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MANDATED AND VOLUNTARY SOCIAL DISTANCING DURING THE COVID-19 EPIDEMIC

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Abstract

During the first half of 2020, the COVID-19 epidemic upended social and economic life in the United States. In an effort to reduce the risk of transmission and infection, people reduced their mobility and interpersonal contact. State and local governments implemented a variety of recommendations, mandates, and business regulations to induce higher levels of social distancing. The epidemic and the social distancing response to the epidemic have led to very high unemployment. Efforts to reopen the economy, lift social distancing regulations, and return to normal life are underway across the country.

This paper makes four contributions to the study of COVID19 policy and mobility patterns during the epidemic. First, we sketch a simple economic model that highlights some incentives and constraints individuals face during the epidemic. Second, we provide a typology of the major state and local government social distancing policies during the shutdown and reopening phases. Third, we review new data sources useful for measuring mobility and contact using cellular device signals. Fourth, we present results from event study regressions that can help disentangle private vs. policy-induced changes in mobility.

During the shutdown phase, we find that large declines in mobility occurred before states implemented or announced stay-at-home (SAH) mandates, and also in states that never adopted SAH mandates. This suggests that a substantial share of the observed decline in mobility was a private response to new information about the risk of infection. Event studies suggest that first case announcements, emergency declarations, and school closures reduced mobility by 1-14% after 5 days and 9-52% after 20 days. Most measures of mobility increase by 1% to 4% within five days after a state reopening policy.

We used our regression results to decompose the trends more formally. For example, we find that during the shut down phase, the PlaceIQ mixing index declined by 142 points. About 65% of that decline is attributable to state emergency declarations; secular trends account for the remaining 35%. Likewise, emergency declarations explain about 51% of the decline in the SafeGraph measure of hours spent at home during the shutdown. In the reopening phase, the mixing index rose by 68 points, and the fraction leaving home increased by 10 percentage points. State reopening policies explain almost none of the increase in mixing and 31% of the increase in the fraction at home.

1 Introduction

During the first half of 2020, social distancing has emerged as the primary strategy for reducing the spread of SARS-COV-2, which is the virus that causes COVID-19. The level of physical mobility and interpersonal contact declined very steeply in the early months of the epidemic. More recently, mobility has started to rise again as people resume some aspects of regular life. The current level of social distancing is partly generated by the private decisions people make in response to the health threat posed by the epidemic. Governments have also adopted a variety of mandates and regulations that are intended to reduce mobility even further. Of course, the production of more social distance is not a typical goal of state and local governments. There is very little guidance from the academic literature on which policy levers can produce the most social distance at the lowest economic cost. 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. Successful efforts to identify principles that can guide the development of social distancing policy and perhaps develop more targeted social distancing policies could have substantial value. In a series of research papers, we have measured levels of social distancing using high frequency data, and assessed 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, 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 organized in 8 sections. Section 2, gives a short discussion of the emerging literature on social distancing. 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 does not reflect key sources of complexity in 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. One of contributions is pointing out the importance of looking at multiple measures of mobility, by showing that take-away messages otherwise vary if one were to use data only from one source. 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

The literature on the design and effectiveness of social distancing policies for managing a large scale outbreak is growing fast (e,g, Ellison (2020); Papageorge et al. (2020); Dave et al. (2020); Aum et al. (2020); Simonov et al. (2020); Coibion et al. (2020)), but there is not much of a literature that existed prior to COVID-19. There is some empirical support for the idea that social distancing policies can reduce the severity of the epidemic from studies of prior epidemics in the U.S. and other countries, and from studies of the COVID-19 epidemic in China (Correia et al., 2020; Fang et al., 2020; Bootsma and Ferguson, 2007; Hatchett et al., 2007). Of course, the current epidemic is much larger than others in recent history, and behavioral responses to an epidemic in the contemporary U.S. may differ from epidemics in earlier historical periods or in other countries.

There are few data systems available to measure the quantity of close physical interaction at a level of frequency and detail that would be useful in the context of an ongoing epidemic (Prem et al., 2020). Traditionally, epidemiologists use contact surveys to study interactions between sub-populations (Kremer, 1996a; Mossong et al., 2008; Rohani et al., 2010; Bento and Rohani, 2016; Prem et al., 2020). These surveys are sometimes used to parameterize epidemiological models (Mossong et al., 2008; Rohani et al., 2010; Bento and Rohani, 2016; Prem et al., 2020). But surveys are expensive and cannot be easily done in a timely manner to guide "nowcasting". Moreover, point-in-time contact surveys are not a useful way of evaluating the causal effects of mitigation policies adopted during an epidemic, or of monitoring levels of compliance with social distancing guidelines (Fenichel et al., 2011). Finding proxy measures of social contact is an important initial objective for policy research related to the epidemic.

Beyond measurement of the contact and social distancing, the pre-COVID literature provides little insight into the likely effectiveness of different policy levers on mobility (Jarvis et al., 2020; Prem et al., 2020). Over the past several months, researchers have worked quickly to fill this gap in the literature. A growing number of studies are concerned with the effects of various social distancing policies on measures of mobility and contact, e.g. (Andersen, 2020; Painter and Qiu, 2020; Gupta et al., 2020; Nguyen et al., 2020; Montenovo et al., 2020; Rojas et al., 2020; Bento et al., 2020; Gupta et al., 2020); ones that use only multiple sources of mobility data demonstrate that its important to view these results in their totality, as specific measures could give varying answers on the importance of policy. A related literature examines the reduced form effects of the policies on measures on COVID-19 transmission and mortality rates (Kaashoek and Santillana, 2020; Friedson et al., 2020; Abouk and Heydari, 2020; Courtemanche et al., 2020). Although the emerging literature is encouraging, identifying the causal effects of public policy changes on first-stage social distancing outcomes and downstream measures of the severity of the epidemic is not a trivial exercise and there are many possibly sources of confounding and bias.

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, 1996b; 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 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:

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

z is a vector of regular commodities, e.g. 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 that is devoted to the production of commodity j. Finally, d_j measures physical interaction with non-household members involved in the production of commodity j. The person produces 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.[1]

The model sets up a trade-off between health and the production and consumption of

[1] 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.

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. 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 $x_z'p + x_o'p + x_h'p = M + we_o$, 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) $x_z'p + x_o'p + x_h'p = M + we_o$, (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 inputs, 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 $x_z = x_z(p, w, F, \rho)$ is 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 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 target physical interactions directly. The government might levy an 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 focuses 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.[2] 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

[2]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.

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 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. (all) **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 1 shows how the share of the U.S. population that was subject to each social distancing policy evolved over time.[3]

[3] 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.

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.[4] 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.

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

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

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 ,[5], 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.[6] 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 Phase2 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 (Figure **??**). 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 **??**(a)). 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 **??** for details). In the remaining states, reopening frequently preceded official expiry of stay-at-home orders on average by a month (32 days).

Figure **??** shows that by June 15 all U.S. states have adopted some form of reopening policy. However, the pace of reopening has been gradual and varied. Figure **??** 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.[7] However, 20 states pursued a more limited strategy by opening only one or two sectors.[8]

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

[5]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.

[6]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).

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

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

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 (?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 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 2 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 2a 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 2 b shows the average "out of county" travel measure, which fell by 38% between March 1 and April 14. Figure 2g 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.[9]

The graphs in figure 2 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

[9]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).

dramatic as in other states. Furthermore, most states with SAH mandates experienced major declines in mobility even before the SAH mandates went into effect.

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 4 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 1 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 1 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, and ** without bold for significant ones 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 4. 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 1 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 1 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 5 and table 2 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 5 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. 2 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 5 and table 3 show decomposition results for the mixing index and the fraction of people who leave home during the day. The solid lines in Figure 5 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 3 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. The remaining 69% of the change would 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.

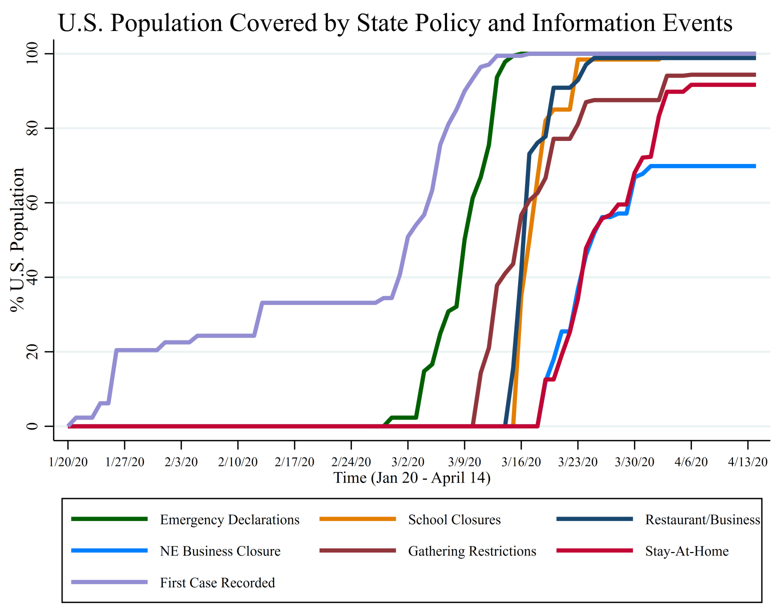
8 Conclusion

We examine human mobility responses to the COVID19 epidemic and to the policies that arose to encourage social distancing. A simple theoretic framework suggests that individuals 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 ..) had the largest effects, while stay at home orders do not. This does not imply that these laws would always have such impacts, as it is possible people simply react to the earliest of the policies, and stay at home orders happened fairly late in the time span. Early state policies appeared to convey information about the epidemic, suggesting that even the policy response mainly operates through a voluntary channel. Given that most states have now undertaken some form of steps to reduce the lockdown, we are able to compare mobility during the closure to mobility during the reopenings. Even though the reopenings are graduate, often with capacity limits for each sector,we find that mobility increases a few days after the policy change and that other factors, such as temperature and precipitation also strongly imply increased mobility across counties. It appears individuals especially increase their visits to a variety of locations, 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 the shortest length, suggesting that closure policies may have represented more of a binding constraint in those 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 tagetted approaches.

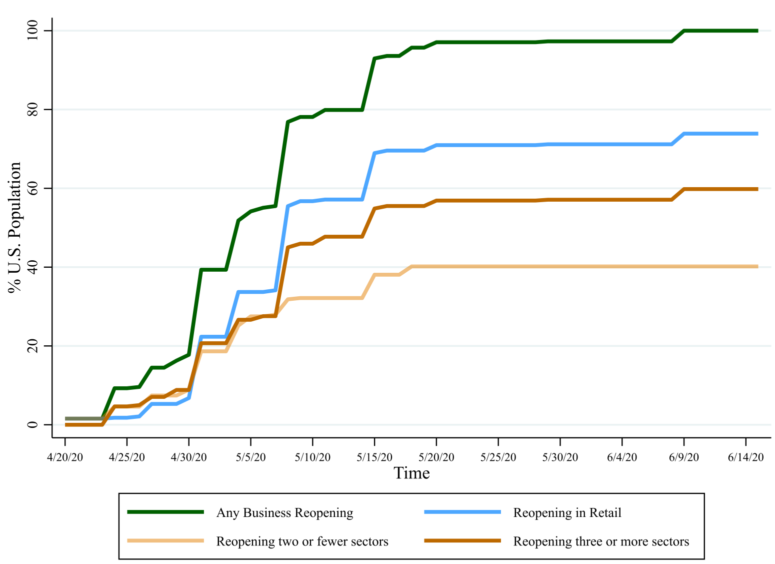
9 Tables and Figures

Figure 1: U.S. Population covered by State Closure and Re-opening Policies

(a)



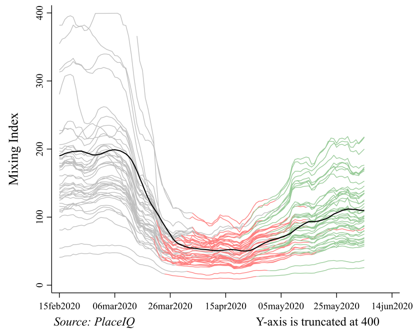
(b)



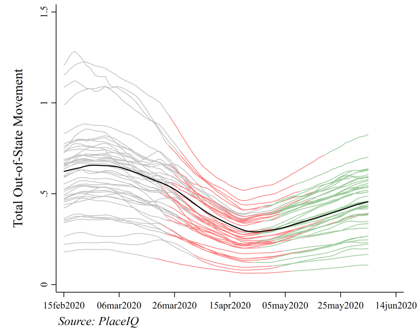
Note: Author's compilations based on several sources. Data covered January 20, 2020 - June 15, 2020.

Figure 2: Trend in mobility changes.

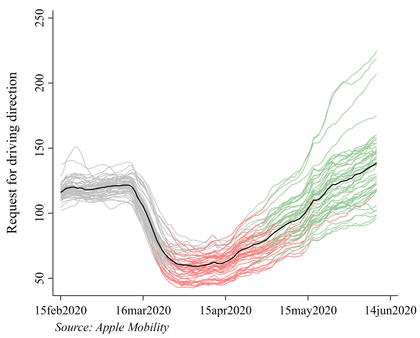
(a) Mixing index.



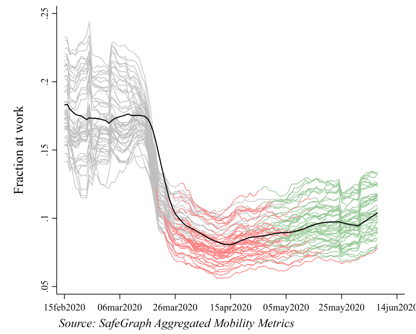
(b) Average out-of-county movement.



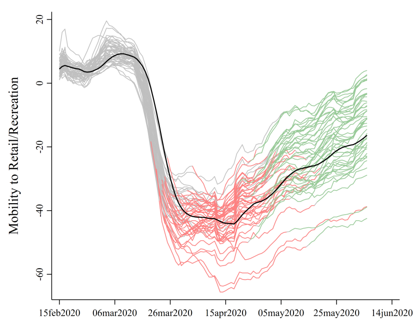
(c) Requests for driving directions



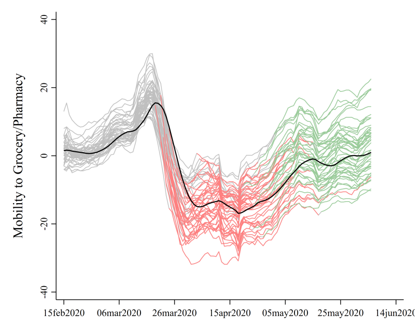
(d) Fraction at Work



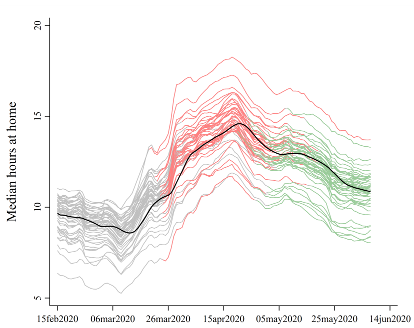
(e) Retail and recreation



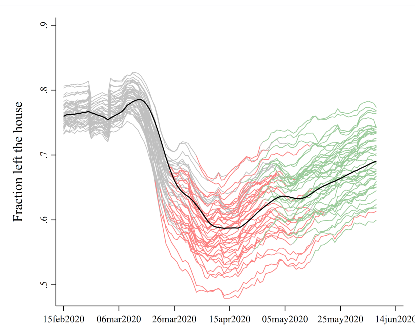
(f) Grocery and pharmacy



(g) Median hours at home.

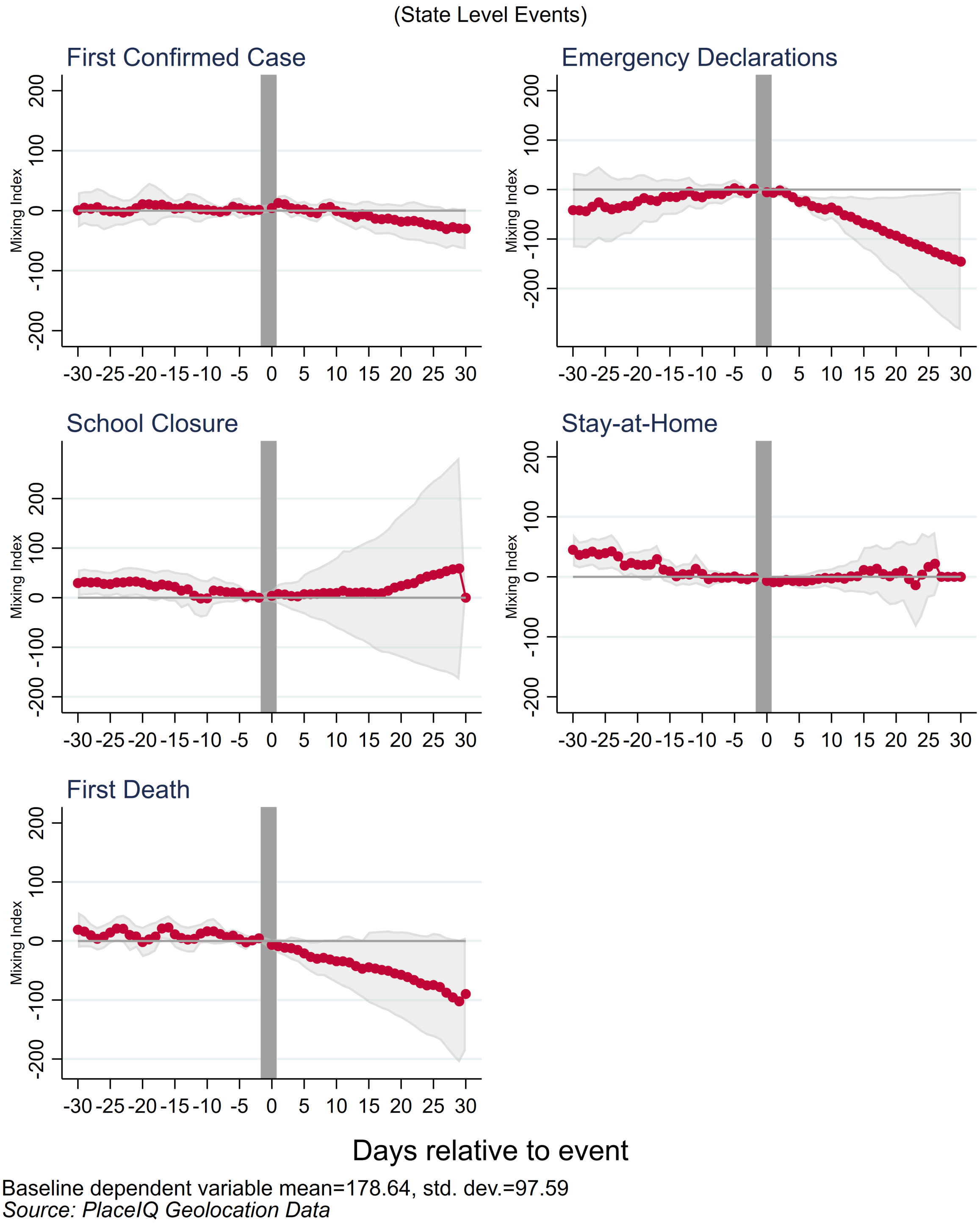


(h) Fraction leaving home.



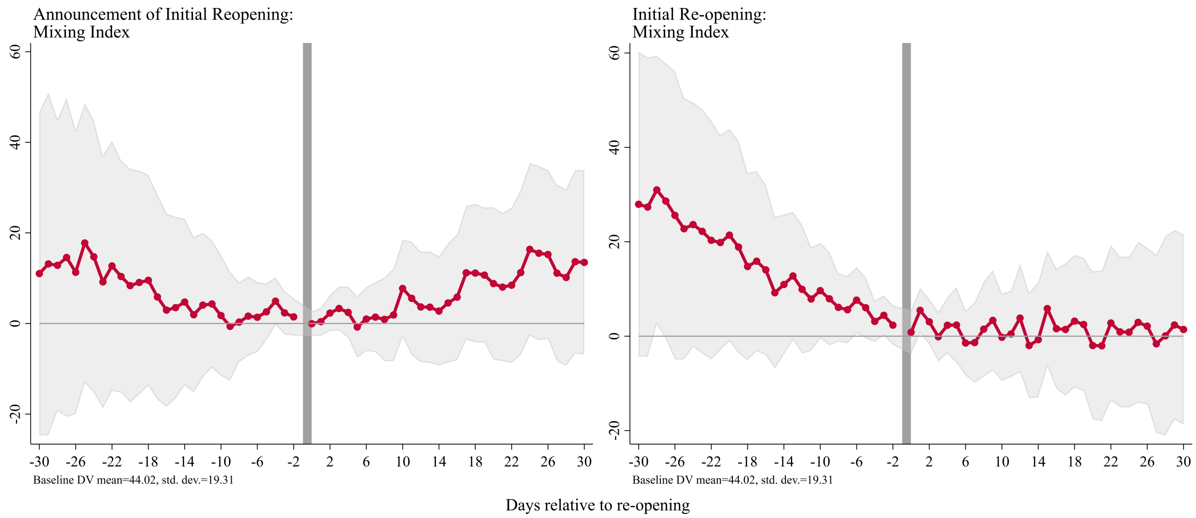
Note: Author's calculation based on data from Apple Mobility, Google Mobility, SafeGraph Aggregated Mobility Metrics and PlaceIQ smart device data. Each grey line represents a state, which turn red after the state implements stay-at-home orders and green after phase 1 of reopening. The thick black line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

Figure 3: 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 4: 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)

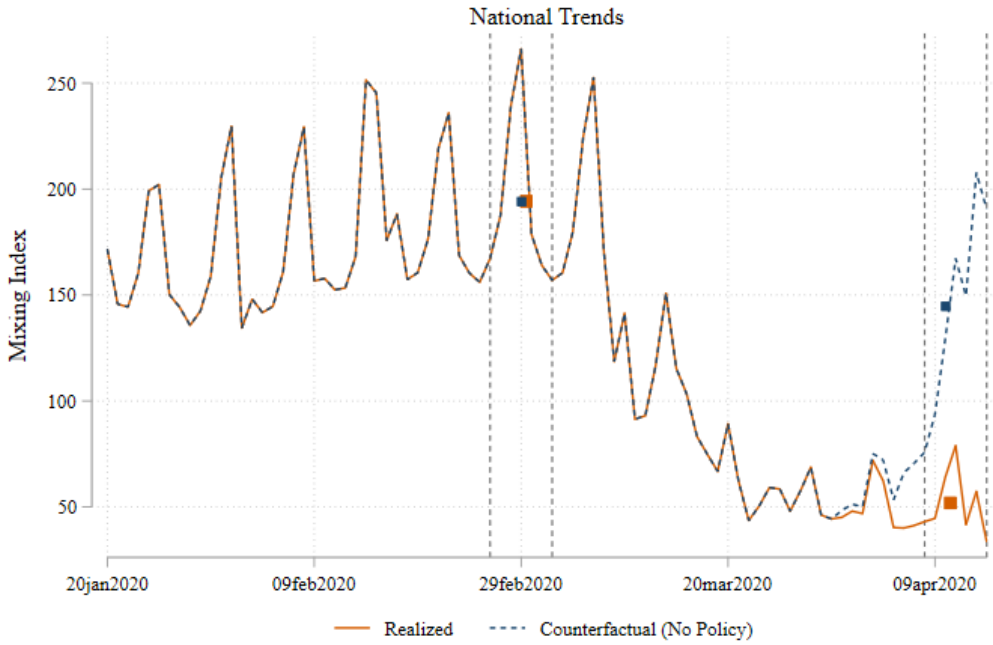
Note: *Note:* The dependent variable shows the state's index for mixing (average amount of mixing within its census block groups). Standard errors are clustered at the state level. Full event study estimates available upon request.

Table 1: 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 5: Change in Social Distancing (Mixing Index) Attributed to Emergency Declarations.



Note: *Note:* Corresponding to Figure 4, Figure 5 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.

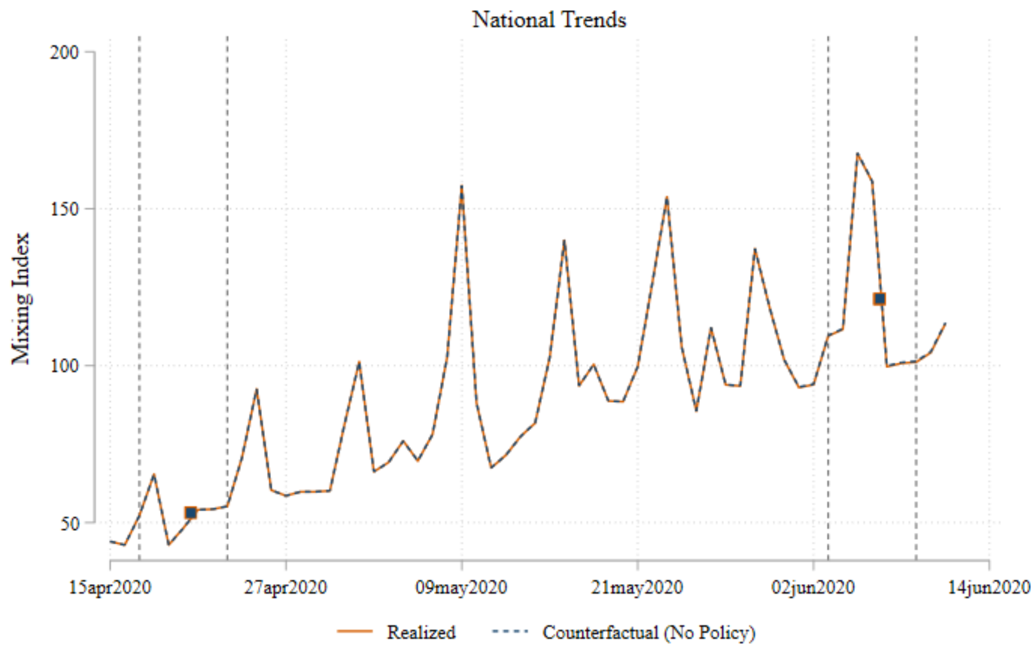
Table 2: Estimated Effects of Emergency Declarations on Mixing Index.

	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

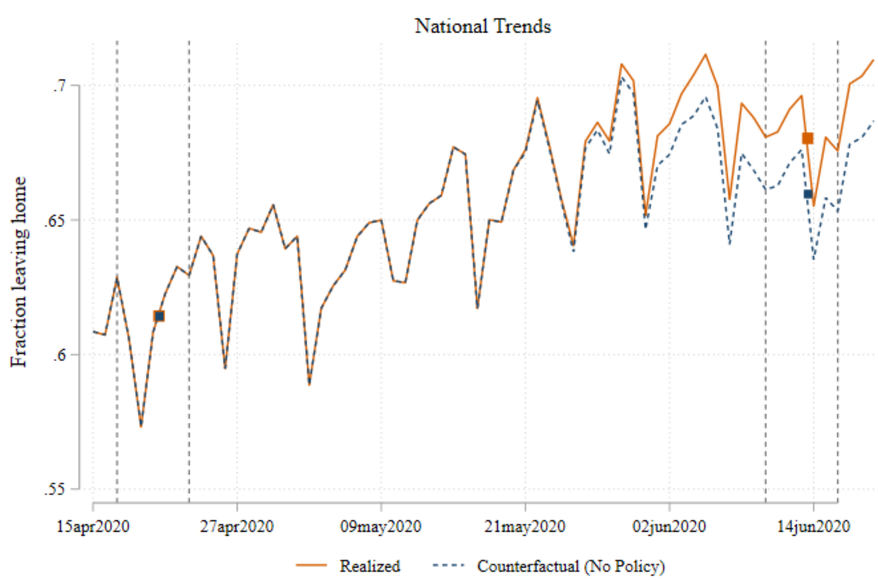
Note: Author's calculation based on decomposition of changes in mobility to share attributable to state emergency declarations and those resulting from secular trends. Related estimates plotted in Figure5.

Figure 6: 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 3: 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 Figure6.

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