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PRIVATE PRECAUTION AND PUBLIC RESTRICTIONS: WHAT DRIVES SOCIAL DISTANCING AND INDUSTRY FOOT TRAFFIC IN THE COVID-19 ERA?

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ABSTRACT

We examine the role of state and local policies to encourage social distancing, including stay at home orders, public school closures, and restrictions on restaurants, entertainment, and large social gatherings. Outcomes come from cell phone records and include foot traffic in six industries (essential and nonessential retail, entertainment, hotel, restaurant, and business services) plus the fraction of cell phones that are home all day. Structural break models show mobility series at the national and state levels start to change dramatically in a short window from March 8-14, well before state or local restrictions of note are in place. In difference-in-difference models, declarations of state of emergency reduce foot traffic and increase social distancing. Stay at home restrictions explain a modest fraction of the change in behavior across outcomes. Industry-specific restrictions have large impacts. For example, restrictions on dining in restaurants reduce traffic in restaurants, hotels, and nonessential retail. Private, self-regulating behavior explains more than three-quarters of the decline in foot traffic in most industries. Restrictive regulation explains half the decline in foot traffic in essential retail and 75 percent of the increase in the fraction home all day. In this latter result, public school closings have a substantial effect.

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I. Introduction

In response to the COVID-19 pandemic in the United States, many state and local governments have adopted a series of orders that encourage social distancing. A variety of scholars have examined the impact of these orders, including Alexander and Karger (2020), Abouk and Heydari (2020), Dave et al. (2020a and 2020b), Gupta et al. (2020), and Goolsbee and Syverson (2020). The focal point for many has been stay at home (henceforth, SAH) restrictions that ask people to shelter in place unless it is necessary to go out. Necessary trips could include shopping for food, medical supplies or other necessities, going to work, seeking medical attention, or using essential services such as the post office, gas stations, car repair, etc. Forty-three states and 294 counties have adopted SAH restrictions, though many have since been relaxed.

The SAH restrictions have been the center of intense political debate. Many see SAH restrictions as a key regulatory intervention to reduce the spread of the virus. The American Medical Association sent a letter to all governors urging states to adopt SAH restrictions.[1] At the same time, many consider SAH restrictions to be the cause of recent wide-spread economic dislocation. Protests against SAH restrictions have occurred in a number of states.[2]

In this paper, we use foot traffic data from cell phone records provided by SafeGraph to estimate the impact of state and county SAH restrictions on foot traffic in six key industries (nonessential and essential retail, entertainment, hotel, restaurant, and business services), plus an aggregate measure of social distancing (the fraction of cell phones home all day). The former six declined substantially as the pandemic aged while the latter increased considerably. However, individuals started to shelter in place before governments adopted these behavioral restrictions. Using structural break models from macroeconomics, we find that in a seven-day period from March 8-14, industry-specific foot traffic measured at the national level dropped dramatically, well before any state or local restrictions of note were in place. For most mobility measures we analyze, the structural shift occurs in most states in a very short period. For example, during the three-day window from March 10-12, 45 states saw a structural break in the fraction of people who stay at home all day.

[1] https://www.ama-assn.org/press-center/press-releases/ama-urges-all-governors-adopt-stay-home-orders-fight-covid-19

[2] https://www.cnn.com/2020/04/16/us/protests-coronavirus-stay-home-orders/index.html.

The similarity of these dates across states and the fact that these dates predate most regularity interventions suggests that individuals and business responded to new information about the pandemic and engaged in self-regulation.

The window when most mobility series break is also a period when many states declared a state of emergency (henceforth, SOE) in anticipation of local infections. We say "in anticipation" because 45 states made declarations before recording their first COVID-related death. These declarations typically grant state governments certain powers and make them eligible for federal funds; however, they impose no restrictions on the behaviors of firms or individuals. Despite this, our results indicate that SOE declarations generated sharp increases in social distancing and declines in foot traffic. Most state and local social distancing orders come one to four weeks after the SOE declaration, after foot traffic has declined precipitously. Our models suggest that SAH orders had modest impacts on mobility, and in most situations, the majority of the decline was a private response to health concerns rather than a response to regulation.

We exploit state and county variation in the adoption date of specific social distancing orders to estimate their impact on the mobility measures outlined above. The orders we consider are declarations of a SOE, public school closings, bans on dine-in restaurants, restrictions on entertainment, bans on gatherings above 50 people, and SAH restrictions. In the business services industry, employers' decisions about employee remote work likely drives the response. In all other industries, foot traffic contains a mix of individual customer responses and supply responses such as business closings.

We highlight five key findings. First, SOE declarations reduce foot traffic and increase social distancing by statistically significant amounts in all models. Between seven and 28 percent of the total decline in mobility is due to SOE declarations. Second, SAH restrictions explain between three and 26 percent of the decline, depending on the mobility measure. Third, restrictions on particular industries have predictable and measurable impacts, similar in magnitude to the SAH restrictions. For example, restrictions on dining in restaurants reduce traffic in restaurants, hotels, and nonessential retail. Entertainment bans reduce traffic in that sector, as well as in restaurants. Fourth, bans on gatherings of 50 or more people have little impact on most sectors. Finally, private, self-regulating behavior explains over three quarters of the decline in foot traffic in discretionary industries (i.e., restaurants, hotels, entertainment, and nonessential retail). Regulation plays a larger role in reducing foot traffic in essential retail, accounting for just under half of the overall decline. Regulation, and the closure of public schools in particular, have a substantial effect on the fraction of the population staying at home all day, accounting for just under three quarters of the overall increase.

We contribute to an expanding economics literature on the impact of government policies to encourage social distancing in the wake of COVID-19. Using a variety of econometric techniques, authors have argued that SAH restrictions increased social distancing by roughly 40% 2-3 weeks after implementation (Abouk and Heydari, 2020; Dave et al., 2020a), which reduced consumer activity (Alexander and Karger, 2020) and case incidence rates (Friedson et al., 2020; Dave et al., 2020a, 2020b). However, Gupta et al. (2020) show that SAH restrictions, which occur late relative to other policies, account for a small share of the total decline in mobility.[3] These authors attribute early mobility declines to SOE declarations, (local) first case and death announcements, and school closures. We extend Gupta et al. (2020) by studying heterogeneity in policy effects across industries and by using event study models that simultaneously account for a number of state and local COVID-19 orders. Finally, Goolsbee and Syverson (2020) also use SafeGraph data to estimate the impact of SAH orders on mobility across industries but use an identification strategy that takes advantage of states in the same commuting zone that impose SAH orders at different times. The authors found that SAH orders account for just 11 percent of the total drop in foot traffic across industries. The authors also show interesting substitution patterns between high and low volume stores, as well as essential vs. nonessential stores in response to the SAH order. We extend Goolsbee and Syverson's (2020) industry-level analysis by estimating the effect of additional local COVID-19 orders and by allowing for policy effects to change over time.

Others have pointed out the rapid decline in economic activity that occurs in the early part of March. Baker et al. (2020) and Cox et al. (2020) show a marked decline in consumer spending that occurs right after

[3] Both Dave et. al (2020) and Gupta et al. (2020) use SafeGraph data and (slightly different) event-study models to estimate the impact of stay at home restrictions on the share of the population staying at home on a given day. Both estimate significant increases in stay at home rates between 1.5 and 4 percentage points.

the national emergency is declared on March 13. Rojas et al. (2020) show a massive increase in unemployment insurance claims starting the week of March 15-21.

Our paper is unique to these in two dimensions. First, our time series models indicate that the timing of the structural break in mobility was incredibly concentrated across industries, suggesting information at the national level was a critical factor in individual decision-making. We also show that structural breaks within industries are concentrated across states. These models indicate that industries specializing in more discretionary items experienced reductions in foot traffic earlier than those selling necessities. Second, we are the first to aggregate policy effects, that allows us to determine the share of the total mobility decline that is due to policies designed to limit mobility and social distancing. An important finding from this work is that between 74 and 83 percent of the drop in mobility to discretionary locals is due to non-regulatory responses by individuals and businesses, while restrictive regulation is effective at inducing more extreme behaviors, such as staying home all day or reducing essential retail shopping.

II. Data

There are two sets of data for this project. The first is from SafeGraph and contains aggregated, high-frequency geolocation data collected across 40 million cellular devices that have opted-in to location sharing services. This data has been used extensively to measure various aspects of the pandemic.[4]

The SafeGraph data contain two data series. The Weekly Places Patterns series (V2.1) has hourly counts of foot traffic to about 4 million points of interest in the US. The data identify a location's NAICS code, which we aggregate to the county-by-industry level. We consider three industries likely impacted by social distancing, including entertainment (NAICS 2-digit code 71), hotels (4-digit code 7211), and restaurants (which includes 7225 for restaurants and 7224 for drinking places). We generate two measures of retail traffic. The first we call essential retail, which includes building material (4441), lawn and garden (4442), grocery (4451), specialty food (4452), and auto part (4413) retailers, as well as car dealers (4411), other general

[4] A short list includes Allcott et al. (2020), Goldfarb and Tucker (2020), Anderson et al. (2020), Dhave et al. (2020a and 2020b), Nguyen et al. (2020), Simonov et al. (2020), Gupta et al. (2020), and Goolsbee and Syverson (2020).

merchandising[5] (452319), and pharmacies (446110). We label the second group nonessential retail and it includes any establishment in the 2-digit sector of 44 or 45 not in the first group.

Any pandemic-related decline in foot traffic to the establishments above would be a combination of demand and supply factors. On the demand side, people may be less willing to visit restaurants or other establishments as the pandemic takes hold. Likewise, this could be supply driven as some establishments, either voluntarily or because of legal restrictions, close down or reduce hours during the pandemic. Therefore, the declines would be a combination of employees not heading to work and customers not visiting these establishments

A final group we consider is labeled business services, which includes the following 2-digit NAICS industries: information (51); finance and insurance (52); real estate (53); professional, scientific, and technical services (54); and management of companies and enterprises (55). Declines in foot traffic in this industry are most likely related to declines in employees heading to work, as the industries are service driven and technical, meaning business can be conducted remotely/virtually.

We use a second SafeGraph series constructed specifically for the pandemic called the Social Distancing Metrics (V2.1) and it includes an omnibus measure of social distancing -- the fraction of cell phones that stay at home all day. A "home" is the common nighttime location at the Geohash-7 level granularity (~153 m x ~153 m) for the device over a 6-week period.

We combine the cell phone data above with a second data set containing the passage date of a variety of state and local orders that encourage social distancing and possibly restrict the activities of individuals. We gathered these data from a variety of sources: the Johns Hopkins University COVID-19 web page;[6] the National Association of Counties;[7] Wikipedia,[8] and Education Week.[9] These sources had considerable variation across them in detail and dates that we reconciled with web searches. We collected passage dates on

[5] This category includes large national retailers such as WalMart, Sam's Club, Costco, Dollar Store, Dollar Tree, and Family Dollar, to name a few.

[6] https://github.com/JieYingWu/COVID-19_US_County-level_Summaries/tree/master/data.

[7] https://ce.naco.org/?find=true.

[8] https://en.wikipedia.org/wiki/U.S._state_and_local_government_response_to_the_COVID-19_pandemic

[9] https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html

seven orders: SOE declaration, SAH restriction, and prohibitions on in-person public K-12 education, dining in restaurants, certain entertainment venues, and gatherings of over 50 people.[10] The first three orders we collect at the county and state level, while the last three (which were rare at the county level) we collect only at the state level. For SOE, SAH, and school closure, we use the earlier date of either the state or the county restriction.[11]

In Figure 1, we report the fraction of the population in the US covered by these orders. We measure population at the county level. There is variation across counties for SOE, SAH, and school closings but only state variation for the other orders. The horizontal axis contains individual days and the vertical axis contains the percent of the population covered by that day. In the graph, we also report the percent of the population that lives in a county that has reported its first COVID-19 case and death.

Twenty percent of the population lives in a county with a case by March 5. This number increases rapidly and is 93 percent by the end of the month. The first regulatory action is typically the declaration of SOE and that number moves from five percent on March 3 to 100 percent by March 16. These declarations impose few, if any, restrictions on individuals and firms. States and local governments can declare a SOE for a variety of reasons including such events as disasters, public health emergencies, climatic events, or civil unrest. The declaration identifies certain rules and regulations that are waived or suspended during the emergency. It also gives the governor, mayor, or county authority to expend funds or deploy personnel, equipment, or supplies. In some cases, a SOE qualifies the state for resources from the Federal Emergency Management Agency.

Washington was the first to declare a SOE, on February 29, the day they experience their first COVID-19 death. Forty-six states then declare emergencies in the nine-day period from March 5 through

[10] Many jurisdictions also imposed bans on gatherings of 500 or more, but we examine this more restrictive measure in this paper.
[11] County SOE declarations commonly follow the state's SOE, meaning the state's SOE takes precedence. Of the 865 local SOE declarations we identify, only 22 precede the state declaration. County SAH restriction are more likely to precede the state. Of the 428 county SAH restrictions we identify, 294 precede the state's restriction. 485 counties closed their public schools prior to the state forcing them to do so. SAH restrictions and public school closures are most common in the largest counties. While just 9 (15) percent of counties passed a SAH (public school closure) prior to their state, the counties contain roughly 30 (29) percent of the US population.

March 13. The last state to declare was West Virginia on March 16. The declaration of a SOE usually comes after states have their first case but before their first deaths. The SOE precedes the first death in 45 states, by an average of 9.5 days.

Public school closures occur at the local level first then gravitate to the state level. We define a county as having a school closure if one public school closes within the county. Almost 500 counties closed schools prior to the state closing all schools. School closures happen as quicky as SOE's but with a lag. Ten percent of the population is covered by a closure on March 12. This increases to 50 percent just 3 days later and 99 percent by the 22nd. State-wide bans on restaurant dine-in, large gatherings, and entertainment venues follow the SOE and over 90 percent of the population is covered by all three by March 23.[12] The last action is the passage of SAH restrictions. No county or state has a SAH restriction on March 15 but 50 percent of the country is covered by March 24 and 80 percent by March 29. About four percent of the population is never covered by a SAH restriction.[13] Of the counties that faced SAH restrictions, they occur on average 15.8 days after a SOE declaration and three days prior to the first death.

III. Some Basic Times Series Data about Social Distancing and Foot Traffic

We outline the basics of our results in a set of four figures. In Figure 2a, we graph the natural log of daily foot traffic in the nonessential retail sector in the US from January 1 to May 15, 2020. Note that traffic was declining slowly through early March, then falls by 60 percent over the next month, and rebounded some after mid-April. In Appendix Figure A1 we report daily foot traffic for the five other industries outlined above (essential retail, entertainment, hotel, restaurant, and business services) and the daily at home rate, an omnibus measure of social distancing, over the same time interval,. These mobility series mirror that of nonessential retail several with commonalities. First, there is a pronounced weekly pattern. Second, most series seem to "break" the week prior to March 15, a topic we return to below. Third, all series bottom out in

[12] Delaware passed a dine-in restaurant ban and entertainment ban the day before their SOE. Both Maine and West Virginia announced the closure of their public schools the day before their SOE. A total of 132 counties, representing 7 percent of the population, closed public schools prior to the SOE. Of these, 73 closed public schools the day before the SOE.

[13] Nebraska, the Dakotas, Arizona, Iowa, Oklahoma, and Utah never passed state-level SAH restrictions, though populous counties in the latter four states passed their own restrictions.

a short window between April 15-19. Fourth, the magnitudes of the declines are dramatic. From the seven-day period ending March 13 through the minimums of seven-day moving averages, declines range from 39 percent (essential retail) to 76 percent (hotels).

Figure 1 indicates that most social distancing orders occurred after March 15 while the results in Figures 2a and Appendix Figure A1 suggest that most series start declining before that date. We can date when these seven national time series break using techniques from macro times series analysis that identify when a likely regime switch occurred.[14]

We use data ranging from January 1 to May 15, 2020. Let y_t be the mobility measure of interest. For a time-series that breaks at period c, we generate a dummy variable A_t^c that equals 1 if $t \geq c$ and zero otherwise. Let $time_t$ be a linear time trend that equals 1 on New Year's Day and increases by 1 each day and $DOW(j)_t$ be a dummy variable for the day of the week (j=1 to 6). The model is cubic in time before and after the break point c and we allow the day of week effects to vary before and after the break. The equation is of the form

$$(1)\quad y_t = \alpha + \sum_{j=1}^{6}[DOW(j)_t(1-A_t^c)\theta_{bj} + DOW(j)_t A_t^c \theta_{aj}] + \sum_{k=1}^{3} time_t^k (1-A_t^c)\beta_{bk} + \sum_{k=1}^{3} time_t^k A_t^c \beta_{ak} + \varepsilon_t$$

where ε_t is a random error. We vary the break point from February 15 to April 15 and select the date c that maximizes the F test for the joint hypothesis that $H_0: \theta_{aj} = \theta_{bj}, \beta_{ak} = \beta_{bk}$ for all j=1, 2, … ,6 and k=1,2,3.

We report in Table 1 the results for the seven national series we consider. The first column lists the series and the second column lists the date when the regime switch occurred nationally. The F-statistic outlined above and the critical value for the F-test is from Andrew (1993).

The table contains three important results. First, the structural breaks all occur in a short window from March 8 to 14, well before most restrictions occur in Figure 1. Second, the order in which industries experienced structural breaks in their foot traffic makes sense. Industries specializing in more discretionary

[14] Quandt (1960) first outlined the methods and Hansen (2001) provides an informative survey.

items are the first to switch (e.g., entertainment, restaurants) and less discretionary items are the last (e.g., essential retail). Third, in all cases, we can easily reject the null hypothesis.

The timing of the structural break is sharp. In Appendix Figure A2 we report the actual time series (black line) and the OLS estimate of equation (1) at the optimal break point (dotted light gray line) for two series: the natural log of non-essential retail visits and the at home rate. On each graph, we also produce the F-statistic when the model is evaluated at different break points. The time series model fits the data well in both cases. The graph of the F-statistic demonstrates there is a sharp break in both series at the break point.

The clustering of the trend breaks across series is mirrored by a clustering of trend break dates across states for a particular series. For each of the outcomes in Table 1, we estimate equation (1) for each state. In the right-hand side of the table, we report the number of states that break on particular days in March. For most outcomes, the breaks are clustered in a small set of dates. The at home rate breaks in a three-day period from March 10-12 for 45 states. Forty-nine states break for restaurants over a six-day period from March 8-13. On March 7 and 8, 30 states break for entertainment and 24 break for hotels. On March 13 and 14, 48 states break for business services, 32 break for nonessential retail, and 44 break for essential retail.

The similarity across states in the break points and the timing of these changes relative to the adoption of social distancing restrictions suggests that individuals and firms reacted to the same set of information across states. This is not surprising. In Appendix Table 1, we produce a timeline of major events relating to the COVID-19 pandemic. Note the events occurring the week before March 15 that illustrate the potential scale of the pandemic, including the WHO declaring COVID-19 a pandemic, the cancellation of the, the NBA, NHL, Premier League suspend operation, and a federal foreign travel ban.

Most of these regime changes are occurring when states are declaring SOEs, potentially providing evidence that governments expect the crisis to be problematic locally. The impact of the SOE on mobility is illustrated in Figure 2b where we aggregate foot traffic data for nonessential retail to the county level, then center the data on the SOE declaration, where the earliest declaration (i.e., state or county) is day zero. We report data starting 20 days before and continuing 30 days after the declaration. This series is relatively flat before the SOE but declines precipitously afterwards suggesting the information provided by the SOE altered behavior. In Appendix Figure A3, we report similar graphs for the five other foot traffic series and the at home rate, in the same order as in Appendix Figure A1. This exercise illustrates there was a dramatic drop in foot traffic across industries following the SOE (Figures A3a-A3f) and an equally large increase in the at home rate. In some cases, there seems to be a slight pre-existing downward trend in foot traffic (e.g., for hotels), but in other cases, the trend is moving opposite expectations (e.g., for the at home rate and essential retail).

In Figure 2c, we center the nonessential retail foot traffic data around the earliest state or county SAH restriction faced by the jurisdiction, excluding counties with no such restriction. This figure demonstrates that much of the decrease in traffic began well before any SAH restrictions were in place. In Appendix Figure A4, we report the data for the other mobility measures. In all cases, large mobility declines are observed prior to any SAH restrictions.

Despite the results in Figure 2c and Appendix Figure A4, SAH restrictions appear to play a role in encouraging social distancing. In Figure 2d, we re-center the nonessential retail data around the earliest declaration of a SOE and graph an index of the outcomes for counties that had and never had a SAH restriction in effect. We use the index to remove scale differences across sectors and set the index to 1 on day -1. Note that as there is a 1-4 week delay between SOE declarations and SAH restriction; the two series track well for about 12 days after SOE declarations but ultimately diverge, with less foot traffic for people in counties under SAH orders. This figure suggests that for this mobility measure, SAH played a limited role. We reproduce this finding in Appendix Figure A5 for the six other mobility measures. These graphs suggest that SAH orders enhanced the decline in foot traffic, with strongest effect in entertainment, essential retail and the at home rate, but with limited impact on business services, restaurants, and hotels.

IV. Main Empirical Specification

We consider next whether the intuitive results from the figures above hold up under a more structured econometric analysis. The problems are two-fold. First, Figures 2b and Appendix Figure A3 suggest that SOE declarations potentially have an impact on mobility. At the same time, that the drop in economic activity across states occurred in a narrow window of time indicates the possibility of a national response. Second, Figures 2c and Appendix Figure A4 indicate there are key pre-treatment trends in outcomes before SAH were adopted. We attempt to control for these factors in an event study design within a difference-in-difference specification that exploits the variation across states and counties in the timing of the various social distancing orders.

Let Y_{ct} denote the mobility measure of interest in county c on day t. The variable is logged for all foot traffic measures and is linear for the at home rate. Define X_c as the date that policy X was passed in county c. We then define $POL_{ct}^{X} = t - X_c$, which measures the days since the policy's passage – e.g., $POL_{ct}^{X} = -7$ a week before policy X passes, $POL_{ct}^{X} = 0$ the day policy X passes, and $POL_{ct}^{X} = 7$ a week after policy X passes. Our econometric specification is then

$$(2) \qquad Y_{ct} = \sum_{k=-10}^{-1} \beta_k^1 1_{\{POL_{ct}^1 = k\}} + \sum_{h=1}^{8} \sum_{j=0}^{T^h} \beta_j^h 1_{\{POL_{ct}^h = j\}} + \alpha_c + \delta_t + \epsilon_{ct}$$

where α_c is a county fixed effect, δ_t is a date fixed effect, and ϵ_{ct} is the econometric error. We measure the impact of six policies, denoted by h, and estimate separate policy effects, β_j, for each day post-passage. County and state policies are not passed in a vacuum. Local infections and deaths influence policy timing as well as individual decision making. As such, we also control for the time since first COVID-19 case ($h = 7$) and time since first COVID-19 death ($h = 8$) in the county. The date fixed effects control for the common response across all counties to the information shocks outlined in the timeline in Appendix Table A1

Since SOEs, $h = 1$, were the first COVID-19 policy in nearly every county, we allow for differential pre-policy effects, β_k^1, in the ten days preceding the SOE declaration. For each county, we include all days between February 15 and 30 days post-SOE, meaning the reference period for SOE effects is the time between February 15 and eleven days prior to the SOE declaration. Because our panel is unbalanced, different counties are exposed non-SOE policies for different lengths of time. As a result, the total number of estimated post-policy effects varies by policy.[15] In all models, we weight observations by the number of devices in a county. We cluster standard errors at the state level.

V. Event Study Results

We present the event study estimates in Appendix Figures A6-A12. Each figure corresponds to one of our seven mobility measures and each panel within a figure corresponds to one of the six policies plus the days in relation to the first death and the first case. Consider, for example, Panel A of Appendix Figure A6. This panel plots a subset of regression coefficients from Equation 2 where the dependent variable is the log of nonessential retail foot traffic. The plotted coefficients measure, relative to baseline, the daily impact of the SOE on foot traffic. The dashed grey lines measure the 95% confidence interval for each parameter estimate.

Given the sheer number of coefficients, in Table 2, we summarize our estimates across mobility measures by reporting regression coefficients 7, 14, and 21 days post-policy. There are several important findings. First, we find that banning gatherings of 50 or more people had little impact on foot traffic across industries. Second, the SOE declaration and SAH restriction significantly reduced mobility by 7 days after passage for all mobility measures. For SAH, 14-day effects remain statistically significant across mobility measures, while for SOE, after 21 days, results remain significant for retail, hotel, restaurant, and business services traffic. Appendix Figures A6-A12 show that SOE effects generally grow over time, while the SAH response tends to be large immediately following the policy, but grows little over time. For all mobility measures other than hotel foot traffic, the two-week SAH effect is larger than the two-week SOE effect.

We find that restaurant dine-in bans have large effects on restaurant foot traffic. In fact, two weeks post-policy, the dine-in ban had a larger effect on restaurants than any other policy – the ban yielded a roughly 15 percent reduction in traffic. Results are similar for entertainment bans on the entertainment industry. The dine-in and entertainment bans lead to large reductions in foot traffic in complementary industries as well. For example, the dine-in ban reduced foot traffic in nonessential retail and hotels, the latter

[15] For the SOE, we estimate policy effects up to 30 days post-policy. For the remaining policies, we estimate the following number of post-policy effects: stay at home order, 19; ban on gatherings greater than fifty, 26; entertainment and gym ban, 26; restaurant dine-in ban, 27; and public-school closure, 28.

of which often contain restaurants; i.e., some of the foot traffic categorized as hotel traffic is truly restaurant traffic. Moreover, the entertainment ban reduced restaurant traffic, which is sensible. If the entertainment ban prevents evenings out for events, then people also avoid restaurants in the process.

Closing public schools reduces foot traffic across industries, while having a substantial effect on the at home rate. That public school closures have the largest effect on the at home rate is unsurprising. A large fraction of cell phone carriers are students, parents of students, or school employees. For these individuals, staying at home all day is virtually impossible when schools are in session, but feasible when not. The fact that public school closures significantly reduced foot traffic in business service and hotel industries highlights the role that parents play as full-time caretakers in the absence of school, as going to the office, much less conducting business travel, becomes difficult once children are home.

Finally, the first death in the county has a very large and statistically significant impact on all mobility measures. In most cases, the impact of the first death is larger than any single policy effect and it grows over time. Importantly, when population weighted, the average county experiences their first death just three days after their SAH restriction; thus, the estimated effect of SAH on mobility is sensitive to the inclusion of time since first death. Though not shown, SAH effects increase by 60 percent on average when we exclude time since first death and case from the model.

VI. Private Precaution vs. Public Restrictions

Next, we use our estimates from the previous section to determine the degree to which COVID-19 mobility changes are attributable to private precautions vs. public restrictions. We begin by predicting the aggregate change in mobility from a baseline period 11 to 17 days prior to the SOE declaration until 25 days after the SOE.[16] We report the aggregate change in the outcome of interest from this baseline period in column (1) of Table 3. This is either the percent reduction for the foot traffic measures or the percentage point change for the at home rate. Next, we predict mobility in the absence of state and county orders, which allow us to calculate what fraction of the total change in mobility is attributable to SOE declarations, SAH

[16] Figure A3 shows that 25 days post-SOE is when foot traffic trends flattened.

restrictions, and all other policies, reported in columns (2)-(4), respectively. In the final column, we report the fraction of the aggregate change due to a private response which is the simply 100% minus the percent changes in columns (3) and (4).

The key result is in the final column. For industries specializing in discretionary goods and services (i.e., nonessential retail, entertainment, hotel, restaurant, and business services), 74 to 83 percent of the decline in foot traffic is due to a private response on the part of citizens and is not a behavioral change due to regulation. About half the decline in essential retail is due to regulation, despite the fact that all restrictions *explicity* allowed for this sort of shopping. This finding suggests that the SAH (as well as other restrictive orders) served as an informational treatment, warning citizens of the severity of the virus locally, in addition to formally restricting mobility. In that sense, the proportion of the overall mobility decline that we attribute to restrictive policy in column 5, which is relatively small, is likely an over estimate. Finally, restrictive regulation has the largest impact on the fraction of individuals staying home all day, accounting for nearly three quarters of the total change. Though not shown, a the most effective policy for keeping individuals at home all day is closing public schools, which alone, accounts for 27 percent of the total change in the at home rate.

VII. Discussion

We find that self-imposed, precautionary behavior accounts for a large fraction of the overall decline in discretionary mobility following the arrival of COVID-19. Restrictive regulations explain half of the decline in foot traffic in essential retail, despite the fact that regulations allowed such shopping, suggesting that even the most restrictive policies had important informational effects that also altered private behavior. Restrictive regulation explains a majority of the increase in individuals staying at home all day; in particular, we find that closing public schools materially changes this outcome.

That precautionary behavior plays a large role is not surprising. Individual businesses were well ahead of most state policy interventions in their response to the pandemic. Google, Twitter, Amazon, Facebook and Microsoft told their workforces by March 6 to work from home.[17] The University of Washington was the first university to move to remote classes on March 6,[18] but by March 13, 300 universities had suspended in-person classes.[19] Macy's, Bloomingdale's, and Nordstrom closed all stores nationwide on March 17,[20] while the largest mall operator in the country, Simons Property Group, closed all its malls the next day.[21]

This paper also contributes to a broader literature in health economics that examines the importance of behavioral responses to external health shocks as a way of mitigating individual risk. Theoretical models have demonstrated that modest changes in avoidance behavior can have important implications for the spread and incidence of an infectious disease (Kremer, 1996; Geoffard and Philipson, 1997; Funk et al., 2009; Chen et al., 2011). At the same time, a large empirical literature demonstrates that individuals respond to external events and adopt avoidance behavior. For example, individuals respond to high pollution level by spending less time outside (Bresnahan et al., 1997; Neidell, 2009;) and purchase particulate-filtering facemasks (Zhang and Mu, 2018). There is some evidence of a reduction in high-risk sexual activity in response to the AIDS epidemic (McKusick et al., 2011; Ng'weshemi et al., 1996; Bloom et al., 2000), although some argue the response was modest at best (e.g., Oster, 2012). Individuals with contaminated town water switch to bottled water (Zivin et al., 2011). Previous viral pandemics provide substantial evidence of avoidance behavior. A summary of 26 surveys from previous pandemics shows broad changes in avoidance behavior across many counties including increased mask wearing, more frequent hand washing, and social distancing (Bish and Michie, 2010). This literature of course has its antecedents – e.g., the classic work of Peltzman (1975) argues rising automobile safety encouraged drivers to take more risks.

We do not intent to suggest that regulation in this context is of little value. Indeed, restrictive policies that encourage social distancing do alter outcomes. Such policies are particularly effective in eliciting

[17] https://www.inc.com/jason-aten/microsoft-google-twitter-are-telling-employees-to-work-from-home-because-of-coronavirus-should-you.html
[18] https://www.nytimes.com/2020/03/06/us/coronavirus-college-campus-closings.html
[19] https://edscoop.com/universities-closed-due-coronavirus-2020/
[20] https://www.usatoday.com/story/money/2020/03/17/macys-coronavirus-all-stores-closing-until-march-31-bloomingdales/5070025002/
[21] https://www.abc57.com/news/all-simon-malls-to-temporarily-close-including-university-park-mall

extreme behaviors, such as preventing essential retail shopping and inducing individuals to stay at home all day. Instead, our findings suggest that governments are well positioned to induce precautionary behavior by informing citizens of the risks they face, as evidenced by the impact of SOEs and the occurring of initial incidence of mortality at a local level on social distancing and mobility.

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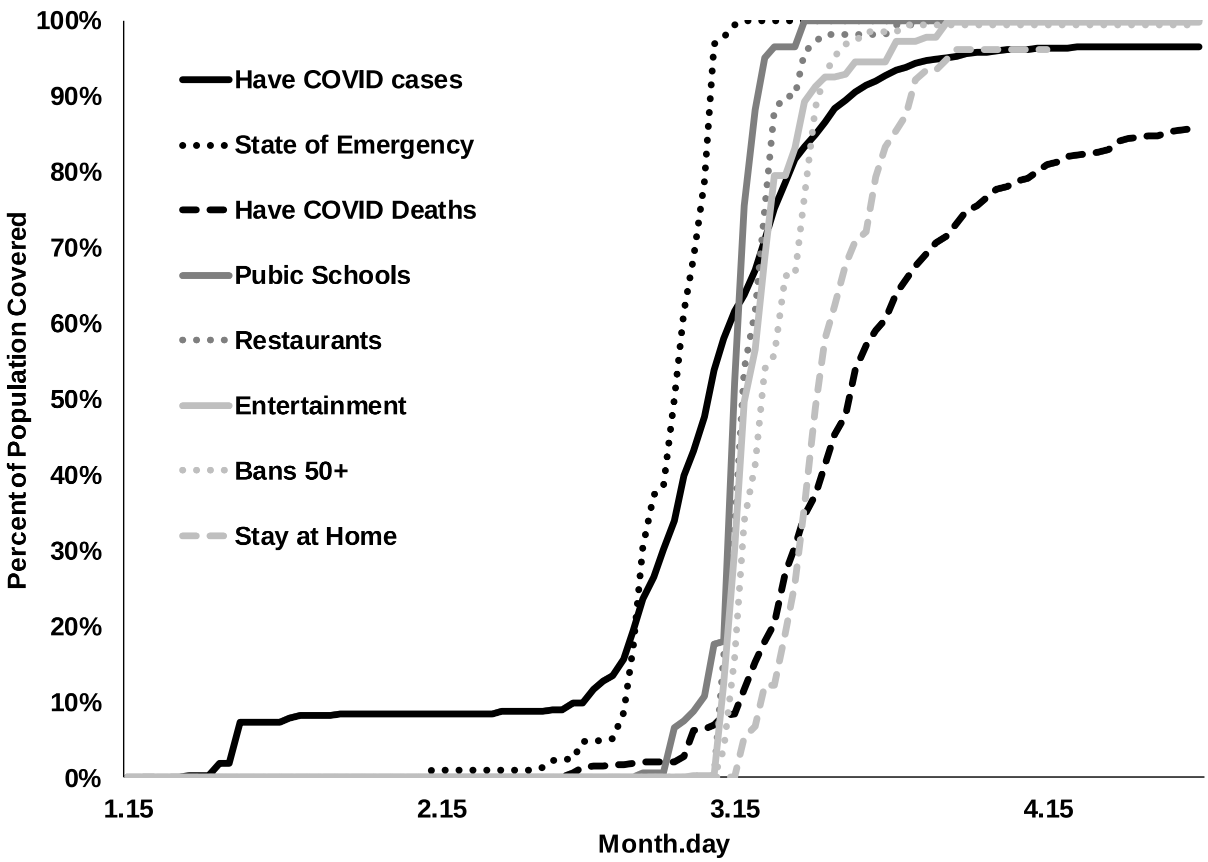
Figure 1
Fraction of the Population Covered by Various Social Distancing Ordinances, and the Fraction that Live in a County that have experienced their First COVID-19 Case and Death



Notes: The data are aggregated at the county level. Dates of restaurant, entertainment, and large gathering orders are measured at the state level. Dates of states of emergency, stay at home restrictions, and school closings are measured at the state and county level, and counties are coded according to first exposure.

Figure 2

The Natural Log of Daily Foot Traffic for Nonessential Retail Stores, for Various Groupings, SafeGraph Data

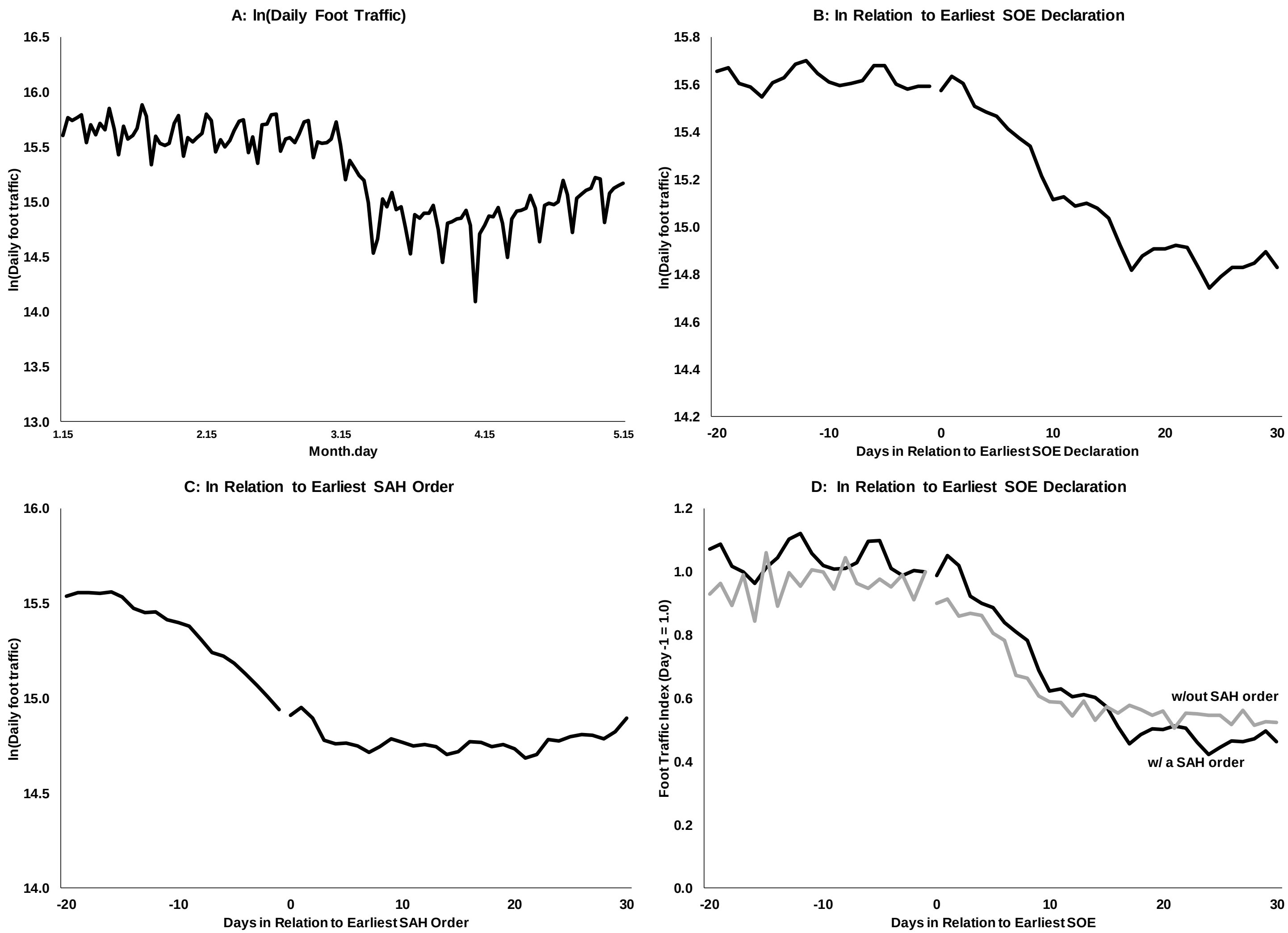


Table 1
Switch Points in Various Daily Time Series, SafeGraph Data, 1/1/2020 – 4/31/2020

Series	Day switch in March for national series	Counts of states that switched their time series on a day in March										
	(F-Test)	<6	6	7	8	9	10	11	12	13	14	>15
Foot traffic												
Noness. retail	13 (417.9)	1	0	0	14	3	0	0	0	23	9	1
Essential retail	14 (393.3)	0	0	0	0	0	0	0	1	38	6	6
Entertainment	8 (520.9)	1	1	4	26	3	6	4	1	3	1	1
Hotels	13 (414.2)	0	0	16	8	2	0	0	1	17	3	4
Restaurants	12 (375.4)	0	0	0	11	6	2	4	15	11	1	0
Business serv.	13 (357.6)	0	0	0	2	0	1	0	0	40	8	0
At home rate	10 (9118.2)	0	0	0	0	0	10	22	13	5	1	0

Notes: Each regression has 121 observations. All models exceed the critical value of the F-test at the p-value of 0.05 of 24.31 (Andrews, 1993).

Table 2

Estimated Impact of State Policy on Mobility 7, 14, and 21 days after Passage

	State of Emergency			Stay at Home			Gather >50 Ban			Public Schools		
	days after			days after			days after			days after		
	7	14	21	7	14	21	7	14	21	7	14	21
Foot traffic												
Noness. Retail	-0.112 ***	-0.122 **	-0.178 **	-0.167 ***	-0.198 ***	NA	0.026	0.014	0.019	-0.063 **	-0.054	-0.073
Essential Retail	-0.044 ***	-0.059 *	-0.099 **	-0.118 ***	-0.144 ***	NA	0.009	-0.012	-0.033	-0.031	-0.013	-0.012
Entertainment	-0.135 ***	-0.126	-0.138	-0.181 ***	-0.183 ***	NA	0.054	0.057	0.110	-0.089 **	-0.087 *	-0.113
Hotel	-0.232 ***	-0.205 *	-0.300 *	-0.109 ***	-0.092 *	NA	0.058	0.056	0.118	-0.133 ***	-0.171 **	-0.238 *
Restaurant	-0.114 ***	-0.090 *	-0.124 *	-0.124 ***	-0.137 ***	NA	0.065 **	0.061	0.074	-0.075 **	-0.062	-0.075
Business services	-0.100 ***	-0.098 **	-0.138 **	-0.168 ***	-0.213 ***	NA	0.049 *	0.058	0.075	-0.056 **	-0.054 **	-0.083 *
At home rate	0.014 ***	0.015	0.023	0.040 ***	0.049 ***	NA	0.002	0.009	0.006	0.021 ***	0.035 ***	0.047 ***
	Dine-in Ban			Entertainment Ban			First Death			First Case		
	days after			days after			days after			days after		
	7	14	21	7	14	21	7	14	21	7	14	21
Foot traffic												
Noness. Retail	-0.082 ***	-0.102 **	-0.079	0.000	-0.024	-0.074	-0.115 ***	-0.175 ***	-0.252 ***	-0.009	-0.023 *	-0.033 ***
Essential Retail	-0.022	-0.020	0.018	-0.010	-0.044	-0.124 ***	-0.053 ***	-0.081 ***	-0.126 ***	0.004	0.005	-0.011
Entertainment	-0.102 *	-0.142	-0.039	-0.038	-0.138 ***	-0.229 **	-0.148 ***	-0.231 ***	-0.358 ***	-0.030 **	-0.042 ***	-0.048 ***
Hotel	-0.214 ***	-0.201 **	-0.183	-0.031	-0.022	-0.047	-0.190 ***	-0.279 ***	-0.442 ***	0.008	-0.014	-0.030 *
Restaurant	-0.139 ***	-0.166 ***	-0.142 *	0.002	-0.023	-0.085 *	-0.099 ***	-0.155 ***	-0.224 ***	-0.025 ***	-0.028 ***	-0.034 ***
Business services	-0.060 *	-0.052	-0.024	-0.018	-0.033	-0.084	-0.136 ***	-0.201 ***	-0.275 ***	-0.025 *	-0.039 **	-0.047 ***
At home rate	0.017	0.013	0.001	0.010	0.017	0.040 **	0.025 ***	0.035 ***	0.046 ***	0.003	0.007 *	0.007 **

Notes: *, **, and *** denote statistical significance at the 1, 5, and 10 percent level. This table contains parameter estimates from seven regressions. Dependent variables are listed in the first column. Note that all foot traffic measures are logged. Mobility measures are regressed on a full set of days after policy dummies (see Equation 2), as well as time since first death and case dummies, though we only report effects at 7, 14, and 21 days in the table. See Figures A6-A13 for a complete set of effect sizes. Regressions include county and date fixed effects. Observation are weighted by the number of devices per county-day. Standard errors are clustered at the state level. Effects at 21 days after the Stay at Home order are not reported because we only estimate effects up to 19 days after the policy.

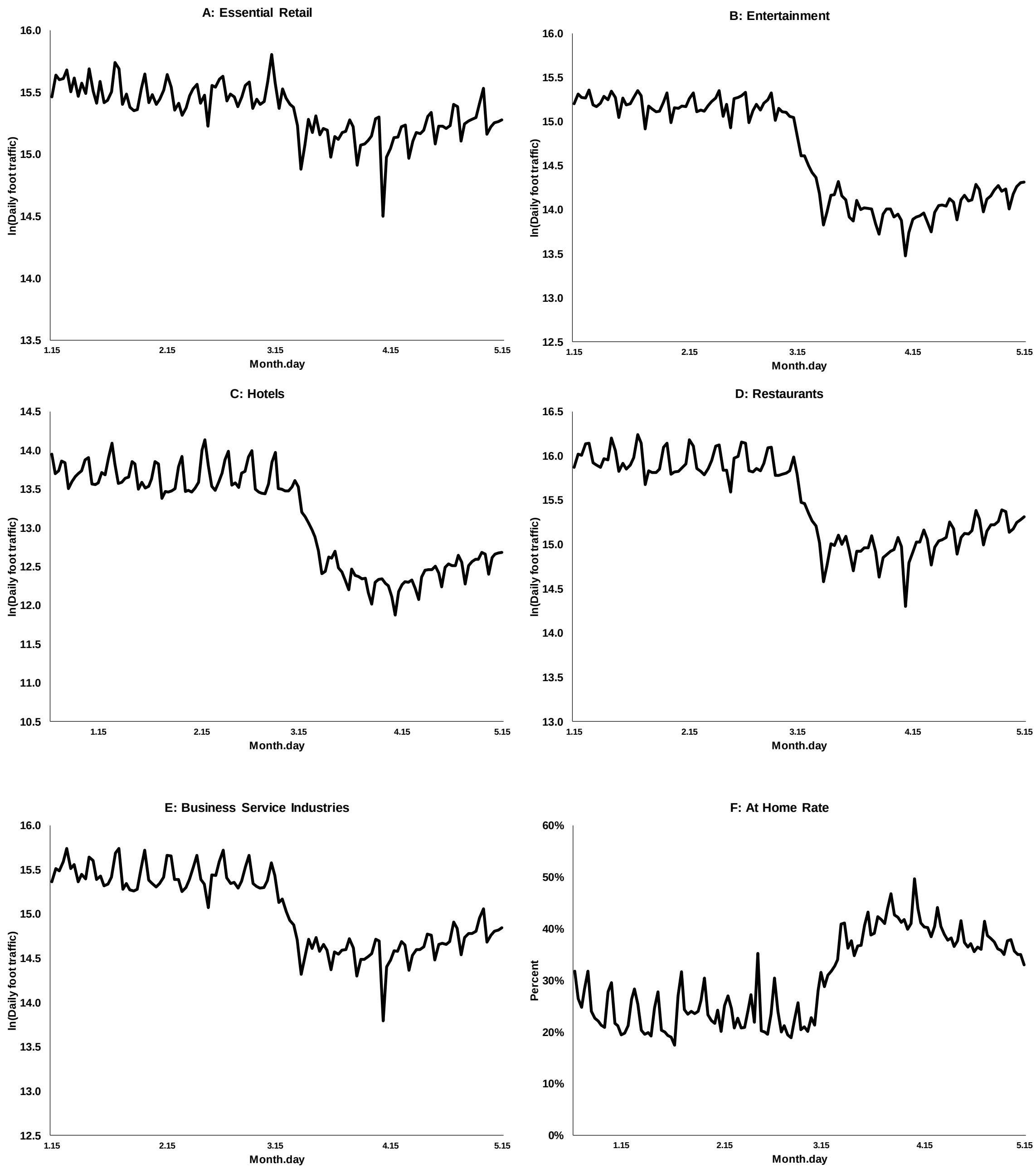
Table 3
Public Restrictions and Private Mobility Responses, SafeGraph Data

Outcomes	% or percentage point change in outcome 25-days after State of Emergency (1)	% Reduction in outcome at 25-days explained by: State of Emergency (2)	Stay at Home (3)	Other Orders (4)	Private Response =100%-(4)-(3) (5)
Foot traffic					
Noness. retail	-60.07%	16.11%	12.48%	13.91%	73.61%
Essential retail	-33.74%	27.69%	25.77%	23.28%	50.95%
Entertainment	-69.59%	7.45%	7.31%	11.92%	80.77%
Hotel	-74.71%	15.88%	3.35%	13.50%	83.15%
Restaurant	-65.46%	8.87%	6.93%	11.98%	81.09%
Business serv.	-60.05%	12.22%	12.77%	8.88%	78.35%
At home rate	0.17	16.00%	22.99%	49.73%	27.28%

Notes: The at home rate is the percentage of residents that stay home all day on a given day. Foot traffic is measured as the number of individuals visiting industry-specific firms on a given day. Firms are classified into industries via NAICS code. Baseline mobility is calculated using predicted average mobility in the 11-17 days prior to a state of emergency order. Other orders include bans on indoor dining, gatherings of more than 50 people, gyms and entertainment, and public school closures.

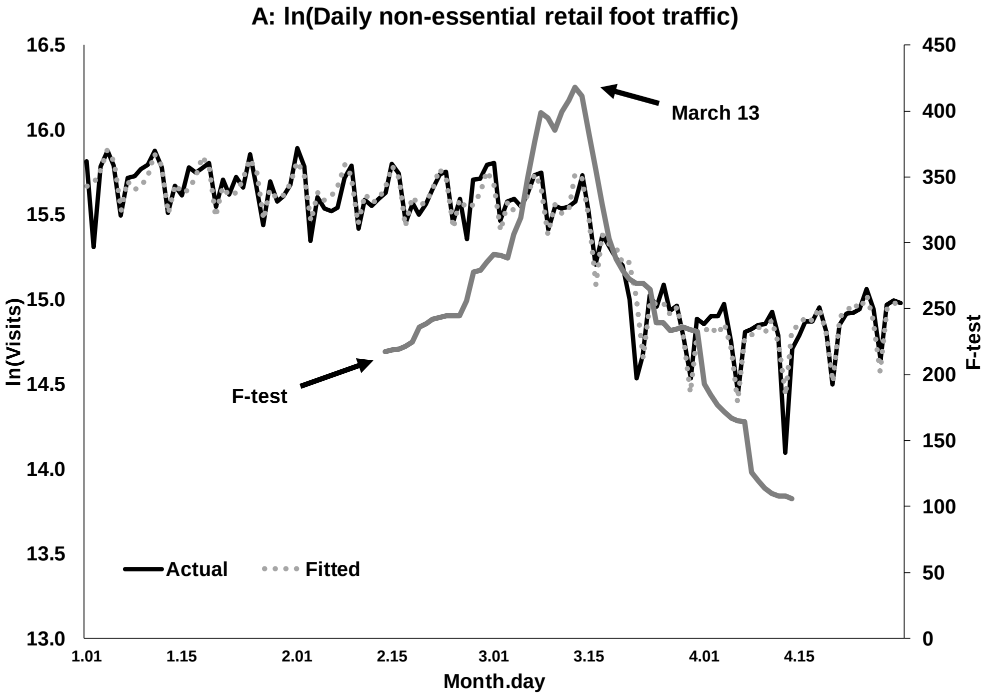
Appendix Figure A1

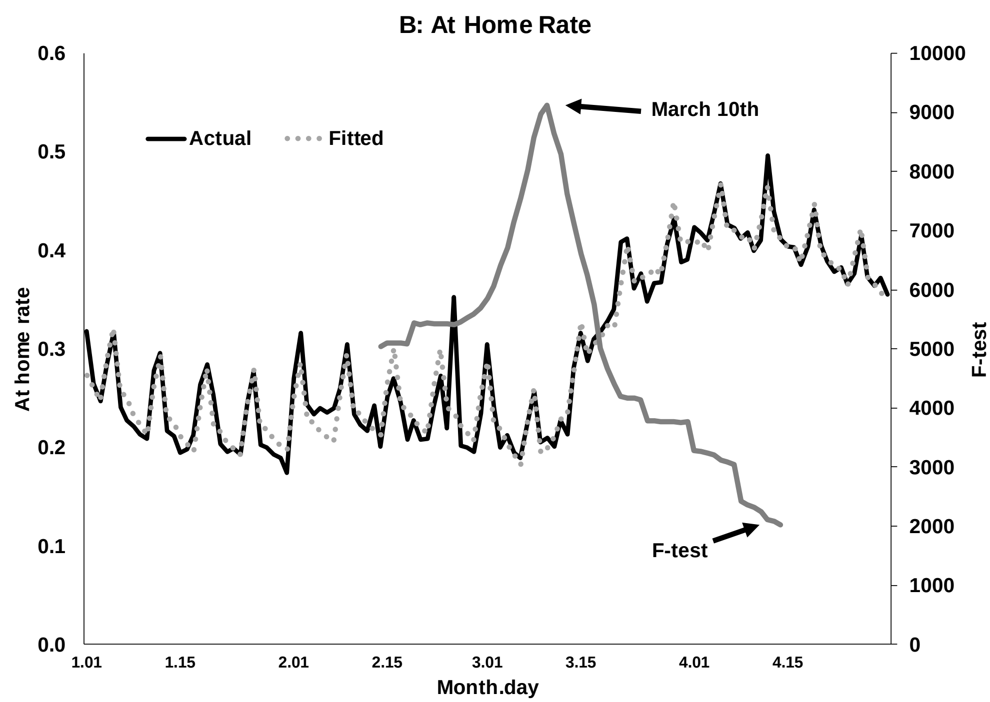
Natural Log of Daily Foot Traffic by Industry Group and the At Home Rate, 1/1/2020 to 5/15/2020, SafeGraph Data



Appendix Figure A2

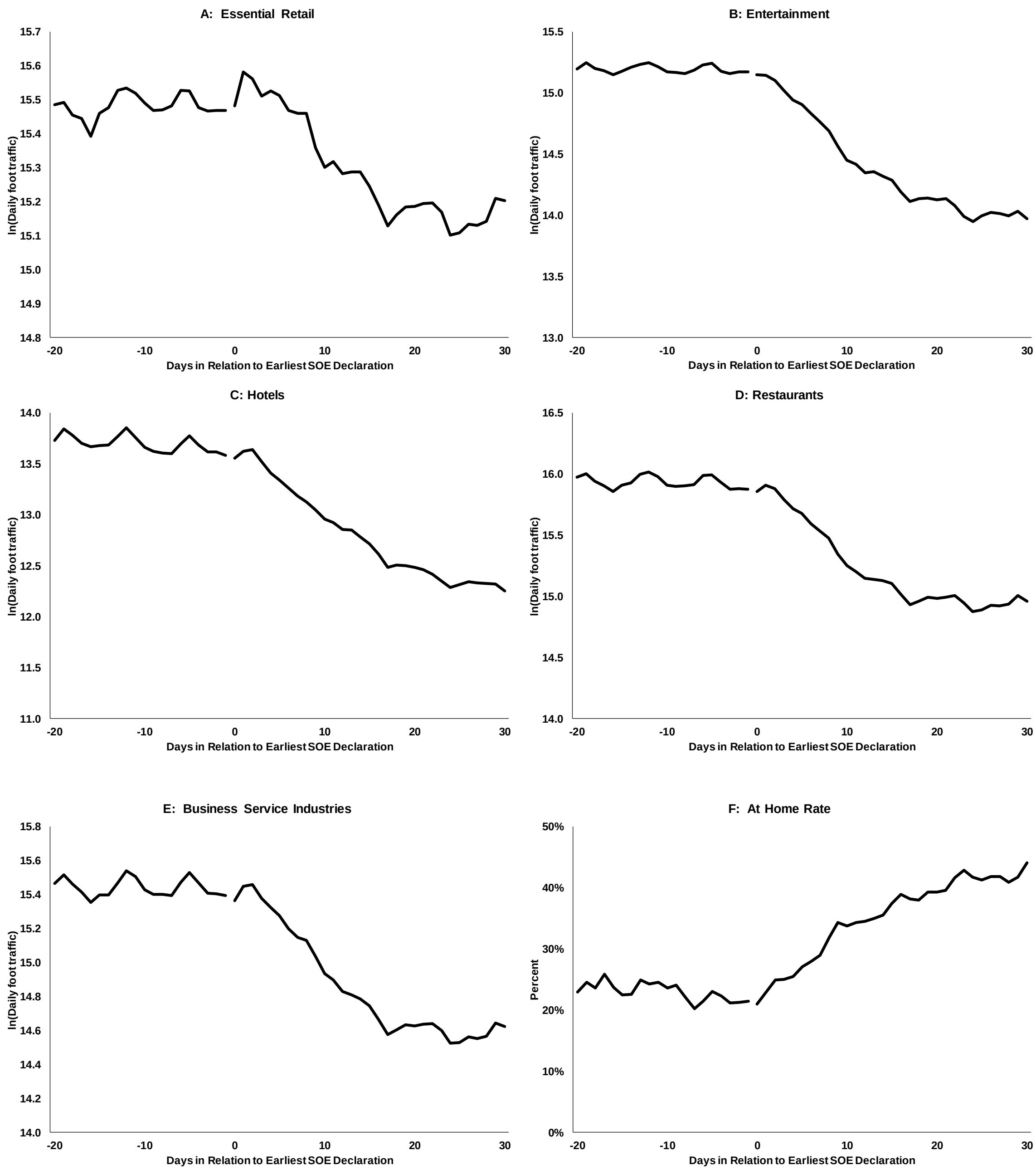
Actual Series and OLS Estimates of Equation (1) for Non-Essential Retail ln(Daily Foot Traffic) and At Home Rate at the Structural Break Period, and the F-test at Different Structural Breaks, SafeGraph Data





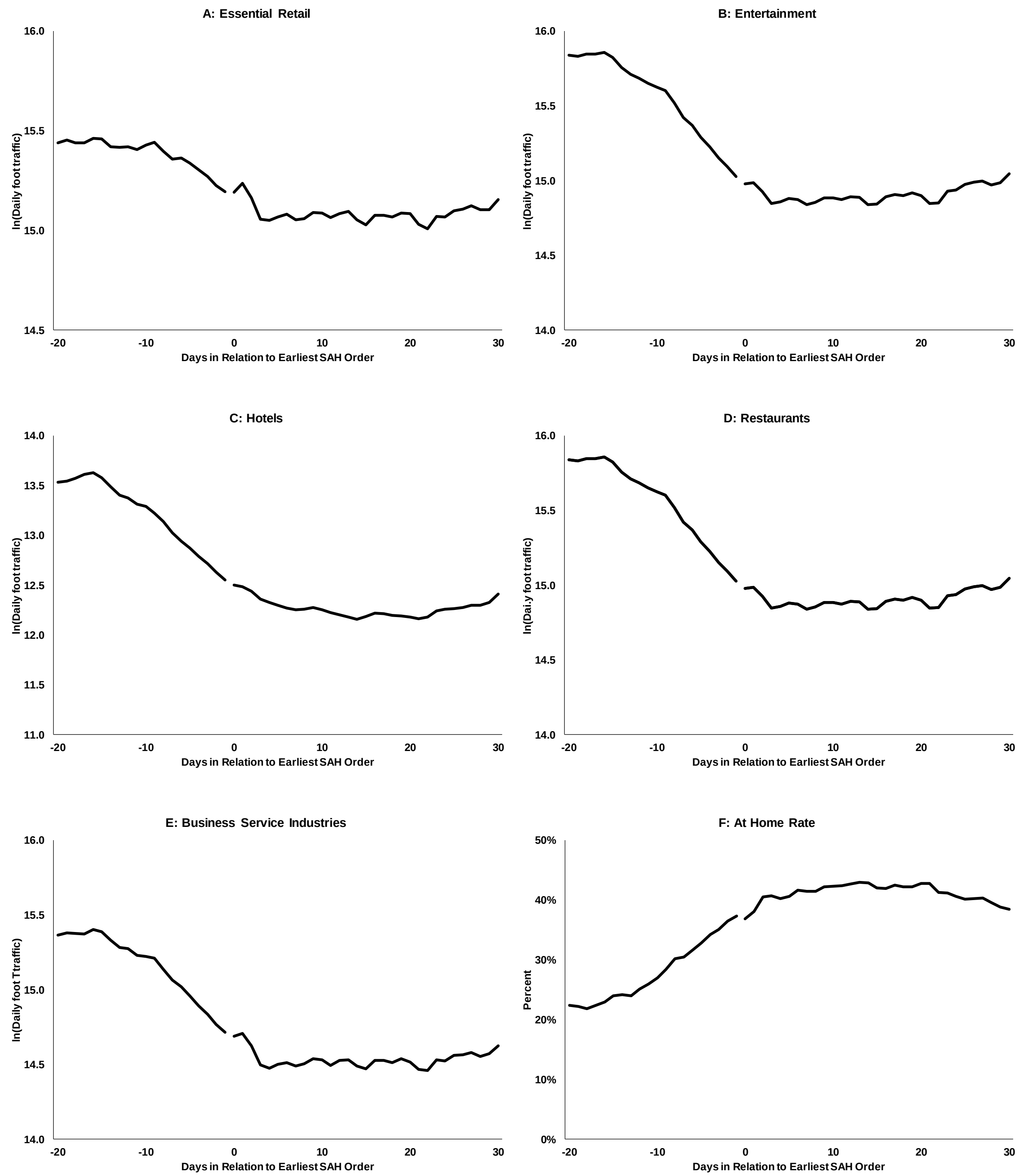
Appendix Figure A3

Natural Log of Daily Foot Traffic by Industry Group and At Home Rate,,
Indexed by the Days in Relation to the Earliest SOE Declaration, SafeGraph Data



Appendix Figure A4

Natural Log of Daily Foot Traffic by Industry Group and At Home Rate, Indexed by the Days in Relation to Earlies SAH Order, SafeGraph Data



Appendix Figure A5

Daily Foot Traffic Index (Day -1 = 1.00) and At Home Rate by Industry Group and County-Level SAH Status, Indexed by the Days in Relation to Earliest SOE Order, SafeGraph Data

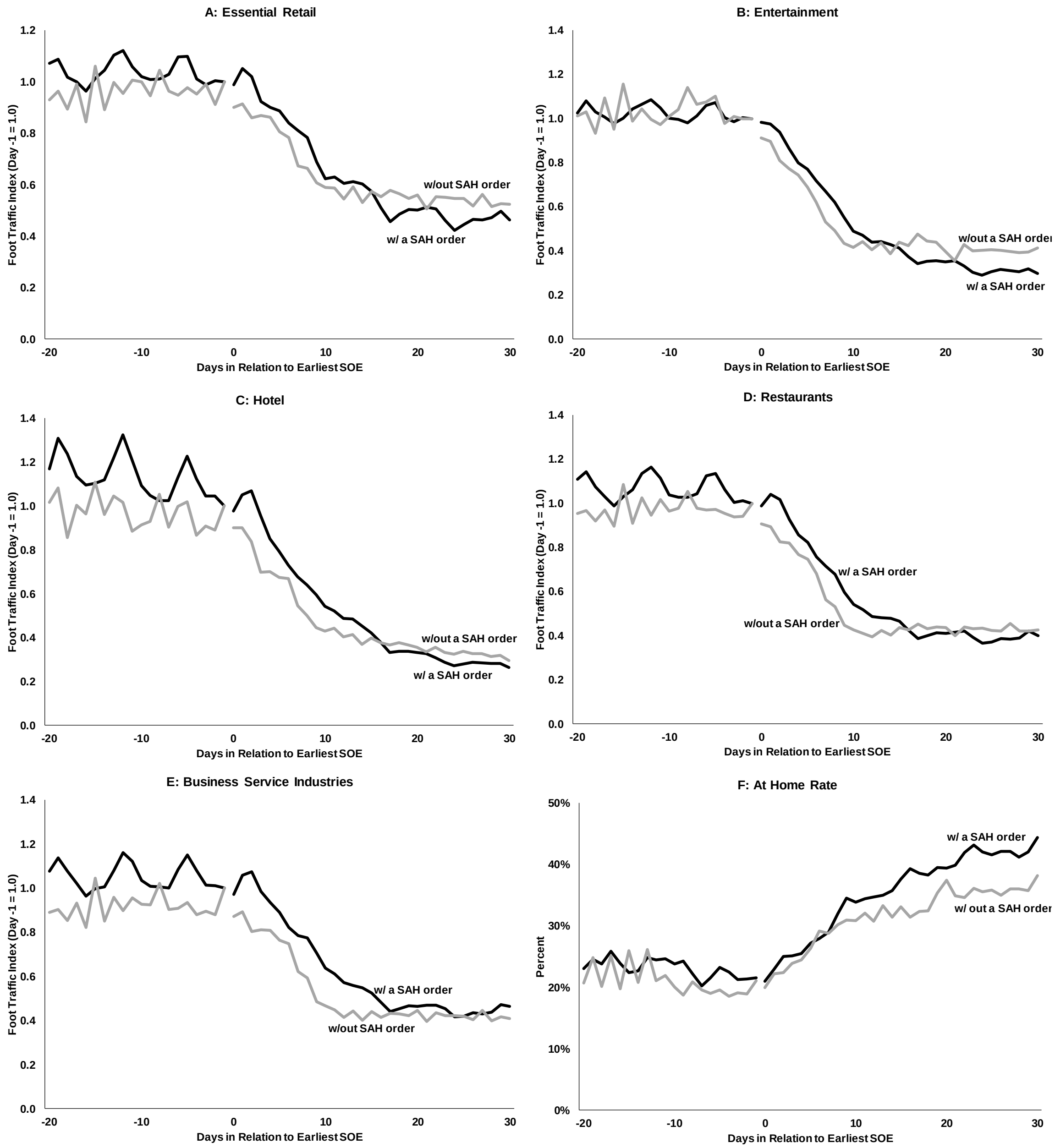
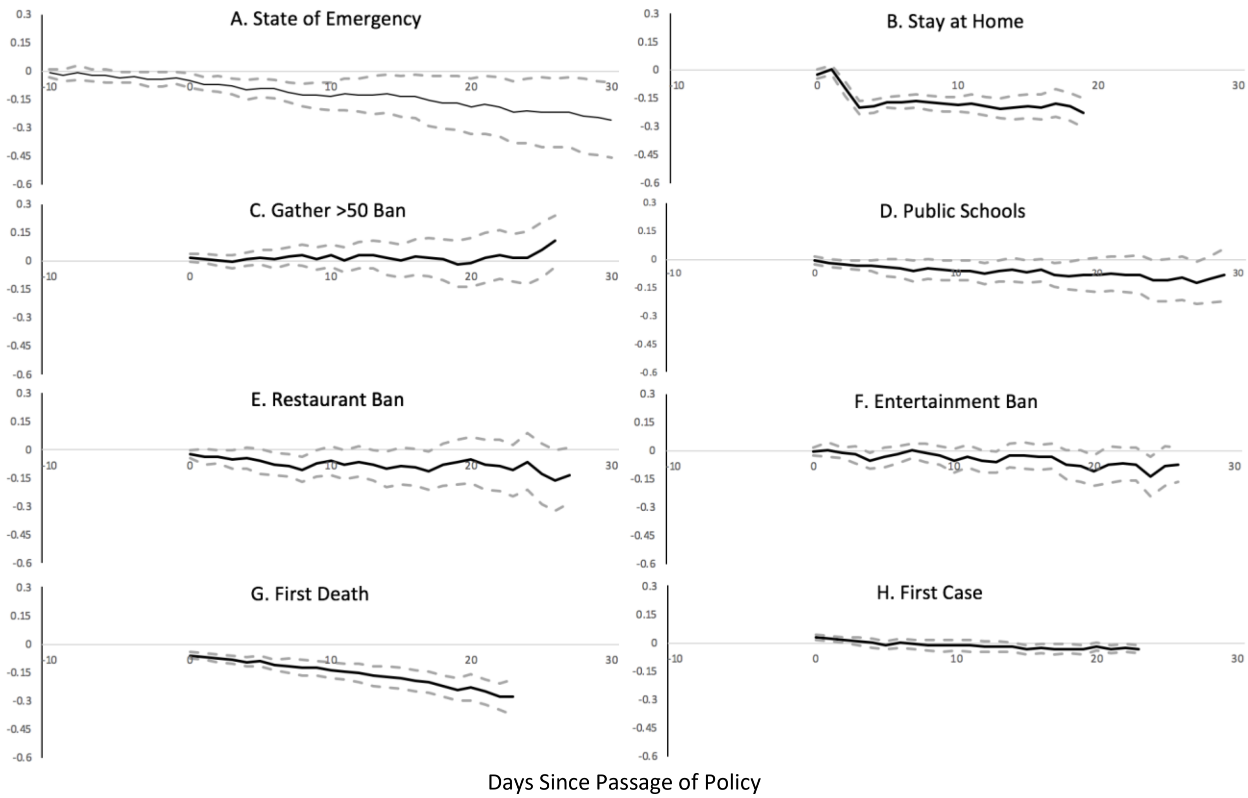


Figure A6

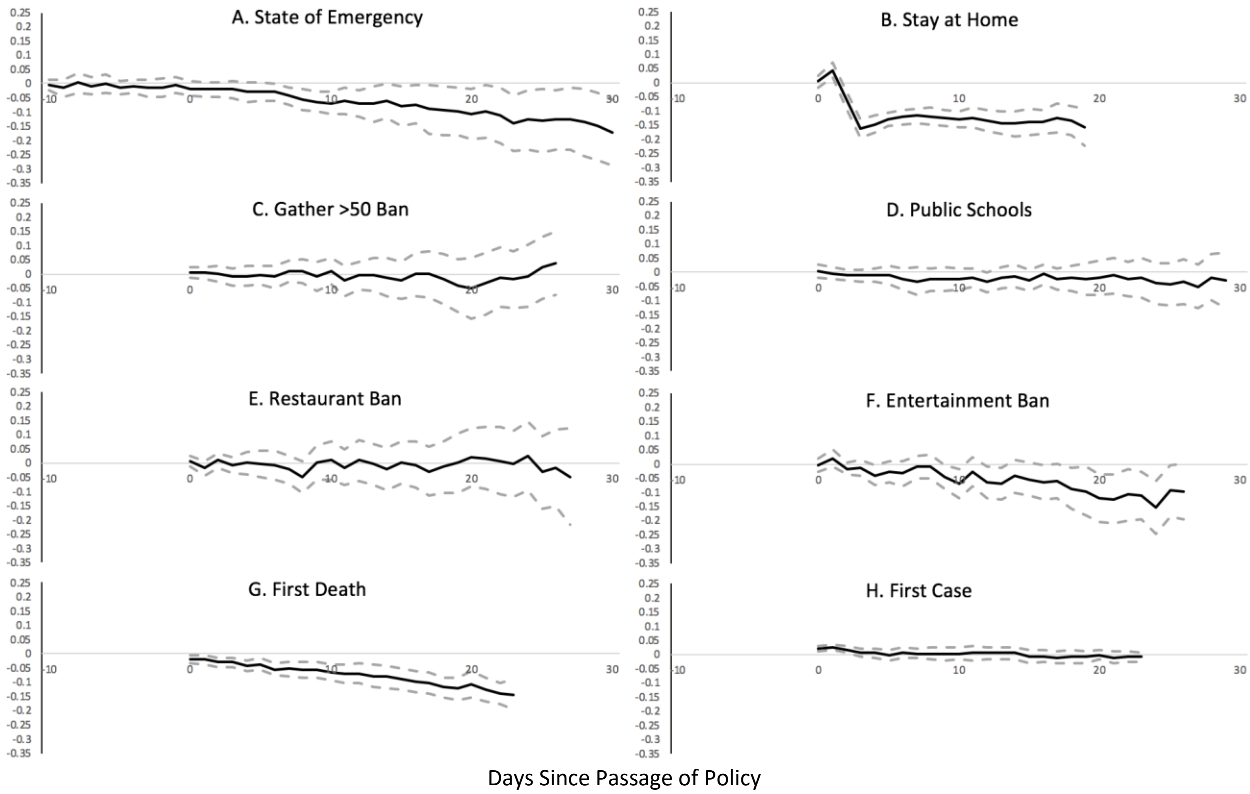
Policy, First Death, and First Case Impact on Nonessential Retail Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily nonessential retail foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Figure A7

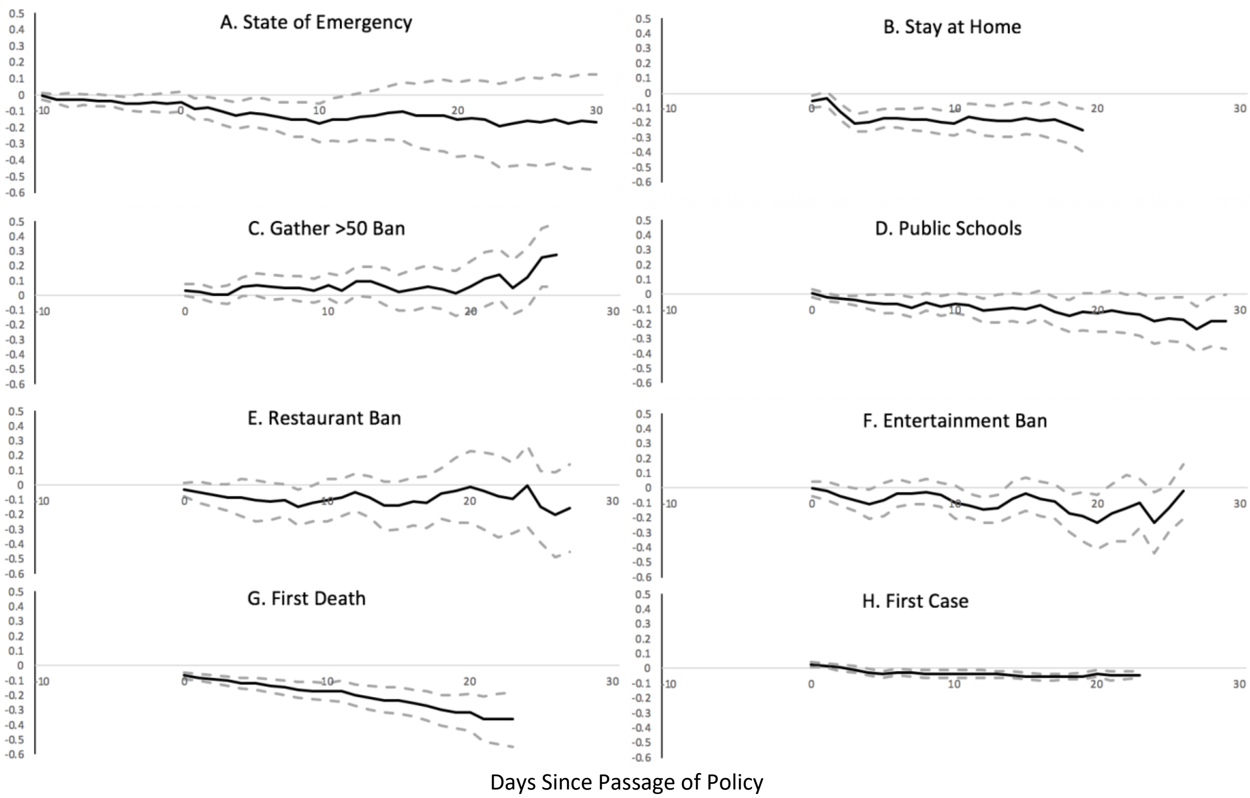
Policy, First Death, and First Case Impact on Essential Retail Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily essential retail foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Appendix Figure A8

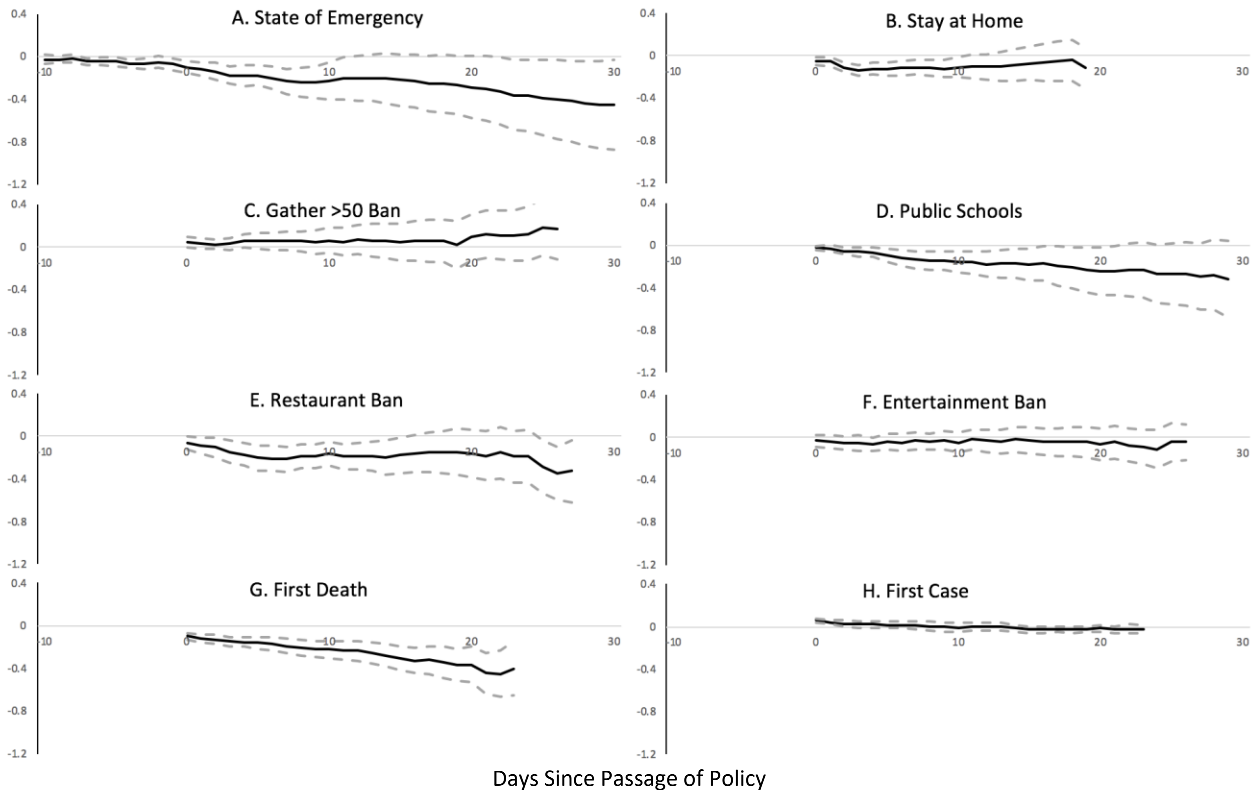
Policy, First Death, and First Case Impact on Entertainment Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily entertainment foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Figure A9

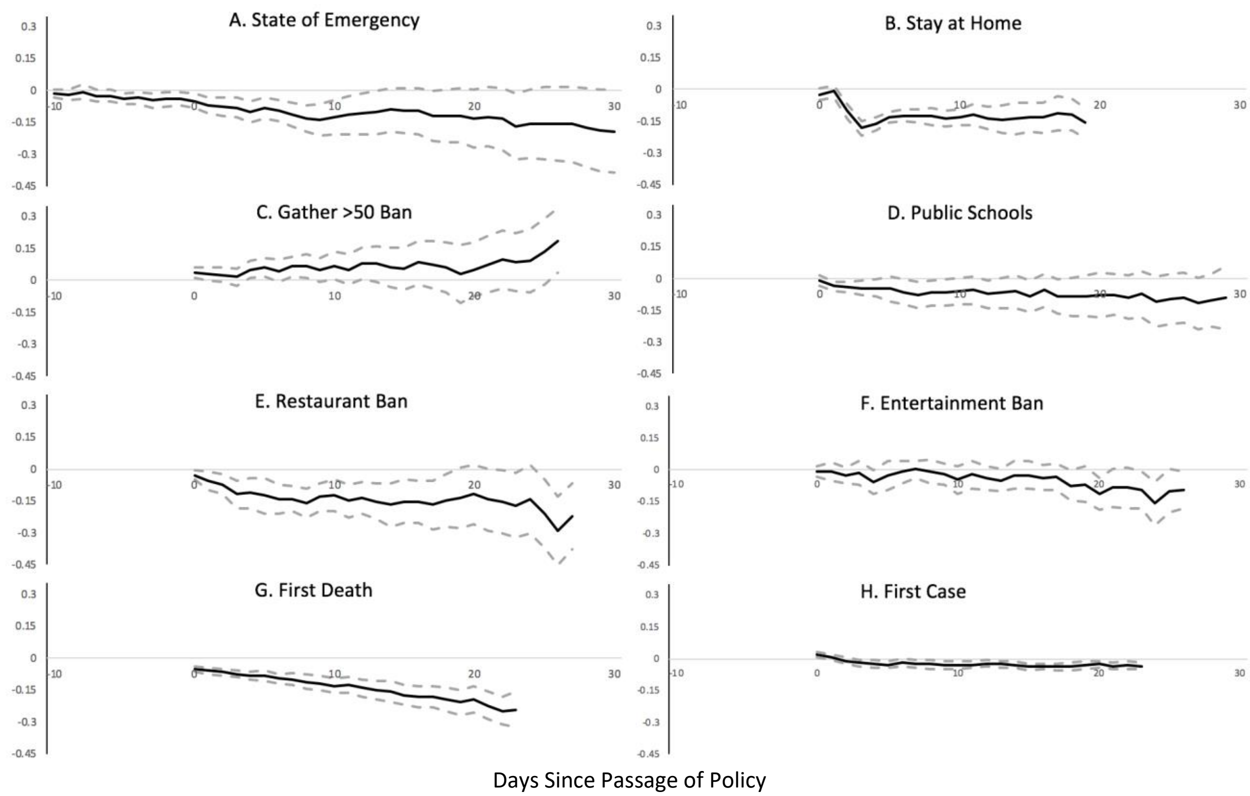
Policy, First Death, and First Case Impact on Hotel Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily hotel foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Figure A10

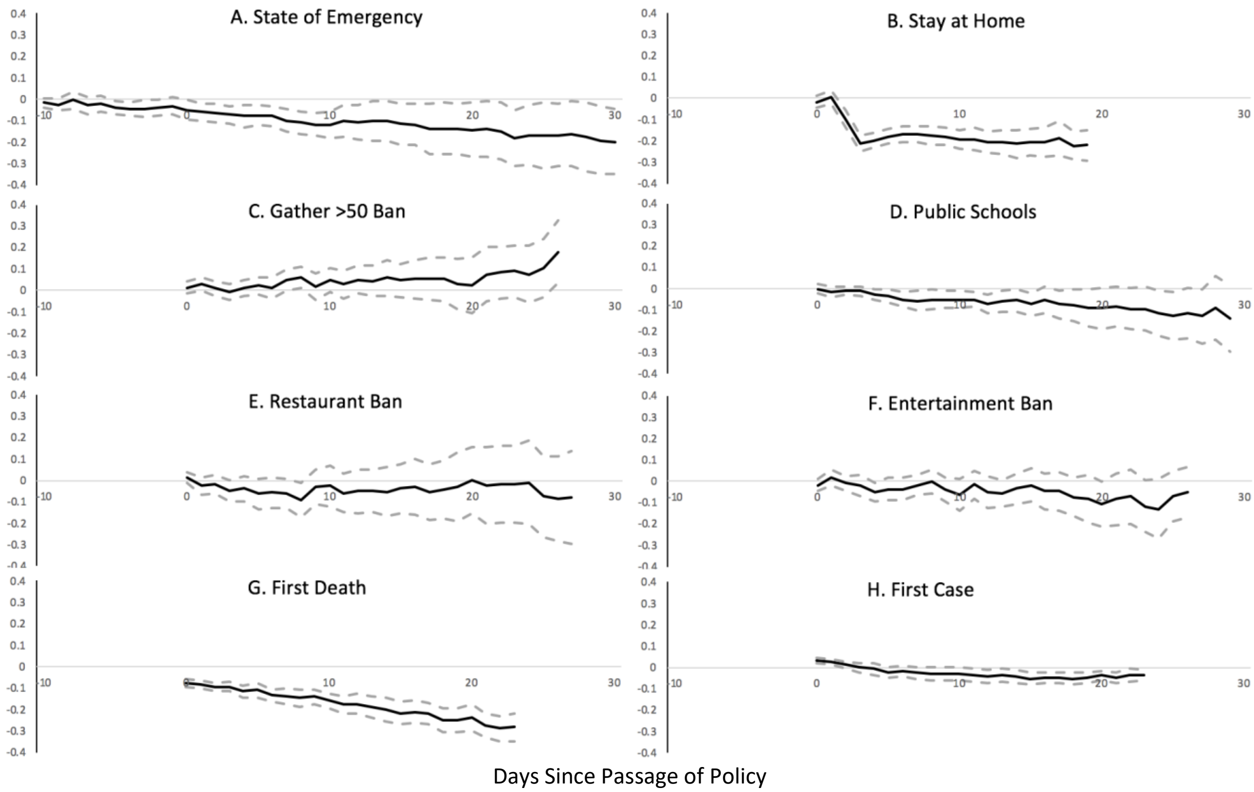
Policy, First Death, and First Case Impact on Restaurant Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily restaurant foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Figure A11

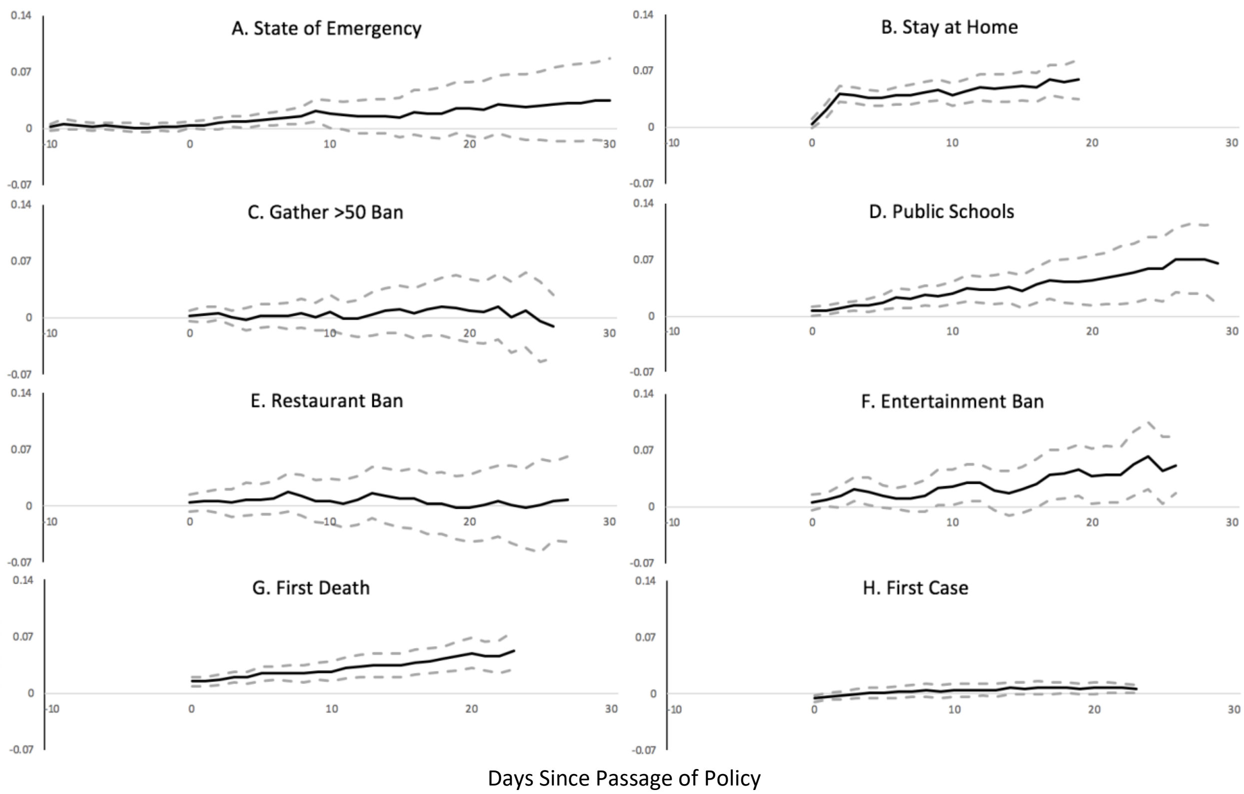
Policy, First Death, and First Case Impact on Business Services Foot Traffic, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of (logged) daily business services foot traffic on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Appendix Figure A12

Policy, First Death, and First Case Impact on Share of Population Staying at Home all Day, SafeGraph Data



Notes: This figure plots parameter estimates from a single regression of the share of the population that stays at their home for the entire day (i.e., "home share") on the days since each policy, first death, and first case occurred (see Equation 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects and weight by the number of devices. Standard errors are clustered at the state level.

Appendix Table 1
Timeline of Key Pieces of Information in the COVID-19 Pandemic in the US, Through 3/31/2020

Date	**Key Events/Milestones**
21-Jan	The United States announced its first confirmed coronavirus case — a man in his 30s in Washington state.
28-Jan	United Airlines suspends all flights to China from the United States.
30-Jan	WHO declared the outbreak a global public health emergency as more than 9,000 cases were reported worldwide, including in 18 countries beyond China.
31-Jan	The White House announced that it would ban entry for most foreign nationals who had traveled to China within the last 14 days.
8-Feb	The first U.S. citizen died from COVID-19 in Wuhan.
29-Feb	President Trump announced additional travel restrictions involving Iran and increased warnings about travel to Italy and South Korea.
29-Feb	The first recorded coronavirus death in the U.S., a man in his 50s in Washington state. Governor declares state of emergency
4-Mar	State of California Declares State of Emergency
6-Mar	President Trump signed an $8.3 billion emergency spending package to combat the coronavirus outbreak, as the number of global cases hit 100,000.
6-Mar	Austin, Texas, cancels the SXSW conference and festivals amid the coronavirus concerns, following the cancellation of other high-profile events across the country.
7-Mar	State of New York Declares State of Emergency
11-Mar	The World Health Organization declared that the coronavirus outbreak "can be characterized as a pandemic," which is defined as worldwide spread of a new disease for which most people do not have immunity.
11-Mar	The NBA suspended all basketball games after a player for the Utah Jazz preliminarily tested positive for COVID-19, the disease caused by the new coronavirus.
11-Mar	President Trump announced a new restriction on many foreign travelers from 26 countries in Europe, except for Ireland and the United Kingdom, for the next 30 days.
11-Mar	The University of Notre Dame suspends in-person classes
12-Mar	MLB announced that it will suspend spring training and delay the start of the regular baseball season by at least two weeks.
12-Mar	The NHL announced that it will pause its hockey season. The league's commissioner did not set an end date for the suspension.
12-Mar	The NCAA canceled both the men's and women's college basketball tournaments, known as March Madness, after most conferences suspended their postseason tournaments.

13-Mar	President Trump tweeted that some cruise lines, including Princess Cruises, Norwegian and Royal Caribbean, will suspend outbound trips, at his request, for 30 days.
13-Mar	President Trump declared a national state of emergency that could free up $50 billion to help fight the pandemic.
13-Mar	States across the U.S., including Michigan, Pennsylvania and Maryland, announced plans to close schools over the coronavirus concerns.
14-Mar	The English Premier League suspended the soccer season until at least April 3. The decision came amid other high-profile sports cancellations and postponements around the world, including the Melbourne F1 Grand Prix, the PGA Tour's Players Championship and the Boston Marathon.
15-Mar	The White House announced that the European travel ban would be extended to include the U.K. and Ireland.
15-Mar	Twenty-nine additional states, including New York, Massachusetts, South Carolina and Hawaii, announced school closures.
15-Mar	The C.D.C. recommended no gatherings of 50 or more people in the U.S.
16-Mar	MLB announced that the start of the season will be pushed back eight weeks, per guidance from the CDC.
16-Mar	President Trump advised all Americans to avoid gatherings of 10 or more people, to avoid going to bars and restaurants and to halt discretionary travel. The guidelines, from the administration's coronavirus task force, will remain in effect for 15 days.
16-Mar	NASCAR announced it would postpone all races until at least the beginning of May.
17-Mar	The Kentucky Derby was postponed until September, along with several other major sporting events, including soccer's 2020 European Championships.
17-Mar	West Virginia, the last state in the U.S. without a confirmed coronavirus case, recorded its first. Confirmed cases across the country rose to more than 5,800 and the death toll surpassed 100.
18-Mar	Canada and the U.S. agreed to close its borders to all "nonessential traffic."
18-Mar	The Trump administration suspended refugee admissions until April 6 due to the coronavirus pandemic.
18-Mar	President Trump signed a coronavirus aid bill into law. The Families First Coronavirus Response Act would provide free coronavirus testing and ensure paid emergency leave for those infected or caring for a family member with the illness, while also providing additional Medicaid funding, food assistance and unemployment benefits.
19-Mar	The U.S. State Department raised the global travel advisory to Level 4: Do Not Travel, warning Americans against traveling internationally and for those abroad to consider returning immediately.
19-Mar	California issued a statewide stay-at-home order asking residents to only leave the house if necessary.
20-Mar	The U.S. announced plans to close the border with Mexico to all "nonessential travel." Acting Homeland Security Secretary Chad Wolf said all immigrants who lack proper entry documentation will be turned away.

22-Mar	President Trump announced that he would activate the federal National Guard to assist Washington, California and New York, three of the states hit hardest by the pandemic.
24-Mar	Japan’s prime minister Shinzo Abe announced that the Tokyo 2020 Olympics will be postponed, adding that the games will be held by the summer of 2021.
25-Mar	The WHO warned that the U.S. could become the global epicenter of the coronavirus pandemic. The country recorded 54,810 coronavirus cases, including 781 deaths.
25-Mar	The 74th Tony Awards and the 2020 Rock and Roll Hall of Fame event were postponed. A new date for the Tony’s was not announced, but the Rock and Roll Hall of Fame event will now take place on Nov. 7.
26-Mar	The United States officially became the country hardest hit by the pandemic
26-Mar	The Indianapolis 500, the world's oldest automobile race, has been postponed until Aug. 23.
27-Mar	President Trump signed a $2 trillion coronavirus economic stimulus bill after the legislation was passed in a bipartisan vote in the House.
27-Mar	Coronavirus cases in the U.S. surpassed 100,000, the most in the world. More than 1,500 deaths were also reported nationwide.
28-Mar	The Centers for Disease Control and Prevention issued a travel advisory for New York, New Jersey and Connecticut, asking residents to refrain from nonessential travel for 14 days.
29-Mar	President Trump extended his administration's guidelines on social distancing until April 30.
31-Mar	The Federal Bureau of Prisons ordered a lockdown of its facilities in an effort to curb the spread of the coronavirus.