Impacts of state COVID-19 reopening policy on human mobility and mixing behavior

Corresponding author: Thuy Nguyen

E-mail address: thuydn@umich.edu

Received: December 18, 2020
Accepted: September 7, 2021

Running Head: Reopening policy and mobility

Impacts of State COVID-19 Reopening Policy on Human Mobility and Mixing Behavior

Thuy Nguyen[1*], Sumedha Gupta[2], Martin Andersen[3], Ana Bento[4], Kosali Simon[5,6], Coady Wing[5]

1 School of Public Health, University of Michigan, Ann Arbor, MI, USA

2 Economics Department, Indiana University–Purdue University Indianapolis (IUPUI), Indianapolis, IN, USA

3 Economics Department, University of North Carolina at Greensboro, NC, USA

4 School of Public Health, Indiana University, Bloomington, IN, USA

5 O'Neill School of Public and Environmental Affairs, Indiana University, Bloomington, IN, USA

6 National Bureau of Economic Research, Cambridge, MA, USA

* Corresponding author

Thuy Nguyen, PhD, University of Michigan School of Public Health, 1415 Washington Heights, Ann Arbor, MI 48109-2029, USA (thuydn@umich.edu)

Running Head: Reopening Policy and Mobility

JEL Classification: I180 , I38, I120

Keywords: Non-pharmaceutical interventions, COVID-19, Reopening, Mobility, Mixing behavior

Acknowledgement

We are grateful to Matthew Eisenberg, Jeanette Samyn, and Jeffrey Bainter for helpful comments. We thank SafeGraph.com and PlaceIQ.com for making data available for research. We thank Elizabeth McAvoy and Ailish Cornwell for excellent research assistance.

Abstract

This study quantifies the effect of the 2020 state COVID economic activity reopening policies on daily mobility and mixing behavior, adding to the economic literature on individual responses to public health policy that addresses public contagion risks. We harness cellular device signal data and the timing of reopening plans to provide an assessment of the extent to which human mobility and physical proximity in the US respond to the reversal of state closure policies. We observe substantial increases in mixing activities, 13.56% at four days and 48.65% at four weeks, following reopening events. Echoing a theme from the literature on the 2020 closures, mobility outside the home increased on average prior to these state actions. Furthermore, the largest increases in mobility occurred in states that were early adopters of closure measures and hard-hit by the pandemic, suggesting that psychological fatigue is an important barrier to implementation of closure policies extending for prolonged periods of time.

1 Introduction

During the early months of the coronavirus disease (COVID-19) pandemic, state governments implemented social distancing policies mandating that certain venues of economic transaction be closed to control the spread of the SARS-CoV-2 virus in the US. These government actions, combined with private responses to the risk of infection, effectively shut down a large share of US economic and social activity. Research based on past epidemics shows that human mobility plays an important role in the spread of many infectious diseases (Wesolowski et al., 2016). In recent work on the COVID-19 pandemic, Gupta et al. (2020) examine the effects of a variety of state and local mitigation actions (emergency declarations, school closures, restaurant dining-in prohibitions, non-essential business closures, and stay-at-home mandates) on cell-phone-based measures of mobility and interaction. Their event studies suggest that state distancing policies lead to small reductions in mobility that grow over time, and also that early and information-focused state policies may have the largest causal influence on mobility patterns.

There is also emerging evidence that state shutdown policies have helped reduce transmission of the virus (Courtemanche et al., 2020; Dave et al., 2020; Friedson et al., 2020). Inducing higher levels of social distancing and keeping transmission rates low may help protect the viability of local health care systems by reducing peak utilization of limited health care resources like Intensive Care Unit (ICU) beds and ventilators. Thus, there is evidence that social distancing policies yield important social benefits, slowing the pace of the epidemic, preventing surges of healthcare demand, and perhaps ultimately saving lives. Nevertheless, these broad-based (non-targeted) social distancing responses have high costs. Over 31 million people filed new unemployment insurance claims between March 1 and May 2, 2020, according to the US Department of Labor. The rise in unemployment was mostly a nationwide response to the epidemic, with early social distancing policies playing a smaller role (Rojas et al., 2020; Kahn et al., 2020).

Job losses during in the early epidemic were less common among people who were able to work remotely and among people working in essential industries (Montenovo et al., 2020). Mass unemployment can strain household and national finances, and the experience of unemployment is damaging to mental and physical health (Sullivan and Von Wachter, 2009; Krueger et al., 2011). Given this situation, the pressure on state governments and individual households to restart economic activity was high (Mervosh et al., 2020).

Most states started to lift some of their social distancing policies in April and May of 2020; the effects of reversing state closure policies are not well understood. In this study, we examine the short-term effects of state reopening policies on mobility and social contact patterns. We use multiple cell-phone-based data sources to measure various dimensions of mobility and to track the variation between and timing of reopening policies across the country. Our paper makes three empirical contributions. First, we document a sudden increase in social contact and mobility in most states starting in mid-April. Whatever the cause of the increase, it is clear that a reopening phase really was underway by late April. The recovery in mobility was small relative to the decline that occurred during the initial lockdown, but it is observable across a broad range of cell-phone-based metrics. Second, we estimate event study models to trace out the ways in which mobility patterns responded to state reopening policies. These estimates suggest that the reopening policies substantially increased social contact; however, mobility outside the home appears to have increased in advance of the reopening policies. Comparing results across pairs of contiguous counties, we further find that the changes in mobility are larger in models that account for spillover effects on neighboring counties, indicating that even "untreated" counties experience increases in mobility when a neighboring county reopens. Third, the reopening effects on the mixing index are largest among states that were either early adopters of closure policies or hard hit by the pandemic.

To the best of our knowledge, this study provides the first comprehensive overview of reopening policies that lift many restrictions on non-essential business activities. Through the lens of home production theory, we can view the COVID-19 pandemic and related regulatory decisions as exogenous changes in the perceived infection risk associated with physical interactions that individuals make in the production of the other commodities. Our findings on immediate increases to social contact following reopening policies are consistent with the idea of pent-up demand for "social contact intensive" activities, such as visits to retail stores, recreation areas, pharmacies, and other places with in-person interactions. Like durable goods, these activities may be most likely to rebound relatively quickly once reopening occurs due to delayed consumption during the restriction period. In the same vein, this study also finds that people in hard-hit areas with a prolonged period of lockdown tend to respond immediately to reopening events by mixing more.

Another important finding of this study is that mobility outside the home tended to increase prior to reopening policies. This result suggests that these policies may have more muted effects on certain work or leisure activities with lower perceived infection risk. For instance, small group gatherings with situational mitigation strategies such as wearing a mask or staying at least 6 feet from others may be considered safe even before the official announcement of reopening policies or the lifting of indoor dining bans. The aggregate area-wide demographic levels associated with cell data analysis, however, are unable to dissect such heterogeneous preferences for various activities.

2 Background

2.1 Roles of Mobility and Physical Distancing Interventions in the Context of a Pandemic

Previous research suggests that human mobility affects the dynamics of infectious diseases (Wesolowski et al., 2016). Recent work suggests that sustained physical distancing interventions are likely to reduce the magnitude of the COVID-19 epidemic's peak (Prem et al., 2020). And other work finds that the lockdown of Wuhan significantly reduced mobility and that social distancing reduced the spread of COVID-19 (Fang et al., 2020).

The early official responses to the COVID-19 pandemic in the US included orders or actions to encourage or mandate physical distancing through emergency declarations, school closures, non-essential business closures, restaurant dining-in prohibitions, and stay-at-home orders and advisories. Stay-at-home orders have received a great deal of attention in public debates, but they were typically the final policy in a series of state and local actions (Gupta et al., 2020). Dave et al. (2020) find that early stay-at-home orders reduced COVID-19 case counts and mortality, but they found that later stay-at-home orders had no effect. Using SafeGraph mobility data, they also find that stay-at-home orders increased the share of devices that stay home by 5.2%. Similarly, Courtemanche et al. (2020) find that stay-at-home orders reduced the COVID-19 case growth rate by 3.0 percentage points in the first five days after implementation and that the effect increases to an 8.6% reduction after 21 days; closing restaurants has similar effects on the growth of COVID-19 cases, although with a flatter trajectory. Friedson et al. (2020) use a synthetic control method to estimate the effect of California's stay-at-home order on COVID-19 case counts. They find that the stay-at-home order reduced COVID-19 cases by approximately 20 to 45 cases per 100,000 two to three weeks after adoption. In log linear models, their estimates indicate that stay-at-home orders reduced COVID-19 case counts by 40 to 50%. Collectively, these papers suggest that stay-at-home orders reduce disease transmission, with the implication that they do so by increasing social distancing.

2.2 Econometric Evidence on Effects of State Closure Policies on Mobility

Prior work has examined determinants of mobility reductions during state closures (Gupta et al., 2020; Painter and Qiu, 2020; Abouk and Heydari, 2020; Andersen, 2020). Specifically, Gupta et al. (2020) provide a comprehensive overview of the kinds of policies states enacted and their timing. They examine five different measures of mobility from SafeGraph and PlaceIQ. Using event study regressions to examine several state information events and policies at both county and state levels, they find little evidence that stay-at-home mandates induced distancing. In contrast, early and information-focused actions have larger effects: first case announcements, emergency declarations, and school closures reduced mobility by 1-5% after 5 days and 7-45% after 20 days. Painter and Qiu (2020) use SafeGraph data on the fraction of cellular devices that remain at home all day and finds that there is an immediate 5.1 percentage point increase in this variable following a stay-at-home order, which is 15% of the reported average overall. Andersen (2020) use a difference-in-difference (DD) framework and SafeGraph data on number of device visits per county per day to examine the impact of stay-at-home orders, banning gatherings of more than 50 or 500 people, closing schools, restricting dining-in restaurants, and closing gyms and entertainment venues. That work suggests that there was a 19.3% change from stay-at-home laws and effects of up to 11% from other laws. Abouk and Heydari (2020) examine mobility indices from Google in a DD framework, studying statewide stay-at-home orders, more limited stay-at-home orders, non-essential business closures, large gathering bans, school closure mandates, and restaurant and bar limits. They find that stay-at-home mandates increased the percent of individuals who are present at home by 600%, with statistically insignificant effect from any other policy.

There are several differences between these existing studies on the largest determinants of mobility slowdowns experienced from early March to early April, and the literature has not fully resolved reasons for differences in conclusions. Other emerging studies emphasize the importance of political variables in understanding mobility responses as well as the role of weather as an instrument for mobility, which holds promise in newly emerging research (Allcott et al., 2020; Kapoor et al., 2020). For instance, Allcott et al. (2020) embed an epidemiological model of disease transmission into an economic model with heterogeneous agents to understand the causes and consequences of pandemic responses. These authors use SafeGraph data to show that areas with more Republicans engaged in less physical distancing after controlling for other factors such as public policies, population density, and local COVID-19 severity measures.

2.3 State Reopening Policies and Private Responses

Between mid-April and early June, all states had started to unwind some of the policies adopted during the shutdown (Mervosh et al., 2020; Raifman et al., 2020). But the details of the reopening policies vary across states. South Carolina was the first state to adopt a reopening policy, on April 20. It was also one of the last states to adopt a stay-at-home order.[1] This April 20 reopening was partial as it started by allowing retail stores to open to 20% of capacity. By April 30, eight states had reopened to some degree (AL, MS, TN, MT, OK, AK, GA, and SC). By June 1, 2020, all states took the first actions to resume non-essential business activity.

Glaeser et al. (2020) introduce a model of learning from deregulation into the emerging literature of the COVID-19 pandemic and emphasize one potential indirect effect of

[1] 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).

lifting the physical distancing restrictions. Specifically, the model predicts that lifting stay-at-home orders can signal that the activities such as restaurant visits are now safe. Using mobility data from SafeGraph and reservations data from Yelp, these authors find that restaurant demand increased sharply shortly after the end of lockdowns suggesting an important signaling effect through a regulatory decision. The effects of reversing state closure policies on diverse activities is not well understood yet.

3 Data

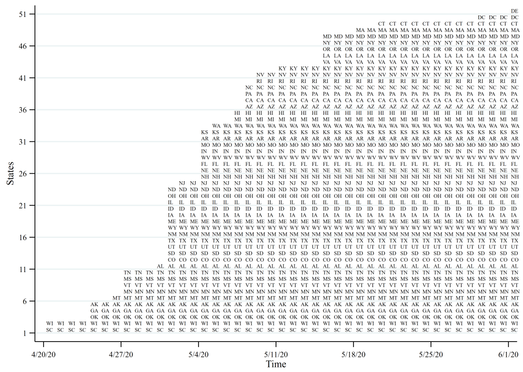
3.1 State Policies

In this study, we mostly define *reopening* as the first action a state takes to resume non-essential business activity. This is not the only way to measure the concept of reopening, of course. Another option is to use the date when stay-at-home (SAH) orders are lifted. In most states, SAH orders end on the same day that some non-essential businesses are allowed to open. A third approach would focus on how gradually vs. suddenly a state reopens its economy.

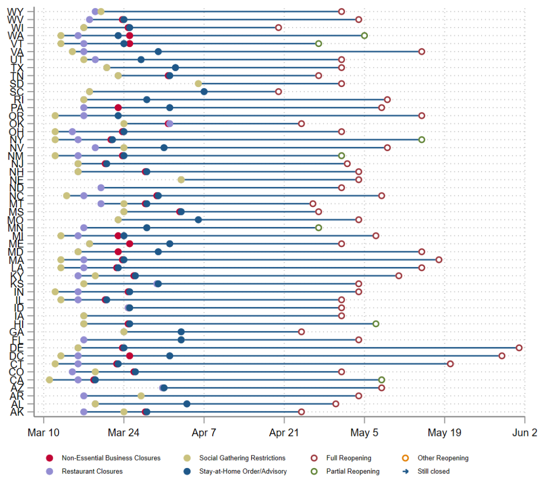
One advantage of the first reopening action definition is that – in a DD framework – the first action may serve as a reduced form measure of the collection of reopening actions that follow. Another advantage is that the first reopening step may send a strong signal that the government thinks it is safe to start returning to regular life. It is possible that people may respond more to the initial reopening order than to incremental changes in the degree of opening. Even before official state closures, attention to the coronavirus as measured by internet search behavior in a state increased suddenly when the state announced its first positive case (Bento et al., 2020). Earlier work on state closures suggests that mobility effects are largest for information-laden policy actions (Gupta et al., 2020).

Figure 1: Timing and U.S. Population Covered by States' COVID-19 Policies

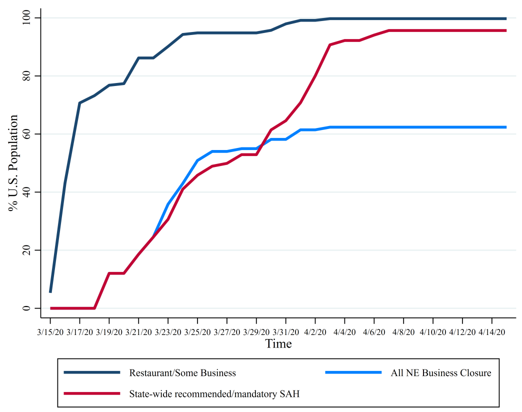
(a) Dates of Reopenings by State



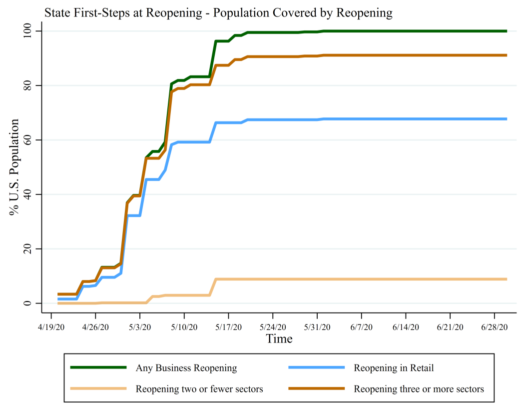
(b) State Policy and Information Timing



(c) Population Covered by Social Distancing Policies



(d) Population Covered by Reopening Plans



Note: Author's compilations are based on *New York Times* and other media databases. The timelines of the presented figures vary by types of state policy or information events. Data covered 4/20/20-6/1/20 for Figure 1-A to capture the timing of state reopenings, data covered 3/10/20-6/1/20 for Figure 1-B to capture the earliest restrictions and reopenings, data covered 3/15/20-4/15/20 for Figure 1-C to reflect the lockdown phase, and data covered 4/20/20-6/30/20 for Figure 1-D to reflect the reopening phase until 6/30/20, the end of our study period. State reopening data are available on GitHub.

We collected data on state reopening policies using media searches, starting with *New York Times* descriptions of reopening plans, combined with additional information on the reopening schedules for each state from news releases of state governor or state health officials. Each state's reopening date was defined as the earliest date at which that state issued a reopening policy of any type. Panel A of Figure 1 lists the states that have reopened on each date since April 20, 2020. By June 1, 2020 all states had officially reopened in some form. The study period ends on June 30, which means that we are able to estimate impacts for at least 4 weeks post reopening using variation from all state reopening polices; we thus report effects as of 4 days, 14 days, and 28 days after the policy.

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, 2020 as the reopening date for many businesses. Our study period commences on April 15, 2020 to ensure that we capture reopenings across all states. We provide the information we have compiled from various sources on GitHub.[2]

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 (Panels B and C of Figure 1). Although for the most part, stay-at-home orders coincided with regulatory orders to close non-essential businesses, restaurants, and other select categories of business. Many business closures started in mid-March, along with school closures (see Figure 2.1 of Gupta et al., 2020). 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

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

(Andersen, 2020; Adolph et al., 2020; Allcott et al., 2020).

The pace of reopening by mid-May 2020 has been gradual. For instance, panel D of Figure 1 shows that by May 13, 63.5% of the US population lived in a state that had adopted some form of reopening policy, only 36.5% of the population lives in states that opened the retail sector, and only 33.6% are in states that opened 3 or more sectors. Of the 36 states that reopened by May 13, 16 states reopened across three or more of the seven sectors that we track while other states pursued a more limited strategy by opening only one or two sectors.[3]

3.2 Mobility Measures

Mobility data in this study come from four cellular signal aggregators who provide their data for free to support COVID-19 research: PlaceIQ (GitHub repository), SafeGraph (provided upon free research agreement), Apple's Mobility Trends Reports, and Google's Community Mobility Reports. Each company has several different measures of mobility, which may provide answers to different questions and have different implications. In this study, we focus on two distinct outcomes based on mobility data from SafeGraph and PlaceIQ: human mobility and social contact.

Human Mobility

We obtain the key human mobility measure, the fraction of devices leaving home, from SafeGraph data. We calculate the fraction of devices at the census block group level that are detected to have left the house and aggregate to county or state by-day levels. SafeGraph also provides some alternative measures of overall movement patterns such as the median hours spent at home by devices as well as the number of devices at the census block group level that are detected to be entirely at home during the day.

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

There are other measures of mobility, which have more specific implications. First, Apple's Mobility Trends Reports (Apple's Maps Site, 2020) are published daily and reflect requests for driving directions in Apple Maps. This measure shows the relative volume of driving directions requests per state compared to a baseline volume on January 13, 2020; no county-level equivalent is available. Second, Google Community Mobility Reports provide 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); and residential (places of residence) (Google's Site, 2020). 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. Third, out-of-state and out-of-county travel indices based on PlaceIQ data measured, 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.

None of these data sources provides a metric of social mobility that is theoretically ideal in any sense. Each metric may capture a different form of underlying behavior, with different implications for the transmission of the virus and economic activity. Given these complexities, we think it is particularly important in this literature to compare across several measures of mobility. A multiple measure approach provides a simple way to assess the robustness and generality of a result; it also may provide opportunities to learn from differences in results across measures.

Social Contact

To reflect mixing patterns, we use a "mixing" index derived from smartphone movement data from PlaceIQ (Couture et al., 2020). This mixing index is an anonymized, aggregated location exposure index that for a given day detects the likely exposure of a smartphone device in a county or state to other devices that day. Specifically, this exposure index value captures a fraction of the number of distinct individuals that also visited any of the commercial venues visited by a device. This measure provides a proxy for actual interactions between people.

3.3 County-Level Characteristics

We collect a vector of county-level covariates to understand heterogeneity in a cross-sectional, descriptive analysis. We derive the socio-demographic data from the 2020 Area Health Resources Files (HRSA, 2020) and County Health Rankings database (County Health Rankings, 2020). We estimate the number of nursing home residents in a county from the 2017 Nursing Home Compare database (CMS, 2020). County incarceration rates are obtained from the Incarceration Trends dataset of the US Department of Justice Bureau of Justice Statistics (Incarceration Trends Dataset, 2020). We collect weather data (temperature and precipitation) from the National Centers for Environmental Information (NCEI, 2020). We use the latest year available in each original source.

4 Conceptual Framework

4.1 Pent-Up Demand for Social Contact Intensive Activities

During a pandemic, social contact intensive activities that are normally considered safe – such as dining out, travelling for work, and socializing in groups – become "risky" behaviors due to the perceived risk of infection. In standard economic models, people will tend to respond to an increase in health risks by reducing their participation in risky activities. Likewise, a return to pre-epidemic levels of participation will depend on individual perceptions about changes in the risks posed by a given activity. Gupta et al.

(2020) sketch a simple home production model – Gronau (1986) – in which social distancing arises as a response to changes in the health risks associated with the production of various types of home produced goods and services. The basic logic of the home production framework is that people derive utility from their own health as well as the consumption of a collection of home-produced goods and services. In the models, people do not obtain goods and services directly from the market. Instead, they create the consumption good using a home production function to combine market inputs, their own time, and contact with other people. Health is produced using a health production function, and – during the epidemic – the health production function is declining in contact with other people. When the health penalty associated with social contact increases because of the epidemic, demand for contact intensive goods and services decline. By reducing demand for contact intensive goods and services, people are implicitly supplying social distancing.

Although the logic of a simple framework like this is easy to understand, it is also possible that maintaining high levels of social distancing for a longer period of time may lead to an accumulation of delayed demand for contact intensive goods and services. Like durable goods, the delayed demand for these activities may be most likely to rebound relatively quickly once stores or restaurants are reopened. Some people may experience *social distancing fatigue*, which could make it harder to maintain high levels of social distancing over a prolonged period of time. Lifting the shutdown mandates may trigger increases in social mixing among individuals from emotional exhaustion, isolation, or boredom. It is also plausible that lifting stay-at-home orders may have indirect effects on social distancing by signaling that these social intensive activities are now safe (Glaeser et al., 2020), and therefore leads to increases in mobility and social contact. The effects of reopening may depend on how binding the various shutdown mandates actually were in practice. If reductions in mobility were primarily driven by "private" responses to the change in public health conditions, then it is possible that lifting a state social distancing mandate will not generate large increases in mobility.

4.2 Heterogeneous Preferences over Health and Non-Health Goods

Some individuals may interpret the government's reopening orders as a signal of safety while other individuals may continue to keep their distance and avoid group gathering places because they are concerned about the health risks of the virus. It is also possible that people behave differently because they hold different beliefs about health risks or are exposed to certain type of misinformation prior to the reopening orders.

In addition, mobility measures may depend on work and consumption decisions. Mobility might not be substantially responsive to the government lifting of restrictions on non-essential business operations if many consumers do not feel that the "rents" from shopping in person are sufficient to justify the health risks of the added exposure. Likewise, people in jobs that can be performed remotely or who have other sources of income may opt to continue staying home (Montenovo et al., 2020). Public policies that are not related to reopening, such as the stimulus payment, enhanced unemployment insurance benefits, and paid sick leave, may affect decisions about mobility during the reopening phase as well (Andersen et al., 2020).

Many people are grappling with the decision of when to resume traveling (perhaps by public transport) to locations away from the home. This decision relates to measures captured by our mobility data: the detection of cell phones in far-away states from their usual location. Measures of out-of-state work or leisure travel will likely be shaped by employer reactions to changes in government restrictions, and to consumer perceptions of risk from exposure. Businesses' decisions to reopen shape demand for labor, work-travel, and leisure-travel; following a reopening, we would expect an increase in travel measures. If many businesses remain partially shut down because consumer demand for their services is depressed even when states allow reopening, then work- and leisure-related mobility measures may not change as much.

Geographic variation in the prevalence of essential industry workers may imply that reopening leads to larger changes in some locations than others. In rural areas, the effects of the stay-at-home orders, in terms of reduction in mobility, were less marked, likely due to the nature of rural work. We might expect that mobility effects would be larger after lockdowns of a longer nature, but there is selection into closing and opening dates: the states that were shut down for longer may proceed more gradually in other ways (especially since the degree of virus spread is information that may lead to policy change).

5 Research Design and Methods

5.1 Event Study Analysis

In this paper, we used event study regression models to examine how measures of mobility evolve during the period leading up to and following state reopening events. Let E_s be the reopening date in state s. Then $TSE_{st} = t - E_s$ measures the number of days between date t and reopening. For example, five days before reopening, $TSE_{st} = -5$. Five days after reopening, $TSE_{st} = 5$. We set $TSE_{st} = -1$ for states that never reopen. We fit event study regression models with the following structure:

$$Y_{st} = \sum_{a=-15}^{-2} \alpha_a 1\left(TSE_{st} = a\right) + \sum_{b=0}^{8} \beta_b 1\left(TSE_{st} = b\right) + W_{st}\sigma + \theta_s + \gamma_t + \epsilon_{st} \tag{1}$$

In the model, Y_{st} is a measure of mobility and θ_s is a set of state fixed effects, which are meant to capture fixed differences in the level of outcomes across states that are stable over the study period. γ_t is a set of date fixed effects, which capture trends in the outcome that are common across all states. ϵ_{st} is a residual error term. α_a and β_b are event study coefficients that traces out deviations from the common trends that states experience in the days leading up to and following a given policy or information event. Specifically, α_a traces out differential pre-event trends in the outcome that are associated with states that go on to experience the policy change or information event examined in the model. β_b traces out differential post-event trends in the outcome that occur after a state adopts the policy or experiences the information shock. The reference period in all event studies is the period before reopening, when $TSE_{st} = -1$.

The main specifications are based on a balanced panel of states that are observed from April 15 to June 30. April 15 appears to be the approximate time when shutdowns had achieved a stable pattern in slowed movement across the nation (Schaul et al., 2020). June 30 is four weeks following the last reopening event (Delaware). To adjust for seasonality, we control for state-by-day weather (average temperature and precipitation). These covariates are represented by W_{st} in the regression. Using the event-study design with a balanced panel mitigates the emerging concern that the two-way fixed-effect models with staggered treatment times may produce biased estimates (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020). Standard errors were clustered at the state level in the regressions. We do not weigh states by population. These estimates should be interpreted as reflecting the experience of the average state rather than the average person. The presence of a pre-trend was based on the statistical significance of the pre-policy event study coefficients. In the summary results, a measure exhibits a pre-trend if at least 30% of the coefficients in the pre-period were statistically significant.

Subpopulation Analysis

In addition to the state-level event-study analysis, a series of heterogeneity analyses were implemented by stratifying the sample in several ways. First, separate regressions for rural counties and metropolitan counties were conducted, expecting that the nature of rural activities might be more essential in nature and less elastic to non-essential business closures. Counties were separated into metropolitan and rural categories using the National Center for Health Statistics Urban-Rural Classification Scheme. Second, separate regressions for states with longer and shorter stay-at-home orders were used to capture variations in psychological fatigue. Longer stay-at-home orders are defined as those implemented more than 25 days prior to reopening (the median implementation period). A final heterogeneity analysis according the baseline COVID-19 death rates was used to test that where deaths were higher, individuals may be more reluctant to move even when restrictions are eased. Higher baseline COVID-19 related death rates are defined as those above the median as of April 15th, prior to reopening.

5.2 Border County Analysis

Finally, models using border county pairs that are adjacent to one another but belong to different states were used to control for unobserved local factors.[4] The border county design provides a way to control for local area unobserved factors that may confound the effect of reopening on mobility, and also gives an opportunity to examine the spillover effects that may occur when one state reopens and another does not.

Specifically, for a pair of counties c and c' (in states s and s', respectively), we define the first event date in the pair as $E_{c,c'} = \min(E_s, E_{s'})$ and an indicator $F_{c,c,c'} = 1$ if $E_s = E_{c,c'}$ and 0 otherwise.[5] We let $TSE_{c,c',t} = t - E_{c,c'}$ be the number of days between date t and the first reopening in the county pair. We set $TSE_{c,c',t} = -1$ if neither county has a reopening event in our data. Our county-pairs model is a modification of the main event study to include county-pair fixed effects and, in some specifications, pair-by-time fixed effects:

$$\begin{aligned} Y_{ct} &= \textstyle\sum_{a=-15}^{-2} (\alpha_a^0 1(TSE_{c,c',t} = a) + \alpha_a^1 1(TSE_{c,c',t} = a) \times F_{c,c,c'}) \\ &+ \textstyle\sum_{b=0}^{8} (\beta_b^0 1(TSE_{c,c',t} = b) + \beta_b^1 1(TSE_{c,c',t} = b) \times F_{c,c,c'}) \\ &+ W_{st}\sigma + \theta_{(c,c')} + \gamma_t + \epsilon_{c,c',t} \end{aligned} \tag{2}$$

[4] Our approach is similar to Dube et al. (2010), which uses contiguous counties to study the effects of minimum wages, and Lin and Meissner (2020), which studies how non-pharmaceutical interventions affect distancing.

[5] Since counties can appear in multiple county pairs, a county may be the early county in one pair, but the late county in another pair. It is also possible that both counties reopened at the same time, in which case $F_{c,c,c,'} = 1$ for both counties.

In the model, Y_{ct} is a measure of mobility for county c at time t. $\theta_{(c,c')}$ is a set of county-pair fixed effects that captures fixed differences in the level of outcomes and timing of reopening across counties. γ_t is a set of date fixed effects that captures trends in outcomes that are common across all counties in the sample. α_a^0 is a set of event study coefficients that trace out how trends in a given pair deviate from the national trend in the lead up to a reopening event in counties that do not reopen, while α_a^1 provides similar estimates for how different the first county to reopen is, relative to the adjacent county that reopens later. β_b^0 traces out changes in counties that did not reopen after the first county reopened. Therefore β_b^0 includes an estimate of the common spillover effect across all county pairs of the first county in the pair reopening. β_b^1 traces the change in outcomes associated with the reopening event in the county that reopened first.

A second version of the county-pairs model allows each county pair to have a separate set of date fixed effects. In this model, the α_a^0 and β_b^0 terms are subsumed by the county-pair-by-date fixed effects. These fixed effects flexibly capture trends in the county that reopened later, including the spillover effect on that county from policy changes in its pair county that opened earlier. Therefore, we refer to the first model without the county-pair-by-date fixed effects as assuming "no spillovers", while the second model assumes that there are "spillovers". Our sample for the county analysis is constructed in a comparable manner to the main, state-level models, including using a balanced panel. Following the state-level analysis, standard errors are clustered on state and estimates are unweighted.

5.3 County Cross-Sectional Regressions

Cross sectional regressions of "long differences" in mobility measures at the county level were used to understand how the mobility changes we observe during the reopening phase differ across geographic areas with varying non-policy factors. The long differences ΔY_c between April 15 and June 30 in the mixing index and fraction of devices that left home were the outcome variables in these regressions. To investigate the overall change in mobility patterns across counties, this analysis linked these long differences ΔY_c with a vector of county-level covariates using the following regression:

$$\begin{aligned} \Delta Y_c \quad = \quad & \beta_1 SES_c + \beta_2 Urban_c + \beta_3 Political_c \\ & + \beta_4 Demography_c + \beta_5 \Delta Weather_c + \epsilon_c \end{aligned} \tag{3}$$

In the model, $Urban_c$ is a vector of covariates reflecting county population, population density, and urbanicity. SES_c is a vector of covariates describing median household income, poverty rate, health-uninsured rates, number of nursing home residents per capita in 2017, incarcerated rate in 2017, and whether the county is a major destination for recreation or retirement. $Political_c$ is the Republican vote share in the 2016 presidential election, and $Demography_c$ includes demographic composition. We also controlled for weather changes in these models. We standardized all variables before estimating this cross-sectional regression to make the estimated coefficients more comparable.

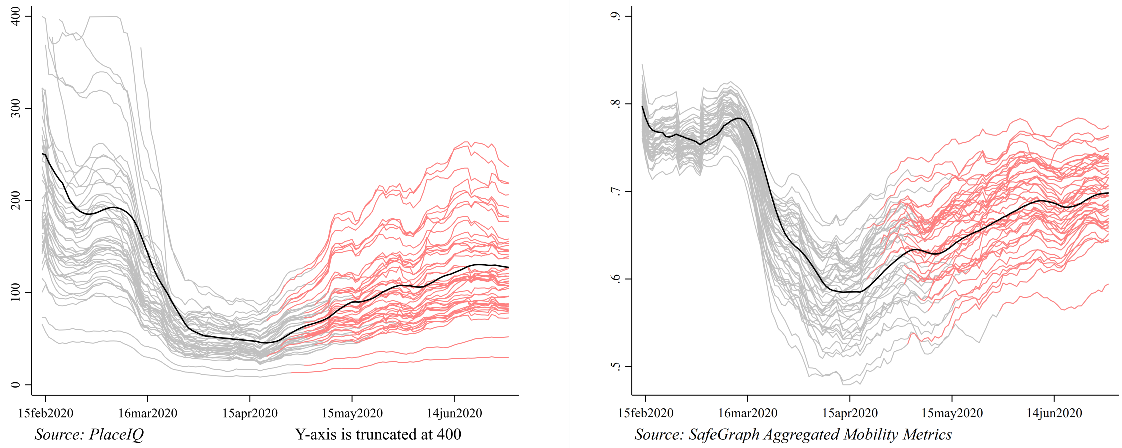
6 Results

6.1 Mobility and Social Contact Patterns During The Pandemic

Figure 2 shows the national and state time series of the mixing index and fraction of devices leaving home from February to June. Both measures fell dramatically during the lockdown phase (mid-March to mid-April), and there is clear evidence across multiple measures that mobility began to increase in mid-April. The timing of the increase in mobility varies across states and across different measures of the outcome. Although the axis scales differ, the times at which dramatic changes occur are nearly the same across all measures.

Figure 2: Trend in Mobility Changes

(a) Trend in mixing index. (b) Trend in fraction leaving home.

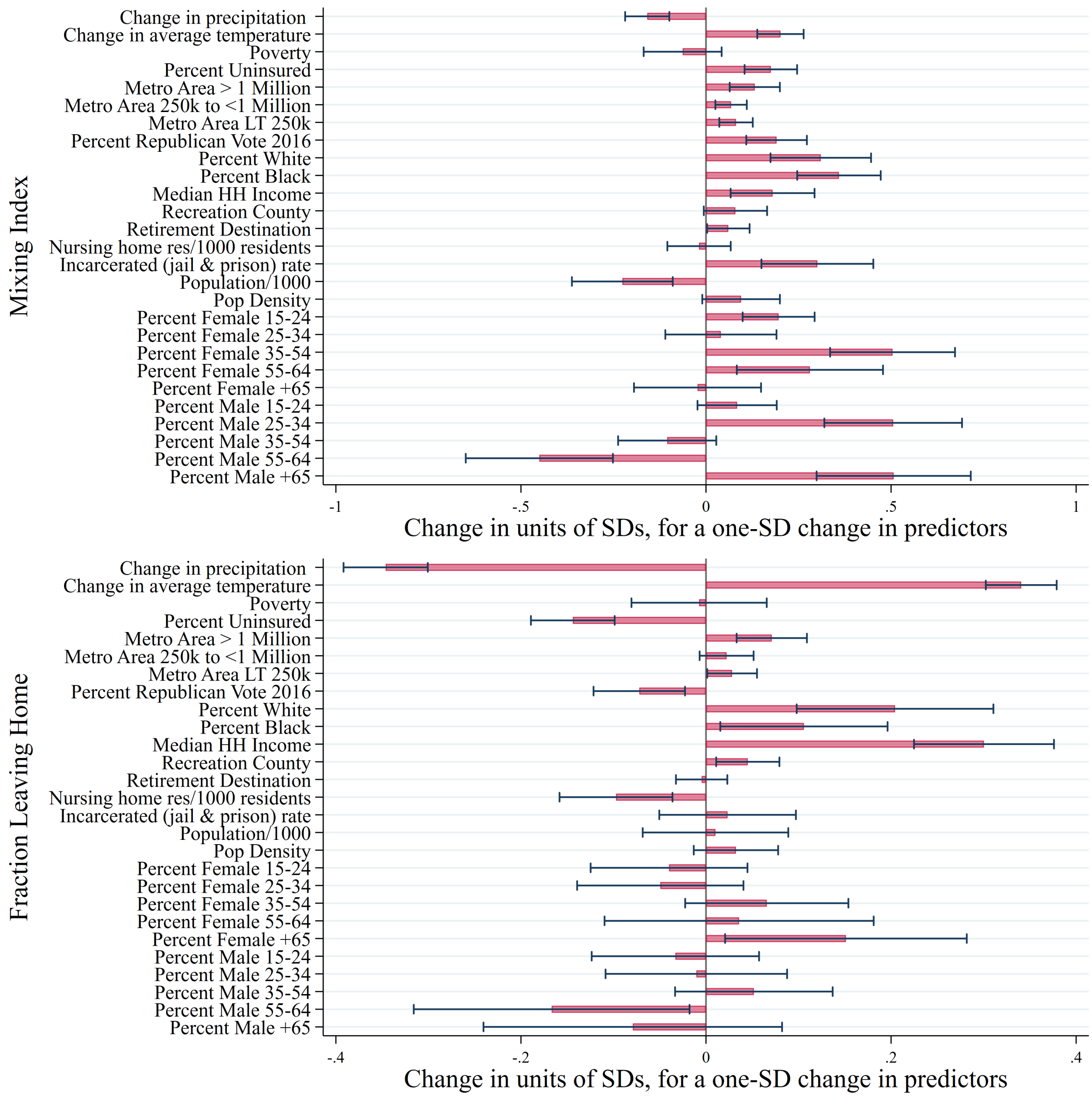


Note: Author's calculation based on data from PlaceIQ and SafeGraph Aggregated Mobility Metrics smart device data. Each grey line represents a state. Red lines represent states which re-opened, for the period after the re-opening. The thick black line represents a "smoothed" 7 day moving average of the states.

The following county-level cross-sectional regression analysis of "long differences" in measures of mobility and social contact was used to show geographic variations in these measures and sociodemographic factors associated with the mobility changes during the reopening phase. Based on the observed heterogeneity in this descriptive analysis, a number of subpopulation event-study analyses were implemented. In the average county, the mixing index increased by 128.1 percentage points between April 15 and June 30 while the fraction of devices leaving home modestly increased by 16.4 percentage points. Figure 3 and Appendix Table A1 show standardized regression coefficients (per standard deviation change in the explanatory variable) from models of the total change in mobility measures between April 15 to June 30.

We found substantial demographic differences in Americans' response to the COVID-19 pandemic across the 2,097 counties with complete data. Urbanicity is associated with the magnitude of mixing increase (0.13 in larger metropolitan areas to 0.08 in metropolitan areas compared to rural areas). We observed smaller correlations between urbanicity and fraction of people (devices) leaving home daily. Not surprisingly, in higher recreation counties, we noted a statistically significant increase in overall

Figure 3: County Level Correlates of Mobility Measures



Note: Specification: simple OLS using cross-sectional data at county level. Each figure represents standardized coefficients and their 95% CIs from a separate regression, where the dependent variable is the outcome listed (long differences between April 15 and June 30).

mobility activity and an insignificant increase in the mixing index. These results are consistent with prior work that find more declines in mobility in urban or recreation areas following stay-at-home orders (Gupta et al., 2020). As racial and ethnic minorities made up a larger share of populations in urban areas, we also observed an increase in movement by black communities: a 0.36 SD increase in the mixing index and 0.11 SD increase in the fraction of devices leaving home.

Social distancing may vary by the neighborhood income level and inequality. Increased mixing index and mobility tend to be higher in counties with higher median household income while there are no significant associations between poverty rates and these measures of mobility. Additionally, difference in average age across counties appears to have a big effect on social mixing patterns, especially among females ages 35-54 (a 0.50 SD increase) and males ages 25-34/+65 (both increasing 0.51 SD). For the most part, difference in average age across counties does not appear to have a big effect on the fraction leaving home, except in females ages +65 increasing their mobility (0.15 SD). These descriptive results may be worrisome as both females and males at 65+, two populations that are known to be at greater risk for severe cases of COVID-19 infection (Wang et al., 2020), appear to become less risk averse, with a marked increase in mobility and social mixing.

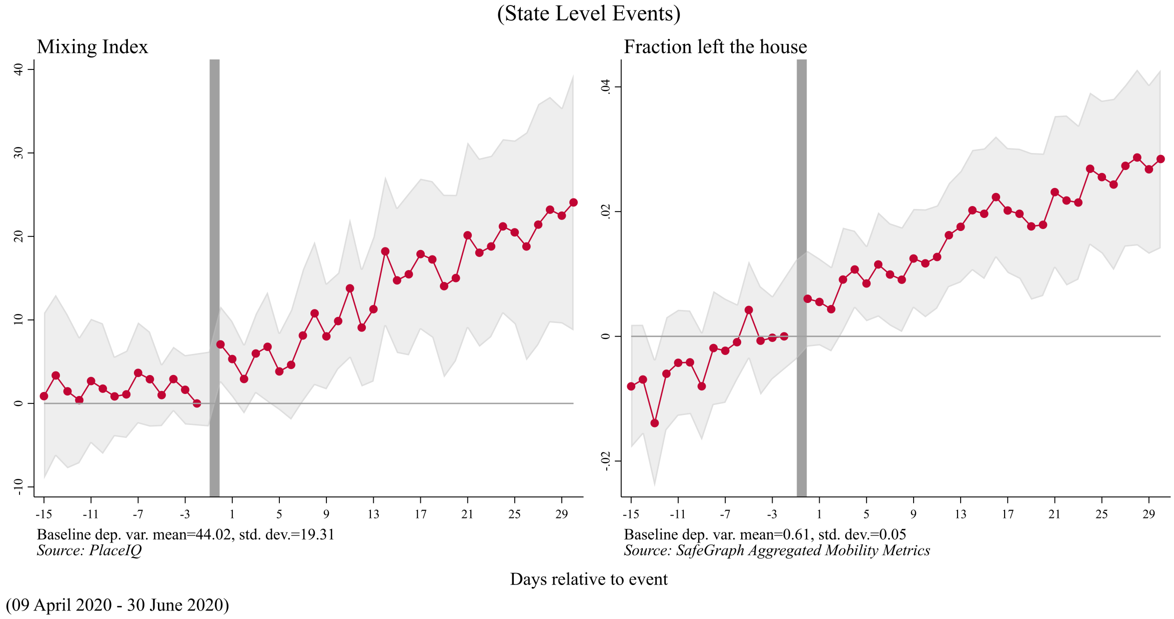
Finally, while counties with a higher Republican vote share were less responsive to social distancing policies (Gupta et al., 2020), we observed an increase in mixing (0.19 SD) and a decrease in fraction of people leaving home (0.07 SD) in such counties. This observation implies an ambiguous impact on potential virus spread regarding political views. These descriptive results suggest that public response to the reopening policies varies across communities and measures of mobility. Further research that uses individual-level data is needed to explore the relationship between demography and socioeconomic factors and mobility changes, as there are severe limits to what can be learned through county-level comparisons. For example, the aggregate mobility measures can not depict levels of actual vs. perceived risk of social contact and workplace's decisions to allow employees to continue working remotely during the reopening phase.

6.2 Event Study Analyses

To understand the connection between recent increases in mobility and state reopening policies, we turn to the following event study regressions. Figure 4 and Table A2 show the state-level event studies for our two social mobility measures: the mixing index and fraction of devices left home. The results indicate that reopening policies generate a substantial increase in the mixing index; there is little evidence of a systematic pre-trend in mixing leading up to reopening. These results suggest a positive effect of state reopening policies in the degree of population mixing which may play an important role for the transmission of COVID-19 post reopening. Though the event study estimates for fraction of devices that left home are noisy, there are observed increases in this mobility measure following reopening events. Interestingly, data shows a clear pre-trend in this outcome, indicating that on average, mobility outside the home increased prior to the reopening events.

To help summarize the results of these baseline models and following heterogeneity analyses, Table 1 reports the estimated effect of a reopening policy 4 days/14 days/28 days after the event for each outcome presented in the event study plots. The effect estimates are presented in percentage terms, relative to the average level on April 15, 2020, to help make the magnitudes as interpretable as possible. Overall, the state-level event study results paint a very clear picture (Column 1). Four days after reopening, there is a statistically significant increase in the mixing index (13.59%, $p<0.05$). One concern is that reopening appears to have a large effect on the mixing index, which is a proxy for actual interactions between people (devices). The effect sizes after 2 and 4 weeks are 25.65% and 48.65%, respectively. This may be worrisome if the mixing index represents a particularly relevant proxy for high transmission rates. This finding suggests that reopening events may signal to people that social interactions have become safer. At the same time, the fraction of devices leaving home has not increased considerably. The clear pre-trend in this mobility measure suggests that a typical

Figure 4: Event Study Regression Coefficients and 95 Percent Confidence Interval of the Effects of State Re-Opening on Mobility Trends



Note: Author's calculations are based on smart device movement data from PlaceIQ and SafeGraph. Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. N=1680. Vertical gray lines depict the day before re-opening. All models include state fixed effects and date fixed effects. Standard errors are clustered at state level. Baseline dependent variable mean as of April 15, 2020.

person may reduce the tendency to stay at home (while keeping social distancing) prior to reopening events. One interpretation is that reopening has increased the diversity of options that people have available to them, and they are more likely to visit a variety of locations that they had avoided in previous weeks, without significantly increasing the time outside the house. Another potential mechanism is that travelers likely respond to official announcements prior to the effective dates of state reopening plans. To verify that the pre-trend in the fraction of devices leaving the house is not due to the announcement of reopening, we tracked the date of official announcements by governors regarding their detailed reopening plans and used these dates in another event-study analysis. We found that a typical state announces their plan about 4 days prior to the official dates of reopening. As expected, the event-study estimates appear similar to the results using the actual initial reopening dates (these results available upon request).

Table 1: Effect Sizes: Percentage Magnitude Effects of Any Re-Opening on Social Distancing Measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any							County Pairs Analysis	
	Re-Opening	Rural	Urban	Shorter SAH	Longer SAH	High Death Rates	Low Death Rates	No Spillovers	Spillovers
Geographic Unit	*State*	*County*	*County*	*State*	*State*	*State*	*State*	*County*	*County*
Effects After 4 days									
Mixing Index									
Coefficient	5.981**	2.849	5.727**	6.042	1.541	7.532**	0.234	5.371	1.929
	(2.434)	(2.294)	(2.208)	(5.500)	(1.021)	(3.261)	(4.222)	(3.595)	(2.771)
Effect size	**13.59%**	7.32%	**11.48%**	11.87%	14.11%	**17.20%**	0.53%	4.61%	3.68%
Fraction Leaving Home									
Coefficient	0.00911**	0.007	0.0113**	0.0121**	0.00196	0.00880	0.00866	0.00241	0.00177
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.00542)	(0.00175)
Effect size	**1.49%**	1.03%	**1.79%**	**1.96%**	0.33%	1.49%	1.37%	0.37%	0.27%
Effects After 14 days									
Mixing Index									
Coefficient	11.29**	4.130	8.344**	8.570	11.69***	18.59***	-8.939	-1.092	2.376
	(4.424)	(3.384)	(4.084)	(10.083)	(3.141)	(4.425)	(8.515)	(4.109)	(2.032)
Effect size	**25.65%**	10.62%	**16.72%**	16.83%	**30.71%**	**42.46%**	-20.19%	-2.61%	5.68%
Fraction Leaving Home									
Coefficient	0.0176***	0.0122*	0.0187**	0.0220***	0.0133**	0.0169***	0.0177**	0.00326	0.00287
	(0.005)	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)	(0.00607)	(0.00223)
Effect size	**2.88%**	**1.79%**	**2.96%**	**3.55%**	**2.21%**	**2.87%**	**2.80%**	0.50%	0.44%
Effects After 28 days									
Mixing Index									
Coefficient	21.41***	7.443	20.69***	22.26	17.67***	30.64***	-6.339	-3.528	-0.215
	(7.360)	(5.420)	(6.725)	(17.713)	(4.689)	(8.712)	(14.699)	(4.958)	(2.778)
Effect size	**48.65%**	19.13%	**41.45%**	43.71%	**46.41%**	**69.98%**	-14.31%	-8.43%	-0.52%
Fraction Leaving Home									
Coefficient	0.0273***	0.0186**	0.0296***	0.0365***	0.0200**	0.0247***	0.0315***	-0.000101	-0.000836
	(0.007)	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.010)	(0.00574)	(0.00227)
Effect size	**4.48%**	**2.74%**	**4.69%**	**5.89%**	**3.33%**	**4.19%**	**4.99%**	-0.02%	-0.13%
Mixing Index mean at baseline	44.02	38.90	49.90	50.91	38.08	43.78	44.28	41.85	41.85
Fraction Leaving Home mean at baseline	0.610	0.680	0.630	0.620	0.600	0.590	0.630	0.656	0.656

Note: Effect sizes are estimated using coefficients in the event-study tables, divided by the dependent variable value as of April 15, 2020. * $p < 0.1$, ** $p < 0.05$ *** $p < 0.01$.

In addition to the state-level analysis, we also fit event study specifications to county-level data and stratify the sample in several meaningful ways. Columns 2-3 in Table 1 show effect size estimates from models that use only data from rural counties and urban counties, respectively (Appendix B). These results suggest that reopening policies have had larger effects on the mixing index in urban areas compared to the negligible effects in rural areas. One possible reason for this heterogeneity is that rural activities are more essential in nature and less elastic to non-essential business closures.

Columns 4-5 show estimates from models that are limited to states that had stay-at-home policies in place for a short vs. a long duration, a proxy for psychological fatigue due to the pandemic (Appendix C). The estimated reopening effects on social mixing are smaller in states that were both late adopters of stay-at-home mandates or with lockdown for only a short time. This seems logical as psychological fatigue is likely more severe in states with longer stay-at-home orders, so lifting the mandate leads to large increases in social interactions.

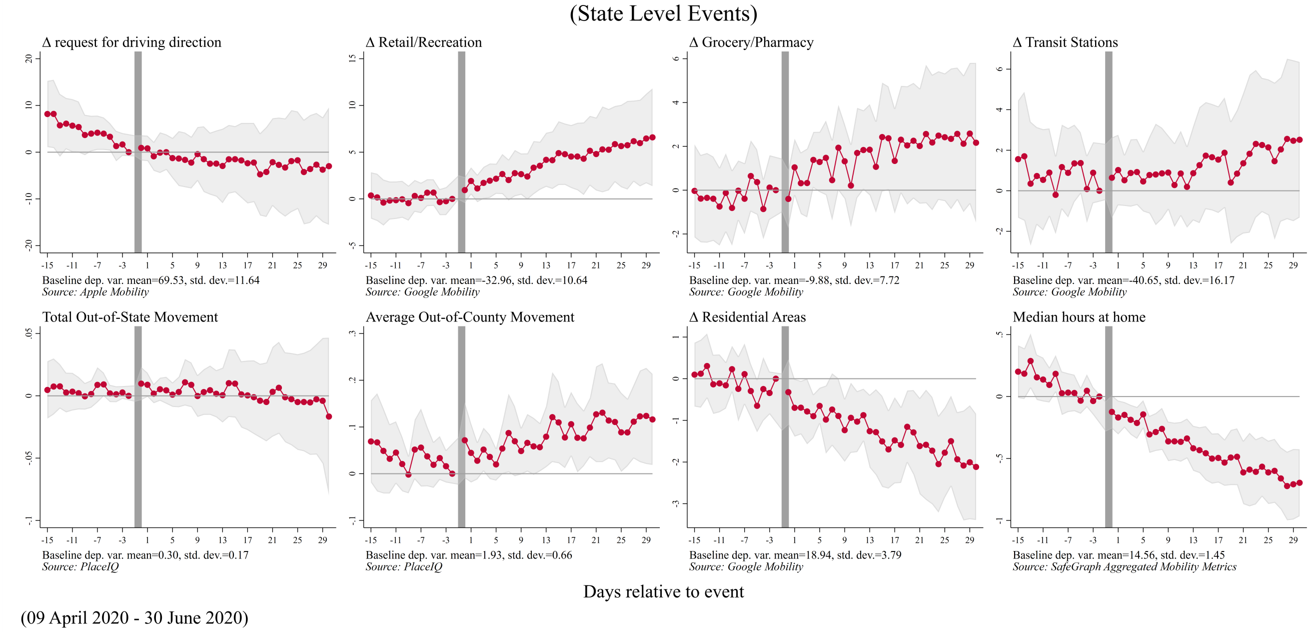
Columns 6-7 of Table A2 show estimates from models that are limited to states that had high COVID-19 mortality rates vs. low mortality rates (Appendix D). Higher and lower baseline COVID-19 related death rates are defined as those above/below the median value prior to reopening events. Data shows that the estimated reopening effects on social mixing are much larger in states that were hard hit by the pandemic. These results are consistent with our social distancing fatigue hypothesis, which has an important policy implication. Specifically, people in hard-hit areas tend to experience more emotional exhaustion, isolation, or boredom, which makes it harder to maintain voluntary social distancing behavior after stay-at-home mandates were relaxed.

Using a multiple measure approach to assess the sensitivity of these findings, similar analyses on additional measures of mobility were reported in Figure 5. Like the results of the mixing index, this sensitivity analysis retained a similar pattern for mobility to retail, recreation places, or pharmacies from Google mobility data: increases following the reopening events without significant pre-trends. There may also have been an increase in mobility to transit stations from Google mobility data, but these estimates are noisier, and it is hard to distinguish the pre-trend and post-trend. Additionally, the data showed declines in median hours at home (SafeGraph) and mobility in residential area (Google data) prior and post reopening events, a similar movement pattern when using fraction of devices that left home to measure mobility. Finally, the out-of-state and out-of-county movement measures from PlaceIQ data and Apple Mobility driving direction requests do not respond much to reopening.

6.3 County Pairs Results

We present event-study-style estimates of the effect of reopening in our county border pairs model, equation (2), in Appendix E. The left panel of Figure E1 (a) presents these estimates for the mixing index assuming that there are no spillovers. The pre-trend,

Figure 5: Event study regression coefficients and 95 percent confidence interval of the effects of state reopening on mobility trends - Alternative measures of mobility



Note: Author's calculation based on smart device movement data from PlaceIQ and SafeGraph. Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. N=1680. Vertical grey line depicts the day before reopening. All models include state fixed effects and date fixed effects. Standard errors clustered at state level. Baseline dependent variable mean as of April 15, 2020.

which reflects how the mixing index differs in the first county to reopen in a pair relative to the other county, is flat. After roughly one week, there is a spike in mixing index relative to the January 3 to February 6 baseline period, however, the estimates are imprecisely estimated. The right panel also provides little evidence for pre-trends, but the estimates are sufficiently noisy that one can not make a definitive statement about changes in mobility from these models that assume no spillovers on behavior.

Figure E1 (b) presents results for our two key measures of mobility, but now we explicitly take spillover effects into account by allowing for a county-pair-specific set of time fixed effects. Similar to the no-spillover effects models, the estimates for the mixing index are too imprecise for reliable interpretations. In contrast, we observed increases in human movement measures (such as fraction of devices that left the house) immediately after a state reopened, although the effect appears to be slightly smaller than in the no-spillover model. The effects from these event studies are summarized in Columns 8-9 of Table 1. In all cases, these results are noisier compared to the state-level analyses and demonstrate weak evidence that reopening increases mobility in states. The implication of these results is that even counties that do not reopen also experience an increase in movement measures, which is consistent with people in neighboring counties crossing state lines to go to retail or recreational locations in newly opened states. Furthermore, there appear to be positive spillover effects onto neighboring counties, since in models that account for spillovers, our estimated changes in movement measures are larger in magnitude.

7 Discussion

From the early phases of the COVID-19 epidemic and especially prior to mass vaccinations, social distancing has been a central strategy for addressing public health. Cell-phone-based metrics show large declines in mobility during lockdowns, and evidence suggests that both government policy and private responses played crucial roles. These actions have likely reduced the spread of the virus and therefore have had important social benefits, although maintaining high levels of social distancing may place a heavy burden on families, businesses, and governments. Regulatory decisions to impose social distancing interventions and ease such restrictions provide a quasi-experimental setting in which to understand compliance with and adherence to these nonpharmaceutical interventions. This study exploits the variation in timing of state reopening policies to examine the short-term effects of these policies on measures of mobility and social contact. Using mobility measures from cell signals and an event-study design, the key findings suggest that reopening policies appear to substantially increase social contact, and that traveling outside the home increases prior to these reopening policies.

Given the dynamic of state reopening and lockdown decisions, the close-to-real-time data in this study is appropriate for understanding immediate private responses to such decisions. We note several key limitations in this study's data and approach. First, this study cannot draw conclusions on the extent to which Americans follow social distancing and COVID-19 risk avoidance guidelines, as cell signal data cannot discern the use of situational mitigation strategies such as wearing a mask or staying at least 6 feet from people who are not of one's household. States have mostly asked businesses that reopen to take steps to reduce transmission, and the CDC has issued guidelines on how to open safely. Therefore, it is possible that these policies and strategies could allow for increased mobility without incurring a substantial increase in new cases. Second, aggregate data from cell signals can not replace individual-level data exploring heterogeneous responses to state reopening policies. Third, there are potential time-variant confounding factors that cannot be captured in our fixed effects models. Our analysis cannot disentangle to what extent mobility increases are rooted in policy vs. other factors such as psychological fatigue, seasonal expectations, political views, and a waning sense of the dangers of the virus.

Given these limitations, our analysis clearly shows that mobility levels started rising in most states beginning in mid-April. During the time period of our study, the increase in mobility was still small compared with the declines that occurred during the lockdown phase; activity levels were not back to normal in June in any meaningful sense. However, the resurgence of mobility is observable across a broad range of indices. The most notable results in our study come from event study regressions. The models suggest that state reopening policies do produce a fairly immediate increase in mixing behavior. After four days of reopening, the mixing index increases by 13.59% (25.65% and 48.65%, in 2 weeks and 4 weeks respectively). Reopening effects are most marked in states that were early adopters of the major closure measures. Importantly, this suggests that fatigue is an important determinant of mixing behavior during the pandemic. Furthermore, the county-pair analysis suggests an increase in movement measures in untreated counties following their neighboring county's reopening.

Research on social distancing policy would benefit from a stronger theoretical analysis of the incentives and constraints that shape individual and group choices regarding social distancing. An economic model of home production could provide an important tool for analyzing how people make decisions about how much social distance to produce relative to complements and substitutes available at home and in marketplaces. Some degree of variation may reflect heterogeneous preferences over health and non-health goods. It is also possible, however, that people behave differently because they hold different beliefs about health risks or are exposed to certain types of misinformation.

References

Abouk, R. and B. Heydari (2020, April). The Immediate Effect of COVID-19 Policies on Social Distancing Behavior in the United States. SSRN Scholarly Paper ID 3571421, Social Science Research Network, Rochester, NY.

Adolph, C., K. Amano, B. Bang-Jensen, N. Fullman, and J. Wilkerson (2020). Pandemic Politics: Timing State-Level Social Distancing Responses to COVID-19. *medRxiv*, 2020.03.30.20046326.

Allcott, H., L. Boxell, J. Conway, M. Gentzkow, M. Thaler, and D. Yang (2020). Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *Journal of Public Economics 191*, 104254.

Andersen, M., J. C. Maclean, M. F. Pesko, and K. I. Simon (2020, May). Effect of a Federal Paid Sick Leave Mandate on Working and Staying at Home: Evidence from Cellular Device Data. Working Paper 27138, National Bureau of Economic Research.

Andersen, M. S. (2020). Early evidence on social distancing in response to COVID-19 in the United States. *Working Paper*, 1–11.

Apple's Maps Site (2020). Mobility Trends Reports. https://www.apple.com/covid19/mobility.

Bento, A. I., T. Nguyen, C. Wing, F. Lozano-Rojas, Y.-Y. Ahn, and K. Simon (2020). Evidence from internet search data shows information-seeking responses to news of local covid-19 cases. *Proceedings of the National Academy of Sciences*.

Callaway, B. and P. H. Sant'Anna (2020). Difference-in-differences with multiple time periods. *Journal of Econometrics*.

CMS (2020). Nursing Home Compare datasets. https://data.medicare.gov/data/nursing-home-compare.

County Health Rankings (2020). County Health Rankings and Roadmaps. http://www.countyhealthrankings.org.

Courtemanche, C., J. Garuccio, A. Le, J. Pinkston, and A. Yelowitz (2020). Strong social distancing measures in the united states reduced the covid-19 growth rate: Study evaluates the impact of social distancing measures on the growth rate of confirmed covid-19 cases across the united states. *Health Affairs*, 10–1377.

Couture, V., J. H. Jonathan Dingel, Allison Green, and K. Williams (2020). Location Exposure Index Based on PlaceIQ Data. https://github.com/COVIDExposureIndices/COVIDExposureIndices/blob/master/documentation/LEX.pdf.

Dave, D. M., A. I. Friedson, K. Matsuzawa, and J. J. Sabia (2020). When do shelter-in-place orders fight covid-19 best? policy heterogeneity across states and adoption time. Working Paper, National Bureau of Economic Research.

Dube, A., T. W. Lester, and M. Reich (2010). Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties. *Review of Economics and Statistics*.

Fang, H., L. Wang, and Y. Yang (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in china. *Journal of Public Economics 191*, 104272.

Friedson, A., D. McNichols, J. Sabia, and D. Dave (2020). Did California's Shelter in Place Order Work? Early Evidence on Coronavirus-Related Health Benefits. *Working Paper*.

Glaeser, E. L., G. Z. Jin, B. T. Leyden, and M. Luca (2020). Learning from deregulation: The asymmetric impact of lockdown and reopening on risky behavior during covid-19. *Journal of Regional Science*.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*.

Google's Site (2020). COVID-19 Community Mobility Reports. https://www.google.com/covid19/mobility.

Gronau, R. (1986). Home production—a survey. *Handbook of labor economics 1*, 273–304.

Gupta, S., T. D. Nguyen, F. L. Rojas, S. Raman, B. Lee, A. Bento, K. I. Simon, and C. Wing (2020, April). Tracking Public and Private Response to the COVID-19 Epidemic: Evidence from State and Local Government Actions. Working Paper 27027, National Bureau of Economic Research.

Gupta, S., K. Simon, and C. Wing (2020). Mandated and voluntary social distancing during the covid-19 epidemic. *Brookings Papers on Economic Activity 2020*(2), 269–326.

HRSA (2020). Area Health Resources Files. https://data.hrsa.gov/data/download.

Incarceration Trends Dataset (2020). County- and jurisdiction-level jail data (1970-2018) and prison data (1983-2016).
https://www.vera.org/in-our-backyards/ending-mass-incarceration-where-it-begins.

Kahn, L. B., F. Lange, and D. G. Wiczer (2020). Labor demand in the time of covid-19: Evidence from vacancy postings and ui claims. Working Paper, National Bureau of Economic Research.

Kapoor, R., H. Rho, B. Sharma, K. Sangha, A. Shenoy, and G. Xu (2020). God is in the Rain: The Impact of Rainfall-Induced Early Social Distancing on COVID-19 Outbreaks. pp. 23.

Krueger, A. B., A. Mueller, S. J. Davis, and A. Şahin (2011). Job search, emotional well-being, and job finding in a period of mass unemployment: Evidence from high frequency longitudinal data [with comments and discussion]. *Brookings Papers on Economic Activity*, 1–81.

Lin, Z. and C. M. Meissner (2020, May). Health vs. Wealth? Public Health Policies and the Economy During Covid-19. Working Paper 27099, National Bureau of Economic Research.

Mervosh, S., J. Lee, L. Gamio, and N. Popovich (2020). See Which States Are Reopening and Which Are Still Shut Down. News Article, The New York Times.
https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html.

Montenovo, L., X. Jiang, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing (2020). Determinants of disparities in covid-19 job losses. NBER Working Paper, National Bureau of Economic Research.

NCEI (2020). Daily Grids and Area Averages of Temperature and Precipitation for the Contiguous United States. ftp://ftp.ncdc.noaa.gov/pub/data/daily-grids/.

Painter, M. and T. Qiu (2020). Political beliefs affect compliance with covid-19 social distancing orders. *Available at SSRN 3569098*.

Prem, K., Y. Liu, T. W. Russell, A. J. Kucharski, R. M. Eggo, N. Davies, S. Flasche, S. Clifford, C. A. Pearson, J. D. Munday, et al. (2020). The effect of control strategies to reduce social mixing on outcomes of the covid-19 epidemic in wuhan, china: a modelling study. *The Lancet Public Health*.

Raifman, J., K. Nocka, D. Jones, J. Bor, S. Lipson, J. Jay, and P. Chan (2020). COVID-19 US state policy database. www.tinyurl.com/statepolicies.

Rojas, F. L., X. Jiang, L. Montenovo, K. I. Simon, B. A. Weinberg, and C. Wing (2020). Is the cure worse than the problem itself? immediate labor market effects of covid-19 case rates and school closures in the us. NBER Working Paper, National Bureau of Economic Research.

Schaul, K., B. Mayes, and B. Berkowitz (2020). Where Americans are still staying at home the most. News Article, The Washtington Post. https://www.washingtonpost.com/graphics/2020/national/map-us-still-staying-home-coronavirus/?itid=hp_visual-stories-8-12_no-name%3Ahomepage%2Fstory-ans.

Sullivan, D. and T. Von Wachter (2009). Job displacement and mortality: An analysis using administrative data. *The Quarterly Journal of Economics 124*(3), 1265–1306.

Wang, L., W. He, X. Yu, D. Hu, M. Bao, H. Liu, J. Zhou, and H. Jiang (2020). Coronavirus disease 2019 in elderly patients: Characteristics and prognostic factors based on 4-week follow-up. *Journal of Infection*.

Wesolowski, A., C. O. Buckee, K. Engø-Monsen, and C. J. E. Metcalf (2016). Connecting mobility to infectious diseases: the promise and limits of mobile phone data. *The Journal of infectious diseases 214*(suppl_4), S414–S420.

Appendix A - Regression Tables

Table A1: County Level Correlates of Mobility Measures.

	(1) Mixing Index		(2) Fraction Leaving Home	
Change in precipitation	-0.16***	(0.03)	-0.35***	(0.02)
Change in average temperature (Celsius)	0.20***	(0.03)	0.34***	(0.02)
Poverty	-0.06	(0.05)	-0.01	(0.04)
Percent Uninsured	0.18***	(0.04)	-0.14***	(0.02)
Metro Area > 1 Million	0.13***	(0.03)	0.07***	(0.02)
Metro Area 250k to < 1 Million	0.07***	(0.02)	0.02	(0.01)
Metro Area < 250k	0.08***	(0.02)	0.03**	(0.01)
Percent Republican Vote in 2016	0.19***	(0.04)	-0.07***	(0.03)
Percent White	0.31***	(0.07)	0.20***	(0.05)
Percent Black	0.36***	(0.06)	0.11**	(0.05)
Median household Income	0.18***	(0.06)	0.30***	(0.04)
Recreation County	0.08*	(0.04)	0.05***	(0.02)
Retirement Destination	0.06**	(0.03)	-0.00	(0.01)
Nursing home res/1000 residents	-0.02	(0.04)	-0.10***	(0.03)
Incarcerated (jail & prison) rate	0.30***	(0.08)	0.02	(0.04)
Population/1000	-0.23***	(0.07)	0.01	(0.04)
Pop Density	0.09*	(0.05)	0.03	(0.02)
Percent Female 15-24	0.20***	(0.05)	-0.04	(0.04)
Percent Female 25-34	0.04	(0.08)	-0.05	(0.05)
Percent Female 35-54	0.50***	(0.09)	0.07	(0.04)
Percent Female 55-64	0.28***	(0.10)	0.04	(0.07)
Percent Female +65	-0.02	(0.09)	0.15**	(0.07)
Percent Male 15-24	0.08	(0.05)	-0.03	(0.05)
Percent Male 25-34	0.51***	(0.09)	-0.01	(0.05)
Percent Male 35-54	-0.10	(0.07)	0.05	(0.04)
Percent Male 55-64	-0.45***	(0.10)	-0.17**	(0.08)
Percent Male +65	0.51***	(0.11)	-0.08	(0.08)
Dep. Variable Mean	0.05		0.05	
Dep. Variable SD	1.04		0.90	
Obs.	1538		2097	
R-squared	0.35		0.50	

Note: Specification: simple OLS using cross-sectional data at county level. Column represents standardized coefficients from a separate regression, where the dependent variable is the outcome listed (long differences between April 15 and May 6, the number of observations varies across different data samples). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$ *** $p < 0.01$.

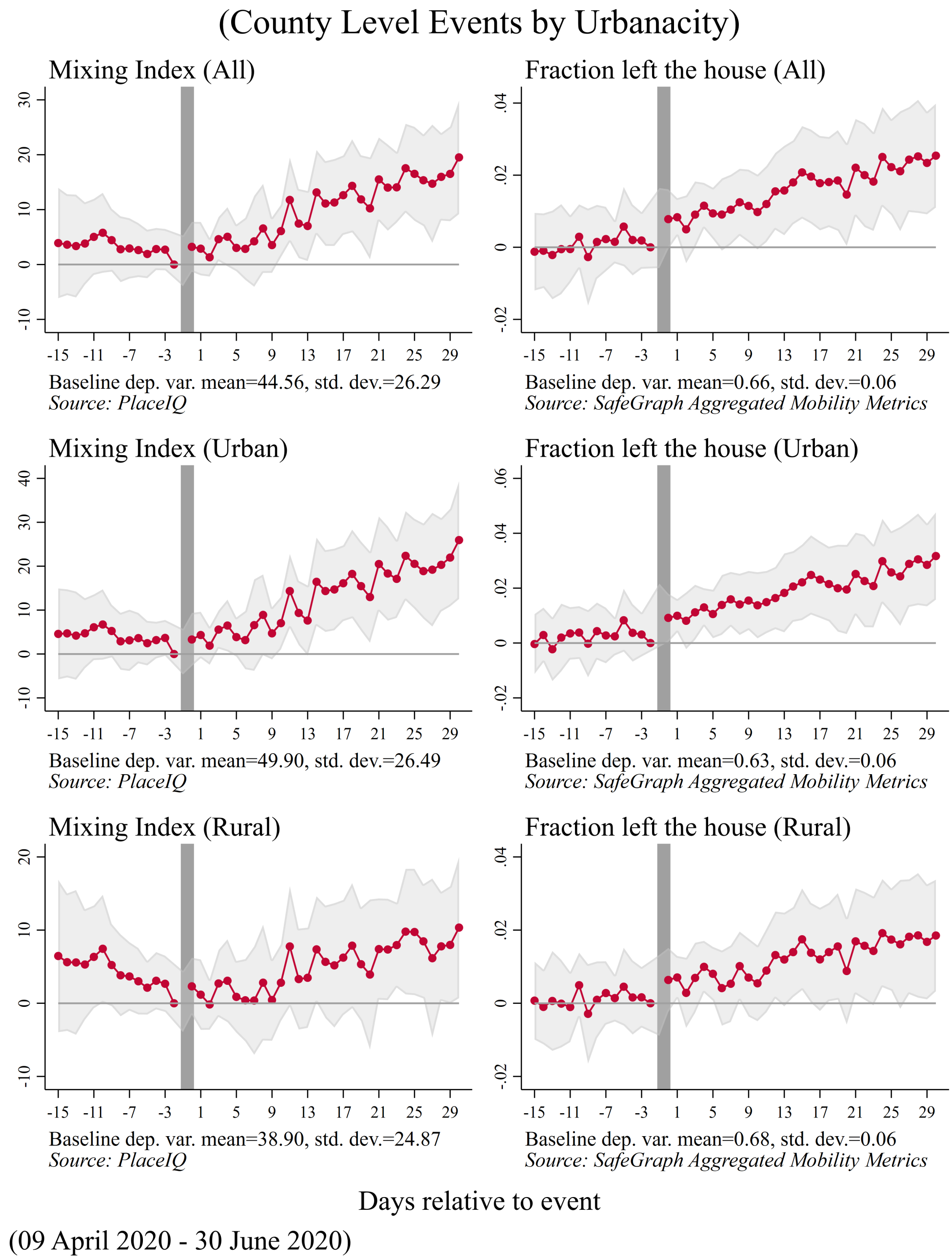
Table A2: Effects of Any Re-Opening on Mobility

	(1)		(2)	
	Outcome 1: Mixing Index		Outcome 2: Fraction Leaving Home	
15 days prior to event	-1.445	(5.502)	-0.019***	(0.006)
14 days prior to event	0.875	(5.079)	-0.008	(0.005)
13 days prior to event	3.354	(4.933)	-0.007	(0.004)
12 days prior to event	1.449	(4.704)	-0.014**	(0.005)
11 days prior to event	0.392	(3.856)	-0.006	(0.005)
10 days prior to event	2.680	(3.805)	-0.004	(0.004)
9 days prior to event	1.769	(3.991)	-0.004	(0.004)
8 days prior to event	0.841	(2.439)	-0.008*	(0.004)
7 days prior to event	1.088	(2.664)	-0.002	(0.005)
6 days prior to event	3.659	(3.092)	-0.002	(0.004)
5 days prior to event	2.901	(2.900)	-0.001	(0.003)
4 days prior to event	0.998	(1.898)	0.004	(0.004)
3 days prior to event	2.914	(1.978)	-0.001	(0.004)
2 days prior to event	1.634	(2.123)	-0.000	(0.003)
Day of event	1.717	(2.286)	0.004	(0.004)
1 day after event	7.071***	(2.333)	0.006	(0.004)
2 days after event	5.317**	(2.324)	0.006	(0.004)
3 days after event	2.927	(2.124)	0.004	(0.003)
4 days after event	5.981**	(2.434)	0.009**	(0.004)
5 days after event	6.783**	(3.367)	0.011***	(0.003)
6 days after event	3.833	(2.367)	0.008***	(0.003)
7 days after event	4.621	(3.354)	0.012***	(0.004)
8 days after event	8.132**	(4.040)	0.010**	(0.004)
9 days after event	10.794**	(4.394)	0.009**	(0.004)
10 days after event	8.029**	(3.240)	0.012***	(0.004)
11 days after event	9.864***	(2.948)	0.012**	(0.004)
12 days after event	13.785***	(4.262)	0.013***	(0.004)
13 days after event	9.085**	(3.603)	0.016***	(0.004)
14 days after event	11.290**	(4.424)	0.018***	(0.005)
15 days after event	18.216***	(4.582)	0.020***	(0.005)
16 days after event	14.739***	(4.441)	0.020***	(0.005)
17 days after event	15.473***	(4.959)	0.022***	(0.005)
18 days after event	17.886***	(4.607)	0.020***	(0.005)
19 days after event	17.247***	(4.785)	0.020***	(0.005)
20 days after event	14.046**	(5.587)	0.018***	(0.006)
21 days after event	15.017***	(5.082)	0.018***	(0.006)
22 days after event	20.139***	(5.685)	0.023***	(0.006)
23 days after event	18.048***	(5.754)	0.022***	(0.007)
24 days after event	18.800***	(5.540)	0.021***	(0.006)
25 days after event	21.201***	(5.332)	0.027***	(0.006)
26 days after event	20.490***	(5.613)	0.026***	(0.006)
27 days after event	18.796***	(6.970)	0.024***	(0.007)
28 days after event	21.414***	(7.360)	0.027***	(0.007)
29 days after event	23.206***	(6.893)	0.029***	(0.007)
30 days after event	22.489***	(6.590)	0.027***	(0.007)
31 days after event	24.072***	(7.834)	0.028***	(0.007)
Precipitation	-0.085	(0.053)	-0.001***	(0.000)
Average Temperature	-0.697**	(0.314)	0.000***	(0.000)
Observations	4032		4032	
Baseline DV mean	44.020		0.610	

Note: Author's calculations are based on smart device movement data from Apple Mobility. Table presents coefficients and standard errors from the the event-study estimation in equation (2). Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. All models include state fixed effects and date fixed effects. Standard errors are clustered at state level are presented in parentheses. Baseline dependent variable mean as of April 15, 2020. * p < 0.1, ** p < 0.05 *** p < 0.01.

Appendix B - Urban and Rural Counties

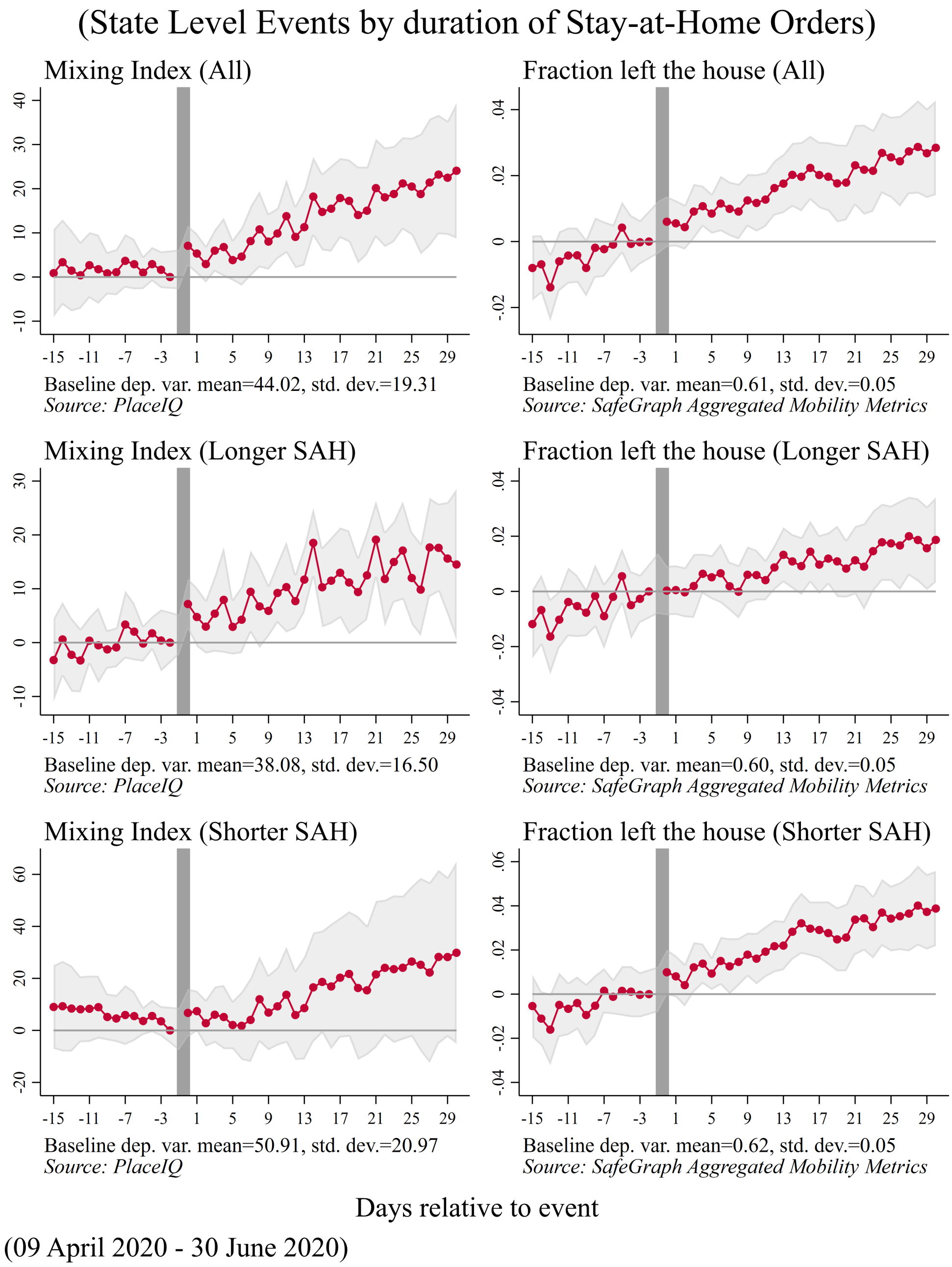
Figure B1: Event Study Regression Coefficients and 95 Percent Confidence Interval



Note: Author's calculations are based on smart device movement data from Google Mobility. Each panel is based on a separate regression. Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. Left panels presents results for urban counties, right panels are for rural counties. Urban/Rural counties defined as metropolitan/non-metropolitan counties. Vertical gray lines depict the day before re-opening. All models include state fixed effects and date fixed effects. Standard errors are clustered at state level. Baseline dependent variable mean as of April 15, 2020.

Appendix C - Duration of Stay-at-Home Orders

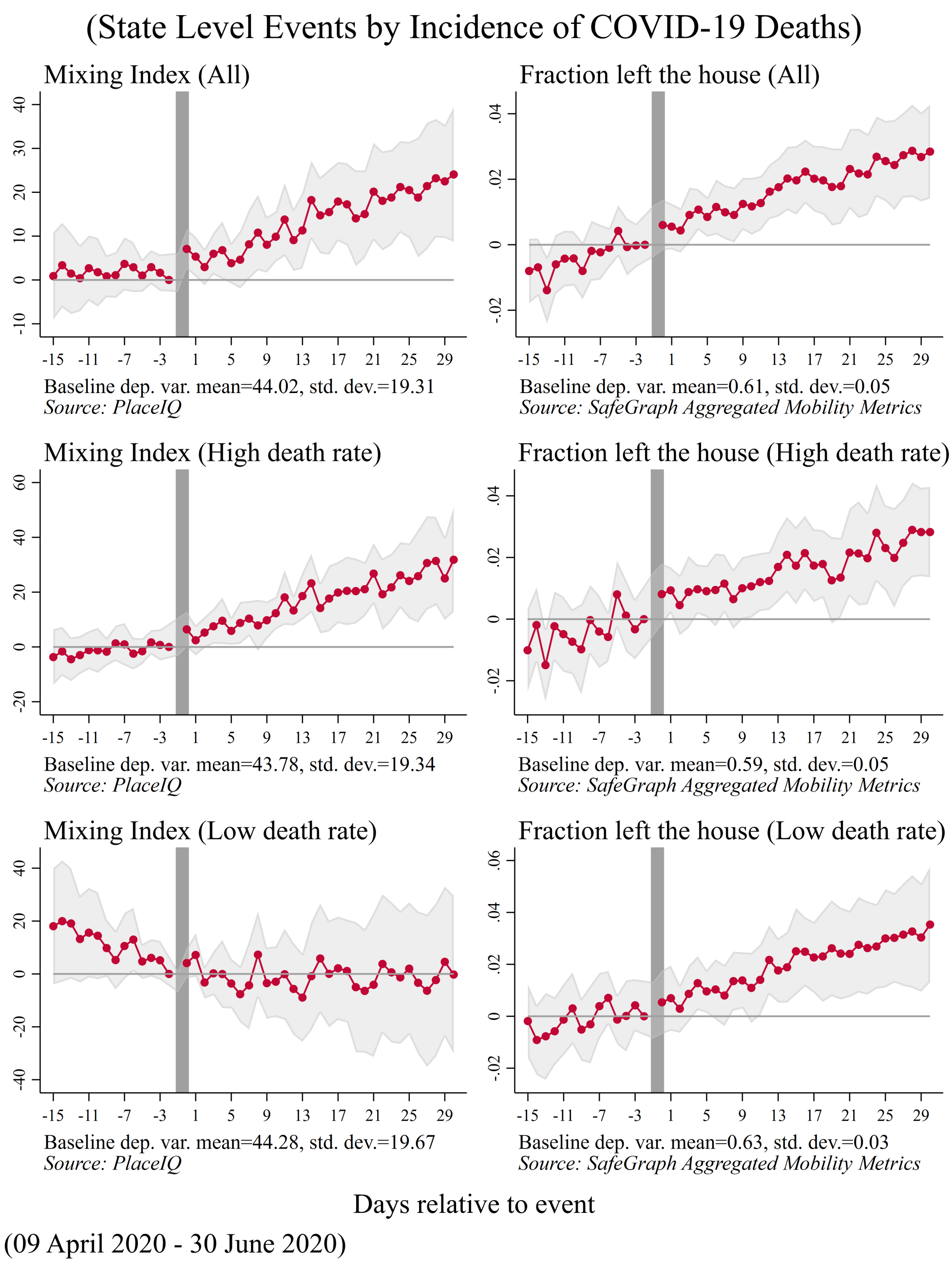
Figure C1: Event Study Regression Coefficients and 95 Percent Confidence Interval



Note: Author's calculations are based on smart device movement data from Apple Mobility. Each panel is based on a separate regression. Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. Longer/shorter Stay-at-home orders are defined as those implemented more/less than the 25 days (median) prior to re-opening. Vertical gray lines depict the day before re-opening. All models include state fixed effects and date fixed effects. Standard errors are clustered at state level. Baseline dependent variable mean as of April 15, 2020.

Appendix D - Baseline COVID-19 Related Mortality

Figure D1: Event Study Regression Coefficients and 95 Percent Confidence Interval

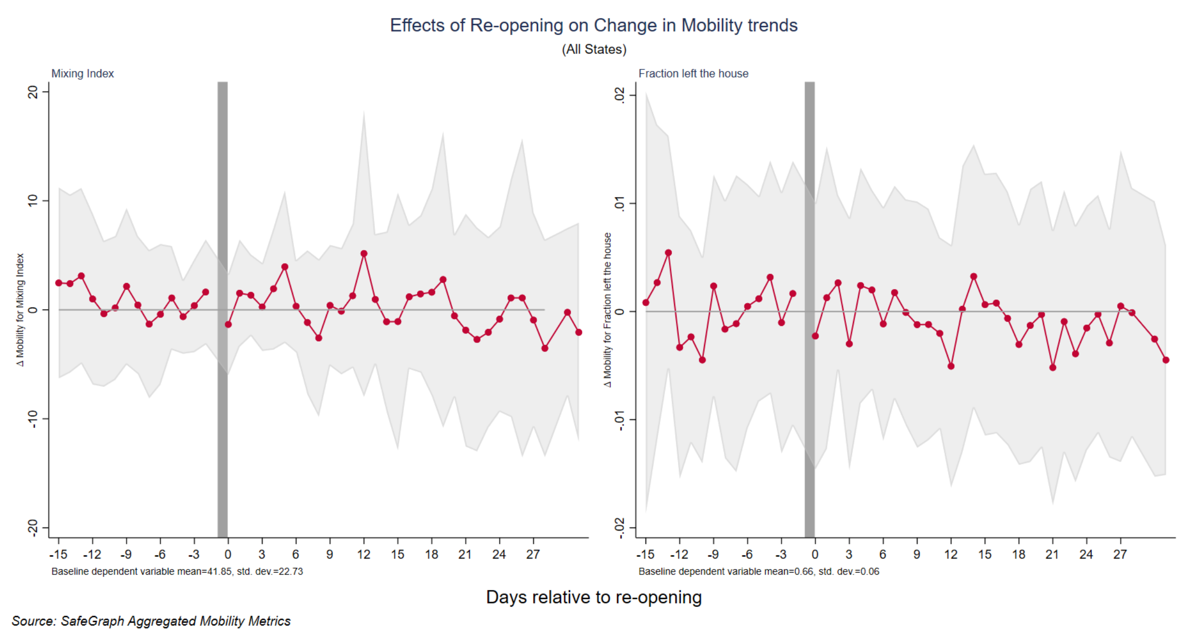


Note: Author's calculations are based on smart device movement data from Apple Mobility. Each panel is based on a separate regression. Each panel is a separate dependent variable. Estimation sample window is April 8, 2020-June 30, 2020. Higher/lower baseline COVID-19 related death rates are defined as those above/below the median prior to re-opening. Vertical gray lines depict the day before re-opening. All models include state fixed effects and date fixed effects. Standard errors are clustered at state level. Baseline dependent variable mean as of April 15, 2020.

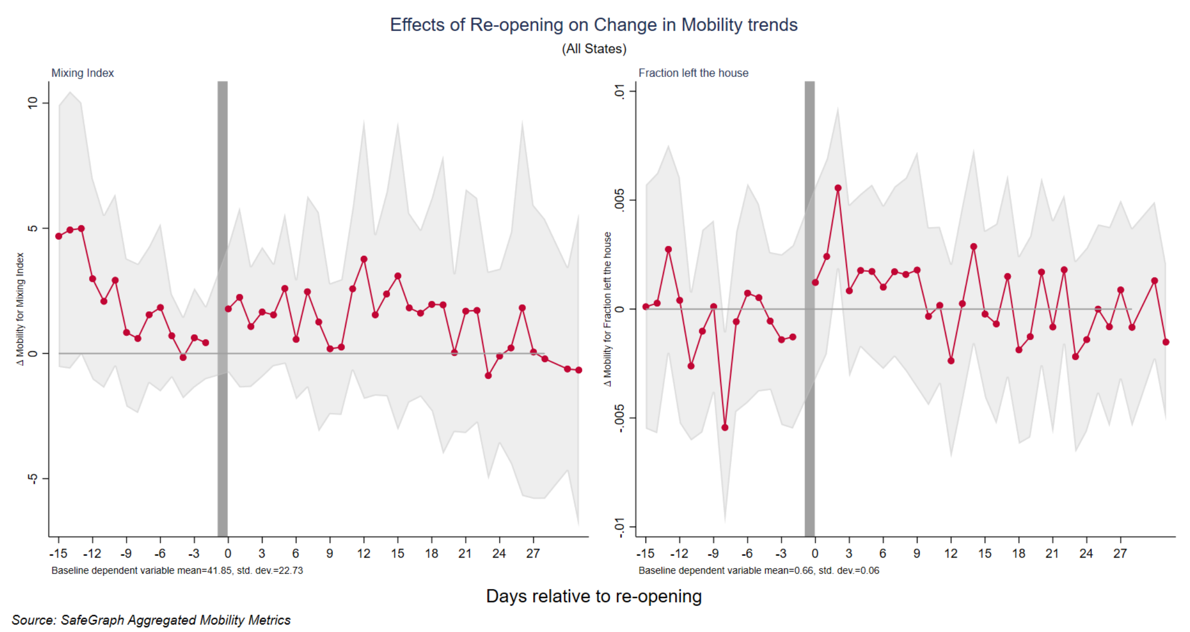
Appendix E - Border Counties

Figure E1: Event Study Regression Coefficients and 95 Percent Confidence Interval

(a) No spillovers



(b) Spillovers



Note: Author's calculations are based on smart device movement data from PlaceIQ (left panel) and SafeGraph Aggregated Mobility Metrics (right panel). Each panel is a separate dependent variable. Estimation sample window is April 15, 2020-June 30, 2020. Vertical gray lines depict the day before re-opening. All models include county pair fixed effects, date fixed effects, and county-by-pair fixed effects. Standard errors are clustered at state level.