeed, a major sub-field examines the economics of risky health behaviors such as smoking, drug use, risky sex, poor diet, and dangerous driving (Cawley and Ruhm, 2011; Viscusi, 1993).

In this section, we sketch a simple microeconomic model in which a utility maximizing agent allocates time and resources between activities with different risks of infection with SARS-COV-2. The basic model is built on the household production model introduced by Becker (1965). The starting point is a utility function defined over a set of commodities or experiences; inputs to the production of these commodities may require physical interaction with others, which may diminish the production of health. We focus on a utility function defined over three commodities:

$$u = u(z, o, h)$$

In the model, z is a vector of regular commodities, such as housing, home-cooked meals, or in-restaurant dining with friends. o represents market work (occupation), which pays a wage that determines the value of a person's time and shapes the person's budget constraint, but also enters the utility function directly. h represent a person's health status.

Each of the commodities in the utility function must be produced with market goods, time, and physical interaction with others. To make these relationships concrete, use $j \in (z, o, h)$ to index the three commodities. Let x_j be an input vector of market goods that may be used in the production of commodity j. p_x is the vector of market prices associated with the market inputs. e_j represents the quantity of a person's time (effort) that is devoted to the production of commodity j. Finally, d_j measures physical interaction (distance) with non-household members involved in the production of commodity j. The person produces the regular commodities z using the production function $z = z(x_z, e_z, d_z)$. Similarly, the person produces the market work (occupation) commodity by combining market goods (e.g. a computer, suitable clothing, a car), time, and physical interaction with non-household members using a production function $o = o(x_o, e_o, d_o)$.

The health production function is somewhat different because it may depend on the infection risk associated with the physical interactions a person makes in the production of the other commodities. For simplicity, we assume that all physical interactions generate the same risk, and we ignore spillovers from behaviors of others in the community. Let $D = \sum_j d_j$ represent the total amount of physical interaction with non-household members that the person experiences across all of his home production activities. The health production function is $h = h(x_h, e_h, \rho D)$. In the model, ρ is an infectious disease risk parameter normalized so that $\rho = 1$ for the health risk associated with physical interaction with other people during "normal" times. We assume that $\frac{\partial h}{\partial \rho D} < 0$, which means that health is declining with physical interaction with other people and with the level of infectious disease risk at that time and local area.[3]

The model sets up a trade-off between health and the production and consumption of other commodities that raise utility but also require potentially health-damaging exposure to the virus. The COVID-19 epidemic can be viewed as an exogenous change in the prevailing level of the infectious disease parameter, ρ. The epidemic does not alter anyone's utility function or production technology.

[3]In our main analysis, we focus on a utility function with a single health commodity. But it is also logical to view h as a vector of health commodities, each element of which may have a production function that depends on physical interaction in a different way. For example, we might say that $h = (m, r)$ is a vector consisting of mental health (m) and respiratory health (r). Then $m = m(x_m, e_m, \rho_m D)$ and $r = r(x_r, e_r, \rho_r D)$ would represent mental health and respiratory health production functions. In this case, it might be reasonable to expect that $\frac{\partial m}{\partial \rho_m D} > 0$ even though $\frac{\partial r}{\partial \rho_r D} < 0$ so that physical interaction improves mental health and worsens respiratory health.

But people faced with higher values of ρ may nevertheless choose a new mix of commodities to produce and consume.

To pay for market goods, at prices p_x, the person relies on earned and unearned income. Suppose that M is the person's non-labor income, w is his/her wage rate, and e_o is hours devoted to occupational work. As above, x_j represents the vector of inputs used in the production of commodity j. The person's budget constraint is $x_z'p_x + x_o'p_x + x_h'p_x = M + we_o$, where e_o is the amount of time the person devotes to market work. In addition to the financial budget constraint, the person has a fixed time endowment so that the sum of his/her time spent in market work and across the production of various commodities must satisfy $T = e_z + e_o + e_h$. The person's problem is to max $u(z, o, h)$, subject to (i) $x_z'p_x + x_o'p_x + x_h'p_x = M + we_o$, (ii) $T = e_z + e_o + e_h$, (iii) $z = z(x_z, e_z, d_z)$, (iv) $o = o(x_o, e_o, d_o)$, and (v) $h = h(x_h, e_h, \rho D)$.

Writing out first order conditions and solving the system of equations would lead to a collection of demand functions for each market input, time use, and level of physical interaction with other people. These demand curves are derived from the person's demand for commodities (z), occupational work (o), and health (h). Let $x_z = x_z(p, w, F, \rho)$ be the person's derived demand for market good inputs into the production of z. Likewise, let $e_z = e_z(p, w, F, \rho)$ represent demand for time devoted to the production of z. And let $d_z = d_z(p, w, F, \rho)$ be the person's demand for physical interaction in order to produce z. Similar input demand functions are defined for for inputs required to produce the occupational work commodity (o), and to produce health (h).

In this framework, the COVID-19 epidemic amounts to an external increase in ρ, which is the infection risk generated by physical interaction with other people. Marginal increases in ρ affect utility through the effect of infection risk on health production. However, larger changes in ρ may also generate indirect effects on utility through behavioral changes in the demand for other commodities, market goods, and time uses. The private responses to the epidemic are captured by partial derivatives of the various demand functions. For example, $\frac{\partial d_j}{\partial \rho}$ is the effect of an increase in infection risk on the person's demand for physical interaction involved in producing commodity j. Typically, we expect $\frac{\partial d_j}{\partial \rho} < 0$ so that infection risk will reduce the demand for physical interaction as an input to other commodities.

The model suggest that an increase in infection risk leads to fewer physical interactions even in the absence of any government policies. Further, the fall in demand for physical interaction is likely to alter the demand for market goods and services that people tend to consume in conjunction with physical interaction. The nature of these changes depends on the commodity production functions. Physical interaction may be a close substitute for market goods in the production of some commodities. In these cases, an increase in infection risk (ρ) will increase the demand for substitute market inputs. In other cases, physical interaction and market goods may be complements in the production function. Then rising infection risk will tend to reduce demand for the market goods that are complements to physical interaction. Similar patterns hold for time use. The change in demand for market goods, time use, and interaction do not flow from a change in preferences. The issue is that people cannot produce certain commodities as safely as they did in the past. In this sense, the disruption from the epidemic flows from a negative supply shock.

Individual reductions in physical interaction may confer benefits on other people. The positive externalities may justify government policies to promote social distancing. One class of social distancing policies would target physical interactions directly. For example, the government might levy a a tax on physical interaction, issue advice and mandates that attach stigma to interactions, or regulate the group size of interactions. These policies will tend to reduce the demand for physical interaction, but they will also affect the demand for various input goods and services.

A different class of policies might focus on market goods that are viewed as strong complements to physical distancing. For example, the government might levy higher taxes on various kinds of public transit, admission to parks and beaches, or restaurant meals. Tax instruments like this have not been widely used during the epidemic. Instead, governments have tended to mandate that certain types of goods and services may not be sold during the epidemic. Closing restaurants and bars reduces demand for the input goods directly, but also could reduce demand for physical distancing which is a complement to visits to these establishments.

A third class of policies might target the infection risk parameter. For example, governments might require people to wear masks during physical interactions. A successful mask policy could be represented as a factor that diminishes the realized effect of the infection risk parameter. For instance, people wearing masks might produce health using $h = h(x_h, e_h, \alpha\rho D)$, where $0 < \alpha < 1$ is the effect of the mask and the "effective" infection risk is now $\alpha\rho < \rho$. At current margins, infection risk mitigation policies might increase the demand for physical interaction and for the goods and services that go along with it. These kinds of policies may have important economic benefits because they would help resolve the supply shock in the economy.

The model we examine here treats infection risk as an aggregate parameter and focuses on the way that changes in infection risk might affect demand for physical interaction, market goods, and time use. A richer model would specify a health production function that varied with characteristics of the person, perhaps including factors like age and pre-existing health conditions that make a person particularly sensitive to COVID-19. In that setting, the magnitude of private responses to changes in infection risk would vary across people, and there would be a case for more targeted government interventions that focused not only on goods and interactions, but also on people with higher health costs of infection.

4 Government Policies During The Epidemic

In this section, we provide an overview and rough typology of the strategies that state and local governments have used during the shutdown and reopening phase of the epidemic.

4.1 Typology of Policies During Shutdown

We assembled data on state and county level events and social distancing policies using information from several policy tracking projects, including from the National Governors Association, Kaiser Family Foundation, national media outlets, Fullman et al. (2020) and Raifman and Raifman (2020). We began with a large collection of 15-20 separate policies that are tracked by one or more outlets. However, many of policies, such as state laws banning utility cancellations for non-payment of bills, are unlikely to directly affect mobility in a major way. In addition, most tracking services record different degrees of the same type of policy, such as gatherings restrictions by the size of the group affected, or closures of different types of economic activity. Policy trackers also differed occasionally in whether they followed only mandates or also reported government recommendations.

Given the difficulty of estimating effects of a large number of policies at once, one of our first tasks was to organize and structure data on the core public policy instruments state governments have been using during the epidemic.[4] We reduced the raw number of policies under consideration by assessing which mandates and information events were logically connected with individual behaviors related to mobility and social distancing. We were also guided by the joint timing of policy changes, whether a policy was adopted by a large number of states, and whether there was concordance about the timing and nature of the policy across multiple sources.

Most of our empirical work distinguishes two broad types of state: informational events, and government mandates. The informational events we consider are the announcement of the state's first COVID-19 case and death; we collect these dates through the CDC website, other repositories, and by searching news outlets. Public information events may induce people to voluntarily engage in individual behaviors that mitigate transmission, including social distancing, frequent hand washing, mask-wearing. Government mandates consist of a considerable set of state level policies related to emergency declarations, school and business closures, and stay-at-home orders. Most of our work revolves around the date at which these mandates became active. However, we often also consider the data of announcement as a sensitivity check and to assess the possibility of anticipatory responses. On average, the announcement and implementation dates were usually about two days apart.

The six state mandates we tracked are listed below, roughly in the order in which they rolled out across states:

1. **Emergency declarations**: These include State of Emergency, Public Health Emergency, and Public Health Disaster declarations. All states issued these policies by March 16th, 2020. The federal government issued an emergency declaration on March 13th, 2020. States may use these declarations in order to pursue other policies such as school closure, to access

[4] In Gupta et al. (2020) we follow county policy making as well, although there was much less activity on that front; we focus only on state policies in this current paper.

federal disaster relief funds, or to allow the executive branch to make decisions for which they would usually seek legislative approval. By statute, states are able to exercise additional powers when they issue emergency declarations. In a typical state, governors are able to declare an emergency, and usually do so for weather-related cases—although some states, such as Massachusetts in 2014, have invoked public health emergencies in order to address addiction-related issues in the state (Haffajee et al., 2014). In some states, city Mayors also may issue emergency declarations. In our conceptual framework, emergency declarations are typically the earliest form of state policy that might induce a mobility response; however, we think that emergency declarations are best viewed as an information instrument that signals to the population that the public health situation is serious and they act accordingly.

2. **School closures**: Some school districts closed prior to state-level actions. However, by April 7, 2020, 48 states had issued statewide school closure rulings(verified through Fullman et al. (2020) and Education Week (2020)). While school closure policies would reduce some travel (of children and staff), they could reduce adult mobility as well if parents changed work travel immediately as a result. School closures may also contribute to a sense of precaution in the community. Although many spring break plans were cancelled, it is possible we might also capture increased travel due to school closures.

3. **Restaurant restrictions and partial non-essential business (NEB) restrictions**: These policies were also fairly widespread, with 49 states having such restrictions by April 7th, according to Fullman et al.. This law would directly restrict movement due to the inability to dine at locations other than one's home.

4. **Gatherings recommendations or restrictions**: These policies range from advising against gatherings, to allowing gatherings as long as they are not very large, to cancellation of all gatherings of more than a few individuals. There was a lot of action on this front: 44 states enacted gatherings policies. In principle, these laws would reduce mobility in a manner similar to restaurant closings. However, gathering restrictions are hard to enforce and rely on cooperation from residents. Their effects on mobility patterns is apt to be negligible, and we generally do not focus on these policies in our empirical work.

5. **Non-Essential Business closures (NEB)**: NEB closures typically occurred when states had already conducted partial closings and then opted to close all non-essential businesses. 33 states acted in this area during our study period. NEB closure could have fairly large effects, as they reduce where purchases happen and also reduce work travel. Moreover, they provide a binding constraint on individual behavior; even those not voluntarily complying with social distancing recommendations had fewer locations to visit.

6. **Stay-At-Home (SAH)**: These policies (also known as "shelter-in-place" laws) are the

strongest and were the last of the closure policies to be implemented. SAH mandates may reduce mobility in very direct and obvious ways. A few states enacted curfews specifying the hours when individuals can leave their homes. However, we do not classify curfew policies as equivalent to SAH mandates. Several states have not issued a SAH in any part of the state (Vervosh and Healy, 2020); as of April 3rd, these included Arkansas, Iowa, Nebraska, North Dakota, and South Dakota.

The state policies adopted during the shutdown phase occurred very rapidly. With an eye towards econometric models, we worked to understand the order and timing of the sequence of policies and to assess the extent to which it is feasible to meaningfully separate the effects of different policies. Figure 2 shows how the share of the U.S. population that was subject to each social distancing policy evolved over time.[5]

Emergency Declarations appear early and separate from the other policies. However, School Closures, Gatherings Restrictions, and Restaurant/Business Closings often coincide so closely in time that it seems infeasible to separately identify their effects in a regression analysis. Given the information on the sequence and timing of state policies, we condensed the seven major policy events in to a set of four major events during the shutdown phase: State First Cases and Deaths, Emergency Declarations, School Closures, and Stay-at-Home mandates.

As this section demonstrates, there are some principles we use for selecting which of the large number of different state policies currently discussed in the COVID-19 policy literature we should track in our research on mobility. The key decision factor was ensuring close connections to our theoretic framework while considering (informally) whether we could plausibly separate the effects of these policies.

4.2 Typology of Reopening Policies

We collected and coded data on state reopening policies, starting with *New York Times* descriptions of reopening plans. We gathered additional information on the reopening schedules for each state through internet searches.[6] We consider two primary reopening dates - date of announcement of upcoming reopenings and dates of actual reopening. We define the state's reopening date as the earliest date at which that state issued a reopening policy of any type. The dates we arrived at as the first reopening event for each state are identical to the ones depicted in figures used by the *New York Times* article. Starting with South Carolina, by June 15, 36 states had officially reopened in some phased form.

[5]Figure 2.2 in Gupta et al. (2020) shows the timeline of the policy changes that occurred in each state, and Figure 3.2 shows the timing of the first cases and deaths by state. There we show that the first COVID-19 case in a state is easily set apart in timing from the other policies, as is the first COVID-19 death.

[6]We provide the reopening policies information we have compiled from various sources at https://github.com/nguyendieuthuy/ReOpeningPlans.

Some states never formally adopted a stay-at-home order, but even these states implemented partial business closures (i.e. restaurant closures) and some non-essential business restrictions. Of course, measures of mobility and economic activity have fallen in these states as well because of private social distancing choices. In addition, the lack of an official closure does not mean that state governments cannot take actions to try to hasten the return to regular levels of activity. For example, South Dakota did not have a statewide stay-at-home order, but the governor announced a "back to normal" plan that set May 1 as the reopening date for many businesses. Our study period to examine the effect of reopenings on mobility commences on April 15 to ensure that we capture reopenings across all states.

Most reopening policies have been centered around seven areas of economic activity: outdoor recreation, retail, restaurant, worship, personal care, entertainment, and industry activities. However, the pace at which states have reopened each of these sectors has varied a lot. Some states reopened most businesses and industries immediately out of ,[7], while others have adopted a much more phased approach. Retail, recreation and restaurants have often reopened first and frequently only at limited capacity.

South Carolina was the first state to reopen on April 20. It was also one of the last states to adopt a stay-at-home order.[8] This April 20 reopening was partial, allowing retail stores to open at 20% of capacity. By April 30, eight states had reopened to some degree (AL, MS, TN, MT, OK, AK, GA, and SC). Eight more states reopened on May 1; by May 13, a total of 36 states had reopened. By June 30th all states have undergone at least the first stage of reopening. In most of our reopening analyses the study period ends on June 15, which means that we are able to estimate impacts for at least 30 days post reopening using variation from all 51 states and DC for Phase 1 and Phase 2 reopening polices.

Stay-at-home orders and non-essential business closures are related but distinct. Several states issued 'stay-at-home' mandates after they issued orders closing all non-essential businesses, or after closing some non-essential businesses (such as gyms) and closing restaurants for on-site dining. Although for the most part, stay-at-home orders coincided with orders to close all non-essential businesses, restaurants and other select categories of business closures started well before stay-at-home orders. Many business closures started in mid-March, along with school closures (see Figure 1). Timing of reopenings have been within 24 hours of lifting of stay-at-home orders in only 7 states (Connecticut, Florida, Idaho, Kansas, Montana, Pennsylvania and Utah, refer Table 1 for details). In the remaining states, reopening frequently preceded official expiry of stay-at-home orders on average by a month (32 days).

Figure 2a shows that by June 15 all U.S. states have adopted some form of reopening policy.

[7] Alaska, Connecticut, Washington DC, Iowa, Indiana, Louisiana, Maryland, Montana, New Hampshire, Nevada, South Dakota and Wyoming WY reopened initially by opening 5+ of the 7 sectors.

[8] Although it issued an emergency declaration fairly early (March 13), South Carolina did not issue a stay-at-home order until April 7. (See Gupta et al., 2020).

However, the pace of reopening has been gradual and varied. Figure 2b shows that by June 15, nearly 75% of the population lives in states that opened the retail sector, but only 60% are in states that opened 3 or more sectors that we track.[9] However, 20 states pursued a more limited strategy by opening only one or two sectors.[10]

States that either implemented fewer social distancing measures or implemented those measures later also tended to reopen earlier, based on time since the first of four major social distancing measures – non-essential business closures, restaurant closures, social gathering restrictions, and stay-at-home orders or advisories. These results may reflect either a lack of political desire to engage in distancing or a more limited outbreak (Andersen, 2020; Adolph et al., 2020; Allcott et al., 2020) .

5 Mobility Data

The data sets typically used in public health research do not provide high frequency measures of social interaction. To make progress, our research program has made heavy use of data from at least four commercial cell signal aggregators who have provided their data for free to support COVID-19 research. Each company has several different measures of mobility, which may capture a different form of underlying behavior, with different implications for the transmission of the virus and economic activity. In addition, each company collects data potentially from different sets of app users, and it is possible that some of the cell signal panels are more mobile than others. Given these complexities, it is important to examine several measures of mobility both to assess the robustness and generality of a result, and to provide opportunities to learn from differences in results across measures. In this paper, we discuss results based on data from Apple's Mobility Trends Reports, Google's Community Mobility Reports, PlaceIQ, and Safegraph.

Apple Mobility Trends. Apple's Mobility Trends Reports (Apple, 2020) are published daily and reflect requests for driving directions in Apple Maps. The measure we use tracks the volume of driving directions requests per U.S. state compared to a baseline volume on January 13, 2020; no county-level equivalent is available.

Google Community Mobility Reports. We extract state-level measures of mobility from Google's Community Mobility Reports (Google, 2020), which also contains county level data. We use the data that reflect the percent change in visits to places within a geographic area, including: grocery and pharmacy; transit stations (public transport hubs such as subway, bus, and train stations); retail and recreation (e.g. restaurants, shopping centers, and theme parks); places of work and residential (places of residence). The baseline for computing these changes is the median level

[9] Following the *New York Times*, we track outdoor recreation, retail, food/drink establishments, personal care establishments, houses of worship, entertainment venues, and industrial areas.

[10] For seven states we could not clearly identify the sectors that would be affected by the reopening decision.

of activity on the corresponding day of the week from January 3 to February 6, 2020.

PlaceIQ. We use two anonymized, aggregated location exposure indices from PlaceIQ data, provided in (Couture et al., 2020): (1) a mixing index that for a given day detects the likely exposure of a smart device to other devices in a county or state on a given day, and (2) out-of-state and out-of-county travel indices that measure among smart devices that pinged in a given geographic location, the percent of these devices that pinged in another geographic location at least once during the previous 14 days.

Safegraph. We use Safegraph data to measure the median hours spent at home by devices as well as the number of devices at the census block group level that are detected at typical work location during the day or to have left the house. We aggregate these to state by-day levels.

6 Econometric Framework

Let Y_{st} be a measure of mobility in state s on date t. E_s is the start date of a closure/reopening policy in state s. $TSE_{st} = t - E_s$ is number of days between t and the adoption date. We fit the following event study regression model:

$$\mathrm{Y}_{st} = \sum_{a=-30}^{-2} \alpha_a 1(TSE_{st} = -a) + \sum_{b=0}^{30} \beta_b 1(TSE_{st} = b) + W_{st}\sigma + \theta_s + \gamma_t + \epsilon_{st}$$

In the model, θ_s is a state fixed effect, which capture time-invariant differences in outcomes across states. γ_t is a date fixed effects, which represents a common trend. W_{st} is a vector of state $\times$ day measures of temperature and precipitation which helps adjust for seasonality. ϵ_{st} is a residual error term, and α_a and β_b trace out deviations from the common trends that states experience in the days leading up to and following a given policy event. Standard errors allow for clustering at the state level.

Our main specifications are based on a balanced panel of states. The models are not weighted and our estimates reflect the average state rather than the average person. The composition of states contributing to event study coefficients is quite stable for a range of 30 days before and after the event. The calendar time covered by the event studies varies somewhat across outcomes and is described along with each set of results. To help summarize results, we assess the presence of a pre-trend based on the statistical significance of the pre-policy event study coefficients. In our summary results, we say that a measure exhibits a pre-trend if at least 30% of the coefficients in the pre-period were statistically significant.

We also use the event study models to decompose the overall change in mobility over time into a share explained by state level policy changes and a share explained by secular trends that are not associated with state policies. To understand the counterfactual exercise, let $\hat{y}_{st}$ be the fitted value for state s on date t from the estimated event study regression. These fitted values are a model based estimate of what actually happened in the state. Let $y^*_{st} = \widehat{y_{st}} - \sum_{b=0}^{30} \hat{\beta}_b 1(TSE_{st} = b)$ is an estimate the counterfactual mobility outcome that would have prevailed in the absence of the state policy. We compute the daily cross-state average of the fitted values and counterfactual estimates to form two national time series of mobility outcomes. A close correspondence between the realized time series and the counterfactual time series would indicate that changes in mobility are mainly from secular trends rather than policy.

7 Results

7.1 Trends in Mobility

The collection of graphs in figure 3 shows the national and state level time series for a subset of the mobility measures we follow in Gupta et al. (2020) and Nguyen et al. (2020). The solid black line indicates the "smoothed" (7-day moving average) national average (not weighted by state population). Each of the light grey lines represents a state. The state lines turn red for the time period when a state implemented a stay-at-home (SAH) order, and then they turn green when a state implements its first reopening stage. This provides a convenient way to observe when the changes in mobility occurred relative to the policy dates.

The overall pattern of results is very consistent across the different measures of mobility. Figure 3a shows the mixing index. Weekend patterns and other seasonal effects are visible, when all lines move together. There is a substantial drop in mixing around mid-march, when the index falls 70% between March 1 and April 14. Figure 3 b shows the average "out of county" travel measure, which fell by 38% between March 1 and April 14. Figure 3g shows trends hours spent at home, which is a state level average of census block group medians. Time at home increased 42% increase between March 1 and April 14. The springtime is typically associated with more mobility and interaction, so any decline during this period is abnormal.[11]

The graphs in figure 3 shows that states with no SAH mandates also experienced large declines in mobility as well as subsequent increases after mid April. Indeed, states with no SAH policies at all – shown in grey throughout – had declines in movement almost as dramatic as in other states. Furthermore, most states with SAH mandates experienced major declines in mobility even before the SAH mandates went into effect.

[11] Data for recent years (2018-2019) from the U.S. Department of Transportation for (seasonally unadjusted) vehicle miles travelled, shows that the March value is typically 20% higher than February's value (U.S. Department of Transportation 2020).

7.2 Mandate Effects

Estimates of the event studies evaluating the effect of closure policies and informational events on each of the mobility measures are presented in Gupta et al. (2020). In Figure 5 we graphically present the event study coefficients of the effect of state policies and informational events on the 'mixing index' available from PlaceIQ (Couture et al., 2020). As noted in Section 5 the mixing index captures the concentration of devices in particular locations and most closely proxies for social distancing and thus transmission. The results suggest that the concentration of devices in particular locations does not trend differentially in the period leading up to any policy or informational event. However, we do not find statistically significant evidence that the policy or information events have induced substantial changes in mixing at the state level except for a large effect of emergency declarations. The event study coefficients imply that emergency declarations reduced the state level mixing index by about 68% after 30 days, relative to the value of the index on March 1st, which is the baseline reference period for all percent effects reported for closure events. The coefficients show a similar pattern for First Deaths, but it is not statistically significant.

Table 2 provides a summary of the results of the event study regressions for each outcome and policy/information event, including other ones for which figures and tables of coefficients are reported in Gupta et al. (2020). Table 2 has a row for each state and county outcome variable, and a column for each policy/information event. The top panel shows the effect size 5 days after the event, expressed as a percentage of the average value of the outcome variable on March 1, 2020. The bottom panel shows the effect size after 20 days, also expressed as a percentage of the average outcome on March 1. We bold and indicate with ** the effects that are statistically significant at the 5% level or better and where parallel trends hold. We use ** without bold for effects that are significant at the 10% level. The cells that are shaded in grey have possible violations of the differential pre-trends assumption and should be largely overlooked; we do not indicate statistical significance for them. First death announcements also carry a large coefficient but it is statistically not significant; school closures and stay at home laws have statistically insignificant and wrong-signed coefficients.

7.3 Reopening Effects

In a manner similar to the event studies for the closure policies, we present results for the initial reopening dates, starting in figure 5. The two panels display effects first where the policy date is the announcement of the re-opening, and second for the actual reopening date. There is a pattern (although not statistically significant) of what appears to be a non-parallel trend prior to the actual reopening date, but is fairly flat prior to the announcement date. None of the estimates are statistically significant, even after the policy is effective, although non-significant coefficients are consistent with an increase in movement after the announcement date. This helps illustrate our finding that it is important to consider a variety of mobility measures to assess the impact of the policies. Table 2 shows that although the mixing index is not statistically precise, there are several other outcomes that are, and do not violate pre-trends concerns. The effect sizes here are, however, considerably smaller than in the closure period. One reason for that maybe that in the reopening phase, we do not have informational events occurring in the same way they did during the closure period. We do not study the impact of changing rates of COVID-19 cases or deaths, as those were often directly referred to as conditions for reopening.

The overall message from table 2 for the reopening dates is that estimates are fairly similar whether we use the announcement date or the actual reopening date, and that effect sizes are fairly small at both 5 days or 20 days, on the order of 1% to 4%. These are not surprising results, given the very limited nature of initial reopening phases. The small effects overall also could mask larger effects in certain situations; event study estimates are summaries of each state's experience Wing et al. (2018) and in Nguyen et al. (2020) we show that effects are larger in states that were the last to close businesses, and also differ along a number of other dimensions.

7.4 The Role of Secular Trends (National sentiment)

One way to interpret our results is to use the event study coefficients to tease apart the amount of the actual change in mobility that occurred during the closure or reopening time periods, into shares explained by state actions, relative to secular changes in sentiment due to other factors. Figure 6 and table 3 show estimates of this decomposition for the mixing index during the shutdown phase. We used event study regressions to estimate the effects of emergency declarations on the mixing index outcome. The solid line in figure 6 shows how the national average mixing index actually changed over time. The dashed line is an estimate of the counterfactual path of the mixing index, which removes the policy effects from the model. The time trends captured by the model imply that in the mixing index would have increased substantially in the absence of the emergency declarations. 3 shows that the emergency declaration event study coefficients account for about 65% of the observed decline in the mixing index that occurred between the first week of March and the second week of April. The remaining 35% was due to secular trends that occurred separately from state emergency declarations. Decompositions like this one imply that both policy and private responses (secular trends) played a key role during the shutdown. However, the specific policy share vs secular share varies across measures of mobility.

We used this same strategy to examine the state reopening policies. Figure 6 and table 4 show decomposition results for the mixing index and the fraction of people who leave home during the day. The solid lines in Figure 6 show how the mixing index (panel a) and the fraction leaving home (panel b) evolved between mid-April and mid-June. Both measures rose substantially during the reopening phase. The dashed lines show counterfactual estimates of the path of each index in the absence of the event study state reopening effects. The results suggest that the reopening policies had almost no influence on the rise of the mixing index. The growth in that variable is almost completely attributable to a nationwide secular trend that occurred separately from reopening events. In contrast, the model suggests that state reopening events did alter the evolution of the fraction leaving home measure of mobility. Table 4 shows that the fraction leaving home grew from about 60% to 70% between late April and mid-June. About 31% of that increase is attributable to the reopening policies because of how much time had passed before policies were adopted. The remaining 69% of the change might have happened even in the absence of state policies, given the common trends implied by the model. These results again suggest that both private responses (secular trends) and state level policies have played a role in generating recent increases in mobility, however the magnitude/share of policy effects varies across measures of mobility and the policy share is perhaps somewhat smaller during the reopening phase than during the shutdown phase.

8 Conclusion

We examine human mobility responses to the COVID19 epidemic and to the policies that arose to encourage social distancing. A simple theoretical framework suggests that people will increase social distance in reaction to information and apprehension regarding the virus, not just in response to state closure or reopening mandates.

We examine closures first, finding that information-based policies and events such as first cases had the largest effects. This does not imply that these laws and events would always have such impacts, as it is possible people simply react to the earliest of the policies, and more restrictive policies like stay at home orders happened fairly late. Early state policies appeared to convey information about the epidemic, suggesting that even the policy response operates partly through a voluntary channel.

Given that most states have now undertaken some steps to reduce the lockdown, we are able to compare mobility during the closure to mobility during the reopenings. Even though the reopenings are gradual, often with capacity limits for each sector, we find that mobility increases a few days after the policy change. There is some evidence that reopenings lead people to increase the number of different locations they visit, rather than increase the total time they are outside their home. Finally, we observe that largest increases in mobility occur in states that were late adopters of closure measures, and thus had these mandates in place for the shortest amount of time. This suggests that closure policies may have represented more of a binding constraint in the late adopting states. Together, these four observations provide an assessment of the extent to which people in the U.S. are resuming movement and physical proximity as the COVID-19 pandemic continues. Given the high costs of broad closures, it behooves researchers to examine possible targeted approaches.

Our own empirical work and our review of the emerging literature supports several broad conclusions. First, the epidemic has led to a massive change in human mobility and contact patterns. This change happened quite early and suddenly and largely across the board. Although much of the decline in mobility appears to be a private response to changing health condition, research also suggests that state and local social distancing policies have helped further depress mobility. Second, measures of economic activity related to both labor market outcomes and consumer spending have changed dramatically in response to the epidemic. The fall in consumer spending occurred despite a large increase in federal spending. The fall in spending occurred throughout the country and does not seem to have been moderated by state and local policies. The decline in employment happened a bit later than the immediate mobility and spending effects, but here as well the evidence suggests that social distancing policies are not associated with large differences in labor market outcomes across localities. Third, there is fairly consistent evidence that the state social distancing policies have helped improve health outcomes as measured by cases and deaths.

The literature on the COVID-19 epidemic has developed at a very rapid pace. The crisis is still only a few months old, but an active research community and new availability of data has contributed to our understanding of the way people are responding to both public health conditions and public policy constraints. But there is still much work to be done. States have started to reopen their economies. School reopenings are a pressing decision. There is also now evidence that caseloads and deaths are beginning to rise again. Congress is currently debating another round of economic aid to protect society financially against the damage caused by the epidemic. It is not clear how long the country can maintain such low levels of physical mobility, and such high levels of unemployment. The next phase of the epidemic may call for more targeted policies that mitigate the spread of the virus with less disruption.

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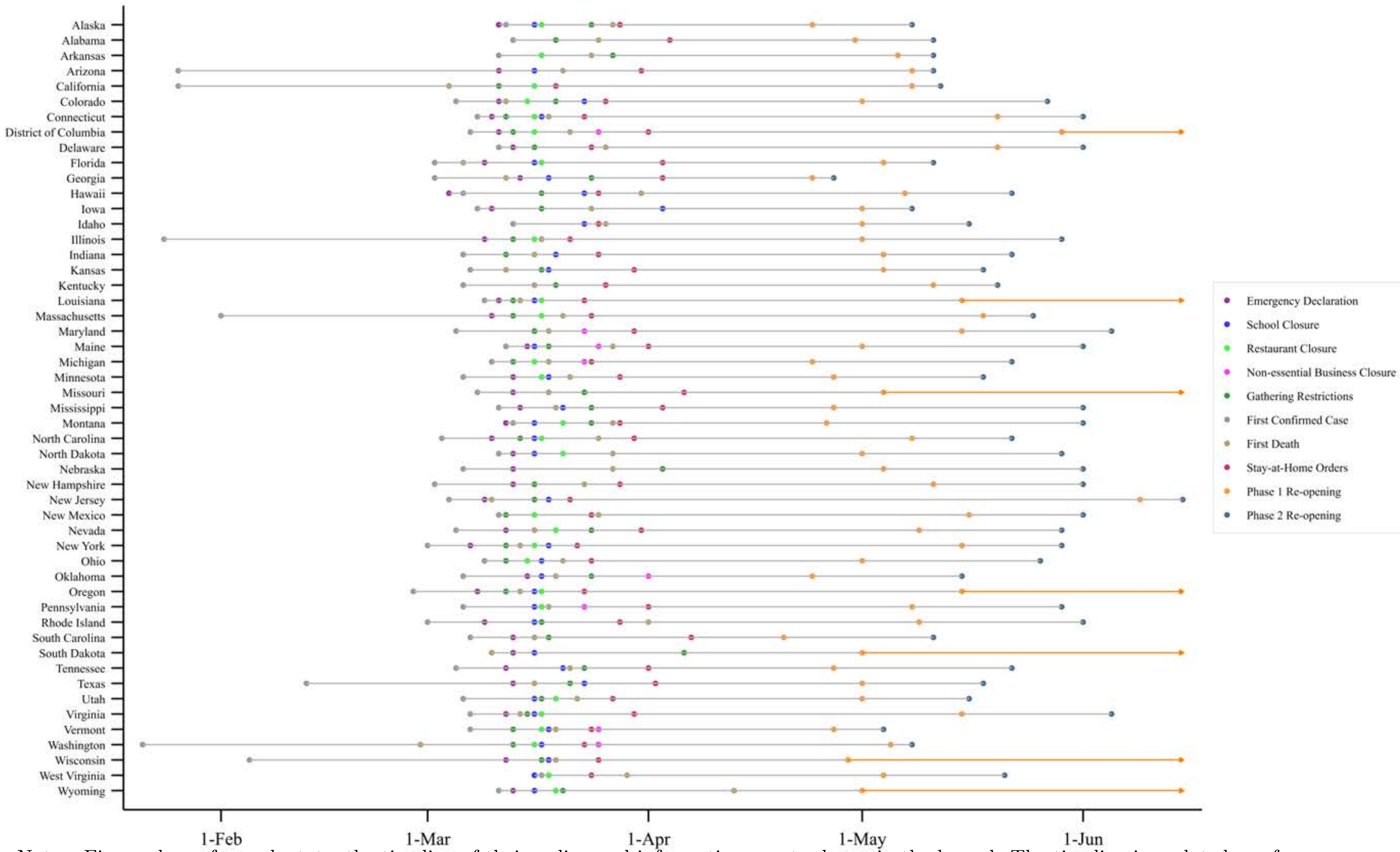
9 Tables and Figures

Figure 1: State Policy and Information Timelines (January 15, 2020 - June 15, 2020)



Note: Notes: Figure shows for each state, the timeline of their policy and information events shown in the legend. The timeline is updated as of June 15. Continuing arrows denote states yet to enter Phase 2 of re-openings.

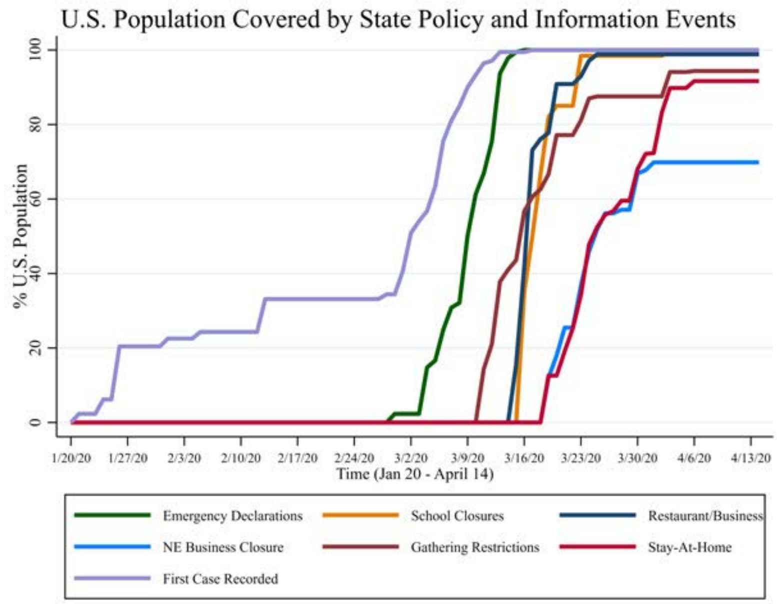
Table 1: State Social-distancing related Policy Enactment and Information Event Dates.

Statename	**Emergency Declarations**	**School Closures**	**Restaurant/Oth Restrictions**	**Garthering Restrict. (Any)**	**Non-Essential Bus. Closures**	**First Confirmed Case**	**First Death**	**Stay-At-Home Orders**	**Initial Re-openings**	**Phase 2 Re-openings**
Alabama	11-Mar-20	16-Mar-20	17-Mar-20	28-Mar-20	24-Mar-20	12-Mar-20	27-Mar-20	4-Apr-20	30-Apr-20	11-May-20
Alaska	13-Mar-20	19-Mar-20	20-Mar-20		20-Mar-20	13-Mar-20	25-Mar-20	28-Mar-20	24-Apr-20	8-May-20
Arizona	11-Mar-20	17-Mar-20	19-Mar-20			11-Mar-20	24-Mar-20	31-Mar-20	8-May-20	11-May-20
Arkansas	11-Mar-20	16-Mar-20	20-Mar-20			26-Jan-20	20-Mar-20		6-May-20	11-May-20
California	4-Mar-20	19-Mar-20	15-Mar-20	19-Mar-20	11-Mar-20	26-Jan-20	4-Mar-20	19-Mar-20	8-May-20	12-May-20
Colorado	10-Mar-20	23-Mar-20	17-Mar-20	26-Mar-20	19-Mar-20	5-Mar-20	12-Mar-20	26-Mar-20	1-May-20	27-May-20
Connecticut	10-Mar-20	17-Mar-20	16-Mar-20	23-Mar-20	12-Mar-20	8-Mar-20	18-Mar-20	23-Mar-20	20-May-20	17-Jun-20
Delaware	11-Mar-20	16-Mar-20	16-Mar-20	25-Mar-20	13-Mar-20	7-Mar-20	21-Mar-20	24-Mar-20	20-May-20	15-Jun-20
DC	13-Mar-20	16-Mar-20	16-Mar-20	24-Mar-20	16-Mar-20	11-Mar-20	26-Mar-20	1-Apr-20	29-May-20	
Florida	9-Mar-20	16-Mar-20	17-Mar-20	30-Mar-20	3-Apr-20	2-Mar-20	6-Mar-20	3-Apr-20	4-May-20	5-Jun-20
Georgia	14-Mar-20	18-Mar-20	24-Mar-20		24-Mar-20	2-Mar-20	12-Mar-20	3-Apr-20	24-Apr-20	27-Apr-20
Hawaii	4-Mar-20	23-Mar-20	17-Mar-20	25-Mar-20	16-Mar-20	6-Mar-20	31-Mar-20	25-Mar-20	7-May-20	22-May-20
Idaho	9-Mar-20	3-Apr-20	17-Mar-20		17-Mar-20	8-Mar-20	24-Mar-20	25-Mar-20	1-May-20	16-May-20
Illinois	13-Mar-20	23-Mar-20	25-Mar-20	25-Mar-20	25-Mar-20	13-Mar-20	26-Mar-20	21-Mar-20	1-May-20	29-May-20
Indiana	9-Mar-20	17-Mar-20	16-Mar-20	21-Mar-20	13-Mar-20	24-Jan-20	17-Mar-20	25-Mar-20	4-May-20	22-May-20
Iowa	6-Mar-20	19-Mar-20	16-Mar-20	24-Mar-20	12-Mar-20	6-Mar-20	16-Mar-20		1-May-20	8-May-20
Kansas	12-Mar-20	18-Mar-20			17-Mar-20	7-Mar-20	12-Mar-20	30-Mar-20	4-May-20	18-May-20
Kentucky	6-Mar-20	16-Mar-20	16-Mar-20	26-Mar-20	19-Mar-20	6-Mar-20	16-Mar-20	26-Mar-20	11-May-20	20-May-20
Louisiana	11-Mar-20	16-Mar-20	17-Mar-20	23-Mar-20	13-Mar-20	9-Mar-20	14-Mar-20	23-Mar-20	15-May-20	5-Jun-20
Maine	10-Mar-20	17-Mar-20	17-Mar-20	24-Mar-20	13-Mar-20	1-Feb-20	20-Mar-20	1-Apr-20	1-May-20	1-Jun-20
Maryland	5-Mar-20	16-Mar-20	16-Mar-20	23-Mar-20	16-Mar-20	5-Mar-20	18-Mar-20	30-Mar-20	15-May-20	5-Jun-20
Massachusetts	15-Mar-20	16-Mar-20	18-Mar-20	25-Mar-20	18-Mar-20	12-Mar-20	27-Mar-20	24-Mar-20	18-May-20	8-Jun-20
Michigan	10-Mar-20	16-Mar-20	16-Mar-20	23-Mar-20	13-Mar-20	10-Mar-20	18-Mar-20	24-Mar-20	24-Apr-20	22-May-20
Minnesota	13-Mar-20	18-Mar-20	17-Mar-20			6-Mar-20	21-Mar-20	28-Mar-20	27-Apr-20	18-May-20
Mississippi	13-Mar-20	23-Mar-20	17-Mar-20		23-Mar-20	8-Mar-20	18-Mar-20	3-Apr-20	27-Apr-20	1-Jun-20
Missouri	14-Mar-20	20-Mar-20	24-Mar-20	31-Mar-20	24-Mar-20	11-Mar-20	19-Mar-20	6-Apr-20	4-May-20	16-Jun-20
Montana	12-Mar-20	16-Mar-20	20-Mar-20	28-Mar-20	24-Mar-20	13-Mar-20	27-Mar-20	28-Mar-20	26-Apr-20	1-Jun-20
Nebraska	10-Mar-20	16-Mar-20	17-Mar-20	30-Mar-20	14-Mar-20	3-Mar-20	25-Mar-20		4-May-20	1-Jun-20
Nevada	13-Mar-20	16-Mar-20	20-Mar-20			11-Mar-20	27-Mar-20	31-Mar-20	9-May-20	29-May-20
New Hampshire	13-Mar-20	3-Apr-20	19-Mar-20		16-Mar-20	6-Mar-20	27-Mar-20	28-Mar-20	11-May-20	1-Jun-20
New Jersey	13-Mar-20	16-Mar-20	16-Mar-20	28-Mar-20	16-Mar-20	2-Mar-20	23-Mar-20	21-Mar-20	9-Jun-20	15-Jun-20
New Mexico	9-Mar-20	18-Mar-20	16-Mar-20	21-Mar-20	16-Mar-20	4-Mar-20	10-Mar-20	24-Mar-20	16-May-20	1-Jun-20
New York	11-Mar-20	16-Mar-20	16-Mar-20	24-Mar-20	16-Mar-20	11-Mar-20	25-Mar-20	22-Mar-20	15-May-20	29-May-20
North Carolina	12-Mar-20	16-Mar-20	17-Mar-20	21-Mar-20	19-Mar-20	5-Mar-20	16-Mar-20	30-Mar-20	8-May-20	22-May-20
North Dakota	7-Mar-20	18-Mar-20	16-Mar-20	20-Mar-20	13-Mar-20	1-Mar-20	14-Mar-20		1-May-20	29-May-20
Ohio	9-Mar-20	17-Mar-20	15-Mar-20	24-Mar-20	12-Mar-20	9-Mar-20	20-Mar-20	24-Mar-20	1-May-20	26-May-20
Oklahoma	15-Mar-20	17-Mar-20	25-Mar-20	26-Mar-20	24-Mar-20	6-Mar-20	19-Mar-20		24-Apr-20	15-May-20
Oregon	8-Mar-20	16-Mar-20	17-Mar-20		16-Mar-20	28-Feb-20	14-Mar-20	23-Mar-20	15-May-20	4-Jun-20
Pennsylvania	6-Mar-20	16-Mar-20	17-Mar-20	23-Mar-20	16-Mar-20	6-Mar-20	18-Mar-20	1-Apr-20	8-May-20	29-May-20
Rhode Island	9-Mar-20	16-Mar-20	16-Mar-20		17-Mar-20	1-Mar-20	1-Apr-20	28-Mar-20	9-May-20	1-Jun-20
South Carolina	13-Mar-20	16-Mar-20	18-Mar-20		18-Mar-20	7-Mar-20	16-Mar-20	7-Apr-20	20-Apr-20	4-May-20
South Dakota	13-Mar-20	16-Mar-20			6-Apr-20	10-Mar-20	10-Mar-20		1-May-20	
Tennessee	12-Mar-20	20-Mar-20	23-Mar-20	1-Apr-20	23-Mar-20	5-Mar-20	21-Mar-20	1-Apr-20	27-Apr-20	22-May-20
Texas	13-Mar-20	23-Mar-20	21-Mar-20	21-Mar-20	20-Mar-20	13-Feb-20	16-Mar-20			18-May-20
Utah	6-Mar-20	16-Mar-20	18-Mar-20		16-Mar-20	6-Mar-20	22-Mar-20	27-Mar-20	1-May-20	16-May-20
Vermont	12-Mar-20	16-Mar-20	17-Mar-20		15-Mar-20	7-Mar-20	14-Mar-20	24-Mar-20	27-Apr-20	4-May-20
Virginia	13-Mar-20	18-Mar-20	17-Mar-20	25-Mar-20	13-Mar-20	7-Mar-20	19-Mar-20	30-Mar-20	15-May-20	5-Jun-20
Washington	29-Feb-20	17-Mar-20	16-Mar-20	25-Mar-20	11-Mar-20	21-Jan-20	29-Feb-20	23-Mar-20	5-May-20	8-May-20
West Virginia	12-Mar-20	18-Mar-20	17-Mar-20	25-Mar-20	17-Mar-20	5-Feb-20	19-Mar-20	24-Mar-20	4-May-20	21-May-20
Wisconsin	16-Mar-20	16-Mar-20	17-Mar-20	24-Mar-20		17-Mar-20	29-Mar-20	25-Mar-20	29-Apr-20	11-May-20
Wyoming	13-Mar-20	16-Mar-20	19-Mar-20		20-Mar-20	11-Mar-20	13-Apr-20		1-May-20	

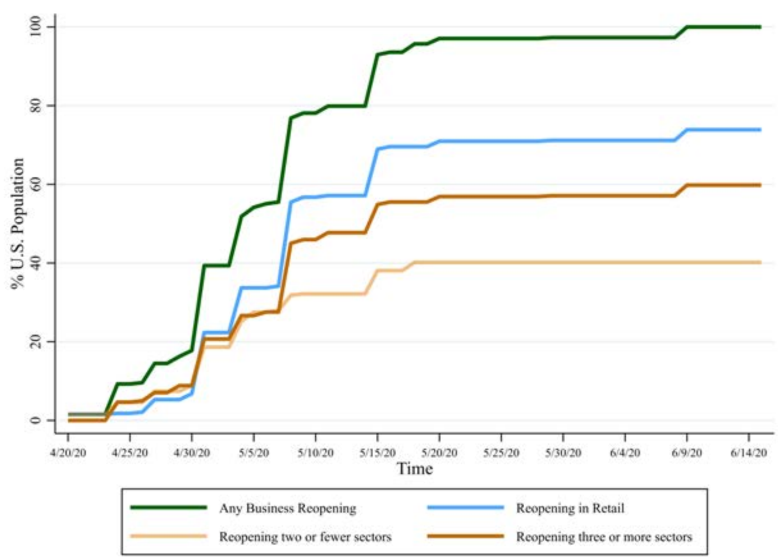
Note: Author compilations based on Fullman (2020), the public use map/tracker of K-12 school closures (Education Week), New York Times and our own compilations; we collected data on the timing of the first COVID-19 case announcements from media reports in each state. Data are current as of June 15, 2020

Figure 2: U.S. Population covered by State Closure and Re-opening Policies

(a)



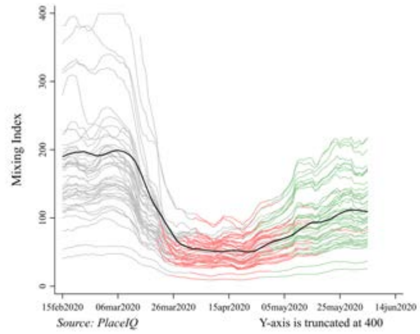
(b)



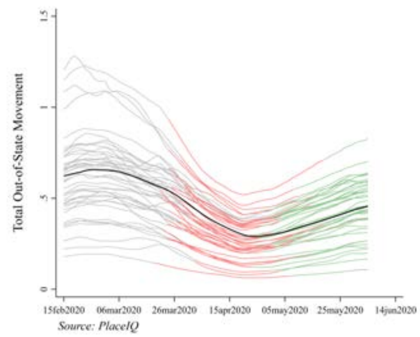
Note: Author's compilations based on several sources. Data covered January 20, 2020 - June 15, 2020.

Figure 3: Trend in mobility changes.

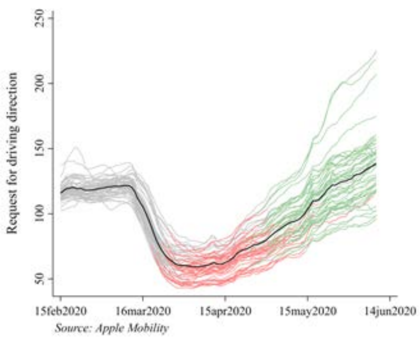
(a) Mixing index.



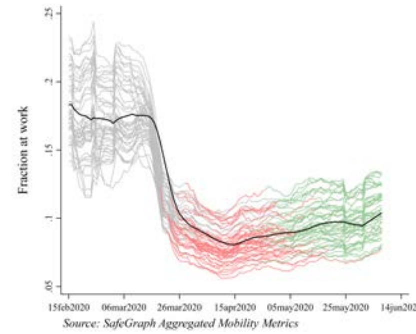
(b) Average out-of-county movement.



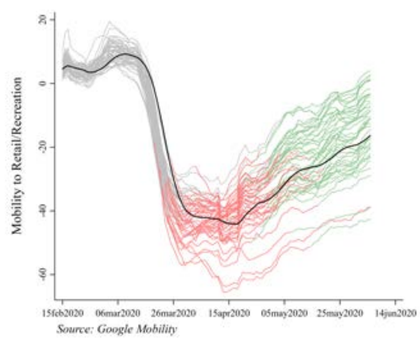
(c) Requests for driving directions



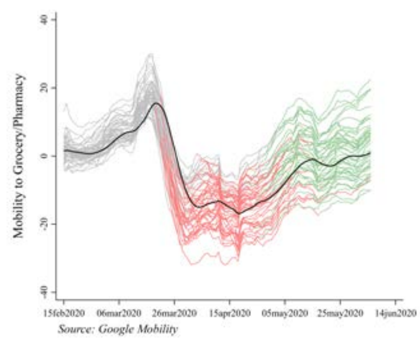
(d) Fraction at Work



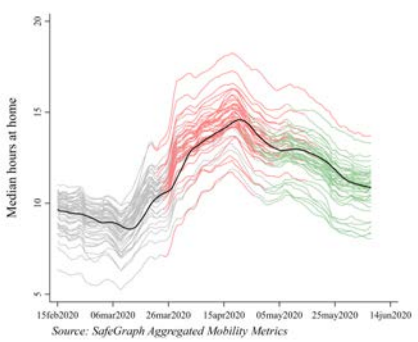
(e) Retail and recreation



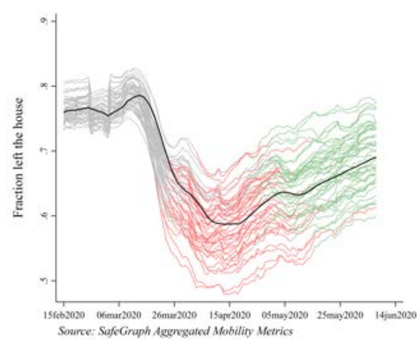
(f) Grocery and pharmacy



(g) Median hours at home.

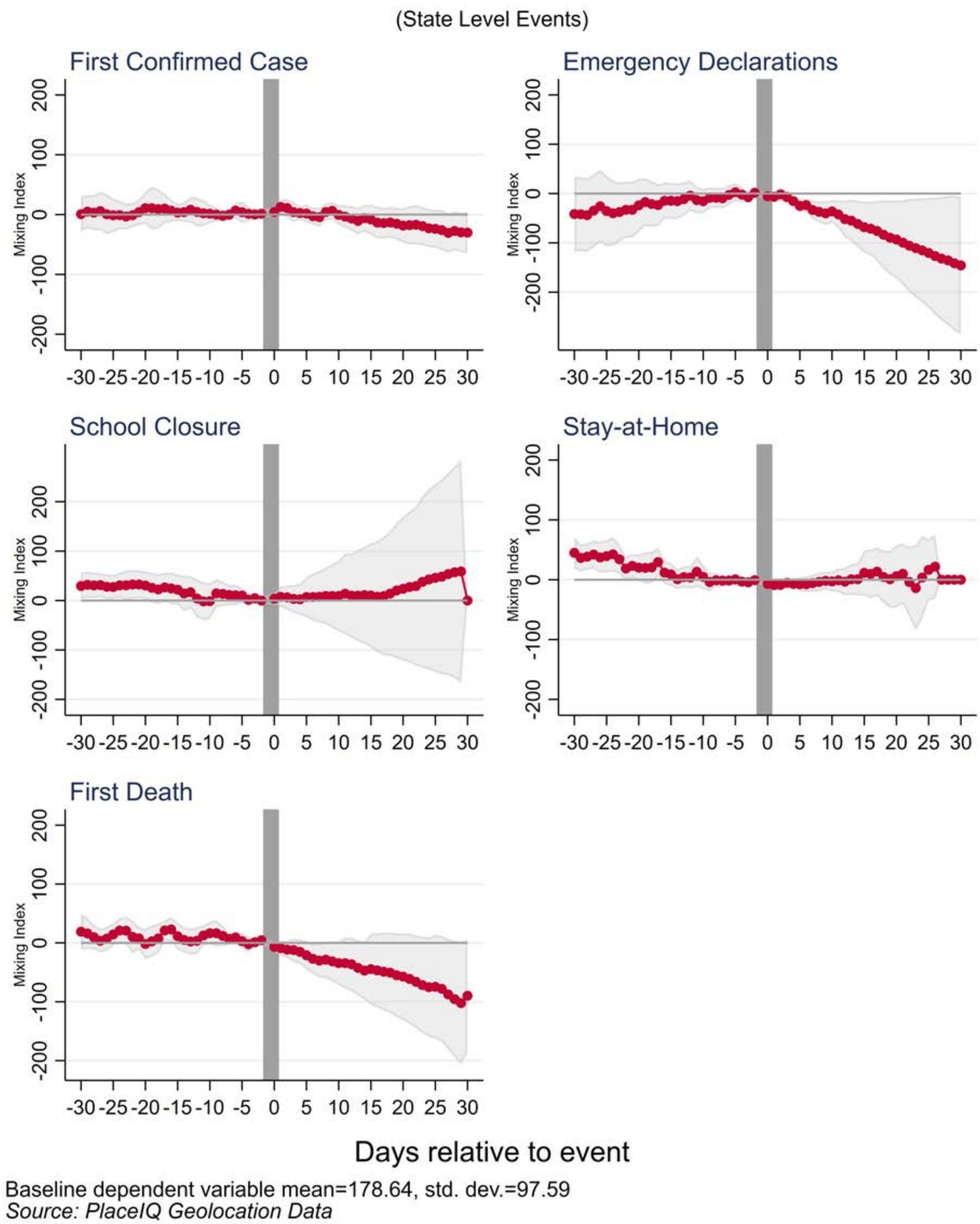


(h) Fraction leaving home.



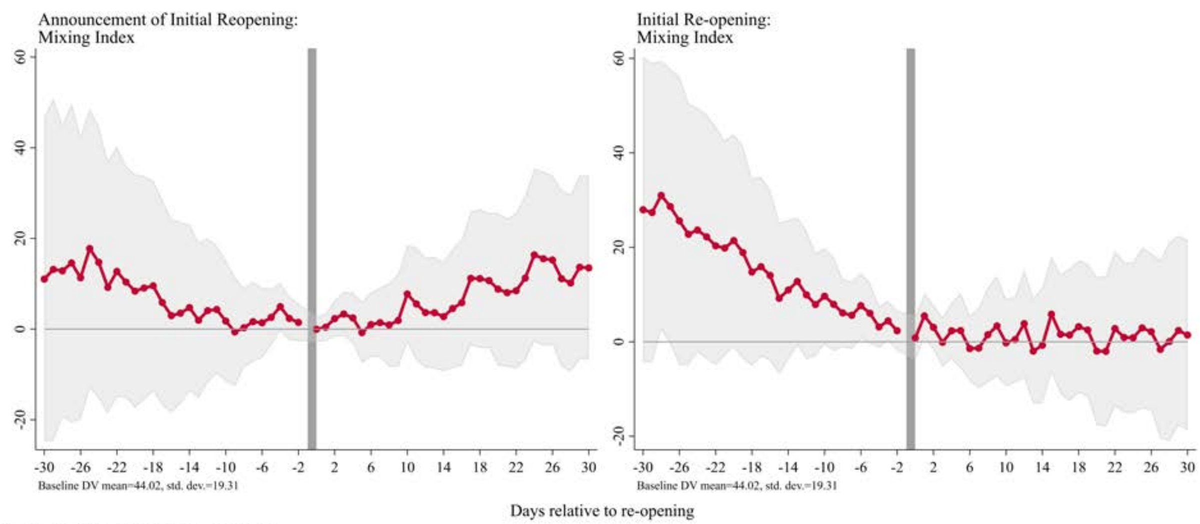
Note: Author's calculation based on data from Apple Mobility, Google Mobility, SafeGraph Aggregated Mobility Metrics and PlaceIQ smart device data. Each grey line represents a state, which turn red after the state implements stay-at-home orders and green after phase 1 of reopening. The thick black line represents a "smoothed" 7 day moving average of the states.

Figure 4: Effects of Mitigation Policies and Information Events on Mixing Index. Regression Results (Coefficients and 95% Confidence Intervals)



Note: The dependent variable shows the state's index for mixing (average amount of mixing within its census block groups). Standard errors are clustered at the state level. Full event study estimates available in Gupta et al. (2020).

Figure 5: Effects of Announcement and Effective date of initial reopening on Mixing Index. Regression Results (Coefficients and 95% Confidence Intervals)



Source: PlaceIQ (09 April 2020 - 11 June 2020)

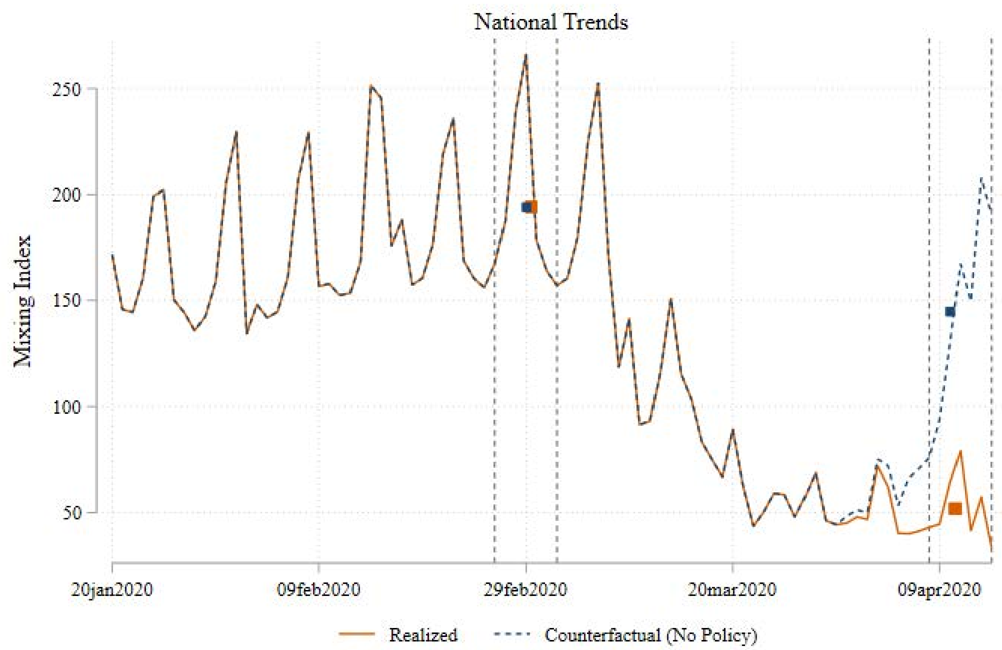
Note: Note: The dependent variable shows the state's index for mixing (average amount of mixing within its census block groups). Standard errors are clustered at the state level. Full event study estimates available upon request.

Table 2: Effect Sizes: Percentage magnitude effects of the policy/informational events on social distancing measures.

	I: Effects of Mitigation Policies and Informational Events				
	First Confirmed Case (FCC)	Emergency Declarations (ED)	School Closure (SC)	Stay-atHome (SAH)	First Death (FD)
	Effects After 5 days				
Mixing Index	1%	**-14%*** **	**4%**	-7%	-11%
Median Hours at Home	**-1%***	**6%*****	1%	5%	**3%***
Fraction Leaving Home	**1%****	**-1%***	-1%	-5%	**-2%*****
Total Out-of-State Movement	**-2%**	-1%	**-4%****	**-1%**	0%
Total Out-of-County Movement	-1%	**-2%****	**-4%*****	**-3%**	-2%
	Effects After 20 days				
Mixing Index	-10%	**-52%*****	**13%**	-8%	-31%
Median Hours at Home	**-2%**	**27%*****	3%	11%	**9%****
Fraction Leaving Home	2%	**-13%*****	-3%	-9%	**-7%*****
Total Out-of-State Movement	**-9%**	-3%	**-13%**	**1%**	5%
Total Out-of-County Movement	-2%	-8%***	**-9%*****	**-2%**	**-6%***
	II: Effects of State Initial reopenings				
	Announcement of Initial Reopening	Initial reopening			
	Effects After 5 Days				
Mobility Measures					
Request for driving directions	**-6%**	**-3%**			
Mobility to retail/recreation	3%	3%			
Mobility to Grocery/Pharmacy	8%	9%			
Mobility to Transit Stations	0%	9%			
Mobility to Workplace	2%	**3%****			
Fraction at Work	-3%*	2%			
Fraction left home	**1%****	**1%****			
Mixing Index	-2%	5%			
Out of state movement	-2%	0%			
Out of county movement	-1%	0%			
Absence of Mobility Measures					
Stay in Residential Areas	-1%	**-4%****			
Median hours at home	**-1%***	**-1%*****			
	Effects After 20 Days				
Mobility Measures					
Request for driving directions	**-15%**	**-15%**			
Mobility to retail/recreation	8%	4%			
Mobility to Grocery/Pharmacy	8%	4%			
Mobility to Transit Stations	0%	-6%			
Mobility to Workplace	4%	1%			
Fraction at Work	-2%	1%			
Fraction left home	**4%*****	1%			
Mixing Index	20%	-4%			
Out of state movement	-1%	-8%			
Out of county movement	2%	0%			
Absence of Mobility Measures					
Stay in Residential Areas	-5%	-4%			
Median hours at home	**-3%*****	**-3%*****			

Note: Each cell is from a separate regression. *** and bold text denotes effect sizes with p-values<0.01. ** and bold text denotes effect sizes with p-values<0.05. * and bold text denotes effect sizes with pvalues<0.10. Grey shaded cells denote violation of pre-treatment parallel trends—we do not denote statistical significance for these cells. Effect sizes for closures are estimated using coefficients in the event-study tables presented in Gupta et al. (2020), divided by the dependent variable value as of March 1, 2020. Effect sizes for reopenings are estimated using coefficients in the event-study tables presented in Nguyen et al. (2020), divided by the dependent variable value as of April 15, 2020.

Figure 6: Change in Social Distancing (Mixing Index) Attributed to Emergency Declarations.



Note: Note: Corresponding to Figure 5, Figure 6 shows calendar time trends of the predicted lines with and without the policy event time terms set to zero, for the Mixing index measure of mobility, and the Emergency Declarations policy measure.

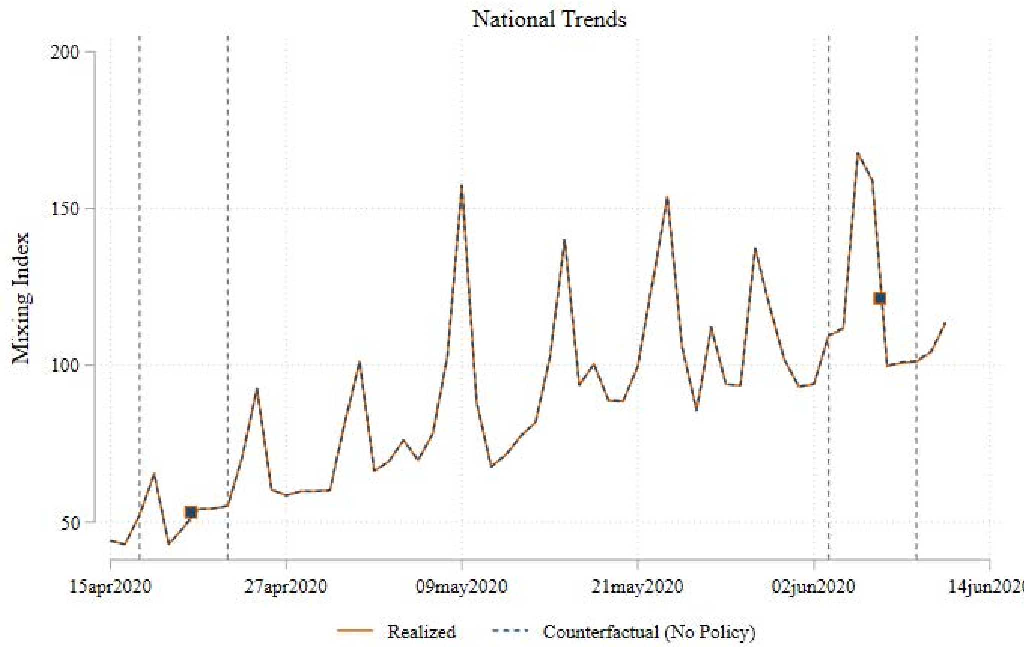
Table 3: Estimated Effects of Emergency Declarations on Mixing Index.

	February 26 - March 3	April 8 - April 14	Change
Actual Mixing Index	194.3	51.9	-142.4
Counterfactual Mixing Index (No policy)	194.3	144.9	-49.4
Secular share of change			0.35
Policy share of change			0.65

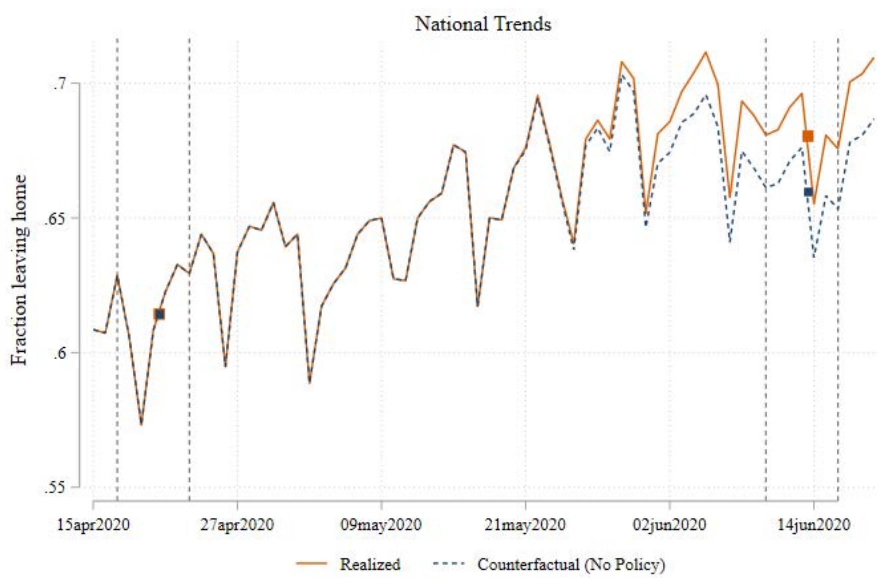
Note: Author's calculation based on decomposition of changes in mobility to share attributable to state emergency declarations and those resulting from secular trends. Related estimates plotted in Figure6.

Figure 7: Change in Social Distancing (Mixing Index and Fraction Leaving Home) Attributed to Initial Reopening.

(a) Estimated Effects of Initial Reopening on Mixing Index.



(b) Estimated Effects of Initial Reopening on Fraction Leaving Home.



Note: Corresponding to Figure5, Figure 6(a) shows calendar time trends of the predicted lines with and without the policy event time terms set to zero, for the Mixing index measure of mobility, and the Emergency Declarations policy measure. Figure 6(b) provides specific values discussed in the text.

Table 4: Estimated Effects of Reopening on Social Distancing.

	April 17 - April 23	June 10 - June 16	Change
Actual Mixing Index	53.2	121.2	68.0
Counterfactual Mixing Index (No policy)	53.2	121.5	68.3
Secular share of change			1.0
Policy share of change			0.0
Actual Fraction Leaving Home	0.6	0.7	0.1
Counterfactual Fraction Leaving Home (No policy)	0.6	0.7	0.0
Secular share of change			0.69
Policy share of change			0.31

Note: Author's calculation based on decomposition of changes in mobility to share attributable to state initial reopening policy and those resulting from secular trends. Related estimates plotted in Figure7.

Appendix

A Relevant Literature

Table A1: Causal Effects of COVID-19 Shutdown Orders.

Study	**Data**	**Finding**	**Effect Sizes**
		Human mobility	
Abouk and Heydari (2020)	Google Mobility	"We show that statewide stay-at-home orders had the strongest causal impact on reducing social interactions." "Other policies such as school closure mandates, large gathering bans, and more limited stay-at-home orders do not show any significant impact on keeping people at home"	>600% increase in staying at home." (Table 2)
Alexander and Karger (2020)	Unacast	"First, stay-at-home orders caused people to stay home: Countylevel measures of mobility declined 8% by the day after the stay-at-home order went into effect."	County level SAH: 8% decline in mobility the day after policy
Andersen (2020)	SafeGraph	"Mandatory measures to increase social distancing appear to be effective, most notably stay at home orders which increase the share of devices at home by 2 percentage points. Social distancing orders also appear to have substantial informational content and, in the case of mask mandates, the informational content appears to be greater than the gross effect of mask mandates on behavior."	5% increase in staying at home(Table 1)
Chen et al. (2020a)	Veraset	"...we observe that by April 30th---when nine in ten Americans were under a SHO---daily movement had fallen 70% from pre-COVID levels. One-quarter of this decline is causally attributable to SHOs..."	0.17 change in index (Table s1)
Cicala et al. (2020)	Unacast	"States that imposed stay-at-home policies before March 28 decreased travel slightly more than other states, but travel in all states decreased significantly." Fig 1a shows that states with early SAH laws had larger drops in vehicle travel than other states.	Not reported
Cronin and Evans (2020)	SafeGraph	"...mobility series at the national and state levels start to change dramatically in a short window from March 8-14, well before state or local restrictions of note are in place. In difference-in-difference models, declarations of state of emergency reduce foot traffic and increase social distancing. Stay at home restrictions explain a modest fraction of the change in behavior across outcomes."	SAH laws increased" at home rate 0.04 , 7 days after the laws (Table 2)
Dave et al. (2020)	SafeGraph	"...we document that adoption of a SIPO was associated with a 5 to 10 percent increase in the rate at which state residents remained in their homes full-time."	5-10 % increase in staying at home
Elenev et al. (2020)		"...decentralized NPI decisions, which does not internalize externalities generated on surrounding locations, could result in lower NPI implementation and weaker reduction in mobility..".."We find that spillover effects range between a third and a half of the direct effect depending on the particular outcome or policy considered."	0.947 increase in hours at home per day due to county SAH (Table 1)
Engle et al. (2020)	Unacast	"An official stay-at-home restriction order corresponds to reducing mobility by 7.87%."	7.87%. reduction in mobility
Goolsbee and Syverson (2020)	SafeGraph	"...legal shutdown orders account for only a modest share of the decline of economic activity (and that having county-level policy data is significantly more accurate than state-level data)."..."While overall consumer traffic fell by 60 percentage points, legal restrictions explain only 7 of that. Individual choices were far more important and seem tied to fears of infection. Traffic started dropping before the legal orders were in place; was highly tied to the number of COVID deaths in the county.."	7 pp drop in consumer traffic from county level policy
Gupta et al. (2020)	PlaceIQ, SafeGraph, Google Mobility, Apple Mobility	"...first case announcements, emergency declarations, and school closures reduced mobility by 1-5% after 5 days and 7-45% after 20 days. Between March 1 and April 11, average time spent at home grew from 9.1 hours to 13.9 hours." "...55% of the growth comes from emergency declarations and 45% comes from ecular (non-spolicy) trends. State and local government actions induced changes in mobility on top of a large response across all states to the prevailing knowledge of public health risks."	2-45% decline in mobility due to state informational events like first confirmed case, emergency declarations, and school closures; 3-4% reduction in mobility due to stay-at-home orders
Lin and Meissner (2020)	Google Mobility	"Stay-at-home is associated with lower workplace and more residential activity, but common shocks matter much more."	9.7% increase in residential mobility from SAH laws (Table A2)
Nguyen et al. (2020)	PlaeIQ, Safegraph, Apple, Google mobiliy	"(four days) after reopening, we observe a 6% to 8% mobility increase."	6% to 8% mobility increase due to state initial reopenings
Painter and Qiu (2020)	SafeGraph	"Democrats are more likely to switch to remote spending after state orders are implemented. Political alignment with officials giving orders may partially explain these partisan differences."	
		Employment Effects	
Baek et al. (2020)	Initial UI claims Bureau of Labor Statistics, Census Bureau	"...each week of Stay-at-Home exposure increased a state's weekly initial UI claims by 1.9% of its employment level relative to other states." "...implies that, of the 17 million UI claims made between March 14 and April 4, only 4 million were attributable to the Stay-at-Home orders. This evidence suggests that the direct effect of SAH orders accounted for a substantial, but minority share, of the overall initial rise in unemployment claims."	additonal week of SAH increased state's weekly UI claims by 1.9% relative to baseline
Cheng et al. (2020)	CPS Monthly data	"...reopening policies generated asymmetrically large increases in reemployment of those out of work, compared to modest decreases in job loss among those employed."	Additional 10 days since reopening employment is 4 percent higher (Table 1)
Chetty et al. (2020)	Homebase, Burning Glass, Earnin and UI claims	"State-ordered reopenings of economies have little impact on local employment."	No effect. (Figure 11)
Coibion et al. (2020a)	customized survey with more than 10,000 respondents	"The imposition of lockdowns can account for much of the decline in employment in recent months as well as declines in consumer spending."	Aggregate consumer spending dropped by 31 log pp; unemployment rate over next year 13 pp higher in counties with earlier lockdown
Kahn et al. (2020)	Burning Glass Technologies	"...collapse was broad based, hitting all U.S. states, regardless of the intensity of the initial virus spread or timing of stay-at-home policies."	No effect of SAH policies; Across the board job vacancies in April 2020 30% lower than level at the beginning of the year.

Table A1: Contd.

Kong and Prinz (2020)	Google search data for employment	"We find that between March 14 and 28, restaurant and bar limitations and nonessential business closures could explain 4.4% and 8.5% of UI claims respectively, while the other NPIs did not increase UI claims"	Restaurant/bar limitations and non-essential business closures explain 4.4% and 8.5% of UI claims respectively; no impact of SAH orders, large-gatherings bans, school closures, and emergency declarations
Gupta et al. (2020)	Google mobility, SafeGraph, Google search data of employment, UI claims, CPS	"...employment rate fell by about 1.7 pp for every extra 10 days that a state experienced a stay-at-home mandate during the period March 12-April 12, 2020; select business closure laws were associated with similar employment effects. Our estimates imply that about 40% of the 12 pp decline in employment rates between January and April 2020 was due to a nationwide shock while about 60% was driven by state social distancing policies."	1.7 pp fall in employment for every additional 10 days of SAH and certain business closures.
Lozano Rojas et al. (2020)	CPS Monthly data, UI claims	"most of the economic disruption was driven by the health shock itself. Put differently, it appears that the labor market slowdown was due primarily to a nationwide response to evolving epidemiological conditions and that individual state policies and own epidemiologic situations have had a comparatively modest effect."	No effect of social-distancing policies.
	Consumer Spending		
Alexander and Karger (2020)	consumer spending at small and large businesses from Womply (county day level) and Second Measure (state day level), both by industry	"stay-at-home orders caused large reductions in spending in sectors associated with mobility: small businesses and large retail stores. However, consumers sharply increased spending on food delivery services after orders went into effect." ".. responses to stay-at-home orders were fairly uniform across the country, and do not vary by income, political leanings, or urban/rural status."	Year-over-year 35% reduction in consumer spending at small businesses; 10% lower in-store large firms , 71% increase online transactions at large firms as of April 15th.
Baker et al. (2020)	Fintech ("Fintech encourages households to increase savings through targeted information and rewards")	"As the number of cases grew, households began to radically alter their typical spending across a number of major categories" (and some analysis that looks at whether declines were larger in states that adopted policies earlier)	General spending declined by approximately 50%; shelter-in-place states decreased restaurant spending by about 31.8%, while users in other states decreased restaurant spending by 12.3%
Chetty et al. (2020)	"daily statistics on consumer spending, business revenues, employment rates, and other key indicators disaggregated by county, industry, and income group"	"We first show that high-income individuals reduced spending sharply in mid-March 2020, particularly in areas with high rates of COVID-19 infection and in sectors that require physical interaction. This reduction in spending greatly reduced the revenues of businesses that cater to high-income households in person, notably small businesses in affluent ZIP codes."	Spending in top-income-quartile households down by 36% relative to pre-COVID levels, as compared with 28% for bottom-income-quartile households. Hours of work, employment and job postings fell by 80%+, 36% and 30% in affluent areas as compared with 30%,11% and 15% in least affluent areas.
Coibion et al. (2020b)	customized survey with more than 10,000 respondents	"The imposition of lockdowns can account for much of the decline in employment in recent months as well as declines in consumer spending"	Aggregate consumer spending dropped by 31 log pp; unemployment rate over next year 13 pp higher in counties with earlier lockdown
	Spread of infections (Cases, Deaths)		
Chernozhukov et al. (2020)	Google mobility	"both policies and information on transmission risks are important determinants of Covid-19 cases and deaths and shows that a change in policies explains a large fraction of observed changes in social distancing behavior."	Mandating face masks for employees on April 1st could have reduced growth rate of cases/ deaths by 10+ pp in late April, and 17- 55% less deaths nationally by end of May. Removing non-essential business closures (while maintaining school closures, restrictions on movie theaters and restaurants) could lead to 20-60% more cases and deaths by end of May; without stay-at-home orders, cases would have been larger by 25 -170%
Courtemanche et al. (2020)	daily growth rate in confirmed COVID-19 cases at the county level	"Adoption of government-imposed social distancing measures reduced the daily growth rate of confirmed COVID-19 cases by 5.4 percentage points after one to five days, 6.8 percentage points after six to ten days, 8.2 percentage points after eleven to fifteen days, and 9.1 percentage points after sixteen to twenty days."	5.4%-9.1% decline in daily growth rate of cases due to social distancing mandates
Dave et al. (2020)	daily state-level coronavirus case data	"approximately three weeks following the adoption of a SIPO, cumulative COVID-19 cases fell by 44 percent"	44% decline in cumulative C-19 cases following SIPO

Table A1: Contd.

Devaraj and Patel (2020)	County coronavirus deaths data	"Our estimation approach relies on county-pairs across state-borders where one state has SIPO whereas the other state does not, controls for matched county-pair fixed effects and day of observation fixed-effects." .."daily COVID-19 incidence case growth rate is 1.994 percentage points lower for counties in SIPO states relative to those bordering in non-SIPO states"	C-19 case growth rate is 1.994 pp lower in counties with SIPO
Friedson et al. (2020)	daily state-level coronavirus data	"California's statewide SIPO reduced COVID-19 cases by 125.5 to 219.7 per 100,000 population by April 20, one month following the order. We further find that California's SIPO led to as many as 1,661 fewer COVID-19 deaths during this period."	36% reduction in C-19 cases in CA 1 month after SIPO
Jinjarak et al. (2020)	"Oxford COVID-19 Government Response Tracker, and daily C19 mortality by country"	"Our results suggest that policy interventions are effective at slowing the geometric pattern of mortality growth, reducing the peak mortality, and shortening the duration to the first peak."	Mortality growth rates in countries with stringent policies on average 22, 17, and 13 pp lower 2, 3, and 4 weeks after. Estimates of policy stringency statistically insignificant when interacted with exogenous country characteristics - implies stringent policies likely to be endogenous
Lyu and Wehby (2020)	Hospitalization data for 25 states from COVID Tracking Project. Hosp and deaths data by state by day	"SIPOs reduced the daily mortality growth rate after nearly three weeks from enactment, and the daily growth rate of hospitalizations two weeks after enactment"	Daily mortality growth rate for states with SIPOs declined by an average of 6.1 pp after 42 days from SIPO enactment
Wang et al. (2020)	SafeGraph, The New York Times' COVID-19 tracking project	"we find that SIP policies increased the median percent of time spent at home by only 2.5%. In contrast, non-policy factors led to an increase of 5.14%."	SIPO increased median percent of time spent at home by 2.5%
Yehya et al. (2020)	Covid-19 cases and deaths from Johns Hopkins Center for Systems Science and Engineering Coronavirus Resource Center	"Later statewide emergency declarations and school closure were associated with higher Covid-19 mortality. Each day of delay increased mortality risk 5 to 6%."	delayed emergency declarations and school closure increased mortality risk 5-6%
	Self reported social distancing, opinions, internet searching		
Barrios and Hochberg (2020)	Google mobility, baseline voter participation in elections	"Using mobile phone and survey data, we show that during the early phases of COVID-19, voluntary social distancing was higher when individuals exhibit a higher sense of civic duty"	
Coibion et al. (2020b)	customized survey with more than 10,000 respondents	"households living in counties that went into lockdown earlier expect the unemployment rate over the next twelve months to be 13 percentage points higher and continue to expect higher unemployment at horizons of three to five years. They also expect lower future inflation, report higher uncertainty, expect lower mortgage rates for up to 10 years, and have moved out of foreign stocks into liquid forms of savings."	Unemployment rate over next year 13 pp higher in counties with earlier lockdown

Note: Studies covered here are limited to ones that (at a minimum) estimate effects of state policies on the outcomes listed, of which we are aware. We limit the data column to the outcome measures of the paper. We limit the effect size discussion to the state policy coefficient. The default is state policy, we note when coefficients relate to county policy. For brevity of table, we select only the quotes that appear the most relevant to this review paper.

Table A2: Other Literature on COVID-19 and Labor Markets, Consumer Spending, Disease Transmission, Social distancing and Mobility.

Study	**Data**	**Finding**
		Human mobility
Allcott et al. (2020)	SafeGraph	"..areas with more Republicans engage in less social distancing, controlling for other factors including public policies, population density, and local COVID cases and deaths."
Huang et al. (2020)	Unacast	"..the average black individual in the US social distanced significantly more than the average white individual, and the average 2016 Clinton voter social distanced significantly more than the average 2016 Trump voter."
Mongey and Weinberg (2020)	Safegraph	"..we show that MSAs with less pre-virus employment in work-from-home jobs experienced smaller declines in the incidence of 'staying-at-home', as measured using SafeGraph cell phone data."
		Employment Effects
Andersen et al. (2020)	Safegraph	" ..(*the temporary federal paid sick leave mandate*) decreased our full-time work proxy and increased our at home proxy. In particular, we find an initial decrease in working full-time of 17.7% and increase in staying home of 7.5%, with effects dissipating within three weeks."
Aaronson et al. (2020)	Google search data, unemployment rates	"Applying our elasticity estimate (*of unemployment insurance filings with respect to search intensity*) to the state-level Google Trends indexes for the topic "unemployment," we show that out-of-sample forecasts made ahead of the official data releases .. predicted to a large degree the extent of the COVID-19 related surge in the demand for unemployment insurance"
Balla-Elliott et al. (2020)	Nationwide survey of small businesses	"..post-lockdown delays in reopening can be explained by low levels of expected demand."
Brynjolfsson et al. (2020)	nationally-representative sample	"Of those employed pre-COVID-19, we find that about half are now working from home, including 35.2% who report they were commuting and recently switched to working from home."
Bui et al. (2020)	CPS Monthly data	"..while previous recessions, in some ways, did not affect employment outcomes for older workers as much, this recession disproportionately affected older workers of ages 65 and older."
Cajner et al. (2020)	ADP (payroll processing data)	"After aggregate employment fell by 21 percent through late-April, we highlight a modest employment rebound through late-May."
Campello et al. (2020)	LinkUp (job postings data)	"Firms have cut back on postings for high-skill jobs more than for low-skill jobs, with small firms nearly halting their new hiring altogether. New-hiring cuts and downskilling are most pronounced in local labor markets lacking depth (where employment is concentrated within a few firms), in low-income areas, and in areas with greater income inequality. Cuts are deeper in industries where workers are more unionized and in the non-tradable sector."
Coibion et al. (2020b)	PanelViews Survey	"..job loss has been significantly larger than implied by new unemployment claims."
Fairlie (2020)	CPS Monthly data	"African-Americans experienced an increase in unemployment to 16.6 percent, less than anticipated based on previous recessions. In contrast, Latinx, with an unemployment rate of 18.2 percent, were disproportionately hard hit by COVID-19." "For African-Americans "slightly favorable industry distribution partly protected them from being hit harder by COVID-19.".. "unfavorable occupational distribution and lower skills contributed to why Latinx experienced much higher unemployment rates than whites."
Fairlie (2020)	CPS Monthly data	"African-American business owners continue to be the hardest hit by COVID-19 experiencing a drop of 26 percent in business activity from pre-COVID-19 levels. Latinx business owners fell by 19 percent, and Asian business owners dropped by 21 percent."
Granja et al. (2020)	Small Business Administration, Womply, and Homebase	"..we do not find evidence that funds flowed to areas more adversely affected by the economic effects of the pandemic,.."
Mongey and Weinberg (2020)	CPS Monthly data	"..we show that both occupations and types of workers predicted to be employed in low work-from-home jobs experienced greater declines in employment according to the March 2020 CPS."
Montenovo et al. (2020)	CPS Monthly data	"...greater declines in employment in April 2020 (relative to February) for Hispanics, workers aged 20 to 24, and those with high school degrees and some college." "...job loss was larger in occupations that require more interpersonal contact and that cannot be performed remotely. Pre-epidemic sorting into occupations with more potential for remote work and industries that are currently essential explain a large share of gaps in recent unemployment for key racial, ethnic, age, and education sub-populations. However, there is a larger unexplained component to the gender employment gaps."

Table A2: Contd.

Spread of infections (Cases, Deaths)		
Bielecki et al. (2020)	Sample of 508 recruited soldiers stationed at a Swiss Army Base in Airolo between 25 March and 14 April 2020.	Social distancing not only can slow the spread of SARS-CoV-2 in a cohort of young, healthy adults but it can also prevent the outbreak of COVID-19 while still inducing an immune response and colonizing nasal passages. Viral inoculum during infection or mode of transmission may be a key factor determining the clinical course of COVID-19.
Chaudhry et al. (2020)	John Hopkins University Center for Science and Engineering (JHU-CSSE), WHO, CDC, Worldometer Coronavirus Statistics website, WHO Situation Reports	"Rapid border closures, full lockdowns, and wide-spread testing were not associated with COVID-19 mortality per million people. However, full lockdowns and reduced country vulnerability to biological threats (i.e. high scores on the global health security scale for risk environment) were significantly associated with increased patient recovery rates."
Chen et al. (2020a)	Veraset	"Linking social distancing behavior with an epidemic model, we estimate that reductions in movement have causally reduced SARS-CoV-2 transmission rates by 49%."
Padalabalanarayanan et al. (2020)	State-level data on COVID-19 cases, tests, and fatalities from the COVID Tracking Project	"...cumulative case rates would have been more than 200% higher and fatality rates approximately 22% higher if there were no SAHOs, as compared with SAHOs fully in place. A higher proportion of African American population was associated with higher case rates (b = 0.045; 95% CI, 0.014 to 0.077; P = .001) and fatality rates (b = 0.068; 95% CI, 0.044 to 0.091; P < .001).
White and Hébert-Dufresne (2020)	Covid-19 cases and deaths from Johns Hopkins Center for Systems Science and Engineering Coronavirus Resource Center	"We find that epidemic dynamics were most strongly associated with non-pharmaceutical government actions during the early phase of the epidemic. In particular, early social distancing restrictions, particularly on restaurant operations, was correlated with increased doubling time.
Wang et al. (2020)	Electronic medical records of healthcare workers of Mass General Brigham tested for SARS-CoV-2 between March 1 and April 30, 2020. Mass General Brigham is the largest health care system in Massachusetts, with 12 hospitals and more than 75 000 employees. Job description for each worker obtained by linking their record to the healthcare system's human resources databases.	Universal masking at MGB was associated with a significantly lower rate of SARS-CoV-2 positivity among healthcare workers.
Wing et al. (2020)	NHL hockey games, National Basketball Association (NBA) games, NCAA men's college basketball games, Major League Baseball (MLB) teams and National Football League (NFL), COVID-19 cases and deaths from The New York Times (2020) database.	"one additional NHL/NBA game leads to an additional 783 COVID-19 cases during March-mid May and an additional 52 deaths." "... an additional NCAA Division 1 men's basketball games results in an additional 31 cases and an additional 2.4 deaths."
Self reported social distancing, opinions, internet searching		
Aksoy et al. (2020)	daily Google searches in a country	".. countries with high levels of public attention are more likely to implement non-pharmaceutical interventions, even after controlling for the number of cases and deaths." "..positive effect of public attention on policy implementation is driven entirely by countries with good institutions."
Allcott et al. (2020)	Original survey	"..significant gaps at the individual level between Republicans and Democrats in self-reported social distancing, beliefs about personal COVID risk, and beliefs about the future severity of the pandemic."
Barrios and Hochberg (2020)	Unacast, Google search trends	"..during the early phases of COVID-19, voluntary social distancing was higher when individuals exhibit a higher sense of civic duty. as measured by smartphone location patterns"
Bento et al. (2020)	Google search trends	"..we show that (*first COVID-19 case public announcement in a state*) increases collective attention to the crisis right away. as measured by smartphone location patterns"
Fetzer et al. (2020)	Google search trends	"..we document a substantial increase in economic anxiety during and after the arrival of the coronavirus."
Simonov et al. (2020)	SafeGraph, HomeBase (firm closure data and employee counts), Facteus (provider of financial data for business analytics)	"..a 10% increase in Fox News cable viewership (approximately 0.13 higher viewer rating points) leads to a 1.3 percentage point reduction in the propensity to stay at home."

Note: These studies represent ones that do not meet the Table A2 criteria for inclusion, but provide background on the topics.We limit the data column to the outcome measures of the paper. For brevity of table, we select only the quotes that appear the most relevant to this review paper.