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Total shutdowns, targeted restrictions, or individual responsibility: How to promote social distancing in the COVID-19 Era? ☆

Christopher J. Cronin[a,*], William N. Evans[b]

[a] University of Notre Dame, IN, United States
[b] University of Notre Dame, NBER and J-PAL, United States

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ABSTRACT

We examine the impact of early state and local COVID-19 policies to encourage social distancing. Outcomes are daily foot traffic at establishments spanning ten key industries, across which transmission risk varies substantially. Policies include state of emergency declarations, blunt general restrictions such as stay-at-home (SAH) orders, and targeted rules such as restrictions on bars, restaurants, entertainment venues, and schools. Exploiting variation in the timing of policies in difference-in-difference models, we show that much of the decline in foot traffic early in the pandemic was due to private precautionary behavior. SAH orders explain almost none of the foot traffic decline in industries with high risk of virus transmission, but they do explain a substantial share of the decline in moderate- to low-risk industries such as outdoor sports and visits to parks. Targeted restrictions tend to impact intended industries, as well as complementary ones. We show that the impact of targeted restrictions is largest in counties with no SAH restrictions, suggesting that better targeting of public restrictions can have important efficiency gains.

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I. Introduction

In the early stages of the COVID-19 pandemic in the United States, state and local governments used a variety of emergency declarations to encourage social distancing. The broadest regulations were stay-at-home (SAH) orders that ask people to remain at home unless it is necessary to go out. Although the specifics of these orders varied across jurisdictions, necessary trips usually included shopping for food, going to work, seeking medical attention, or using essential services such as the post office, gas stations, car repair, etc.[1] In March and April of 2020, forty-three states and 294 counties adopted SAH restrictions, though almost all were relaxed during the late spring and summer of 2020. A surge of cases in the late fall and early winter of 2020 forced many jurisdictions to again

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* Corresponding author.
E-mail address: ccronin1@nd.edu (C.J. Cronin).

[1] Compared to some places outside the US, few US jurisdictions rigorously enforced (much less took punitive actions against those ignoring) local SAH restrictions. Thus, while SAH restrictions were imposing in that they applied to the broadest set of locations, behavioral responses to the policy should be interpreted as mostly voluntary.

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reconsider SAH measures. For example, on November 22, California adopted regional SAH restrictions that went into effect based on intensive care unit capacity.[2]

Stay-at-home restrictions have been the center of intense political debate. Many see them as a critical regulatory intervention to reduce the spread of the virus. In early April, the American Medical Association sent a letter to all governors urging states to adopt SAH restrictions.[3] Public support for SAH restrictions has been high throughout the pandemic. A nationwide survey of 2,200 adults by Morning Consult found that 69 percent of respondents supported SAH orders in June, falling only to 68 percent by November.[4] Despite their popularity in these surveys, many also consider SAH restrictions to be the cause of recent wide-spread economic dislocation. Alexander and Karger (2020) show that SAH restrictions reduced spending at small businesses and large retail stores. Moreover, protests against SAH restrictions have occurred in a number of states,[5] with court cases filed in numerous jurisdictions challenging the constitutionality of SAH orders.[6]

While SAH orders have received both praise and vitriol, academic research, mostly by economists, has questioned the impact of these orders on social distancing. A variety of scholars have examined the impact of these orders, including Alexander and Karger (2020), Abouk and Heydari (2021), Dave et al. (2020a and 2020b), Gupta et al. (2020a and 2020b), and Goolsbee and Syverson (2021). Gupta et al. (2020c) provide a detailed review of this literature. A large cross-section of this literature argues that the bulk of the decline in measures of social distancing that occurred in the early months of the pandemic was not due to SAH restrictions, but rather to voluntary precautionary behavior on the part of individuals. Goolsbee and Syverson (2021) estimate the impact of SAH orders on foot traffic across industries using an identification strategy that takes advantage of states in the same commuting zone that impose SAH orders at different times. Their work concludes that "legal shutdown orders account for only a modest share of the decline of economic activity." Exploiting the variation across states in the timing of SAH orders, Gupta et al. (2020b) conclude that information such as the first case in an area drove increased social distancing much more than SAH orders.

As the literature on what drives social distancing has advanced, so has our knowledge of how the virus is transmitted. Chang et al. (2020) use cell-phone records to model mobility and subsequent case counts and argue that 80 percent of COVID-19 infections can be traced to a small number of super-spreader locations such as restaurants, bars, gyms, hotels, and houses of worship. Using case-control methods Fisher et al. (2020) confirm the impact of eating and drinking establishments as a source of high transmissions. In contrast, surveillance data suggests that daycare centers (Gilliam et al., 2021) and elementary schools (Oster, 2020) are not particularly important sources of transmission. Likewise, outdoor activities appear to pose much lower risk to participants than virtually all indoor activities (Weed and Foad, 2020; Garcia et al. 2020; Bulfone et al., 2020). The data on supermarkets is mixed. A study by the Public Health Service in England found that among those that tested positive, the most frequent recent activity was shopping[7] and the result has been interpreted by many to suggest supermarkets are super-spreader locations.[8] Grocery store workers appear to be at a high risk of infection. A study of 104 grocery store employees in Massachusetts found an infection rate of 20 percent (Lan et al., 2020). Despite this, a study that examined an outbreak of COVID-19 among supermarket employees found high rates of transmission from employees to family members but low rates of infection among store customers (Zhang et al., 2020).

This research seeks to merge these two literatures by considering the efficiency of social distancing policies. The findings from recent research on establishment-specific transmission risk is mostly expected. Early in the pandemic, it was assumed that the virus was transmitted similar to other respiratory viruses (e.g., influenza), meaning tightly-packed indoor spaces where eating and drinking occurred should be more dangerous. Presumably, self-interested individuals would avoid such locations independent of policy. Less clear is the impact that blunt policy instruments, such as SAH restrictions, would have on industry-specific foot traffic. The heterogeneity in transmission risks across types of locations suggests that more targeted types of mobility restrictions might offer a more efficient way to increase social distancing. As such, we return to the question considered by many of the papers listed above and use cell phone records to estimate the impact of state and county COVID-19 policies, including SAH restrictions, on foot traffic. Unlike the existing literature, we focus on the differential effect that both targeted and non-targeted restrictions have on industries that expose patrons and employees to various levels of transmission risk. Consistent with Chang et al. (2020), we consider foot traffic patterns in 10 industries that we categorize into three different groups: higher transmission risk venues (restaurants, bars, hotels, churches, and indoor entertainment), medium-risk venues (essential retail, non-essential retail, and business services), and lower-risk venues (outdoor sports and parks). We also use one omnibus measure of social distancing: the fraction of cell phones that are home all day. All ten industry-specific foot-traffic measures declined substantially as the pandemic aged while the latter increased considerably.

We begin by documenting what others have found – much of the increase in social distancing is not attributable to SAH restrictions but, rather, precautionary behavior on the part of individuals. We show this in two ways. First, we use structural break models to show that the most dramatic declines in foot traffic occurred prior to the adoption of legal interventions. In particular, 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

[2] https://www.cnn.com/2020/12/05/us/southern-california-san-joaquin-stay-home-orders/index.html

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

[4] https://morningconsult.com/2020/11/30/covid-19-restrictions-polling-november/

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

[6] https://www.kff.org/coronavirus-covid-19/issue-brief/litigation-challenging-mandatory-stay-at-home-and-other-social-distancing-measures/

[7] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/936672/Weekly_COVID-19_and_Influenza_Surveillance_Graphs_w47.pdf

[8] https://www.independent.co.uk/news/uk/home-news/covid-supermarkets-uk-exposure-nhs-b1748906.html

in a very short period. For example, during the five-day window from March 8-12, all states saw a structural break in the fraction of cell phones that are home all day.

Second, we exploit state and county variation in the adoption date of specific social distancing orders in difference-in-differences models to estimate their impact on the mobility measures outlined above. The orders we consider are state of emergency declarations (SOE), public school closings, bans on dine-in restaurants, restrictions on entertainment, bans on gatherings above 50 people, and SAH restrictions. The business services industry is unique in that employers' decisions about employee remote work likely plays a larger role in driving the response than customer mobility. In all other industries, foot traffic likely contains a more even mix of individual customer responses and supply responses such as business closings. In these models, we control for county and day fixed effects, as well as quadratics in average daily temperature and precipitation at the county level. We illustrate that these controls are key in eliminating pre-treatment trends in event-study results present in some earlier studies. We then use these difference-in-differences results to decompose how much of the decline in foot traffic in the early stages of the pandemic can be attributed to precautionary behavior, SAH restrictions, and other industry-specific orders.

We report several key findings. First, from peak to trough, the decline in foot traffic is both massive and correlated with the risk-level of the establishment. We document declines between 67 and 84 percent for establishments that are higher risk and 41 and 69 percent for medium or lower risk. Second, unlike some work that finds no impact of government restrictions, we find that SAH restrictions explain between two and 25 percent of the mobility decline, depending on the mobility measure. Moreover, we are the first to show that the share of the decline explained by SAH orders is closely related to the riskiness of the activity. Almost none of the decline in foot traffic in high-risk establishments is due to SAH orders; however, a quarter of the decline in essential retail and 10-16 percent of the decline in outdoor activity is due to SAH orders. 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, but also in complementary industries such as hotels and indoor entertainment venues (e.g., movie theaters and bowling alleys). Fourth, after aggregating policy effects, we confirm that the majority of the decline in foot traffic is due to precautionary behavior rather than induced by policy.

These results indicate that precautionary behavior was tied closely with underlying risk, with individuals avoiding the riskiest venues the most. At the same time, the bluntness of the SAH order meant that the impact of the restriction was greatest in establishments with the lowest transmission risk. SAH orders never applied to essential retail but they reduce traffic in those venues by 25 percent. Likewise, SAH orders had a large impact on outdoor activity, which has little risk of transmission and may be beneficial if they allow exercise or an escape from the quarantine.

These results led us to consider whether more targeted policies could potentially have an impact. While our previous analysis showed that the most well targeted policy to date, restaurant dine-in bans, reduced restaurant foot traffic, most jurisdictions faced a SAH restriction shortly after their dine-in ban, potentially mitigating any long-run effects. To address this, we reduce the sample to the 455 counties facing neither state- nor county-level SAH restrictions, but a variety of other state-level restrictions, including restaurant dine-in bans. In these models, we find that restaurant dine-in bans yielded large, statistically significant reductions in restaurant foot traffic, without lowering foot traffic in unrelated industries. In fact, the estimated effect of this targeted policy in counties without a SAH restriction is more than twice as large as in counties with a SAH restriction. These results suggest that mobility restrictions targeted towards industries associate with higher virus transmission risk possibly offer a more efficient means of reducing virus spread than blunt SAH restrictions.

The remainder of this paper is organized as follows: Section II details the mobility and policy data used in our analysis. In Section III, we present basic time-series for industry foot traffic and social distancing, establishing that mobility declines began well in advance of most legislative actions. In Sections IV and V, we use difference-in-differences models to estimate the impact of both targeted and non-targeted policies on mobility. In Section VI we aggregate policy effects in order to calculate the total share of mobility declines attributable to public legislation. In Section VII, we estimate the effect of highly targeted restaurant dine-in bans in the absence of SAH restrictions. In Section VIII, we conclude and discuss future policy implications.

II. Data

We use 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. These data have been used extensively to measure various aspects of the pandemic.[9]

The SafeGraph data contain two data series. Weekly Places Patterns (V2.1) has hourly counts of foot traffic to about 4 million points of interest in the US. Locations have a corresponding NAICS code and we aggregate to the county-by-industry level. Following Chang et al. (2020), we consider ten industries that vary substantially in the transmission risk patrons and employees face in visiting an establishment. High-risk establishments typically involve large, indoor crowds partaking in risky activities such as eating, drinking, or singing. Such establishments include bars (NAICS code 722410), restaurants (7225), hotels (7211), churches (813110), and indoor entertainment and exercise venues, which we define as gyms (713940), bowling alleys (713950), movie theaters (512131), performance theaters (711110), and arcades (713120). At medium-risk establishments, patrons and employees are indoors, but typically interact in smaller crowds and/or with more physical distancing and are involved in less risky activities. Specifically, these are retail

[9] An incomplete list includes Allcott et al. (2020), Goldfarb and Tucker (2020), Anderson et al. (2020), Dave et al. (2020a and 2020b), Nguyen et al. (2020), Simonov et al. (2020), Gupta et al. (2020a and 2020b), and Goolsbee and Syverson (2021).

Table 1
Descriptive statistics for foot traffic and at home variables.

Industry		Counties w/ data	Daily average 1/15 – 3/7	Daily average 3/1 – 3/7	Daily avg. during lowest week ending 5/16	Dates of average lowest* week	% Δ from week of 3/1 – 3/7
Higher risk							
	Bars	1,161	341 (501)	319 (446)	52 (75)	4/12 - 4/18	-83.7%
	Restaurants	3,105	31,933 (51,726)	30,458 (48,303)	9,946 (15,729)	4/5 – 4/11	-67.3%
	Hotels	2,954	3,304 (5,528)	3,031 (4,837)	640 (1,009)	4/12 – 4/18	-78.9%
	Churches	3,086	2,108 (3,284)	1,927 (2,746)	546 (846)	4/12 – 4/18	-71.7%
	Indoor entertainment	2,663	7,415 (11,762)	7,036 (11,000)	1,297 (2,065)	4/12 – 4/18	-81.6%
Medium risk							
	Non-essential retail	3,115	22,461 (36,782)	21,341 (34,032)	7,867 (12,389)	4/12 – 4/18	-63.1%
	Essential retail	3,117	16,665 (25,035)	16,075 (23,779)	9,425 (13,532)	4/12 – 4/18	-41.4%
	Business services	3,097	19,792 (30,969)	19,204 (29,338)	6,875 (10,573)	4/12 – 4/18	-64.2%
Lower risk							
	Parks	2,805	5,054 (8,319)	5,026 (8,089)	1,534 (2,185)	4/12 – 4/18	-69.5%
	Outdoor sports	2,669	1,473 (2,533)	1,453 (2,420)	519 (919)	4/12 – 4/18	-64.3%
At home rate		3,133	0.234 (0.047)	0.227 (0.023)	0.432 (0.061)	4/5 – 4/11	90.3%

*Notes: For the at home rate, we use the highest weekly average. Means are weighted by county population. The sixth column calculates the lowest weekly average among the ten weeks following 3/7. The seventh column calculates the percent change from columns (5 and 4).

shopping and office settings. We decompose retail shopping into that which is essential – 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 merchandising[10] (452319), and pharmacies (446110) – and non-essential – which includes all retail establishments (2-digit codes 44 or 45) that are not essential. We label office-based establishments as business services, which includes: information (51); finance and insurance (52); real estate (53); professional, scientific, and technical services (54); and management of companies and enterprises (55).[11] Finally, low-risk establishments are outdoors and involve lots of physical distancing. This describes both nature parks (712190) and zoos (712130) as well as outdoor sporting venues, which we define as golf courses (713910), skiing facilities (713920), and marinas (713930).

We use a second SafeGraph series called Social Distancing Metrics (V2.1), which 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^2) for the device over a 6-week period.

Table 1 contains summary statistics for our ten foot traffic measures and the fraction of cell phones home all day. In the second column, we report the number of counties for which we have data. In the third column we report the mean and standard deviation of daily foot traffic in the pre-COVID period from January 15 through March 7th. The third column reports the 7-day average by industry for the week of March 1 to 7. In the fourth column, we identify the week with the lowest average daily foot traffic over the next 10 weeks and in the fifth column, the dates of that week. In the final column we calculate the percent difference between the lowest week (column four) and the first week of March (column three).

The table highlights several features of the data. Nearly all counties have restaurants, hotels, churches, essential and non-essential retailers, and business service firms. Only 37 percent of counties have bar foot traffic, 85 percent have outdoor sporting foot traffic, and 90 percent have park foot traffic. Comparing columns two and three, the first week of March was fairly representative of the early months of the year. Looking at the final three columns, the largest declines are observed in industries with the greatest transmission

10 This category includes large national retailers such as WalMart, Sam's Club, Costco, Dollar Store, Dollar Tree, and Family Dollar.

11 Any pandemic-related decline in establishment foot traffic results from a combination of demand and supply factors. On the demand side, people may be less willing to visit establishments as the pandemic takes hold. Likewise, this could be supply driven as some establishments close down or reduce hours. Among establishments discussed thus far, those offering business services are unique in that foot traffic is dominated by employees heading to work, meaning observed declines result in large part from the ability of these firms to offer their services virtually.

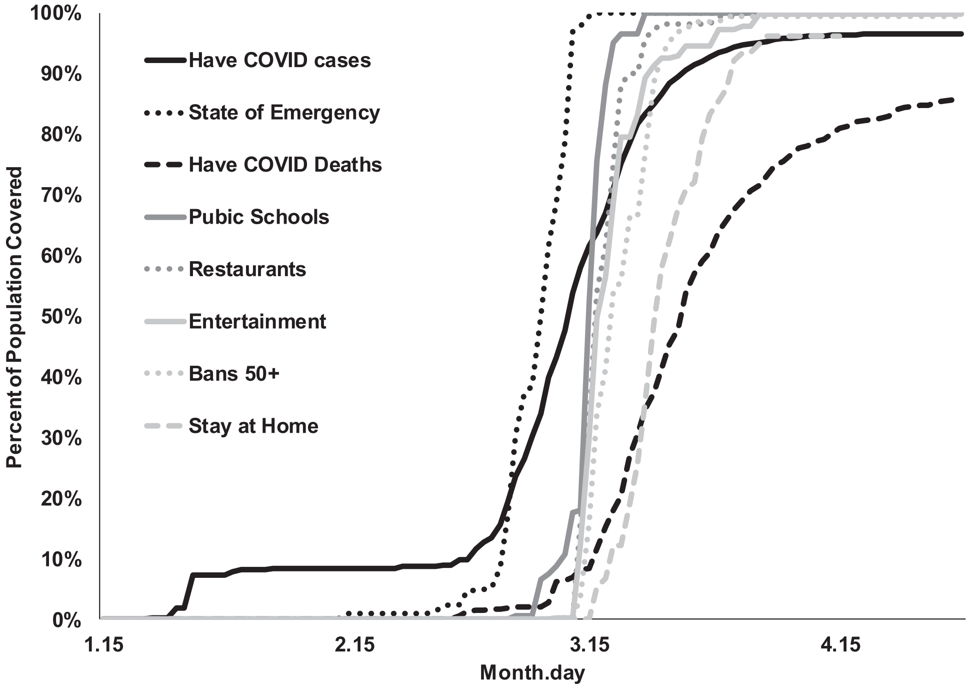

Fig. 1. Fraction of the Population Covered by Various Social Distancing Ordinances, and the Fraction that Live in a County that have experienced their First COVID-19 Case and Death.
Notes: The data are aggregated at the county level. Dates of restaurant, entertainment, and large gathering orders are 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.

risk; a 67 to 84 percent decline.[12] Setting aside essential retail, medium- and low-risk industries witnessed a smaller decline in foot traffic; a 63 to 69 percent decline. Essential retailers are unique in that the goods supplied by these firms have few substitutes. Given the essential nature of the goods and moderate transmission risk, it's unsurprising that these establishments would observe the smallest foot traffic decline at 41 percent. An interesting result is that all measures reach their lowest value in either the sixth (April 5-11) or seventh week (April 12-18).

We combine the cell phone data described above with a second data set containing the passage date of a variety of state and local orders designed to encourage social distancing. We gathered these data from a variety of sources: Johns Hopkins University COVID-19 webpage;[13] National Association of Counties;[14] Wikipedia,[15] and Education Week.[16] We reconciled discrepancies across sources with web searches. We collected passage dates on six 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. 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. Note further that the first three orders are also studied by Gupta et al. (2020b), while the latter three are not. For SOE, SAH, and school closure, we use the earlier date of either the state or the county restriction.

In Fig. 1, we report the fraction of the population (measured at the county level) in the US covered by these orders. 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.[17] This number increases rapidly to 93 percent by March 31. The first regulatory action is typically the declaration of SOE, which most commonly occurs following the state's first case, but

[12] The smallest decline among these high-risk locations is restaurants, which are unique among the group in that goods and services could still be provided via carryout. The decline in in-person dining is almost certainly larger.
[13] https://github.com/JieYingWu/COVID-19_US_County-level_Summaries/tree/master/data.
[14] https://ce.naco.org/?find=true.
[15] https://en.wikipedia.org/wiki/U.S._state_and_local_government_response_to_the_COVID-19_pandemic
[16] https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html
[17] It is now understood that cases (and to some extent, deaths) were substantially undercounted early in the pandemic. These dates represent the first reported cases. For the purposes of our study, the discrepancy between actual first case and reported first case generates no concern for bias, as individuals could only respond (with their mobility) to cases they knew about at the time.

prior to (9.5 days on average) the first death. On February 29, Washington reported their first COVID-19 death and declared a SOE the same day. Forty-six states declare emergencies in the nine-day period from March 5 through March 13; 100 percent of the population was covered by March 16.[18] These declarations impose no restrictions on individuals and firms. States and local governments can declare a SOE for 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 governing official authority to expend funds or deploy personnel, equipment, or supplies. In some cases, a SOE qualifies the state for federal resources.

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 quickly as SOE's but with a lag. The percent of the population covered by a school closure goes from 10 percent on March 12, to 50 percent just 3 days later, to and 99 percent by March 22. 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.[19] 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. County SAH restrictions often precede the state; of the 428 county SAH restrictions we identify, 294 precede the state's restriction. About four percent of the population is never covered by a SAH restriction.[20] Of the counties with SAH restrictions, they occur on average 15.8 days after a SOE declaration and three days prior to the county's first death.

III. Some basic times series data about social distancing and foot traffic

We outline some basic results in a set of four graphs, Fig. 2a-2d, which report data for nonessential retail as an omnibus example. We report corresponding data in the appendix for foot traffic in the other nine industries and for the fraction of cell phones home all day, which show very similar patterns.

In Fig. 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 rebounds some after mid-April. In Appendix Fig. A1 we report daily foot traffic for the nine other industries outlined above and the daily at home rate over the same time interval. We group the graphs by industry transmission risk with high-risk (bars, restaurants, hotels, indoor entertainment, and churches), medium-risk (essential and non-essential retail and business services), and low-risk (parks and outdoor sports) industries in separate graphs. The final graph in Fig. A1 is for the at home rate. These mobility series mirror that of nonessential retail with several commonalities. First, there is a pronounced weekly pattern with mobility spikes on weekends. Second, most series seem to "break" the week prior to March 15, a topic we return to below. Third, all series bottom out in 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).

Fig. 1 indicates that most social distancing orders occurred after March 15 while the results in Figs. 2a and Appendix Fig. A1 suggest that most series start declining before that date. We can date when these 11 national time series break using techniques from times series analysis that identify when a likely regime switch occurred.[21]

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

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

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 and k.

We report in Table 2 the results for the 11 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 shows that the structural breaks all occur in a short window from March 8 to 14, well before most restrictions occur in Fig. 1, and well before most SAH restrictions. In all cases, we can easily reject the null hypothesis. The timing of the structural break is sharp. In Appendix Fig. A2 we report the actual time series (black line) and the OLS estimate of Eq. (1) at the optimal break point (dotted light gray line) for two series: the natural log of nonessential retail visits and the at home rate. On each graph, we also

[18] County SOE declarations most commonly follow the state's, meaning the state's SOE takes precedence; of the 865 local SOE declarations we identify, only 22 precede the state declaration.

[19] There are some exceptions: 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.

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

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

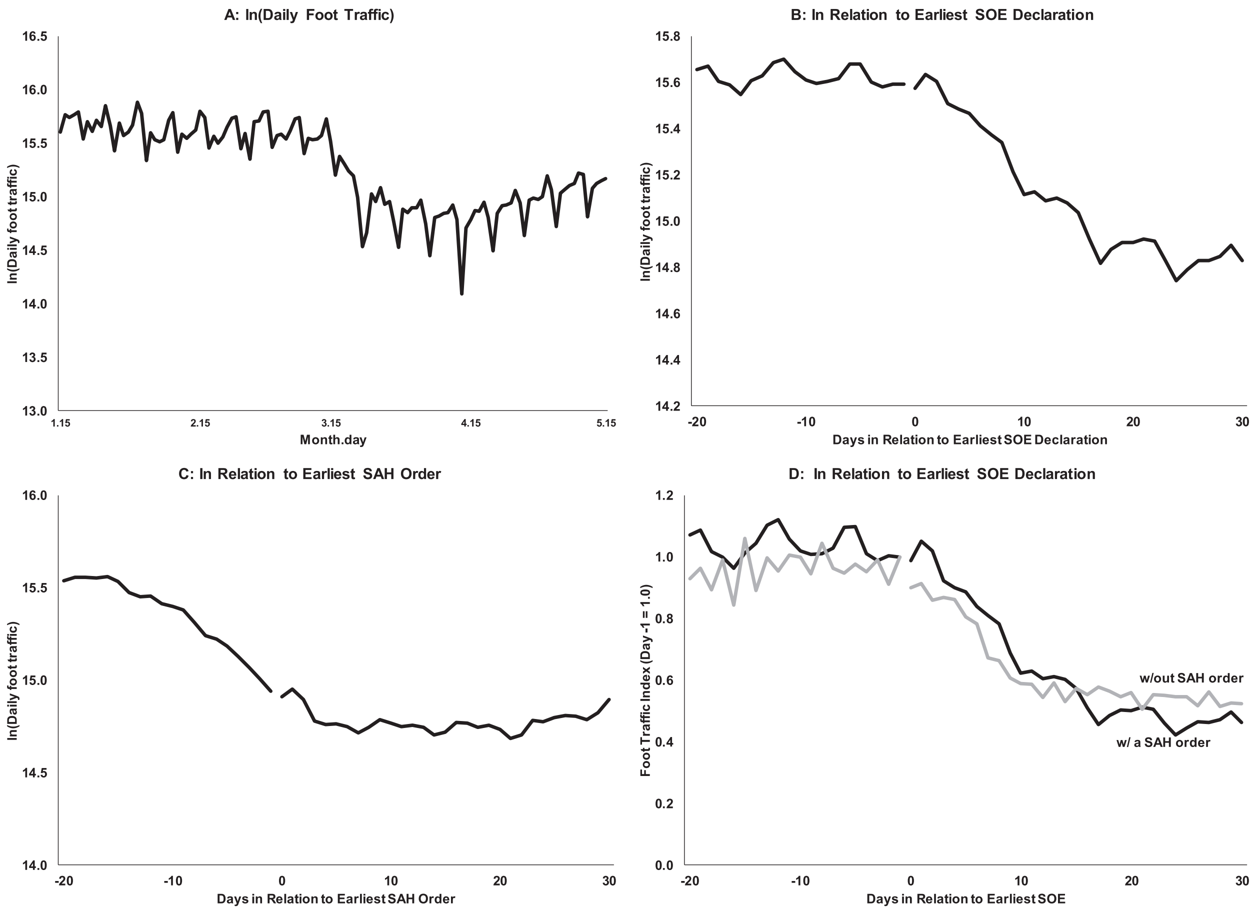

Fig. 2. The natural log of daily foot traffic for nonessential retail stores, for various groupings, SafeGraph Data.

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.

For each of the mobility series in Table 2, we estimate Eq. (1) for each state. On 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. Among high-risk establishments, 80% of the series break between March 8 and 13. In the two-day period from March 13-14, medium-risk nonessential retail, essential retail, and business service series all break for 31, 46, and 48 states, respectively. All 51 jurisdictions break for the at home rate in the five-day period March 8-12. Among low-risk establishments, the state-level structural breaks are notably more dispersed across time than high- and medium-risk establishments. One interpretation is that this pattern reflects rationality by citizens; namely, individuals responded to the onset of pandemic news by reducing travel to the most dangerous establishments, but not safer ones.

The similarity across states in the break points for high- and medium-risk establishments 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 concern, including the WHO declaring COVID-19 a pandemic, the NBA, NHL, Premier League all suspend operation, and a federal foreign travel ban.

Most of these regime changes are occurring when states are declaring SOEs, potentially providing evidence that citizens responded to a government signal that the crisis will be problematic locally. In Fig. 2b, 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 continue 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 Fig. A3, we report similar graphs for the other industries and the at home rate, in the same order as in Appendix Fig. A1. This exercise illustrates there was a dramatic drop in foot traffic across industries following the SOE and an equally large increase in the at home rate. In some cases, there is 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).

Table 2
Switch points in various daily time series, SafeGraph Data, 1/1/2020 – 4/31/2020.

Series	Day switch in March for national series (F-Test)	Counts of states that switched their time series on a day in March: <5	6	7	8	9	10	11	12	13	14	≥15
Foot traffic												
Higher risk												
Bars	13 (239.1)	1	0	0	10	0	0	4	13	9	9	5
Restaurants	12 (376.0)	0	0	0	10	6	2	4	16	11	2	0
Hotels	13 (414.2)	0	0	16	8	2	0	0	1	17	3	4
Churches	11 (254.9)	0	0	0	0	2	20	13	3	5	0	8
Indoor Enter.	11 (356.5)	0	0	0	15	7	2	17	7	3	0	0
Medium risk												
Noness. retail	13 (418.6)	1	0	0	14	3	0	0	0	23	9	1
Essential retail	14 (392.3)	0	0	0	0	0	0	0	1	13	33	4
Business services	13 (357.6)	0	0	0	2	0	1	0	0	40	8	0
Lower risk												
Parks	8 (575.0)	7	2	8	15	3	6	3	2	1	1	3
Outdoor sports	8 (372.5)	5	2	3	5	2	6	2	3	7	4	12
At home rate	10 (9118.2)	0	0	0	6	8	15	21	1	0	0	0

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

In Fig. 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 Fig. 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 Fig. 2c and Appendix Fig. A4, SAH restrictions appear to play a role in encouraging social distancing. In Fig. 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 measure, SAH played a limited role. We reproduce this finding in Appendix Fig. A5 for the ten other mobility measures. These graphs suggest that SAH orders enhanced the decline in foot traffic, with noticeable impacts in entertainment, essential retail and the at home rate. By far the biggest difference in series is for parks and outdoor sports where SAH impacts appear to be quite large. We verify the results from these graphs in the regression models below.

IV. Main empirical specification

We next consider whether the intuitive results from the figures above hold up under a more structured econometric analysis. The problems are two-fold. First, Fig. 2b and Appendix Fig. 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, Fig. 2c and Appendix Fig. 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. Define X_c as the date that policy X was passed in county c. We then define $POL^X_{ct} = t - X_c$, which measures the days since the policy's passage – e.g., $POL^X_{ct} = -7$ a week before policy X passes, $POL^X_{ct} = 0$ the day policy X passes, and $POL^X_{ct} = 7$ a week after policy X passes. Our econometric specification is then

$$Y_{ct} = \sum_{h=1}^{7} \sum_{j=-7}^{T^h} \beta_j^h 1_{\{POL^h_{ct}=j\}} + \gamma W_{ct} + \alpha_c + \delta_t + \varepsilon_{ct} \tag{2}$$

Where W_{ct} controls for a set of weather variables, α_c is a county fixed effect, δ_t is a date fixed effect, and ε_{ct} is the econometric error.[22] We measure the impact of five policies, denoted by h, and estimate separate policy effects, β_j, for each day pre- and post-passage.[23] County and state policies are not passed in a vacuum. Local infections and deaths influence policy timing, as well as

[22] We control for average temperature and total precipitation on the county-day, allowing both linear and quadratic effects. We also divide the country into quadrants by latitude and allow the temperature effects to vary by latitude. We thank John Davis for assistance in collecting these data, which can be accessed here: https://www.kaggle.com/johnjdavisiv/uscountiesweather2020?select=US_counties_weather_2020.csv

[23] The five policies are SOE, SAH, public school closure, restaurant dine-in bans, and entertainment bans. In early iterations of this paper, we also considered the impact of policies banning gatherings of 500 or more and 50 or more people. These policies routinely show no impact on mobility when analyzed in isolation and, at times, generated multicollinearity issues when analyzed along-side the other policies. As such, we do not consider these policies in the current manuscript.

individual decision making. As such, we also control for the time since first COVID-19 case ($h = 6$) and time since first COVID-19 death ($h = 7$) 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. For each county, we include all days between February 15 and 30 days post-SOE, meaning the reference period for each policy effect is the time between February 15 and eight days prior to the policy's passage. Because our panel is unbalanced, different counties are exposed to non-SOE policies for different lengths of time. As a result, the total number of estimated post-policy effects varies by policy.[24] We drop counties with no foot traffic over the course of the sample period for the industry in question. In all models, we weight observations by the county population. We cluster standard errors at the state level.

Note that industry foot traffic is transformed using the inverse hyperbolic sine function because the counts are both highly skewed and zeros are prevalent for certain establishments (e.g., bar and church traffic is low on weekdays). As the function closely mirrors the natural log, coefficients can be loosely interpreted as percentage changes in mobility caused by the policy.

Our use of county fixed effects in an event-study design that simultaneously controls for multiple policies distinguishes our analysis from others in the literature.[25] Conducting analysis at the county, rather than state, level is important because while only 9 percent of US counties passed SAH restrictions ahead of their state, the counties that did so are large, containing 30 percent of the US population. As such, conducting analysis at the state level using state SAH dates, as in Gupta et al. (2020b), assigns 30 percent of the US population the wrong date. When Gupta et al. (2020b) conduct robustness analysis at the county level using (i) county dates and (ii) no controls for other policies, cases, or death (see Figure 6c), they show significant pre-policy effects for some outcomes, such as the share of the population that stays at home all day, an outcome we also consider. In Appendix Fig. A6, we show that across virtually all of our outcomes, county-level event studies that do *not* control for other policies, first case, and first death display substantial pre-policy mobility changes. Controlling for these confounding effects eliminates the pre-policy effect in our main specification, highlighting the importance of these controls.

V. Event study results

Given the large number of coefficients associated with the estimates of model (2), we present the event study results in a series of graphs. The estimates for non-essential retail are presented in Fig. 3 to illustrate the structure of the graphs. The estimates for the remaining outcomes are reported in Appendix Figures A7-A16. In Fig. 3, we present a different graph for each of the five policies plus the days in relation to the first death and the first case. In each of these seven graphs, we report the subset of regression coefficients from Eq. 2 where the dependent variable is the inverse hyperbolic sine of nonessential foot traffic. In the top graph in the second column, for example, the plotted coefficients measure, relative to baseline, the daily impact of the SAH order on foot traffic. The dashed grey lines measure the 95% confidence interval for each parameter estimate.

A few brief words about the Fig. 3 and Appendix Figures A7–A16. First, for the five policy variables, there are no persistent pre-treatment trends in outcomes. This stands in stark contrast to what happens when we consider SAH restrictions in isolation (Appendix Fig. A6), as many papers have done, where in that case there are large pre-treatment trends. There are noticeable pre-treatment trends in the first COVID cases and deaths but we are not attaching a causal interpretation to these results. Instead, we use these as control variables in the regressions to soak up trends. Second, multi-collinearity is a relevant concern given the close timing of many of these ordinances. With near multi-collinearity, the $(X'X)$ matrix approaches singularity and the standard errors increase, so a standard diagnostic is imprecise results. This is not the case. In the restaurant models, SAH, restaurant bans and SOE orders are all statistically significant. In the at home models, SAH and public-school closures have statistically significant effects.

Given the sheer number of coefficients estimated in these 11 event studies, in Table 3 we summarize our estimates across mobility measures by reporting regression coefficients 7, 14, and 21 days post-policy. There are several important findings. First, the SOE declaration has little sustained impact on mobility. Seven days post declaration, restaurants, hotels, nonessential retail, and business services all have significantly lower foot traffic, but these effects do not persist to the 14-day mark. This suggests that the breaks in mobility trends outlined in Table 2 are best explained by national news and overall fear of the virus; i.e., though the Fig. 2a and A3 suggest SOE declarations were important in reducing foot traffic, they were not. On the other hand, the SAH restriction significantly reduced mobility to all locations by 14 days after passage. Fig. 2 and Appendix Figs. A7-A16 show that the SAH response tends to be immediate and grows little over time. Moreover, the figures show little evidence of mobility changes pre-SAH.

Closing public schools is found to have no statistical impact on industry foot traffic 14 days post-policy, but has 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.

We find that restaurant dine-in bans, which are notably more targeted than SAH restrictions or public-school closures, have large effects on restaurant foot traffic. Two weeks post-policy, the ban yielded a roughly 11 percent reduction in traffic. Interestingly, the dine-in bans led to large reductions in foot traffic in complementary industries as well. For example, the dine-in ban reduced foot traffic in indoor entertainment venues, which are often visited in conjuncture with restaurants on evenings out (e.g., dinner and a movie), and hotels, which often contain restaurants; i.e., some of the foot traffic categorized as hotel traffic is truly restaurant traffic.

[24] 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; entertainment and gym ban, 26; restaurant dine-in ban, 27; and public-school closure, 28.

[25] Goolsbee and Syverson (2021) do not estimate event-studies and focus only on commuting zones that span jurisdictions facing differing legal restrictions. Alcott et al. (2020) conduct their analysis at the CSA level, excluding any county not located in a CSA.

Table 3
Estimated Impact of State Policy on Mobility 7, 14, and 21 days after Passage.

	State of Emergency days after			Stay at Home days after			Public Schools days after			Dine-in Ban days after		
	7	14	21	7	14	21	7	14	21	7	14	21
Foot traffic												
Higher Risk												
Bars	-0.038	0.055	0.164	-0.098	-0.081 *	NA	-0.170 **	-0.144	-0.113	-0.080	0.060	0.194
Restaurants	-0.047 **	-0.005	-0.001	-0.123 ***	-0.134 ***	NA	-0.065	-0.040	-0.037	-0.084 **	-0.114 **	-0.103
Hotels	-0.100 **	-0.036	-0.065	-0.105	-0.065 *	NA	-0.144	-0.163	-0.200	-0.204 ***	-0.206 **	-0.197
Churches	0.050	0.108	0.150 *	-0.062	-0.075 *	NA	-0.106	-0.081	-0.074	0.100	0.127	0.239 *
Indoor Enter.	0.050 *	0.133 **	0.227 ***	-0.186 ***	-0.219 ***	NA	-0.070 *	-0.021	-0.021	-0.139 *	-0.210 *	-0.274 **
Medium Risk												
Noness. Retail	-0.043 **	-0.033	-0.052	-0.165 ***	-0.196 ***	NA	-0.057	-0.041	-0.045	-0.048 *	-0.072	-0.073
Essential Retail	-0.022	-0.025	-0.046	-0.107 ***	-0.140 ***	NA	-0.018	0.002	0.015	-0.002	-0.004	0.007
Business services	-0.051 **	-0.041	-0.067	-0.162 ***	-0.199 ***	NA	-0.037	-0.029	-0.038	-0.017	0.001	0.019
Lower Risk												
Park	-0.073	-0.080	-0.097	-0.155 ***	-0.130 *	NA	-0.029	0.028	0.063	0.042	-0.014	0.135
Outdoor Sports	-0.045	-0.085	-0.079	-0.191 **	-0.263 **	NA	-0.026	0.031	0.076	0.051	-0.082	0.038
At home rate	0.003	0.003	0.006	0.045 ***	0.055 ***	NA	0.021 **	0.034 **	0.045 **	0.006	0.003	-0.007

	Entertainment Ban days after			First Death days after			First Case days after		
	7	14	21	7	14	21	7	14	21
Foot traffic									
Higher Risk									
Bars	-0.067	-0.056	-0.042	-0.236 ***	-0.358 ***	-0.435 ***	0.021	-0.031	-0.062 **
Restaurants	-0.004	-0.025	-0.074 *	-0.119 ***	-0.175 ***	-0.242 ***	-0.001	-0.004	-0.021 **
Hotels	-0.028	-0.009	-0.015	-0.242 ***	-0.334 ***	-0.492 ***	0.061 ***	0.033 *	-0.006
Churches	-0.092 *	-0.119	-0.202 **	-0.145 ***	-0.207 ***	-0.303 ***	0.014	-0.015	-0.035 **
Indoor Enter.	-0.075	-0.095	-0.134	-0.155 ***	-0.212 ***	-0.290 ***	-0.066 ***	-0.073 ***	-0.068 ***
Medium Risk									
Noness. Retail	-0.007	-0.027	-0.067	-0.132 ***	-0.189 ***	-0.270 ***	0.025	0.010	-0.015
Essential Retail	-0.009	-0.040	-0.112 ***	-0.055 ***	-0.083 ***	-0.134 ***	0.026 *	0.024 *	-0.005
Business services	-0.014	-0.030	-0.073	-0.165 ***	-0.224 ***	-0.306 ***	0.016	0.001	-0.024 *
Lower Risk									
Park	0.008	0.050	0.042	-0.138 ***	-0.196 ***	-0.265 ***	0.037 *	0.047 ***	0.019
Outdoor Sports	-0.124 *	-0.180 *	-0.402 **	-0.138 ***	-0.184 ***	-0.356 ***	0.071 **	0.040	-0.008
At home rate	0.009	0.012	0.033 *	0.027 ***	0.036 ***	0.044 ***	-0.006	-0.002	0.001

Notes: *, **, and *** denote statistical significance at the 1, 5, and 10 percent level. This table contains parameter estimates from eleven regressions. Dependent variables are listed in the first column. Note that all foot traffic measures are transformed using the inverse hyperbolic sine. Counties with zero foot-traffic counts over the sample period are dropped. 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 A7-A17 for a complete set of effect sizes. Regressions include county and date fixed effects, as well as weather controls. Observation are weighted by the county population. 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.

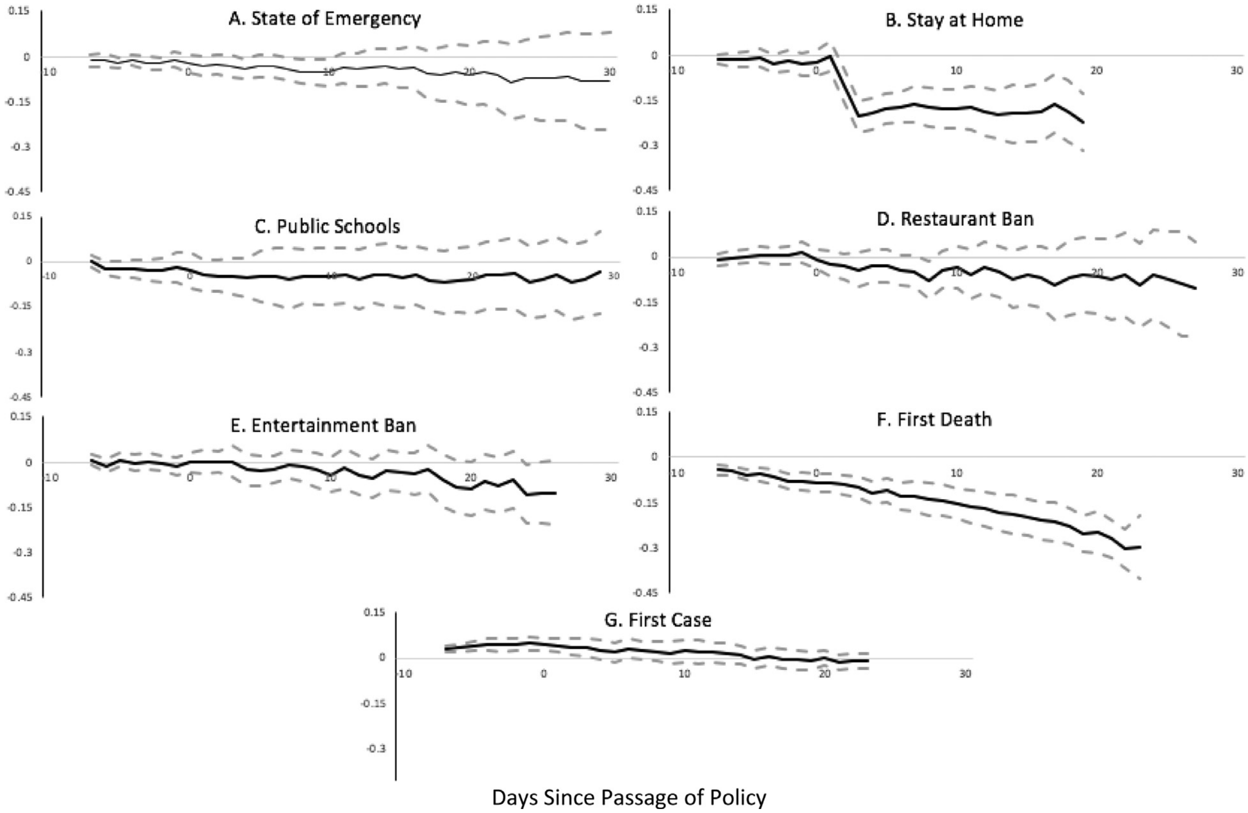

Fig. 3. Policy, First Death, and First Case Impact on Nonessential Retail Foot Traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily nonessential retail foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

The entertainment ban reduced foot traffic to indoor entertainment venues, but the decrease is not statistically different from zero. One likely reason is self-regulation – movie theater and bowling alley trips are in no way essential, so patrons didn't need policy makers to tell them to avoid these more dangerous locations. Another possibility is that many entertainment bans focused on "live entertainment", which makes up a small share of indoor entertainment. Interestingly, the entertainment ban significantly reduced foot traffic to churches and outdoor sporting facilities. The lion's share of outdoor sporting facilities are golf courses and/or country clubs, many of which regularly host live entertainment. The impact on churches is interesting; though not targeted explicitly by the entertainment ban, it's likely that churchgoers found bans focusing on live entertainment to suggest that church attendance was also high risk.

Finally, the first death in the county has a very large and statistically significant impact on all mobility measures, while first case has no impact; however, these estimates should be interpreted with caution, as most models show significant mobility declines prior to the first death, which accelerate following the death. In most cases, the impact of the first death is larger than any single policy effect and grows over time.

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.[26] We report the aggregate change in the outcome of interest from this baseline period in column (1) of Table 4. 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 the fraction of the total change in mobility attributable to SOE declarations, SAH restrictions, and all other policies, reported in columns

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

Table 4
Public restrictions and private mobility responses, SafeGraph Data.

Outcomes	% or percentage point change in outcome 25-days after	% Reduction in outcome at 25-days explained by:			
	State of Emergency (1)	State of Emergency (2)	Stay at Home (3)	Other Orders (4)	Private Response= 100%-(4)-(3) (5)
Foot traffic					
Higher Risk					
Bars	-82.51%	-3.58%	1.66%	1.10%	97.23%
Restaurants	-65.38%	0.69%	6.88%	10.33%	82.79%
Hotels	-74.61%	3.87%	2.82%	14.21%	82.97%
Churches	-70.62%	-5.77%	2.59%	1.87%	95.54%
Indoor Enter.	-77.98%	-6.73%	5.44%	10.07%	84.50%
Medium Risk					
Noness. Retail	-60.40%	5.00%	12.30%	10.93%	76.77%
Essential Retail	-33.84%	14.50%	24.98%	11.61%	63.41%
Business services	-59.79%	6.15%	12.62%	4.91%	82.46%
Lower Risk					
Park	-54.93%	10.59%	10.28%	-9.16%	98.88%
Outdoor Sports	-56.77%	9.12%	16.38%	18.23%	65.40%
At home rate	0.18	5.06%	25.34%	34.69%	39.97%

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 average mobility in the 11-17 days prior to a state of emergency order. Other orders include bans on indoor dining, gyms and entertainment, and public school closures.

(2)-(4), respectively.[27] 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).

In the first column, we present the percentage change. Putting aside visits to essential retailers, the column shows a monotonic, positive relationship between transmission risk and foot traffic decline – the most dangerous places saw the biggest declines and the safest places saw the smallest declines. As mentioned above, foot traffic to essential retailers is unique because essential retail goods have more limited substitutes, such as online delivery, meaning any changes in foot traffic would represent a more extreme action taken by individuals, independent of the risk involved. Moreover, few essential retailers closed, meaning supply reductions are less likely to contribute to overall mobility declines. As such, one might expect to find, as we do, that foot traffic changed least for this measure.

A second key result is in the third column. Our estimates show that SAH restrictions explain between just 2 and 7 percent of the total mobility decline to high-risk locations. Given the controversy surrounding these restrictions, these effects seem incredibly small. Put differently, if these high-risk locations are the primary drivers of virus transmission, then these restrictions are very unlikely to pass any sort of reasonable cost-benefit test. On the other hand, again setting aside travel to essential retailers, the lower half of the table suggest that the restrictions explain a larger share of the mobility decline to medium and low-risk places, 10 to 16 percent. Again in a class of its own, analysis suggests that a full quarter of the change in foot traffic to essential retailers is explained by SAH restrictions. SAH restrictions had a similarly large impact on another mobility measure representing a more dramatic shift from normalcy, the share of the population remaining at home all day, also explaining a quarter of the change.

The somewhat sizable impact on essential retail foot traffic is interesting to consider. First, note that SAH restrictions explicitly allowed for essential shopping; thus, our finding may suggest that the restriction served as an informational treatment, warning citizens of the severity of the virus locally, in addition to formally restricting mobility. Consumer behavioral adaptations like online delivery and curbside pick-up, the latter of which is less likely to be measured as a visit, likely explain part of the decline. Another possibility is that while these retailers are "essential," not all visits to these locations necessarily are. Trips to the grocery store for one or two items "on the way home from work" or "only because I was already out" never occur if SAH restrictions prevent one from being out or at work in the first place. Regardless of the primary mechanism, these adaptations were almost certainly beneficial for those staffing these locations; a group of (mostly) hourly workers that must work in person or risk losing their job.

[27] Both predictions require that the inverse hyperbolic sine of foot traffic be re-transformed to its natural scale. Assuming errors are distributed $N(0,\sigma^2)$, this can be done using the hyperbolic sine function; namely, $y = .5(\exp(\hat{y} + \widehat{\sigma^2}/2) - \exp(-\hat{y} + \widehat{\sigma^2}/2))$In this exercise, parks stand out as unique. Despite SAH restrictions explaining (a relatively large) 11% of the mobility decline, the table suggest that 98 percent of the change in park foot traffic is due to private response. This seemingly counterintuitive finding is explained by school closures, dine-in bans, and entertainment bans having a net *positive* impact on park foot traffic (see Figure A14). Though these effects are statistically different from zero, that these policies would positively impact park traffic is certainly reasonable, particularly if individuals respond by substituting away from more dangerous establishments and towards parks.

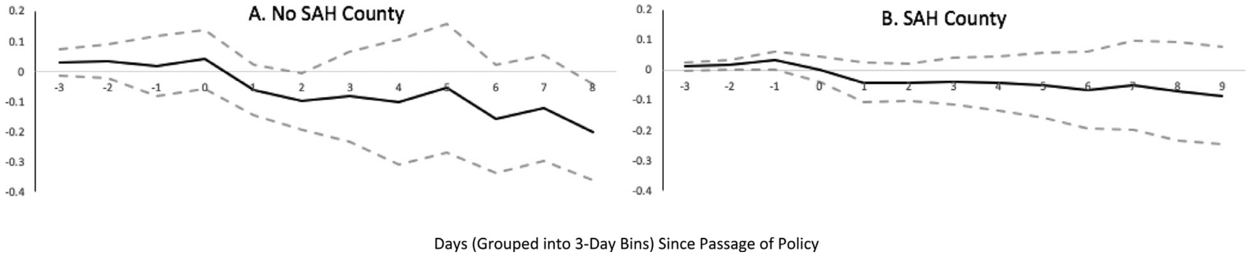

Fig. 4. Restaurant Dine-in Ban on Restaurant Foot Traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from two regressions of the inverse hyperbolic sine of daily restaurant foot traffic on the days since each policy, first death, and first case occurred. The specification varies slightly from Eq. 2, as policy-by-day effects are grouped into three-day bins. Thus, "-3" on the horizontal axis represents 9 to 7 days pre-policy, "-2" represents 6 to 4 days pre-policy, etc. The first regression (panel A) limits the sample to counties that never experienced a county or state SAH policy. The second regression (panel B) limits the sample to counties that experienced either a county or state SAH policy. The plots display the restaurant dine-in regression coefficients in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the number of devices. Standard errors are clustered at the state level.

These results offer a sensible depiction of the individual mobility response to the pandemic. Faced with pandemic related risk and uncertainty, individuals stopped going to the most dangerous places. Several weeks into the pandemic, after many behavioral changes had already taken place, SAH restrictions were passed and had differential effects across industries. In high-risk industries where traffic had already been greatly reduced, the SAH restriction did little. In low-risk industries where traffic had not been reduced greatly, the restrictions had a larger effect. Finally, SAH restrictions had the largest effect on mobility measures that are the most difficult for individuals to change.

There is some possibility that the large foot traffic declines in high-risk establishments are explained not by private behavior, but by other non-SAH restrictions. In the final column we account for this, calculating the share of the total mobility decline explained by private precaution. With one exception (parks)[28], we find the largest private response to the most dangerous locations (83-97%), a smaller private response to safer locations (65-83%), and the smallest private response among difficult to alter mobility measures (40-63%).[29]

VII. Targeted policies

The analysis above suggests that the most dangerous establishments have experienced larger foot traffic declines than safer establishments. Self-imposed, precautionary behavior was shown to account for the majority of this decline. Controversial SAH restrictions were shown to do a particularly poor job in reducing traffic to high-risk locations, instead reducing travel to less-risky locations. In light of these findings, we consider whether restrictions targeted directly at the most dangerous locations offer an effective, less disruptive means by which the disease spread can be managed. Already, we have shown the restaurant dine-in bans, the most targeted mobility ban we analyze, successfully reduced foot traffic to restaurants and complementary establishments. That said, SAH bans quickly followed restaurant bans for many – 9 days later on average – possibly weakening the long-run effectiveness of the restaurant dine-in ban.

To better understand the impact of targeted mobility restrictions in the absence of SAH restrictions, we re-estimate the restaurant foot traffic event study, but separate counties by whether they ever experienced a SAH restriction. A total of seven states never passed a SAH restriction, including AR, IA, ND, NE, OK, SD, and UT; thus, our first group is comprised of the 455 counties in these states that did not pass their own SAH restriction. This decomposition greatly reduces our sample, requiring two deviations from Eq. 2. First, rather than allowing policy effects to vary by each day post-policy, we group days into bins of three, allowing for three pre-policy periods (9-7 days, 6-4 days, or 3-1 days pre-policy) and up to ten post-policy periods. Second, all seven no-SAH states pass a restaurant dine-in ban on the same day as their entertainment ban, except South Dakota, which never passes an entertainment ban. As such, we do not control for the entertainment ban for either group (otherwise, the impact of the restaurant dine-in ban in the no-SAH group would be identified by South Dakota only).

Fig. 4 contains two event study plots. Panel A shows the impact of the dine-in ban on restaurant foot traffic in locations with no SAH restriction. Panel B shows the same relationship for locations with a SAH restriction. Though we lack statistical precision, particularly in the smaller sample, the impact of the restaurant ban on restaurant foot traffic is more than twice as large in locations

[28] Interesting, though not shown, closing public schools is equally as effective as SAH restrictions in keeping individuals home all day. Closing public schools accounts for 23 percent of the total change in the at home rate.

[29] Two important caveats: First, this conclusion clearly assumes that success of the restaurant dine-in ban would translate to other high-risk industries, such as hotels, bars, and indoor entertainment venues. Second, this conclusion assumes a close relationship between the magnitude of the mobility decline and reductions in infections/deaths. We acknowledge the possibility that a small reduction in mobility to risky locals could yield large reductions in cases and deaths. Thus far, researchers have documented both large (Courtemanche et al., 2020) and moderate-to-small (Chernozhukov et al., 2021) effects of SAH orders on COVID-19 cases.

without SAH restrictions, than in locations with SAH restrictions. For example, 4-6 days post-policy, restaurant foot traffic is down roughly 10 percent (p-value = 0.040) in locations without a SAH restriction, but just 4 percent (p-value = 0.193) in locations with a SAH restriction. These figures are 20 percent (p-value = 0.019) and 7 percent (p-value = 0.386), respectively, 24-26 days post-policy. Though not shown, among counties with no SAH restriction restaurant dine-in bans are also found to reduce traffic to indoor entertainment venues (a complementary industry); however, the bans do not reduce traffic to any other of the industries we study.

VIII. Discussion

Though the COVID-19 pandemic has threatened American lives for over a year, and will continue to do so into the foreseeable future, intense political debate regarding the government's role in promoting social distancing persists. Of particular interest is the efficiency of stay at home restrictions, which impose massive costs on individuals and businesses, without regard to industry-specific transmission risks.

In discussing our event-study results, we claim to estimate the impact of various ordinances on outcomes, but more introspection and humility is warranted. In order for these difference-in-differences estimates to provide unbiased estimates, it must be the case that the policy is functionally exogenous conditional on covariates. It is certainly difficult to make that case, even when it appears that the usual diagnostics (e.g., parallel trends) appear to hold. Large urban areas were hit hard by COVID in the early months and casual empiricism suggests counties with urban centers acted quite differently than more rural locations. Likewise, precautionary behavior on the part of people followed some specific patterns. For example, a consistent result in the literature is that social distancing and mask wearing was less likely among Republicans than Democrats (Lazer et al., 2020). If politicians respond to these interests with both the speed and severity of distancing ordinances, then our models are potentially subject to an omitted variables bias, meaning we may not be able to pin down the exact policy effects. Despite this shortcoming, the overall pattern of results reveals a rather consistent pattern of what has happened and we believe our findings offer several contributions to the policy debate.

The first key finding, that at the start of the COVID-19 pandemic, individuals willingly reduced foot-traffic to the most high-risk locations, is the most generalizable. The finding shows that citizens internalized information on industry-specific risks and acting accordingly. Given a similar information set, we would expect individuals to respond similarly to both future pandemics, which could present different risk factors, as well as future outbreaks of COVID-19. For example, we should expect future waves and/or vaccine-resistant variants to have a larger impact on indoor-dining than trips to the golf course.

The second key finding, that at the start of the COVID-19 pandemic, less than 20 percent of the decline in foot-traffic to the most high-risk locations can be explained by public restrictions, is most valuable when considering the policy response to a future pandemic. Early in this pandemic, US media reporting on the COVID-19 was overwhelming, leading to a considerable amount of fear and uncertainty that ultimately lead to a substantial reduction in mobility. Importantly, much of what was reported involved information provided by or actions of the federal government. Our paper shows that in this setting, the broad SAH restrictions issued by state and local governments did little to further reduce trips to the highest risk locations and had a somewhat larger impact on trips to lower risk locations. This conclusion, paired with the third key finding in this paper, that the most targeted restriction imposed at the start of the COVID-19 pandemic (i.e., restaurant dine-in bans) significantly reduced mobility to the targeted industry without spill-overs to unrelated industries, suggests a clear strategy for future pandemics. The federal government should play an important role in communicating risk factors to citizens and if/when it is deemed that local restrictions are necessary, they should be targeted towards high-risk behaviors.[30] Given the controversy surrounding SAH restrictions discussed above, this strategy aims to optimally balance the potential gains from mobility restrictions with the obvious costs.

A brief discussion on what conclusions should not be drawn from these results is warranted. Our analysis is limited to February 15th - April 15th of 2020. During this time, there was relatively little variation in public opinion regarding the severity of the virus and "pandemic fatigue" had not yet set in. It is in this environment that we find a strong private and little public response. Our results have little to say about how state restrictions would impact mobility months or years into this pandemic, for example, in response to a new wave or vaccine resistant variant. Making such policy predictions from information on previous policy responses is always challenging, but maybe more-so in a pandemic setting. As it has been witnessed in the US over the past year, the inherent risk of any particular activity has become increasingly individualized as we learn more about the virus (Chang et al., 2020; Fisher et al., 2020) - e.g., Is the activity indoors or outdoors? Are participants young or old? Are participants vaccinated, wearing masks, social distancing, etc.? This says nothing of perceived risks, which are also personal and evolve over time. These dynamics make predicting responses to future policies from past data incredibly challenging and potentially impossible.

Finally, 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 show that modest changes in avoidance behavior can have important implications for the spread of an infectious disease (Kremer, 1996; Geoffard and Philipson, 1997; Funk et al., 2009; Chen et al., 2011). Likewise, empirical work demonstrates that individuals respond to external events and adopt avoidance behavior in response to air or water pollution (Bresnahan et al., 1997; Neidell, 2009; Zhang and Mu, 2018; Zivin et al.,

[30] Two important caveats: First, this conclusion clearly assumes that success of the restaurant dine-in ban would translate to other high-risk industries, such as hotels, bars, and indoor entertainment venues. Second, this conclusion assumes a close relationship between the magnitude of the mobility decline and reductions in infections/deaths. We acknowledge the possibility that a small reduction in mobility to risky locals could yield large reductions in cases and deaths. Thus far, researchers have documented both large (Courtemanche et al., 2020) and moderate-to-small (Chernozhukov et al., 2021) effects of SAH orders on COVID-19 cases.

2011), sexually transmitted diseases (McKusick et al., 1985; Ng'weshemi et al., 1996; Bloom et al., 2000; Oster, 2012), or the flu (Bish and Michie, 2010). This literature has its antecedents in the classic work of Peltzman (1975).

Author Statement

Professors Cronin and Evans have nothing to disclose.

Appendix

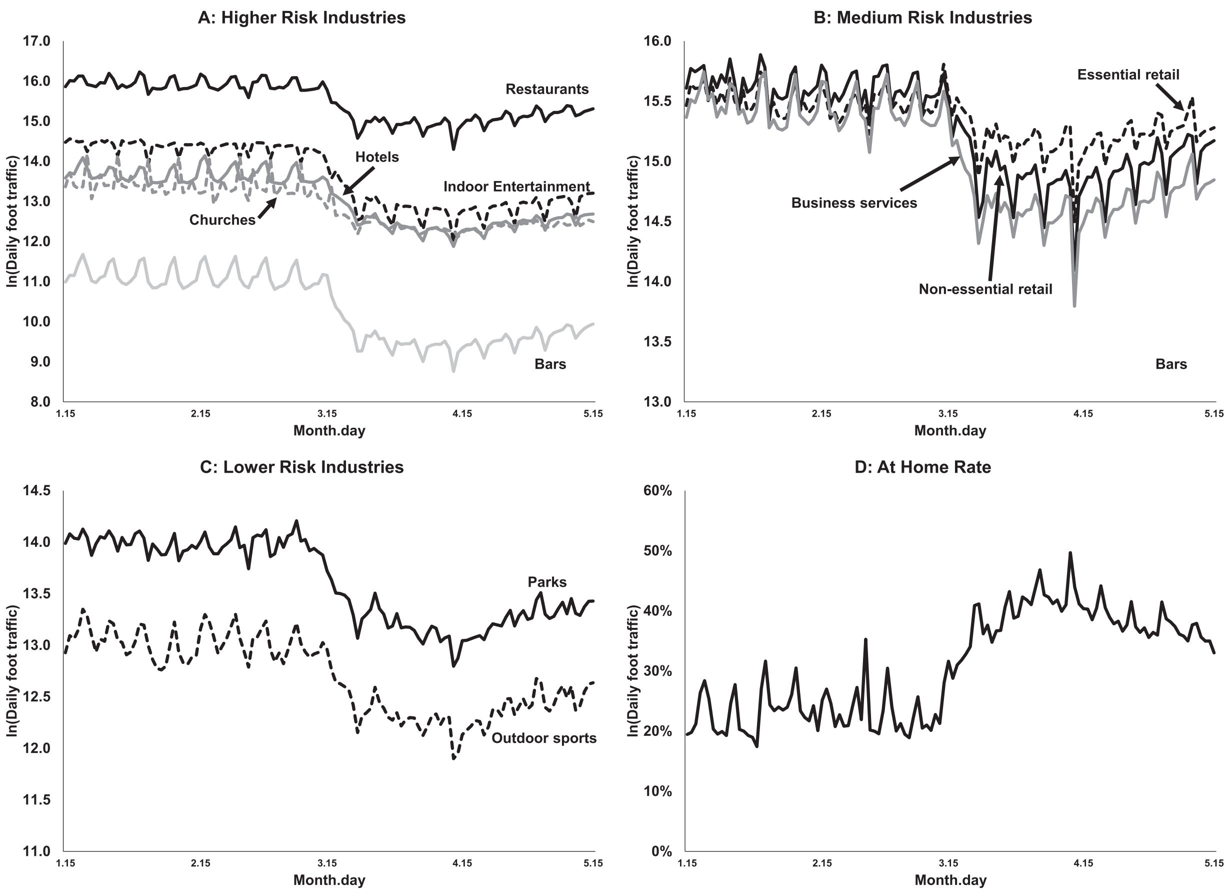

Fig. A1. Natural log of daily foot traffic by industry group and the at home rate, 1/1/2020 to 5/15/2020, SafeGraph Data.

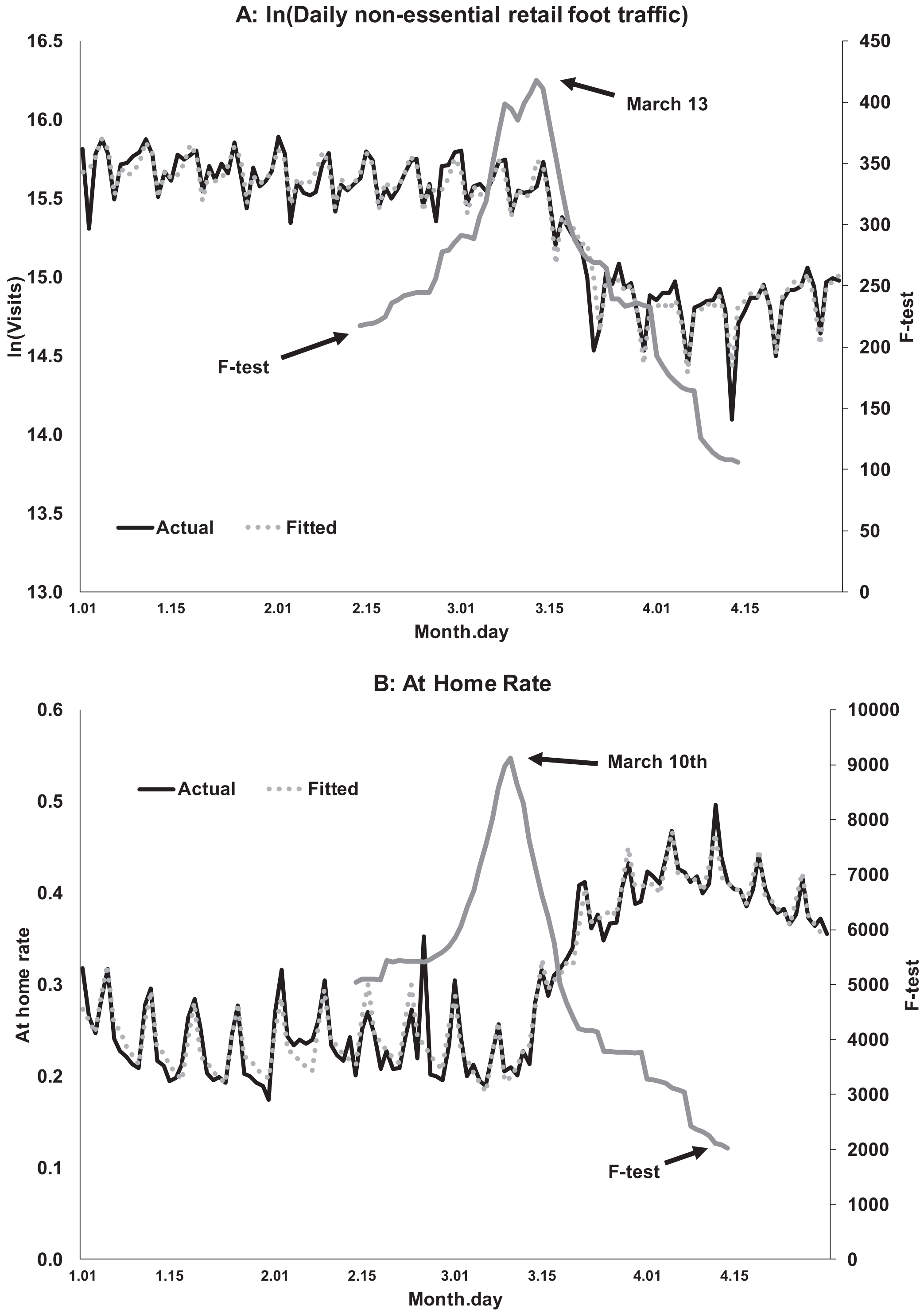

Fig. A2. Actual series and OLS estimates of Eq. (1) for non-essential. Retail ln(Daily Foot Traffic) and At home rate at the structural break period, and the F-test at different structural breaks, SafeGraph Data.

Table A1
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.

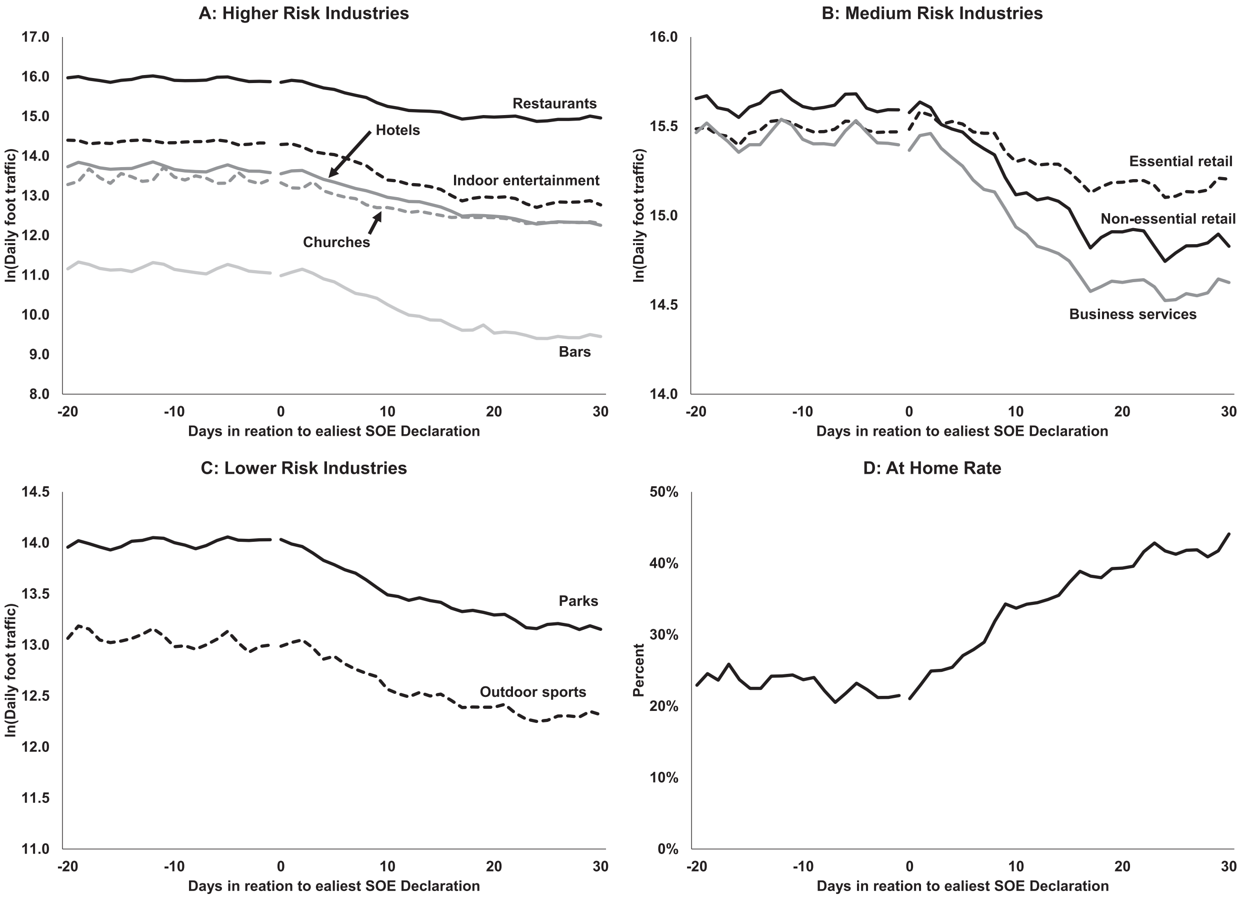

Fig. A3. Natural log of daily foot traffic by industry group and at home rate, Indexed by the days in relation to the earliest SOE declaration, SafeGraph Data.

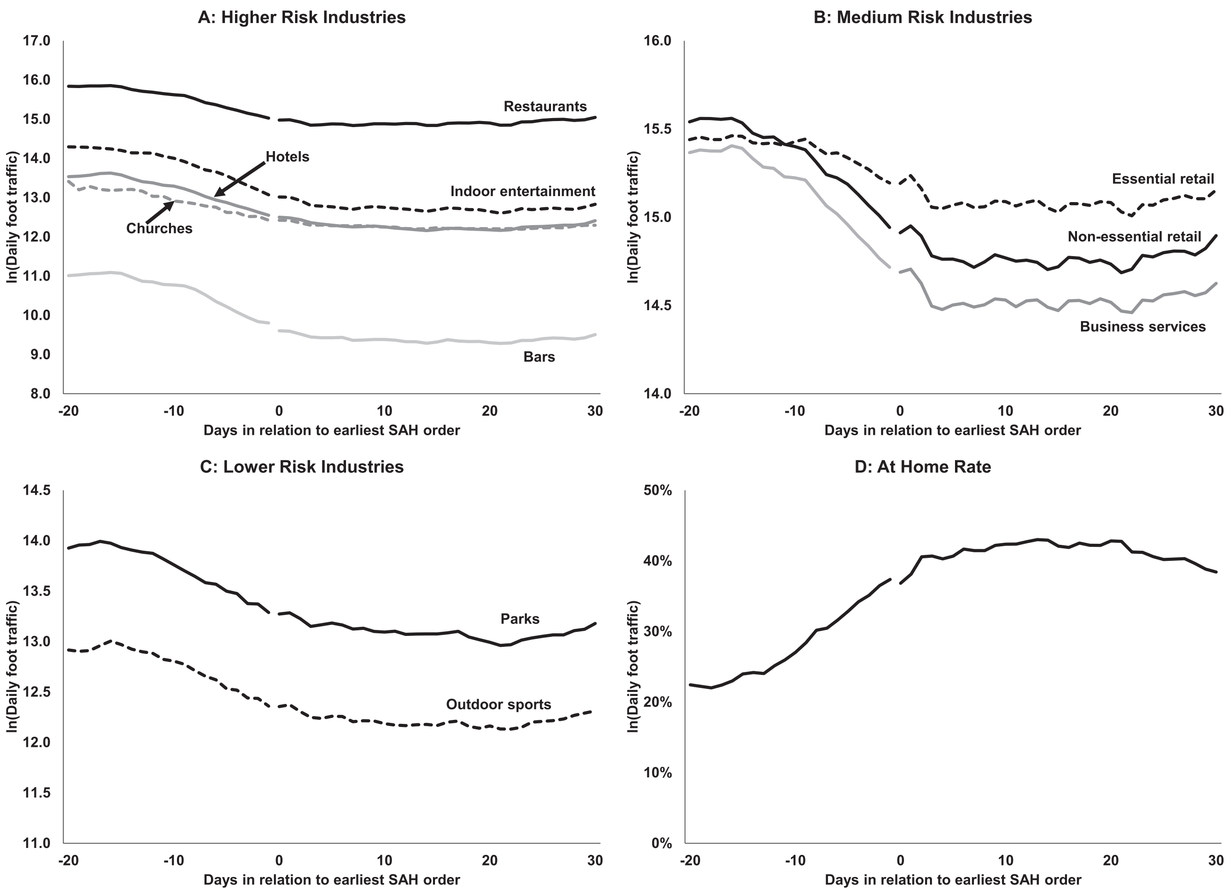

Fig. A4. Natural log of daily foot traffic by industry group and At Home Rate, Indexed by the days in relation to earlies SAH order, SafeGraph Data.

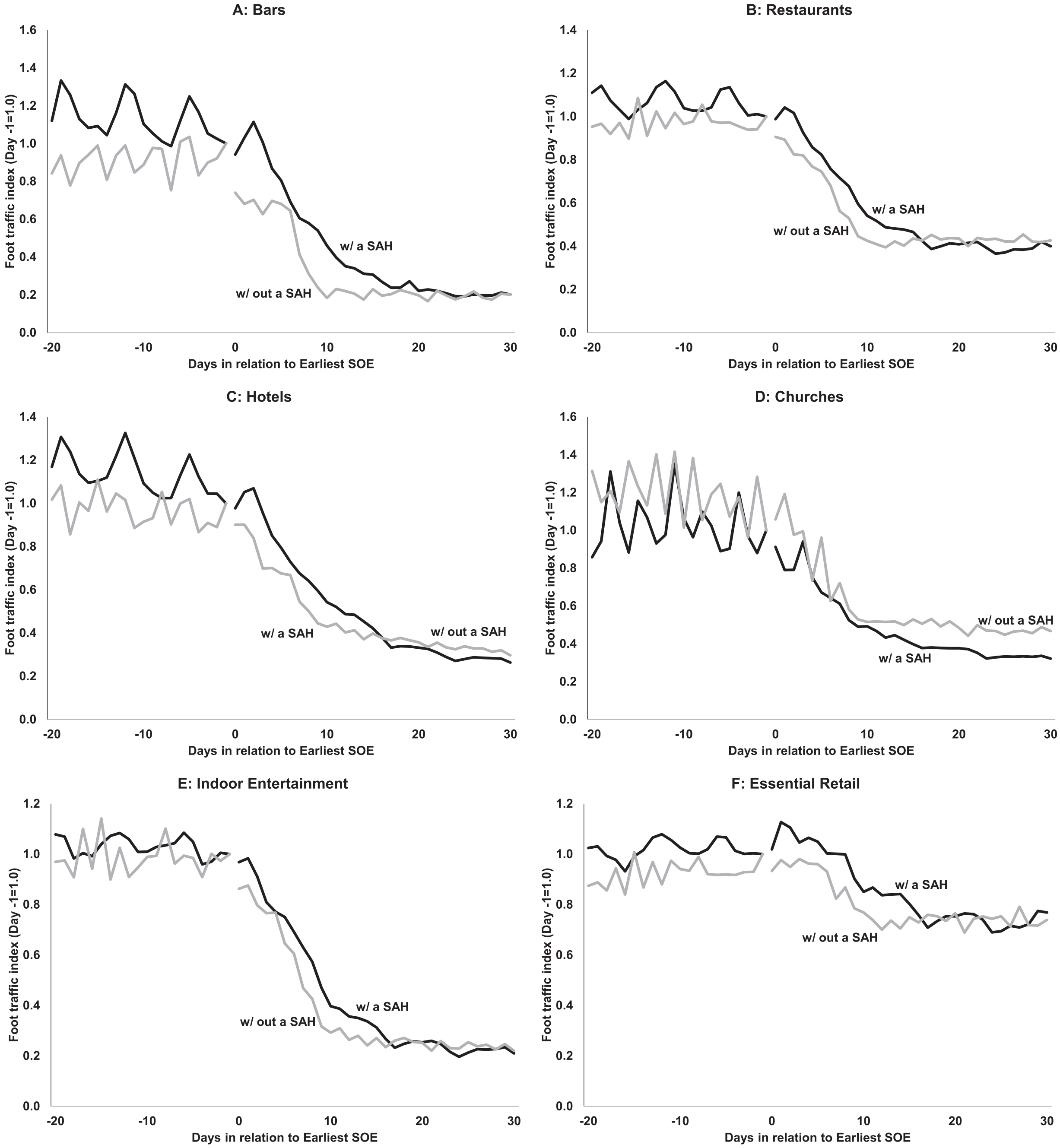

Fig. A5. Daily foot traffic index (Day -1 = 1.00) and at home rate by industry group and county-level SAH status, indexed by the days in relation to earliest SOE order, SafeGraph Data.

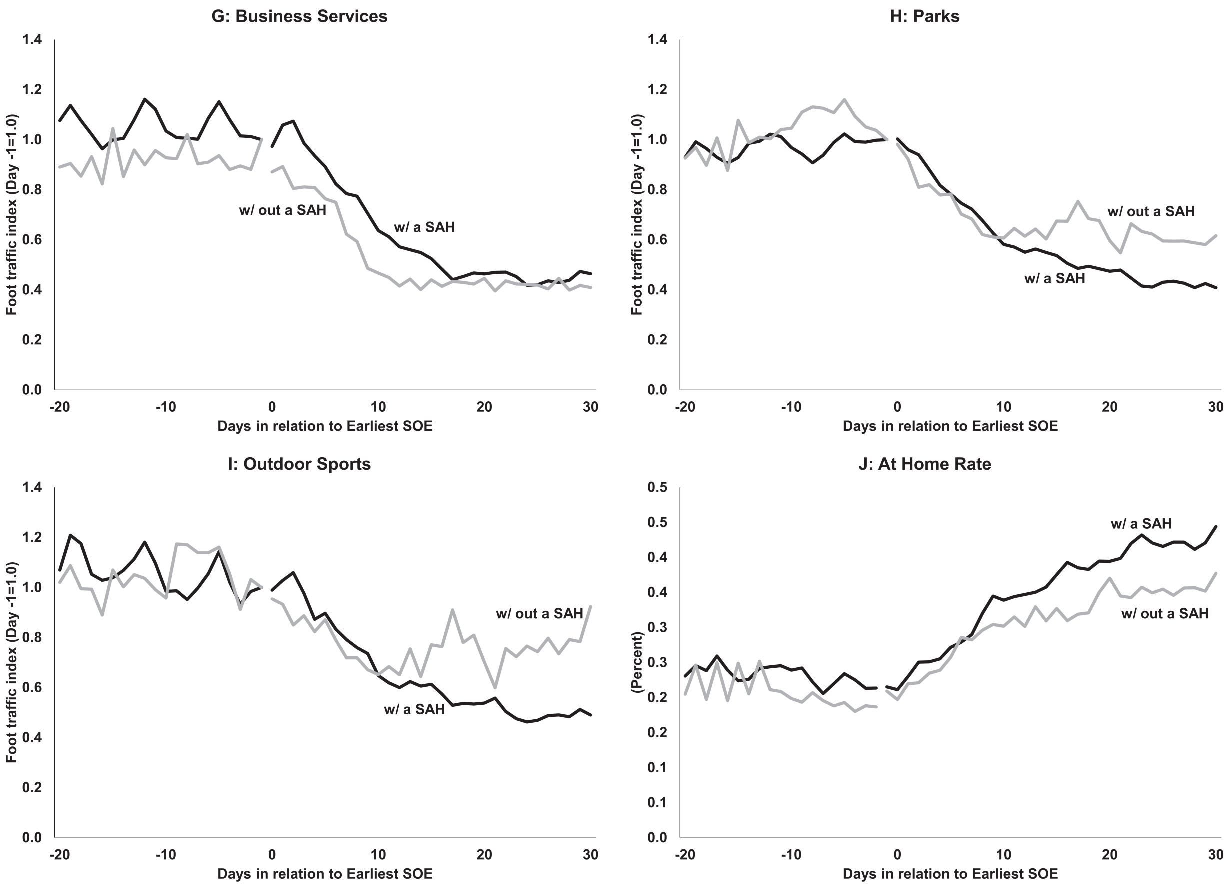

Fig. A5. Continued

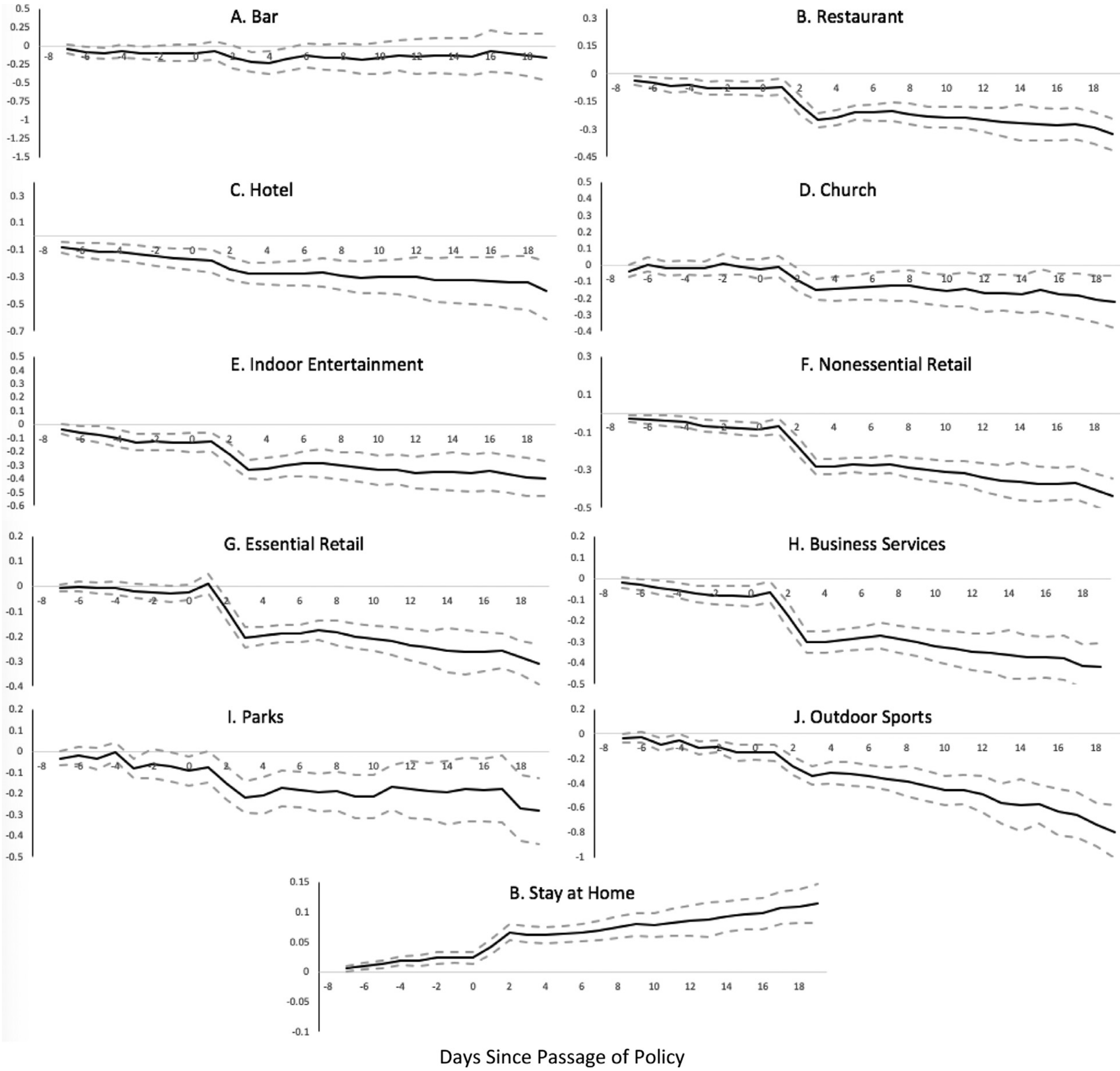

Fig. A6. SAH impact on various foot traffic measures, no controls, SafeGraph Data.
Notes: This figure plots parameter estimates from 11 regressions of the inverse hyperbolic sine of a foot traffic measure or of the at home rate on the days since a SAH restriction was passed. Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

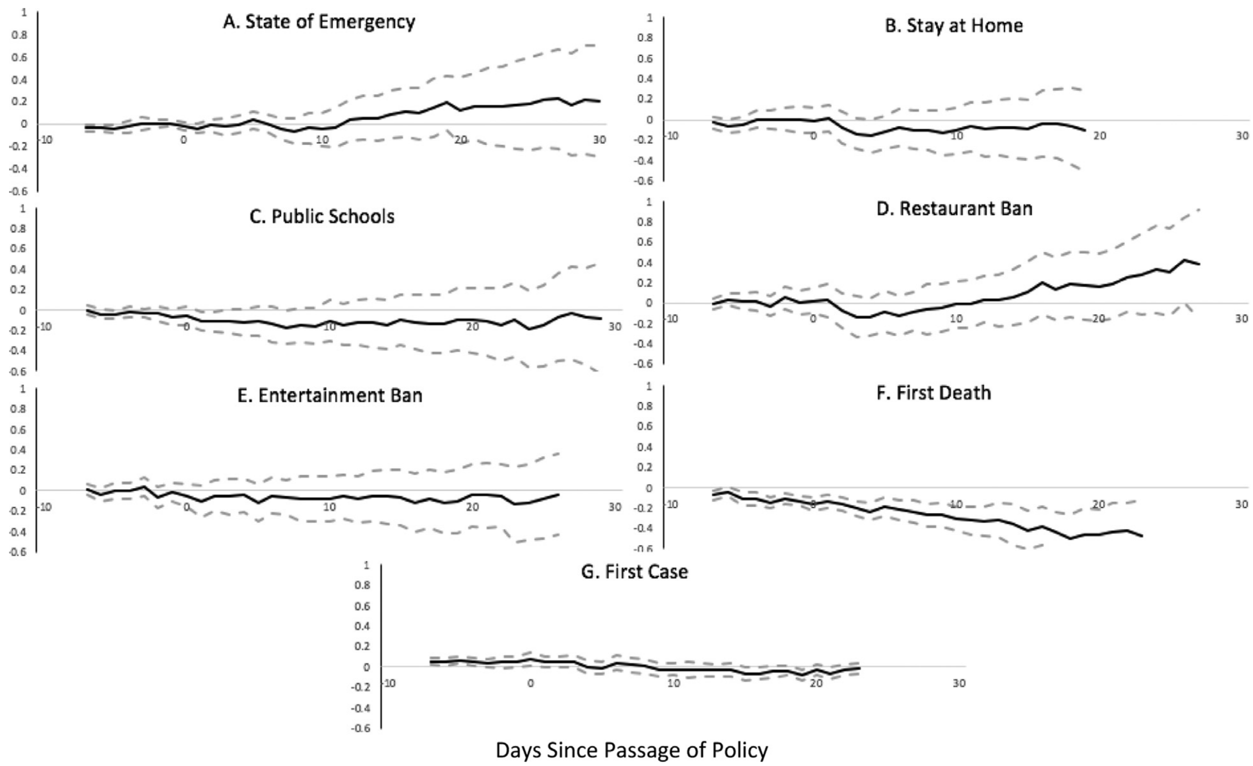

Fig. A7. Policy, first death, and first case impact on bar foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily bar foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

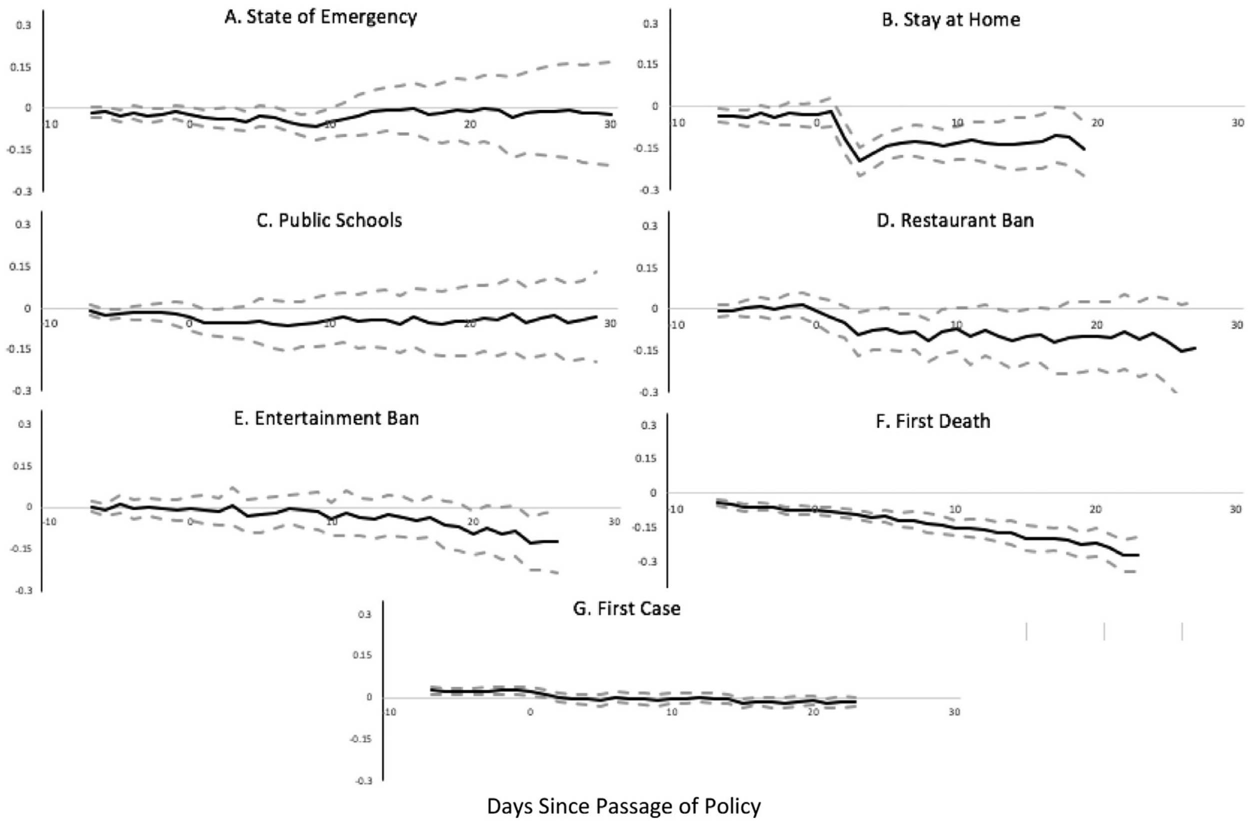

Fig. A8. Policy, first death, and first case impact on restaurant foot traffic, SafeGraph Data.

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

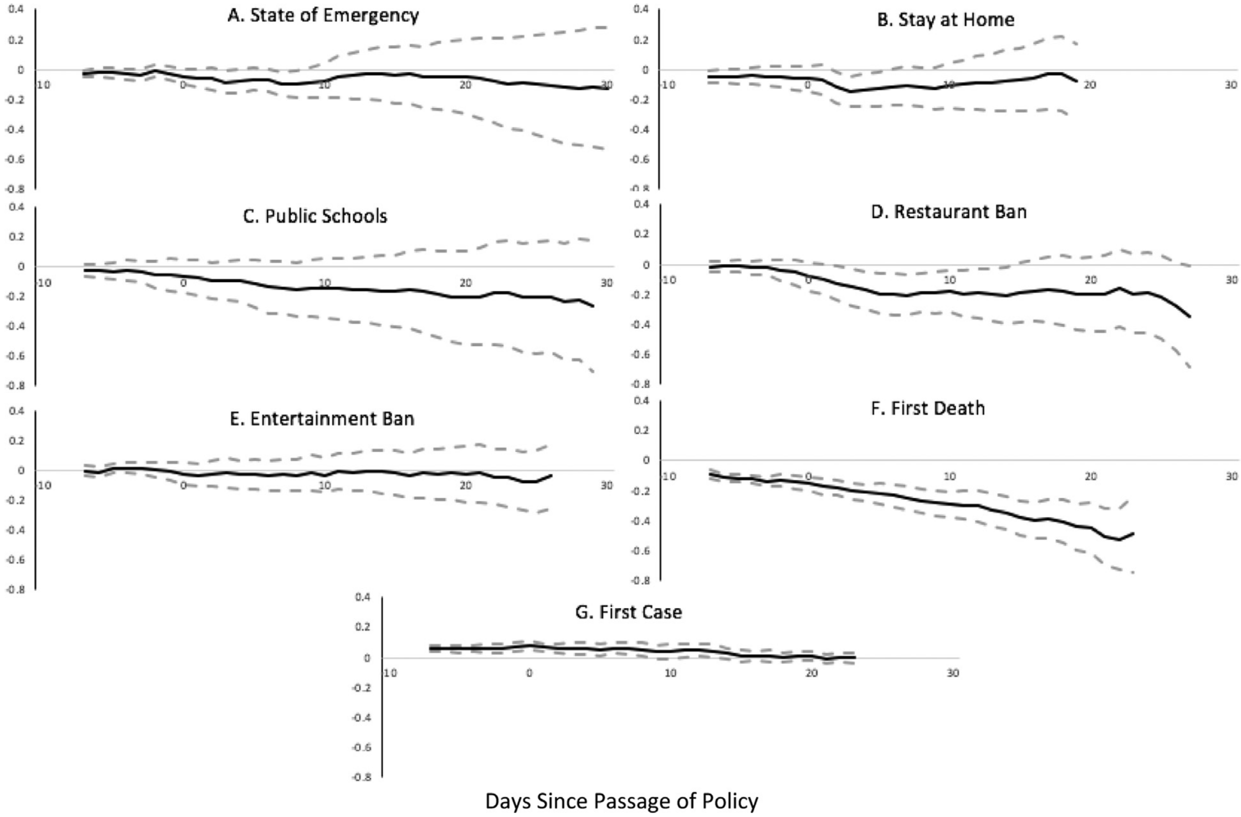

Fig. A9. Policy, first death, and first case impact on hotel foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily hotel foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population Standard errors are clustered at the state level.

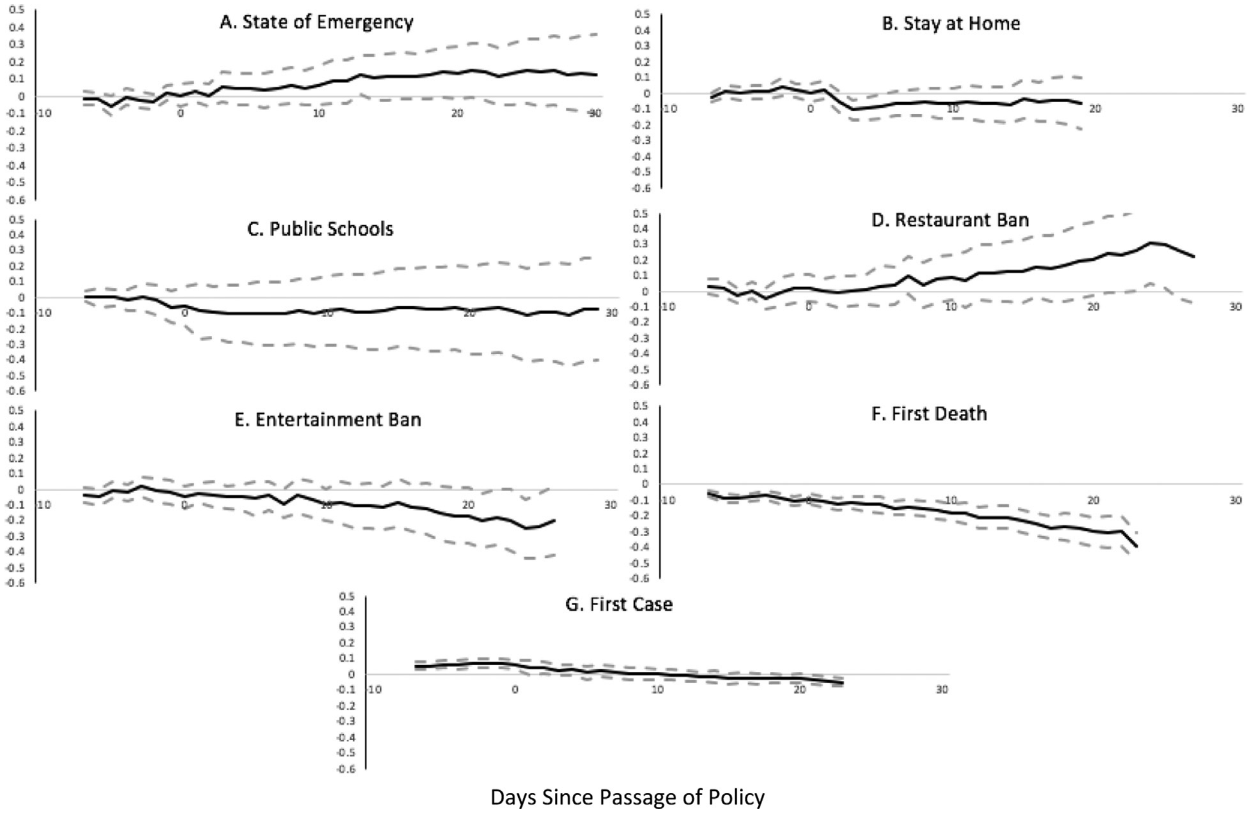

Fig. A10. Policy, first death, and first case impact on church foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily church foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

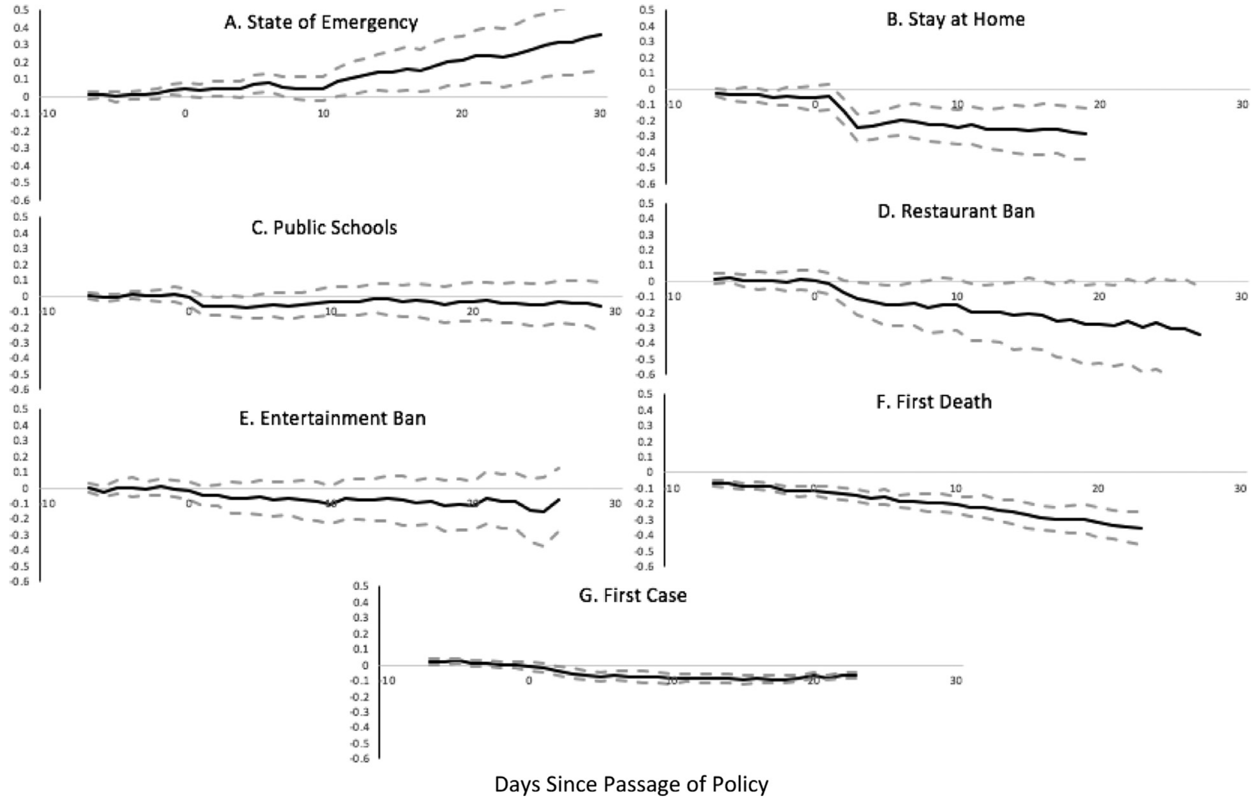

Fig. A11. Policy, first death, and first case impact on indoor entertainment foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily indoor entertainment foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

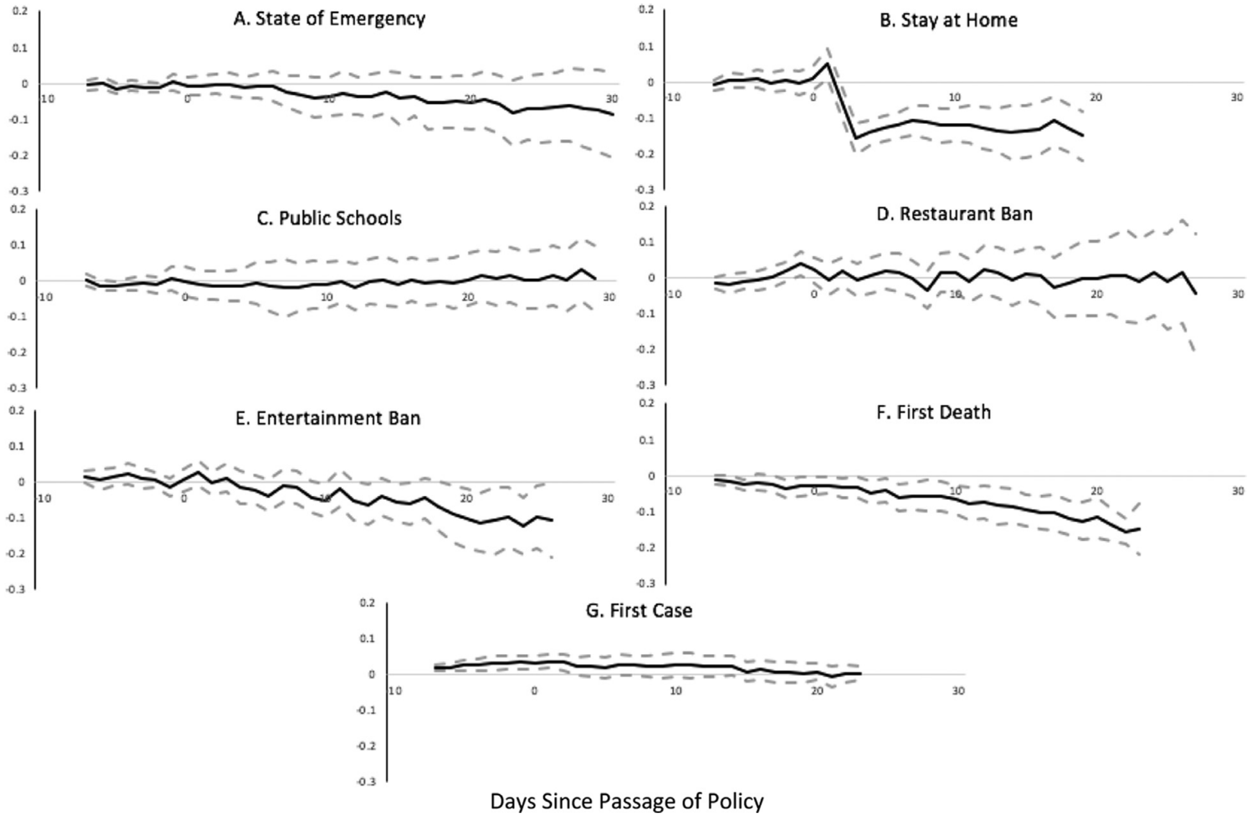

Fig. A12. Policy, first death, and first case impact on essential retail foot traffic, SafeGraph Data.

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

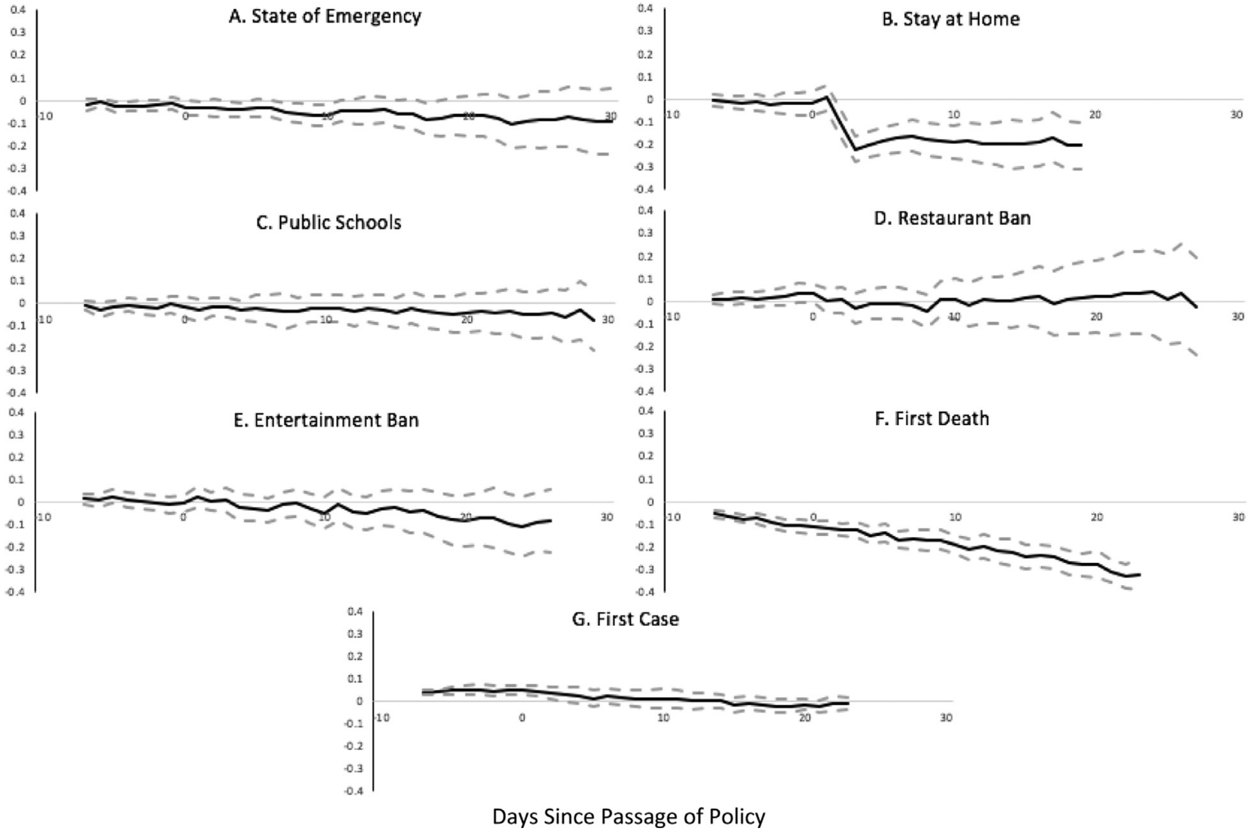

Fig. A13. Policy, first death, and first case impact on business services foot traffic, SafeGraph Data
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily business services foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

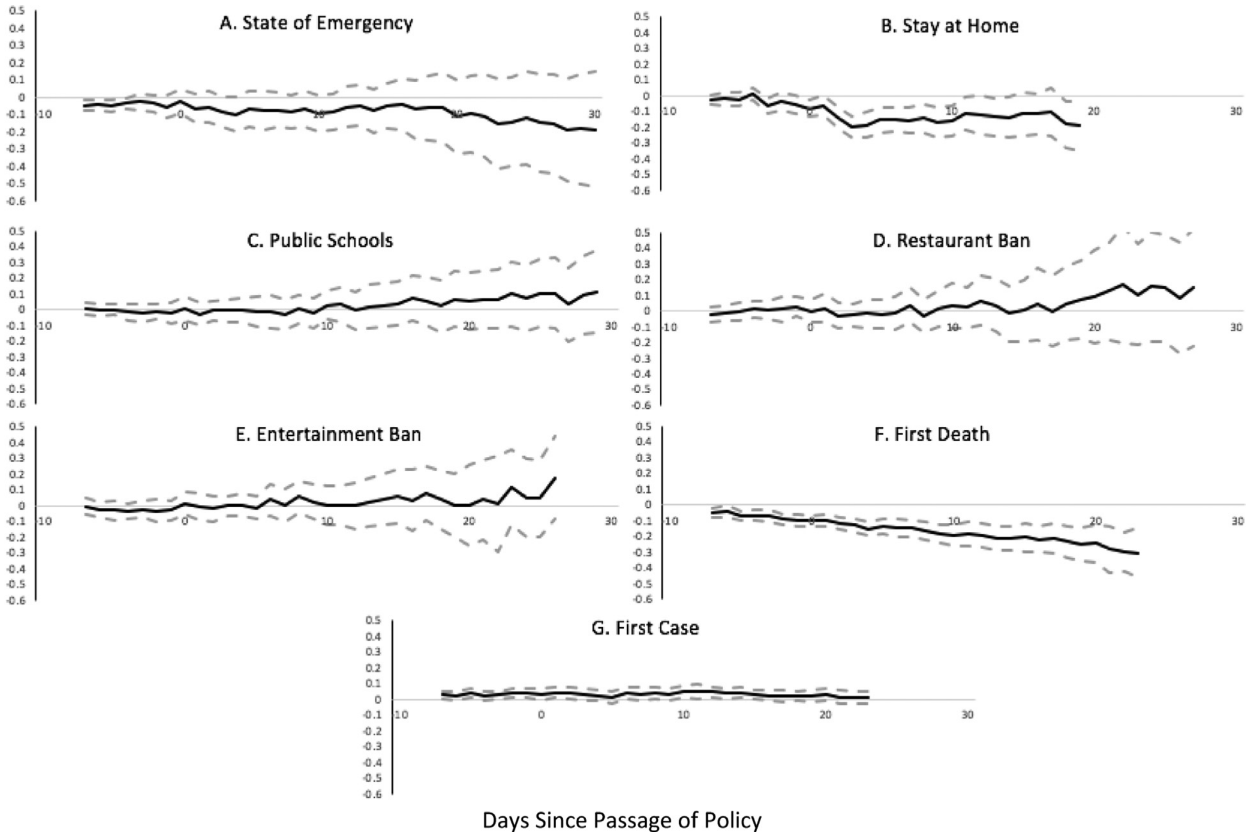

Fig. A14. Policy, first death, and first case impact on nature park foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily nature park foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

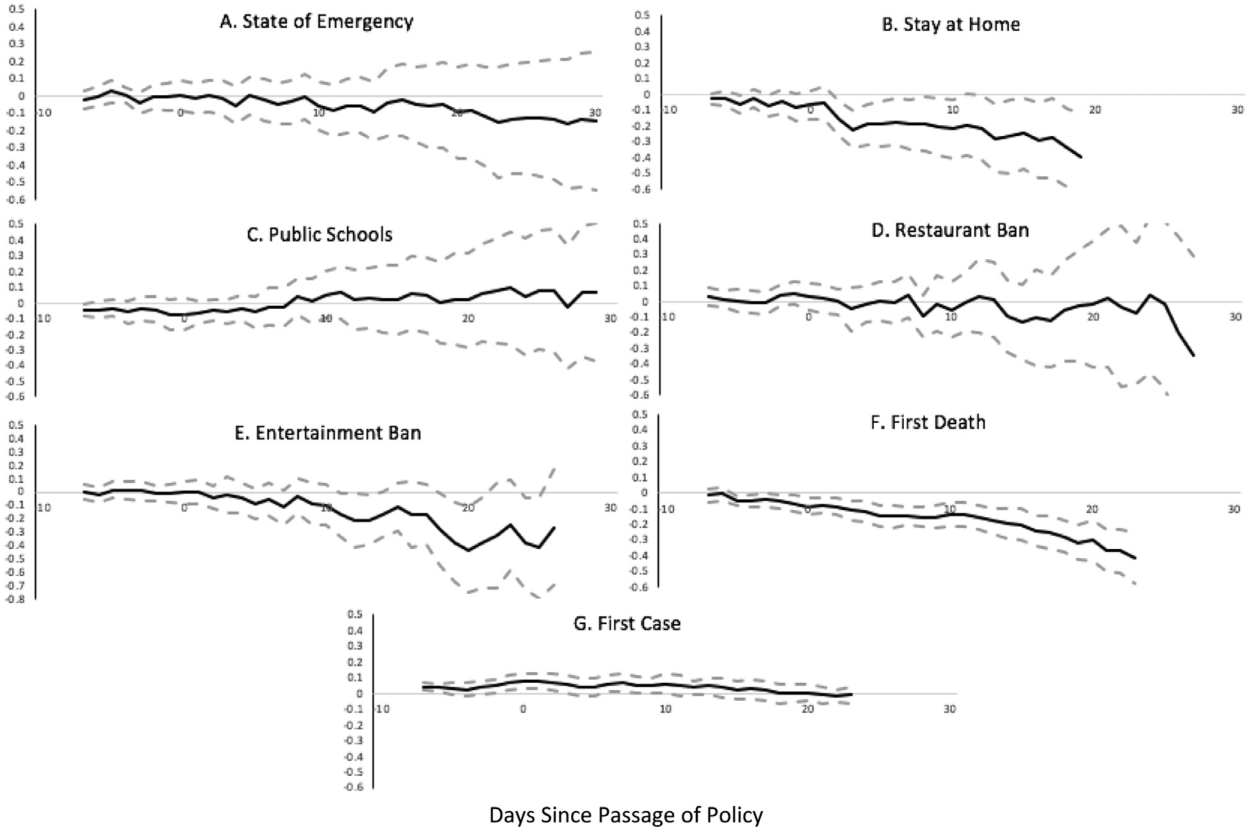

Fig. A15. Policy, first death, and first case impact on outdoor sporting foot traffic, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the inverse hyperbolic sine of daily outdoor sporting foot traffic on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

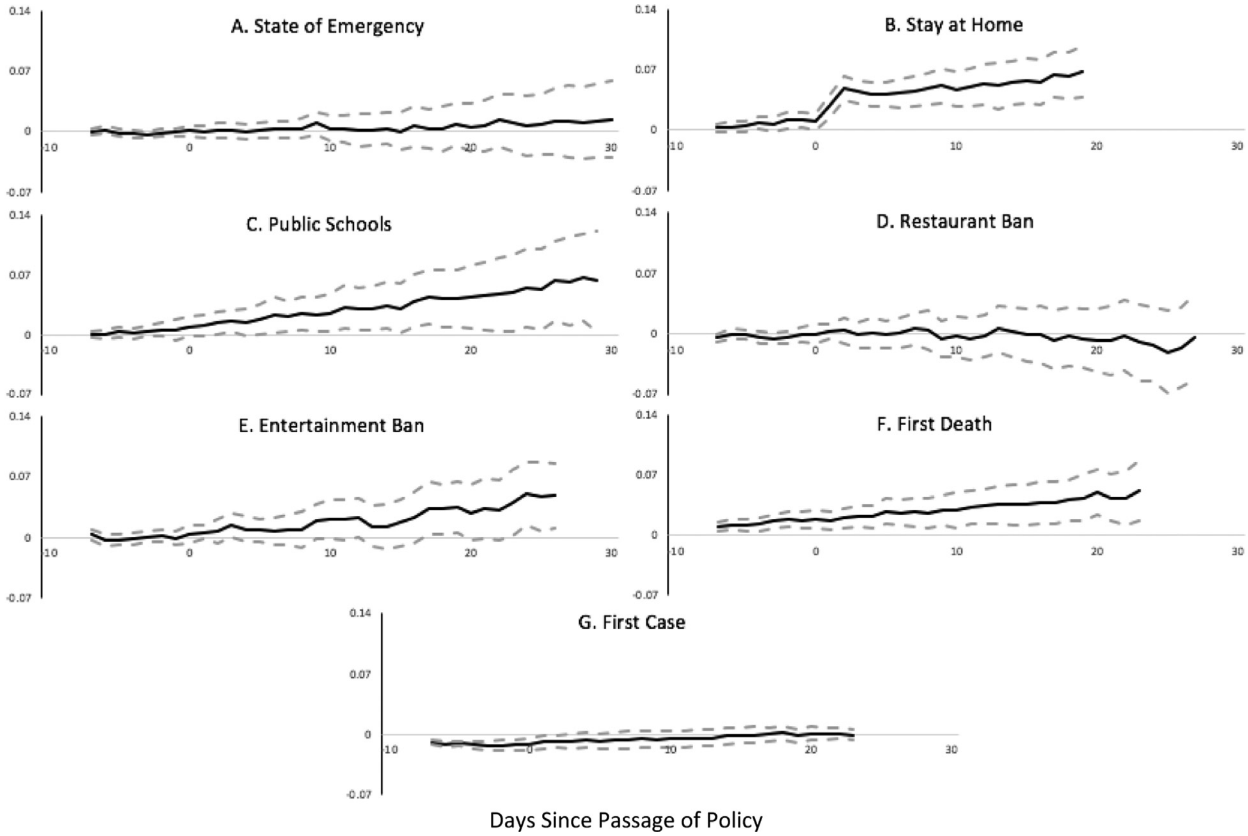

Fig. A16. Policy, first death, and first case impact on share of population staying at home all day, SafeGraph Data.
Notes: This figure plots parameter estimates from a single regression of the share of the population that stays at their home for the entire day (i.e., "home share") on the days since each policy, first death, and first case occurred (see Eq. 2). Regression coefficients are measured in solid black and 95% confidence intervals in dashed grey. We include county and date fixed effects, weather variables, and weight by the county population. Standard errors are clustered at the state level.

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