

Alexander, Diane; Karger, Ezra

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Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior

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Diane Alexander and Ezra Karger

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Do stay-at-home orders cause people to stay at home?

Effects of stay-at-home orders on consumer behavior

For most recent version, see:

www.dropbox.com/s/6ile54ne7j6v81b/covid19.pdf?dl=0

Diane Alexander*

**Federal Reserve Bank
of Chicago**

Ezra Karger[†]

**Federal Reserve Bank
of Chicago**

April 18, 2020

We link the county-level rollout of stay-at-home orders to anonymized cellphone records and consumer spending data. We document three patterns. First, stay-at-home orders caused people to stay at home: county-level measures of mobility declined by between 9% and 13% by the day after the stay-at-home order went into effect. Second, stay-at-home orders caused large reductions in spending in sectors associated with mobility: restaurants and retail stores. However, food delivery sharply increased after orders went into effect. Third, there is substantial county-level heterogeneity in consumer behavior in the days leading up to a stay-at-home order. While people living in Democrat- and Republican-supporting counties responded similarly to the orders themselves, those in Democrat-supporting counties also reduced their movement and restaurant spending well before stay-at-home orders went into effect. This pattern was less clear in Republican-supporting counties. These differences are not explained by the fact that Democrat-supporting counties instituted stay-at-home orders earlier than Republican-supporting counties, on average.

*dalexand@frbchi.org; 230 South LaSalle Street, Chicago, IL 60604.

[†]karger@uchicago.edu; 230 South LaSalle Street, Chicago, IL 60604.

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During the Covid-19 pandemic, many cities, counties, and states have requested or required that their residents stay at home. These “stay-at-home” orders generally restricted people from leaving their homes for anything other than essential activities.¹ Policymakers assumed that stay-at-home orders would reduce social interactions. But some waited to implement stay-at-home orders, citing the likely impact the orders would have on consumer spending, especially at hard-hit small businesses.

We find that stay-at-home orders immediately change behavior. We link a county-day level panel of stay-at-home orders to aggregated cellphone location data from Unacast, a company that uses cellphone locations to construct measures of mobility. By the day after counties enacted a stay-at-home order, people traveled 9% less than they did before the order and made 13% fewer visits to non-essential businesses.

Stay-at-home orders also successfully encouraged people to stay at home and avoid in-person shopping, which resulted in sharply reduced spending at certain types of business. We use two panels of consumer spending data to estimate the effect of stay-at-home orders on consumer spending. The first is a county-day level panel of small business spending from Womply, and the second is a state-day level panel of large business spending from Second Measure. Stay-at-home orders decreased spending at restaurants and retail stores, but had negligible effects on consumer spending at non-restaurant small businesses. We also show that stay-at-home orders caused large increases in spending on food delivery services.

While ordering people to stay at home had a similar effect on consumer behavior across different types of counties (for example, by political leanings or by income), behavior in the days leading up to the order differed sharply across county characteristics. In Democrat-leaning counties, both mobility and restaurant spending were sharply declining before a stay-at-home order went into effect. However, in Republican-leaning counties, these pre-trends were much flatter.² These findings suggest that the orders were broadly effective, despite local politics. However, it also suggests that Republican-leaning counties may have waited longer to change their behavior. These patterns are not explained by the fact that on average, Republican-leaning counties implemented the stay-at-home orders on later dates.

While stay-at-home orders caused large changes in consumer behavior, these effects are not the whole story, as in many places consumers were already reacting to Covid-19 before stay-at-home orders went into

¹Most states still allowed residents to leave their homes to shop for groceries and other essential goods and services, to exercise outdoors, and to use health care services, though each state or locality’s order was slightly different.

²Similar patterns are also observed when splitting the data by income instead of by political leanings.

effect. In addition, some states and localities used other measures such as closing schools and non-essential businesses, in addition to stay-at-home orders. We show that Covid-19 as a whole reduced consumer spending in a panel of over 1 million small businesses by 40% year-over-year. Conversely, Covid-19 did not affect aggregate consumer spending at 3,600 large businesses.³ This stable spending at large businesses masks heterogeneity by spending type. Consumer spending at the brick-and-mortar stores of large firms fell by 9%, but online transactions at these large firms increased by 56%.

In this paper, we use county-day level variation in stay-at-home orders and examine the causal effect of these orders on consumer behavior. Our paper has two main contributions over previous work. First, our use of a county-day level panel lets us precisely measure the effect of stay-at-home orders, and distinguish this effect from aggregate pre-existing trends. This level of disaggregation also allows us to examine heterogeneity in responses to stay-at-home orders by county-level characteristics. Second, we use two different sources of data on consumer spending that span both large and small businesses.

To the best of our knowledge, our paper is the first to look at the causal effects of stay-at-home orders. However, in the past two weeks, economists have released dozens of working papers related to Covid-19. Baker et al. (2020) also use a dataset of consumer spending from a panel of households to measure the relationship between Covid-19, state-level stay-at-home orders, and consumption. They find that consumers ramp up spending in certain sectors in response to news about Covid-19. These consumers then reduced consumption dramatically in late-March. In a similar framework, Lewis, Mertens, and Stock (2020) combine economic indicators to produce a weekly index of economic activity. They document a sharp drop in economic activity in mid-March. And Bartik et al. (2020) use a survey of small businesses to show that 43% of the surveyed businesses have temporarily closed because of Covid-19, with many businesses reducing their employee count and anticipating additional financial fragility. We differ from these papers by using a daily event study framework at the county level and two larger panels of consumer spending to precisely estimate daily consumption patterns related to Covid-19 and stay-at-home orders.

In other related work, Barrios and Hochberg (2020) use Google Search data to show that searches for Covid-19 in a given county increase after the first Covid-19 death in that county. This response is less

³This unchanged spending at large businesses may be partially due to Easter seasonality, but in the two weeks before Easter, spending at large businesses was also not much lower in 2020 vs. 2019.

sharp in Republican-leaning areas. Barrios and Hochberg also use Unacast data to measure the relationship between Covid-19 deaths and mobility, comparing this relationship in counties that voted Republican in the 2016 election and counties that did not. And in a similar vein, Alcott et al. (2020) use smartphone location data from SafeGraph to show that Republicans engage in social distancing at a lower rate than Democrats, even after controlling for state-level features such as Covid-19 cases, population density, and state-by-date fixed effects. Our county-level heterogeneity analyses show that these differences in political preferences are not only associated with differences in search behavior and social distancing, but also correlate with differences in consumer spending patterns.

Lastly, Fang, Wang, and Yang (2020) show that the lockdown of Wuhan successfully reduced inflows of people into Wuhan and outflows of people away from Wuhan. They further show that social distancing in cities outside of Wuhan reduced inflows from Wuhan, providing additional evidence that government policies requiring social distancing or encouraging people to stay at home affect behavior. And Aaronson et al. (2020) examine the effect of stay-at-home orders on unemployment insurance claims.

Data

We hand-collect stay-at-home orders for each county in the United States.⁴ We gather information about the exact time and date when the stay-at-home order went into effect. Although the content of stay-at-home orders varies across places, most stay-at-home orders follow a simple formula: residents of a county or city are encouraged not to leave their homes to visit non-essential businesses, like restaurants or hair salons.⁵ Stay-at-home orders have been issued at the city, county, and state level. In cases where a city imposed a stay-at-home order, we map that city to the county containing the city. In this paper we use the date when each stay-at-home order went into effect.⁶

⁴The starting point for this data collection effort was a New York Times article “See Which States and Cities Have Told Residents to Stay at Home” (<https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html?smid=em-share>), which tracked stay-at-home orders across the US. We used each order reported in the article and added orders for all other counties to construct a complete county-day level panel.

⁵For an example of a stay-at-home order, see San Francisco’s current order at <https://sf.gov/stay-home-except-essential-needs>

⁶Many counties or states announced stay-at-home orders 1-2 days before the order went into effect. However, it appears the bulk of the response came when the order went into effect, rather than on the date of announcement.

In Figure 1, we show that 32 states have no within-state variation in the timing of stay-at-home orders. As of April 15, five states have not implemented stay-at-home orders and contain no counties that implemented their own stay-at-home orders. An additional 22 states implemented an order state-wide before individual counties implemented stay-at-home orders on their own. However, in 23 states (including Texas, Pennsylvania, and Florida), there is significant variation in the effective date of each county's stay-at-home order. As of April 7, 2020, 96% of U.S. residents were living under some form of stay-at-home order. Seven counties in the San Francisco Bay Area put into effect the first stay-at-home orders in the United States on March 17, 2020.⁷ More recently, South Carolina implemented a state-wide stay-at-home order on April 7, 2020.

To add context to the stay-at-home orders, we link our county-day level panel of stay-at-home orders to counts of Covid-19 cases and deaths, collected by the New York Times.⁸ In March, 1,006 counties reported no Covid-19 cases and 2,651 counties reported no Covid-19 deaths. Counties in our sample reported an average of 43.4 Covid-19 cases and 0.8 deaths due to Covid-19 during March. In Figure 3, we plot the distribution of cases and deaths across the 3,143 counties in the United States during March, 2020. The y-axis indicates the population-weighted average number of cases or deaths for five groups of counties: counties that put into place a stay-at-home order by March 21 (early), between March 22-26 (mid), between March 27-31 (later), between April 1-7 (late), and counties without a stay-at-home order as of April 7 (no order). There is significant variation in the distribution of cases and deaths across these five groups of counties because stay-at-home orders are an endogenous responses to Covid-19 cases. In states with an early order, cases and deaths grew significantly faster than in counties with no current stay-at-home order. This may reflect differences in testing, but it also reflects the fact that the counties hardest-hit by Covid-19 responded more quickly.

To look at the effect of stay-at-home orders on mobility, we link our panel of stay-at-home orders to data from Unacast. Unacast produces two daily measure of mobility at the county-level: (1) average distance traveled and (2) visits to non-essential businesses. Unacast reports these metrics as percent differences

⁷For more details about the timing of the first stay-at-home orders, see <https://www.nytimes.com/2020/03/17/us/california-shelter-in-place-coronavirus.html>.

⁸The New York Times shares the data on Github here: <https://github.com/nytimes/covid-19-data>.

relative to pre-epidemic levels.⁹ In Figure 2, we show the daily level of Unacast’s two mobility measures across the United States from January 1, 2020 to the present. There is an 8% national drop in distance travelled and visits to non-essential businesses from March 11-17. This precedes the first stay-at-home order (on March 17) and reflects other national changes in awareness about Covid-19. From March 17 to April 7, mobility fell an additional 27%.

To look at the effect of stay-at-home orders on spending at small businesses, we combine our data on stay-at-home orders, Covid-19 cases, and mobility with consumer spending data from a company called Womply. Womply has collected 13 billion credit and debit card transactions totaling almost 1 trillion dollars between 2015 and the present. Womply collects this data directly from payment processors used by more than 1 million physical businesses in the United States. Womply filters its data, removing inactive businesses and businesses with sales larger than the Small Business Association’s size threshold that define which firms are small businesses.¹⁰ Womply provided the data to us as a daily time series, aggregated to the county*sector level. For example, Womply’s data describes consumer spending at restaurants in New York County during each day in March. Womply updates the data on a daily basis, with a 5-day lag. In Figure A2, we present a county-level map of the United States with color shading indicating the amount of per capita consumer spending at firms in the Womply panel, in each county in the United States, during the first week of March, 2020. And in Figure 5, we show the evolution of total consumer spending at businesses tracked by Womply from March 1, 2020 to the present.

While Womply’s panel is not representative of consumer spending as a whole, it does provide a high frequency, real time measure of consumer spending at a large set of small businesses in 2020. For the purposes of our analysis, we divide the Womply spending data into two types of business: restaurants (including bars, sit-down restaurants, and fast food businesses) and non-restaurant businesses (auto services, pharmacies, etc.).¹¹

⁹For more details about these two measures, see Unacast’s description of how they calculate these measures: <https://www.unacast.com/post/unacast-updates-social-distancing-scoreboard>.

¹⁰See the spreadsheet at this link for the definition of those thresholds by industry: <https://www.sba.gov/document/support--table-size-standards>.

¹¹Here are the types of businesses that we classify as restaurants: 100 types of restaurants, as well as bars, lounges, beer and liquor stores, convenience stores, farmers markets, bakeries, candy and dessert stores, delis, grocery stores and supermarkets, butchers, coffee shops, cafes and street vendors. We classify all other businesses as ‘other.’ We cannot currently separate out grocery stores from delis and bakeries in the consumer spending data from Womply, but

In Table A1, we list the sub-categories of businesses in Womply’s data, the average amount of daily revenue (across counties) at businesses in that sub-category during the first week of March 2020, and the aggregated category we use in our analyses (restaurant or other spending). We separate out restaurants because they are among the businesses most heavily hit by Covid-19.¹² In Table A1, we show that the average county contains \$318,981 per day of revenue from the Womply panel, with \$55,424 (17%) coming from our aggregated restaurant category. There is significant variation across counties, because counties vary in population. In Table A2, we show the same summary statistics on a per capita basis, dividing total Womply revenue at the day*category level by 2018 county-level population counts. We weight this table by county-level population. For example, the last row of the table, indicating overall spending, shows that the average person in the United States spends \$1.75 each day at firms in Womply’s panel. \$0.36 (21%) of that amount is spent on purchases at restaurants. We use this per capita measure in our event studies.

To get a more complete picture of consumer spending, we supplement the small business spending data from Womply with data on consumer spending at large firms from Second Measure. Second Measure tracks a panel of over 4.1 million consumers’ credit card, debit card, and bank transaction data. It aggregates and standardizes this transaction-level data and produces daily national and state-level time series describing how much money its panel of consumers spends at 3,600 firms operating in 2019-2020. For example, in the Second Measure data we can see the total amount of money spent by Second Measure’s panel of consumers at Amazon.com, Walmart, Whole Foods, Nike, and Costco. The national (state) data are available at a 5 (14) day lag.¹³ In Tables A3 and A4, we show summary statistics describing state-level and per capita spending data in the Second Measure panel.¹⁴ In an average state, consumers in Second Measure’s panel (roughly 1% of U.S. consumers) spend \$4.6 million each day on firms tracked by Second Measure, with a plurality of that spending (\$2.0 million) coming from firms in the retail trade sector, examples of which are Walmart

we plan to do so in the next draft of this paper.

¹²See, for example, Womply’s blogpost about how different sets of small businesses have been affected by Covid-19: <https://www.womply.com/blog/data-dashboard-how-coronavirus-covid-19-is-impacting-local-business-revenue-across-the-u-s/>.

¹³We report aggregates at a 14-day lag due to data disclosure requirements, but we use 5-day lagged spending measures in our event studies.

¹⁴Our per capita measure divides total Second Measure spending in a category*date by state-level population counts from 2018. Second Measure represents roughly 1% of U.S. consumers, and in the future we plan to use weights provided by Second Measure to adjust spending totals and event study estimates to reflect national trends in consumption. This draft of the paper presents raw per capita amounts for the sake of expediency.

and Costco. We also separate the Second Measure data into industries for our event study analyses.¹⁵ For example, in Table A3 you can see that 5.0% of the spending in this panel comes from Amazon.com. In Table A4, we present the same summary statistics, but we divide the revenue totals by state-level population to produce per capita estimates at the state level. We weight these per capita averages, quantiles, and standard deviations by state-level population. So for example, the average person in the United States spends \$0.58 on firms in Second Measure’s panel each day.

While the data from Womply and Second Measure are not necessarily mutually exclusive, they broadly cover different portions of the economy. Throughout the paper we refer to the Womply data as covering small businesses, and the Second Measure data as covering large businesses. In Figure 2, we present 17 daily measures of mobility and consumer spending in 2020, using data from Unacast, Womply, and Second Measure. In Panel A, we show that overall spending at Womply’s panel of small businesses fell by 40% year-over-year.¹⁶ At the same time, Unacast’s measure of distance travelled fell by 36% and visits to non-essential businesses fell by 53%.¹⁷ Meanwhile, online spending at large firms in Second Measure’s panel surged, increasing by 56% year-over-year and sales at brick-and-mortar stores in Second Measure’s panel fell by 9% year-over-year.¹⁸ Total spending at the larger firms in Second Measure’s panel rose by 8% year-over-year.

In Panel B of Figure 2, we plot consumer spending at the firms in Second Measure’s panel, broken out by industry. We also separately display spending at Amazon.com. Consumers are spending 89% less on transportation than they did last year. Spending on accommodation and food services (including hotels and restaurants) has fallen by 45%. At the same time, spending on food delivery services and Amazon.com has increased by 101% and 61% respectively. And overall spending on retail trade at these larger firms is flat year-over-year. Lastly, we collect a series of county-level characteristics describing population, income,

¹⁵Throughout this paper, we divide the Second Measure data into 21 categories. 17 of those categories are non-overlapping and based on NAICS code sectors. The remaining four: wholesale trade, grocery stores, pharmacies, and Amazon, are categories that we construct ourselves by hand-collecting firms and combining them into groups. For example, the Pharmacy sector contains CVS, Walgreens, Rite Aid, and a handful of smaller pharmacies.

¹⁶Data reported as of April 11, 2020.

¹⁷Data reported as of April 11, 2020.

¹⁸Aggregate trends from Second Measure reported as of April 2, 2020. Second Measure only classifies sales as being online vs. brick-and-mortar for a smaller set of companies in their coverage list, so this overall percentage does not indicate the fraction of online sales for a specific company or for their entire sample of firms. Still, we believe it is informative.

urbanity, and educational attainment from the United States Department of Agriculture (USDA). The USDA sources these summary statistics from the Bureau of Labor Statistics, the U.S. Census Bureau, and American Community Survey 2014-2018 summary tables.¹⁹ We also collect information about which counties voted Republican in the 2016 presidential election.²⁰ We use this information to split our sample of counties by type: high- vs. low-income and Republican-supporting vs. Democrat-supporting in our analysis of heterogeneity in the effects of stay-at-home orders on consumer behavior.

Empirical strategy

We are interested in measuring the effect of stay-at-home orders on household mobility and consumer behavior. We use an event study framework, comparing mobility and spending patterns immediately before and after counties implement stay-at-home orders.

Our main specification is:

$$Y_{c,t} = \sum_{s=-10}^{10} \beta_s 1(event\ occurred)_{c,t-s} + \lambda_c + \lambda_t + \varepsilon_{c,t}$$

In our analysis, Y_t is one of four outcomes:

- (1) Percentage change in distance traveled (distance)
- (2) Percentage change in visits to non-essential businesses (visits)
- (3) Per capita daily spending at restaurants
- (4) Per capita daily spending at small businesses that are not restaurants

In this model, λ_c and λ_t are county and date fixed effects. In robustness checks, we include state-by-date fixed effects, relying on within-state variation in the timing of county-level stay-at-home orders to drive our results. The coefficients of interest, β_s , represent the days-since-event fixed effects. $1(event\ occurred)_{c,t-s}$ is 1 if the event occurred in county c as of time $t - s$ and 0 otherwise.

¹⁹To access the raw data describing county-level information, see <https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/>.

²⁰We gather this data from work done by Tony McGovern to collect vote margins at the county-level for U.S. presidential elections from 2008-2016. See documentation here for more details: https://github.com/tonmcg/US_County_Level_Election_Results_08-16 This data was initially scraped from Townhall.com.

We also perform similar event studies at the state-level using data from Second Measure, relying on the same empirical model. In those event studies, we include state and date fixed effects and estimate the coefficients of interest: (β_s) . Second Measure provides data at the firm*state level, so we use state-level variation and not county-level variation in these regressions. In the state-level event studies, we define the “event” as the date when at least half of a state’s population was covered by a stay-at-home order.

In our county-level event studies, we analyze changes in consumer behavior around two distinct types of events: the first date of a stay-at-home order and the first date when a Covid-19 death was reported in the county.²¹ The date of first death can be thought of as alternative event, which could have caused large changes in consumer behavior. However, in practice, consumer behavior is smooth around the date of first death, suggesting it is more useful as a “placebo event”. This placebo event allows us to difference out common trends, and focus on the causal effect of the stay-at-home order. In all specifications, we peg $t = 0$ to be the first day for which the county had the relevant event. Because some stay-at-home orders are quite recent, we perform this analysis on an unbalanced panel of counties. We will extend these results in the future as we gather additional weeks of data.

Results

Stay-at-home orders sharply reduce mobility. In the top left panel of Figure 5, we plot the Unacast measure of distance travelled relative to the pre-pandemic period. We separately plot changes in distance travelled for counties with early, middle, later, and late stay-at-home orders. Before March 8th, these counties show virtually no differences in distance travelled. Between March 9th and March 16th, gaps open up. Residents of each of the five groups experiences a decline in distance travelled, and that decline is steeper in the states with early stay-at-home orders, even though those orders have not gone into effect yet. This reflects the fact that in counties that were the worst-hit by Covid-19, people chose to travel less, even before a stay-at-home order came into effect. But, after the early stay-at-home orders go into effect, we see a widening of the gap between distance travelled in counties that implemented early and late stay-at-home

²¹In our state-level event studies we only examine the stay-at-home order event because in most states, the date of the first death was less salient.

orders. We explore this in later event studies. In the top right panel of Figure 5, we show that the same patterns appear in Unacast’s measure of visits to non-essential businesses.

In the bottom panel of Figure 5, we show the same plots, but with our aggregated measures of spending data from Womply. In the left panel, we plot per capita expenditures on restaurants. On February 26, 2020, Womply’s panel tracked around \$0.40 of consumer spending, per person in the United States, at small businesses specializing in food services. There is a strong day-of-the-week cyclical in this figure, but you can see an overall decline in consumer spending on small businesses that specialize in food services (restaurants). In the event studies, we explore the causal effect of stay-at-home orders on these spending quantities. In the bottom right panel, we present the same measure but for non-restaurant expenditures. Here, we also see the general decline in consumer spending at small businesses.

We now turn to our event studies, which allow us to precisely estimate the effects of stay-at-home orders hinted at in Figure 5. These event studies rely on the model discussed above. In Figure 6, we plot two event studies: in blue, we show the effect of a county instituting a stay-at-home order. In red, we plot the equivalent event study estimate around the date of a county’s first Covid-19-related death (our “placebo event”). In the top panel of 6, we see large differences in how people respond to the first death and the stay-at-home order. People travel less in the days immediately preceding both the first Covid-19 death and the first stay-at-home order. But by the day after the first death in each county, people continue traveling less and visiting non-essential businesses less at roughly the same trend. For the stay-at-home orders, we see sharp decreases of 9-13% in distance travelled and the probability a person visits a non-essential business by the day after a stay-at-home order was imposed.

In the bottom left graph in Figure 6, we produce the same plots for spending at restaurants. Here we see similar patterns. Stay-at-home orders reduced spending at restaurants in the Womply panel by \$0.10 per person by the day following the stay-at-home order relative to a baseline of \$0.36 cents in the sample. In the bottom right panel, we show that the same pattern does not hold for other types of small businesses. While small businesses earn less revenue in the days preceding and immediately following a stay-at-home order, there is no sharp effect of the stay-at-home order on spending relative to the general downward trend in spending in the days preceding the stay-at-home order. For the restaurant sector, 28% of the overall reduction in consumer spending occurred by the day after a stay-at-home order went into effect. While a

large reduction in spending at non-restaurants also occurred in the days following a stay-at-home order, this does not appear to be immediately caused by the stay-at-home orders.

In Figure 7, we perform the same event studies at the state-level for eight different groupings of firms from Second Measure's panel of 3,600 larger firms. We focus on the changes in spending surrounding stay-at-home orders. We divide these firms into sectors and show that spending on accommodations and food services and transportation fell in the days preceding a stay-at-home order and continued to fall after the stay-at-home order was implemented. But we see a sharp increase in consumer spending on food delivery services in the days immediately following a stay-at-home order. And we see sharp declines in spending on firms in the general/wholesale retail sector and in retail trade. Lastly, in Figure 8 we show that even though spending at Amazon.com has surged during the Covid-19 pandemic, there is no sharp change in spending on Amazon.com in the days immediately preceding and following a stay-at-home order.

County-level heterogeneity

In Figures 9 and 10, we look at how the effects of stay-at-home orders vary along three dimensions: high/low-income counties, Republican-supporting and Democrat-supporting counties in the 2016 presidential election, and counties that implemented stay-at-home orders early (before March 27th) or later.

In Figure 9, we examine measures of mobility. Residents of high-income counties were travelling less in the days preceding a stay-at-home order but visiting relatively more non-essential businesses. In low-income counties, the gradient was more shallow, with less of a change in travelling behavior in the days before a stay-at-home order. However, people in both groups of counties respond similarly to stay-at-home orders. We find similar patterns when we split the data by 2016 vote share; in the middle panels from Figure 9, residents of Republican-supporting counties also changed their behavior less in the days preceding a stay-at-home order. Residents of Democrat-supporting counties reduced their travel time significantly before the effective date of the stay-at-home order. But for both of these groups of counties, the stay-at-home order decreased distance traveled by roughly 10%. Lastly, in the bottom row of panels from Figure 9, we see that counties implementing stay-at-home orders before March 27th or on/after March 27th experience similar trends in mobility before and after stay-at-home orders.

In Figure 10, we show that the effect of stay-at-home orders on expenditures at restaurants is driven almost entirely by high-income counties, where residents reduced their spending in the run-up to a stay-at-home order and then reduced spending even more by the day following a stay at home order. Residents of low-income counties do not change their spending behavior in the days preceding a stay-at-home order and only marginally reduce their spending in the days following a stay-at-home order. Again, we find residents of Republican-supporting counties do not change their spending behavior significantly in the days preceding a stay-at-home order, but they do respond to the stay-at-home order, reducing spending at restaurants. The effect is even larger in Democrat-supporting counties, where residents (1) reduce their spending at restaurants by more in the days preceding a stay-at-home order, and (2) experience sharper declines in spending at restaurants in the days following a stay-at-home order.

High and low-income counties and Republican-supporting and Democrat-supporting counties do not vary significantly in the change in average spending on non-restaurants in the days surrounding the stay-at-home order. This is true in the days immediately preceding and following a stay-at-home order.

The results of Figures 9 and 10 show similar patterns between high income and Democrat-supporting counties, and low income and Republican-supporting counties, reflecting some overlap between these designations. The split that tends to make the distinctions the most precise, however, is political leanings. One potential confounder for interpreting differences by political leanings is that Republican-supporting counties implemented stay-at-home orders later in the sample period than Democrat-supporting counties. Thus, in Figure 11, we present figures showing event studies for Republican-supporting vs. Democrat-supporting counties. But, within each political persuasion, we divide counties by early vs. late stay-at-home orders. This figure shows that Republican counties which implemented stay-at-home orders early and late in the period look similar to each other, suggesting differences by politics cannot be explained by Republican counties acting later. Figure 11 also suggests that Democrat-leaning counties that implemented orders later are more similar to Republican counties in their response.

Robustness

The results we have presented so far are not typical event studies. Usually, one expects to see a flat average value of an outcome in the pre-period followed by a sharp break after the event. In the event studies we have shown you so far, we ask you to compare trends over time in mobility and sales in the days surrounding a stay-at-home order and in the days surrounding the first Covid-19 death in a given county. We believe that the ‘pre-trend’ here is an important part of the story. People changed their behavior in response to general awareness of Covid-19, which varied systematically within a county and over time. But stay-at-home orders had only small (but measurable) effects on mobility and spending relative to the immediate national change in mobility and spending soon after March 11th.

In Figure A3, we show county-level event studies using the Unacast and Womply data as outcomes, but we include state-by-date fixed effects as controls. Otherwise, these event studies are the same as those shown in Figure 6. Including these fixed effects allows us to control non-parametrically for state-level trends over time in mobility and spending. As state policymakers made a series of policy decisions that were unrelated to stay-at-home orders during March and April 2020, these policies might confound our results.

In these event studies with the Womply data and state-by-date fixed effects, we can see that several of the patterns discussed above still hold true. Stay-at-home orders decreased distance travelled by 4% and decreased visits to non-essential visits by 7% in our sample of counties that provided within-state variation in stay-at-home orders. The magnitude of these changes is smaller than in our main specifications, described in the previous section. The difference in the magnitude of the effect is unsurprising because our variation in stay-at-home orders is coming from a different sample of counties. Most of the within-state variation in stay-at-home orders comes from Southern states, where counties instituted stay-at-home orders before state-wide orders went into place. Meanwhile, in Northern and Western states, states imposed stay-at-home orders before counties. See Figure A1 for a map describing the source of variation once we control for state-by-date fixed effects.

Lastly, in Figure A6, we present the Second Measure event studies described above, but we restrict our dataset to states that implemented state-wide stay-at-home orders only. This has no effect on our results. Although as a note of caution, only 23 states have within-state variation, and the standard errors presented

in this figure are clustered at the state level.

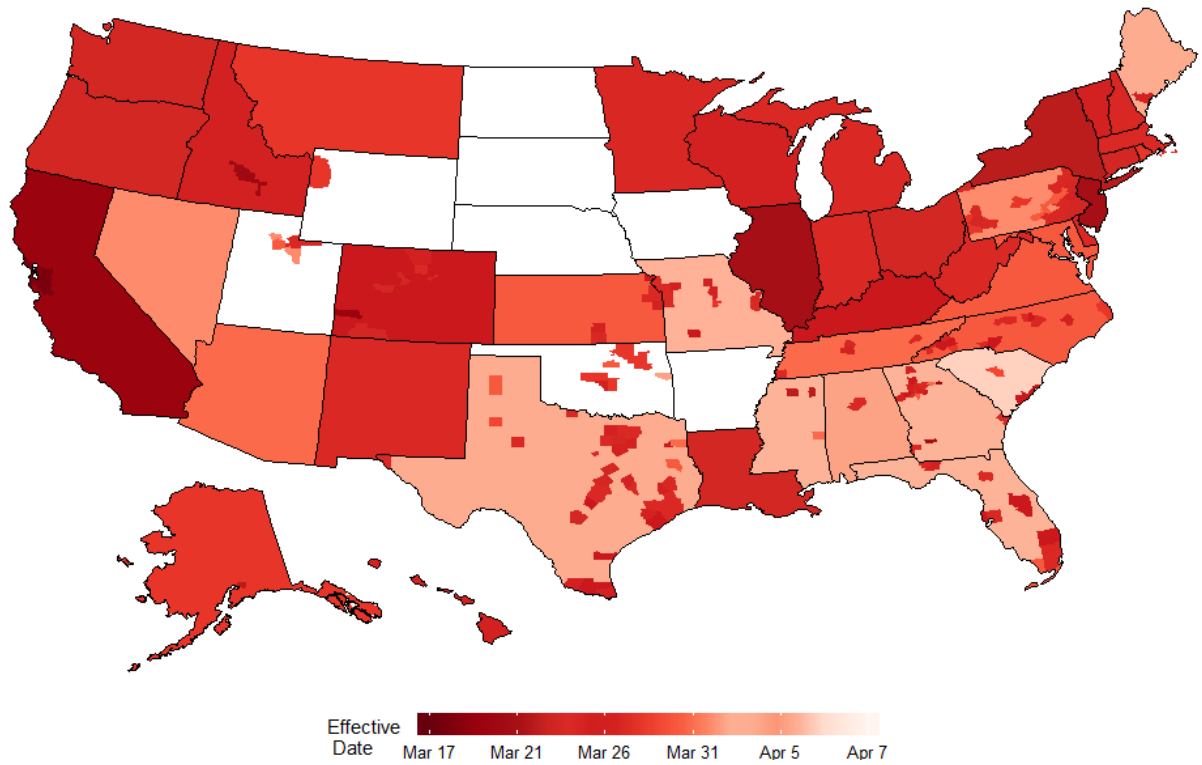
Conclusion

As the Covid-19 pandemic expands across the United States, states and counties are using stay-at-home orders to encourage social distancing. We first show that Covid-19 has had large effects on consumer behavior, reducing spending at small businesses and physical stores of large businesses. We also show that Covid-19 has sharply increased online consumer spending at large firms. We then turn our attention to stay-at-home orders, a policy where local or state officials encourage residents to stay at home. Stay-at-home orders do cause noticeable changes in consumer behavior, but these effects explain only a small fraction of the change in consumer behavior and spending since mid-March.

References

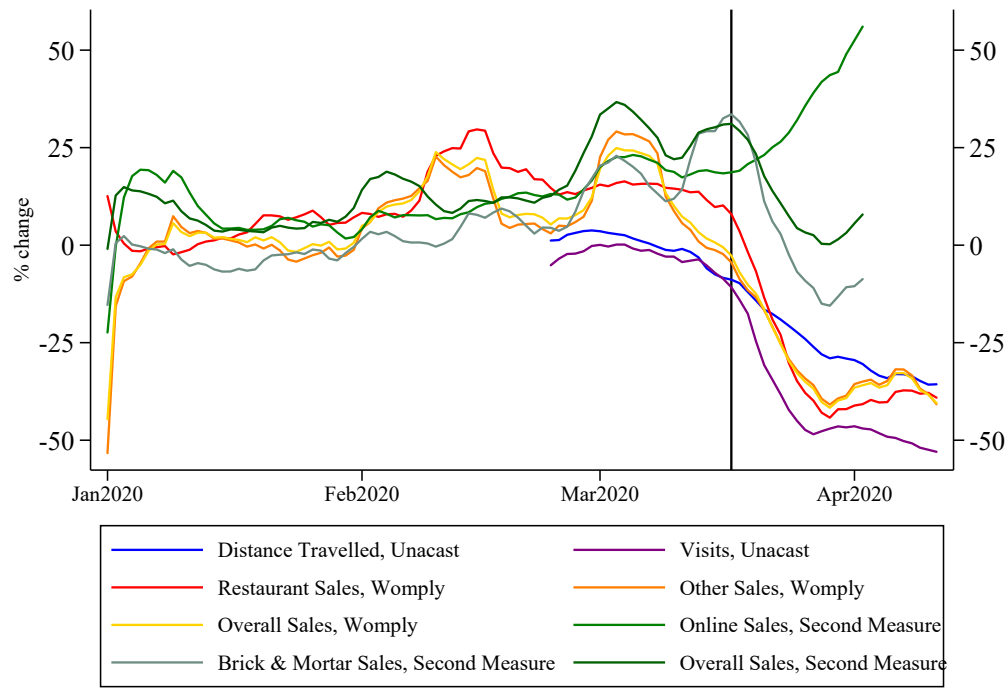
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Figure 1: Stay-at-home order timing



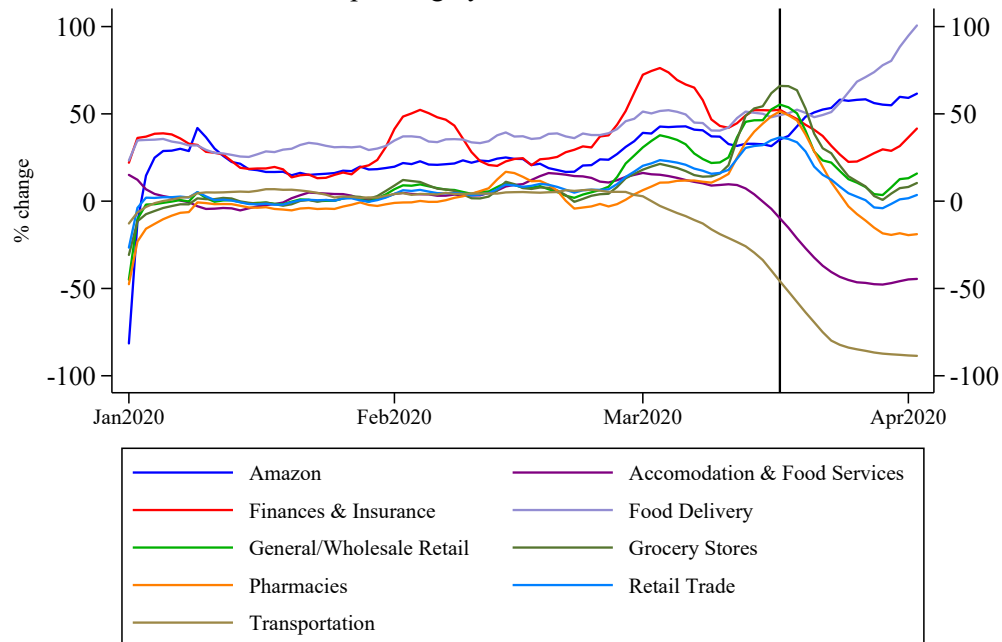
Notes: Data shown through April 7. A lighter color indicates a later stay-at-home order (like Missouri, implemented on April 6, 2020). Darker colors indicates states with earlier stay-at-home orders (like California, implemented on March 19, 2020). The color gradient then varies depending on the timing of the stay-at-home order.

Figure 2: Aggregate trends



Note: Vertical line marks the date of the first stay-at-home order (March 17th, 2020).

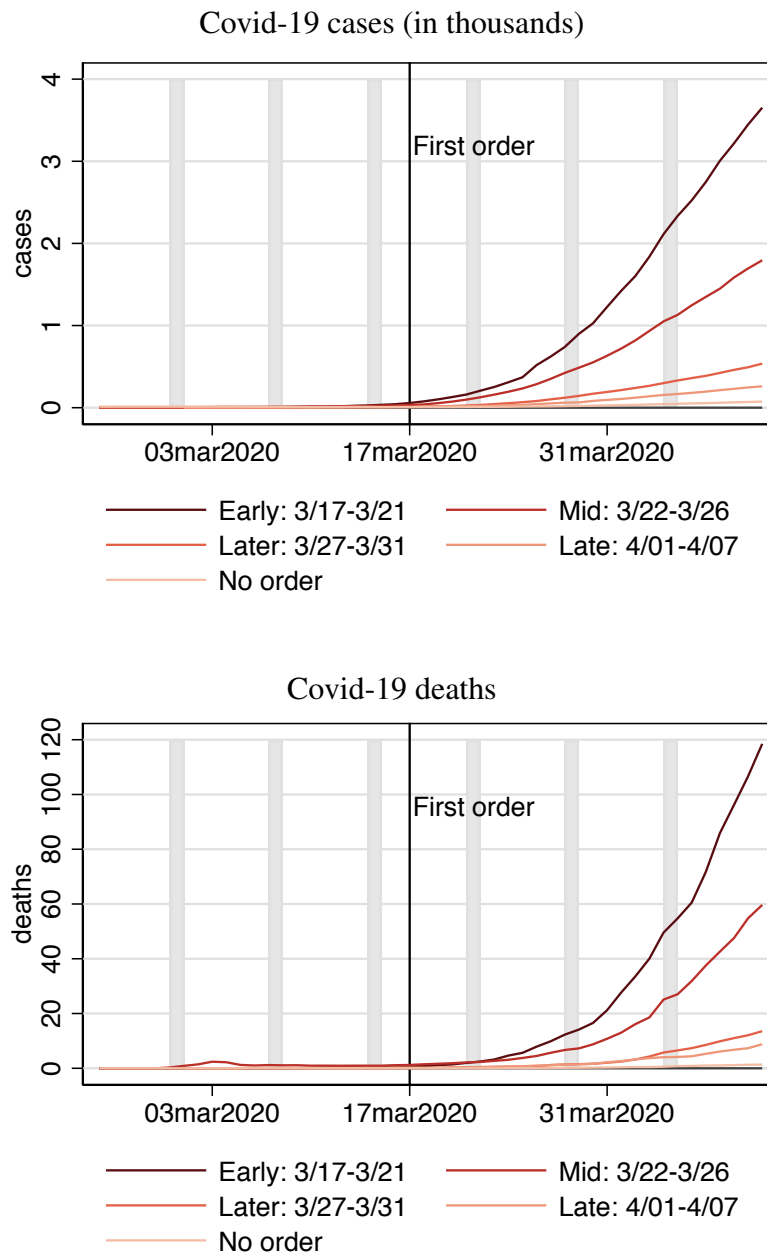
Consumer Spending by Sector, from Second Measure



Note: Vertical line marks the date of the first stay-at-home order (March 17th, 2020).

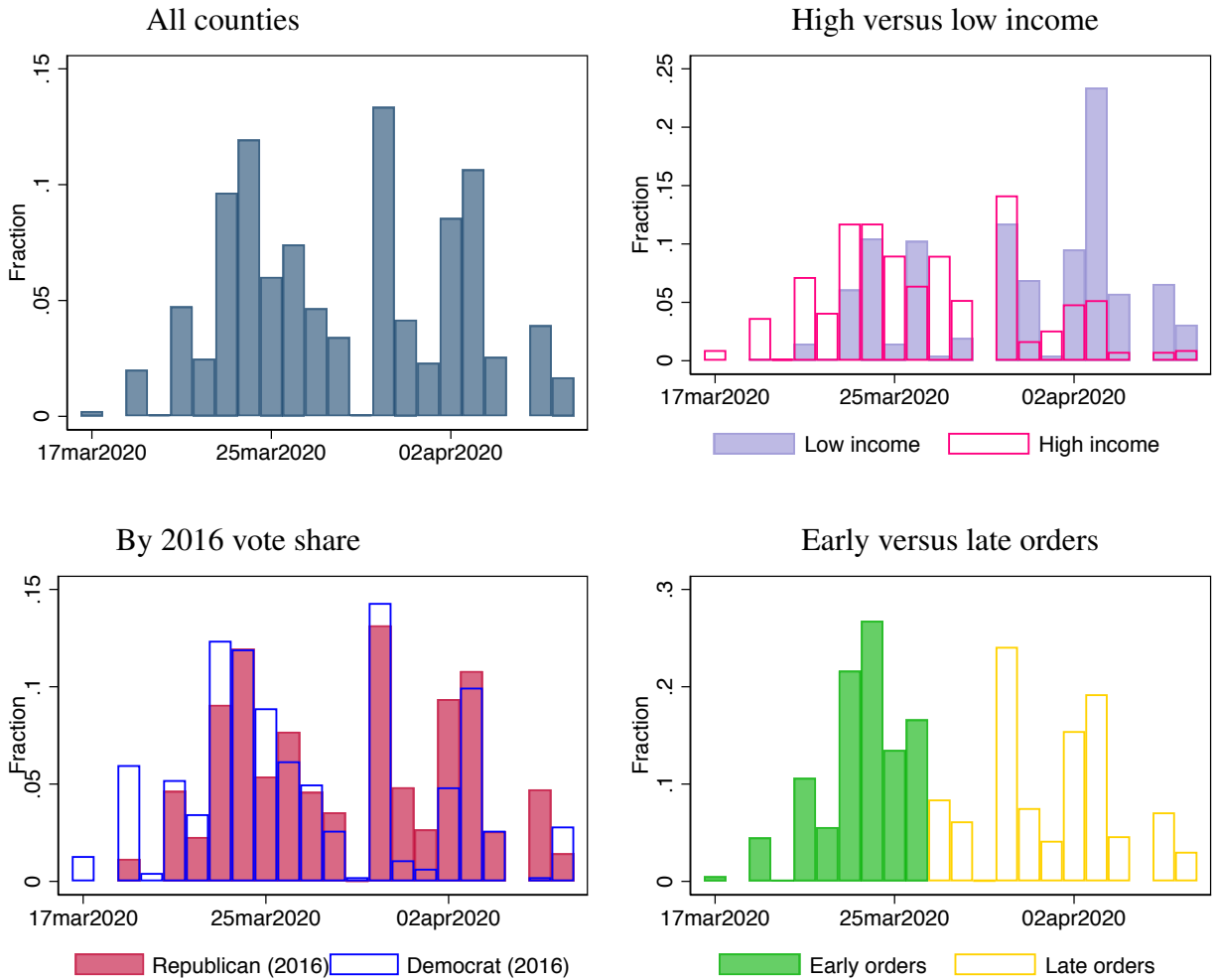
Notes: Plotted values for sales are 7-day moving averages of percent changes in average daily sales from a year ago, same weekday. Values for distance travelled and visits (from Unacast) are 7-day moving averages of percent changes in mobility relative to the week since the national emergency was announced. Spikes in sales around the first of the month are due to online subscriptions and regular payments made on a monthly basis.

Figure 3: Stay-at-home orders and disease spread



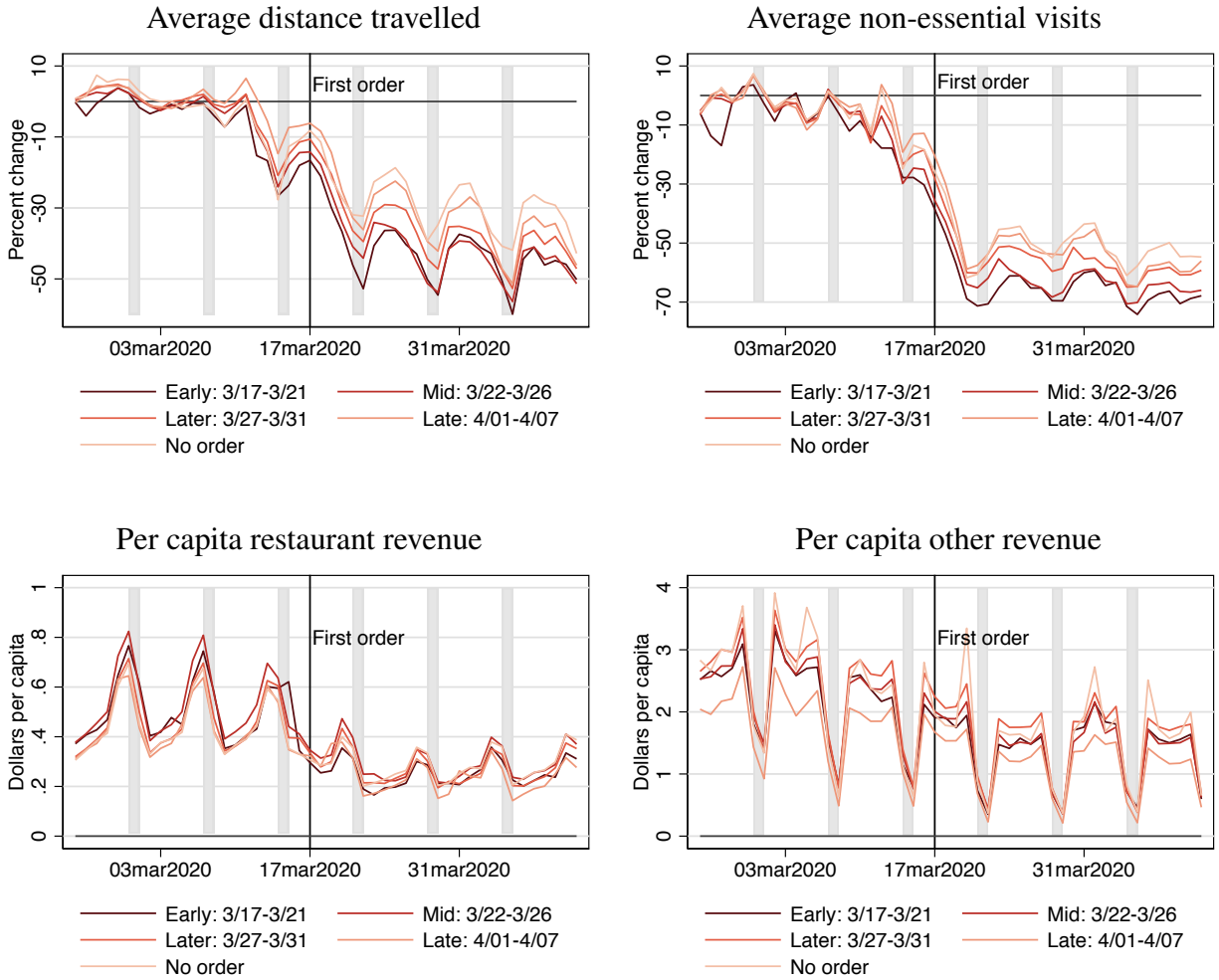
Notes: Shaded bars denote weekends. Vertical line marks the date of the first stay-at-home order (March 17th, 2020). Data drawn from the New York Times' publicly available Covid-19 case and death counts. Data are population-weighted county-level averages of cumulative case counts and death counts.

Figure 4: Histograms of stay-at-home effective dates



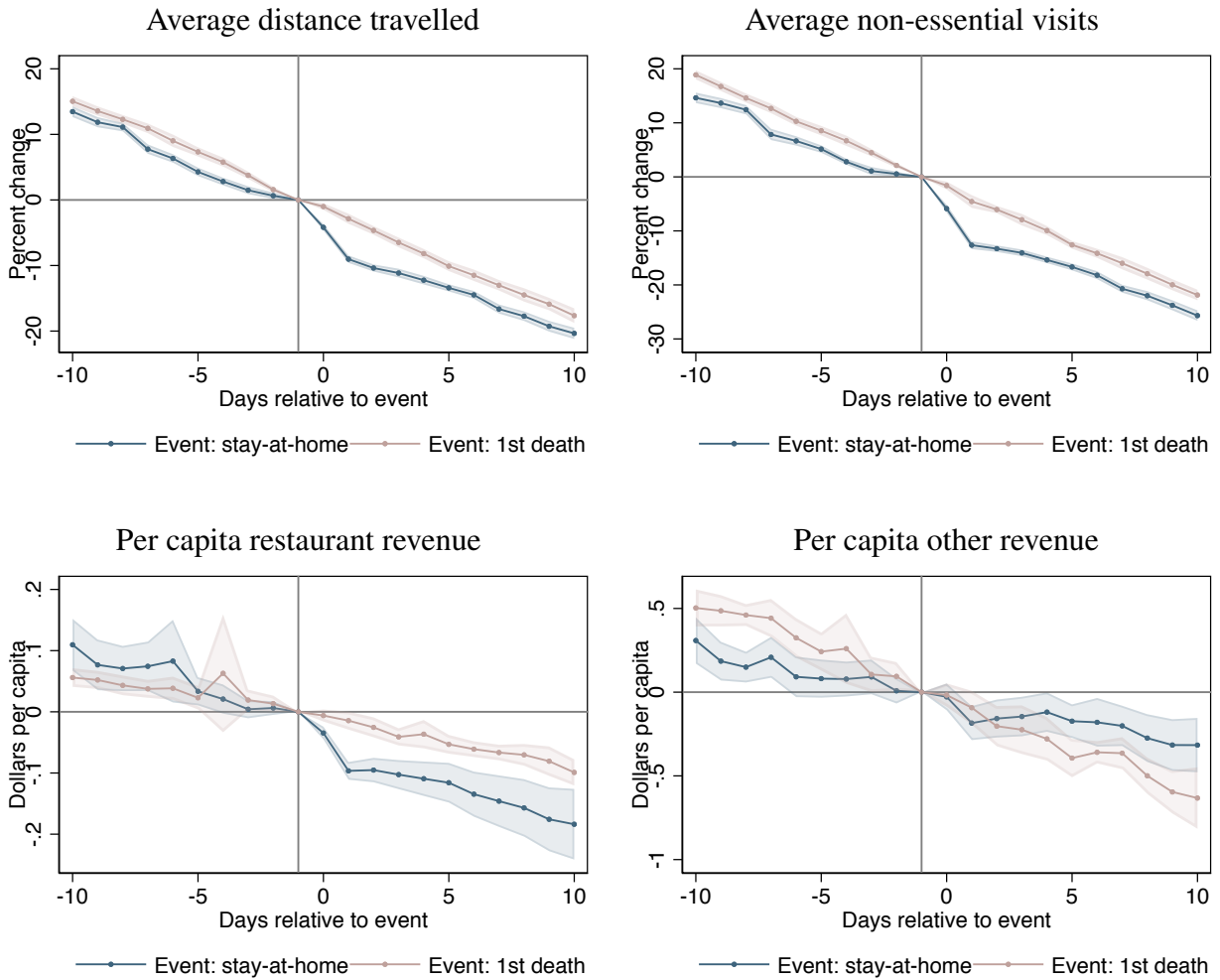
Notes: Stay-at-home orders drawn from our hand-collected county-level dataset. Histograms shows the distribution of stay-at-home orders across counties. Low-income and high-income counties are defined using the bottom-25% and top-25% of the median household income distribution. Republican and Democrat-supporting counties are defined using 2016 vote share, splitting counties by whether they supported or opposed a Republican in the 2016 presidential election.

Figure 5: Effect of stay-at-home orders on mobility and revenue: calendar time



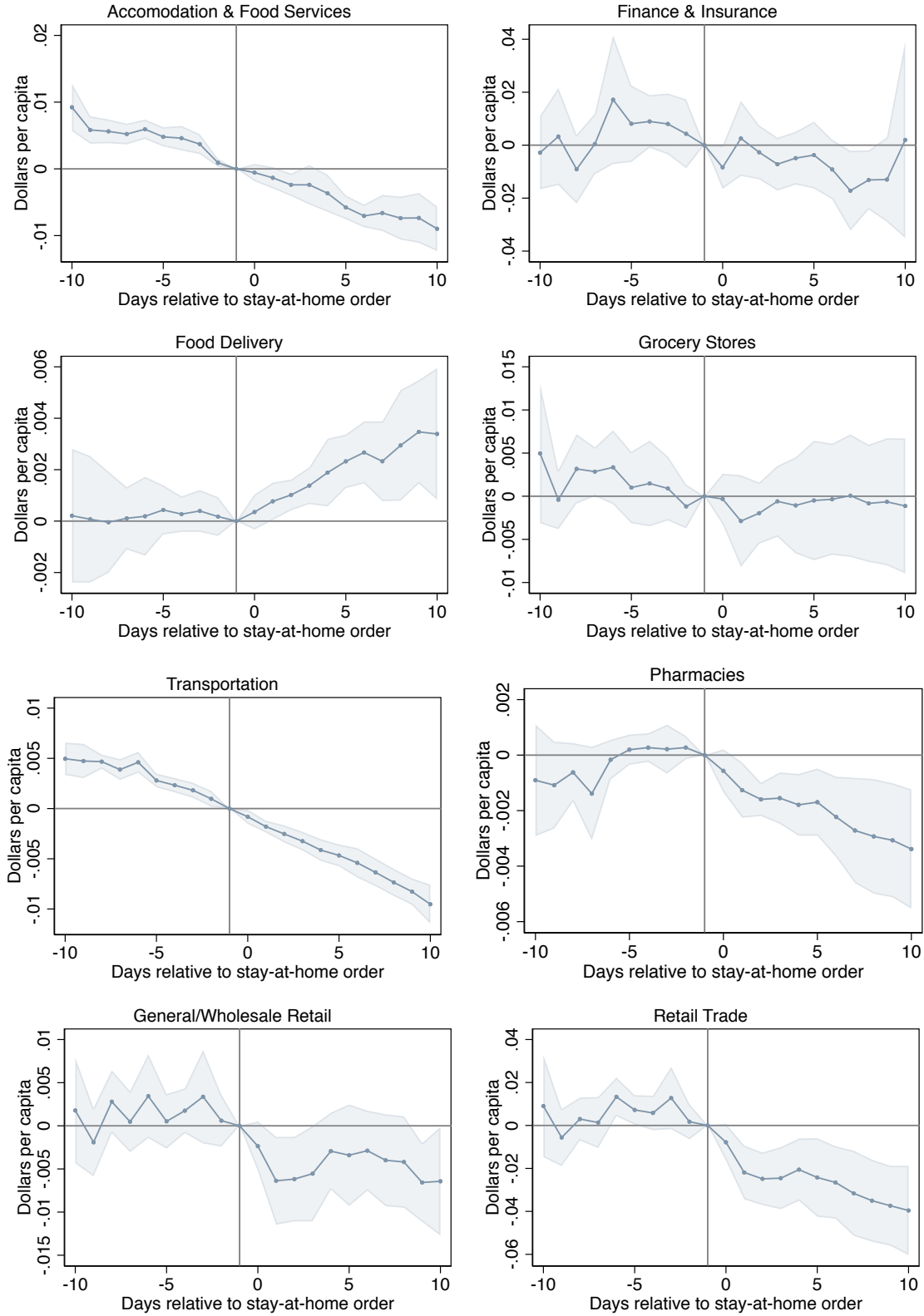
Notes: Shaded bars denote weekends. Vertical lines marks the date of the first stay-at-home order (March 17th, 2020). Mobility outcomes derived from Unacast data. Per capita revenue outcomes derived from Womply's panel of small businesses. Data are population-weighted county-level averages of per capita spending by category.

Figure 6: Effect of stay-at-home orders on mobility and revenue: event time



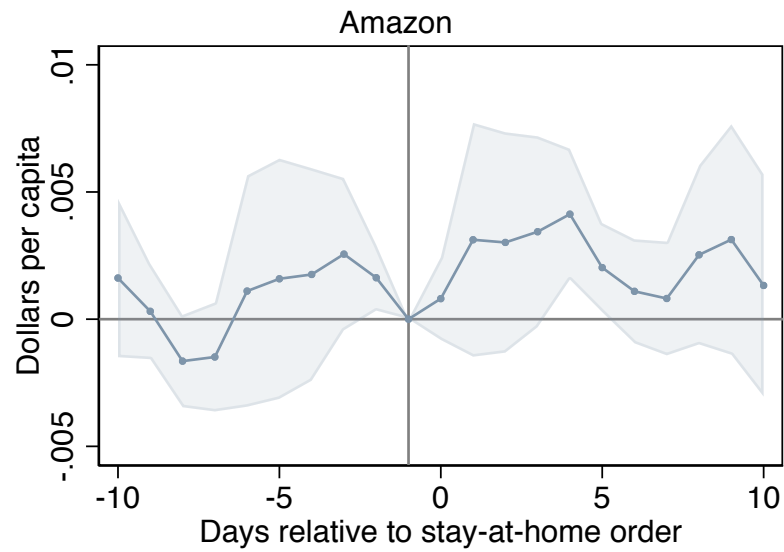
Notes: Data at the county-day level. Plotted are coefficients on event time dummies from a regression which also includes date and county fixed effects, weighted by county-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Mobility outcomes derived from Unacast data. Per capita revenue outcomes derived from Womply's panel of small businesses.

Figure 7: Consumer spending at large businesses, in event time (Second Measure)



Notes: Data at the state-day level. Plotted are coefficients on event time dummies from a regression which also includes date and state fixed effects, weighted by state-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the date >50% of the state population was covered by a stay-at-home order. Only states with at least 5 days of post-event data included (event time 0-4). Consumer spending data derived from Second Measure's panel of large firms.

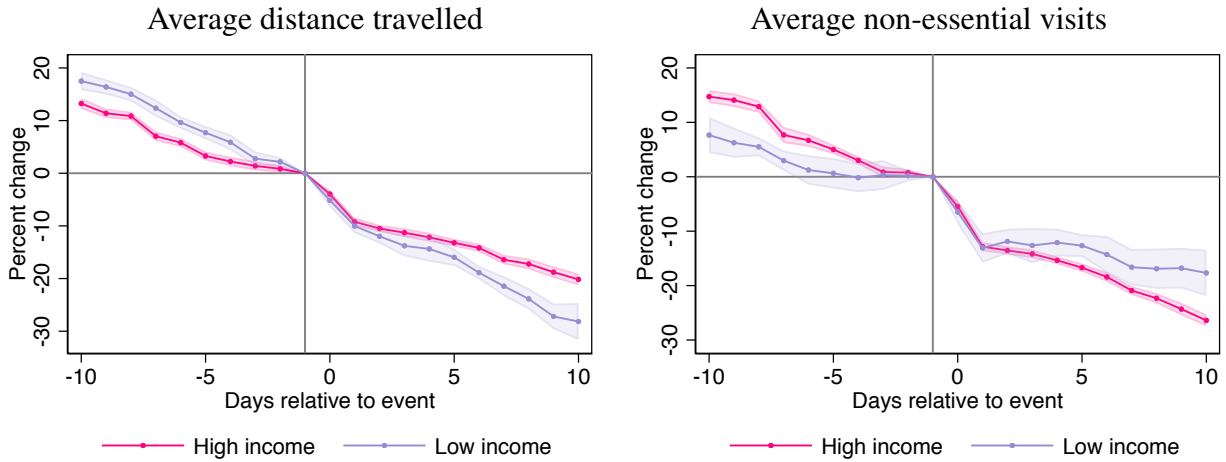
Figure 8: Second Measure in event time: Amazon



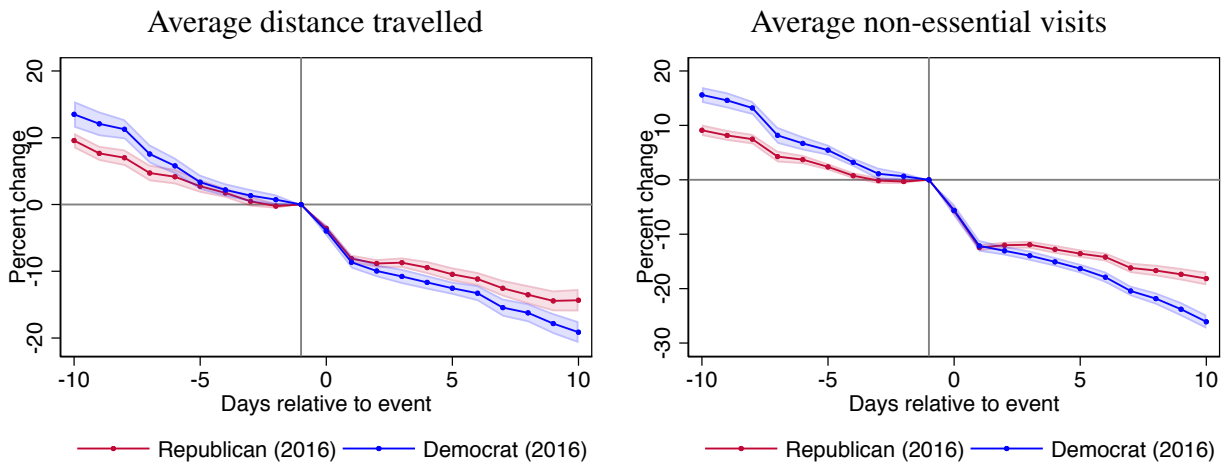
Notes: Data at the state-day level. Plotted are coefficients on event time dummies from a regression which also includes date and state fixed effects, weighted by state-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the date >50% of the state population was covered by a stay-at-home order. Consumer spending data derived from Second Measure's panel of large firms.

Figure 9: Unacast in event time: by county characteristics

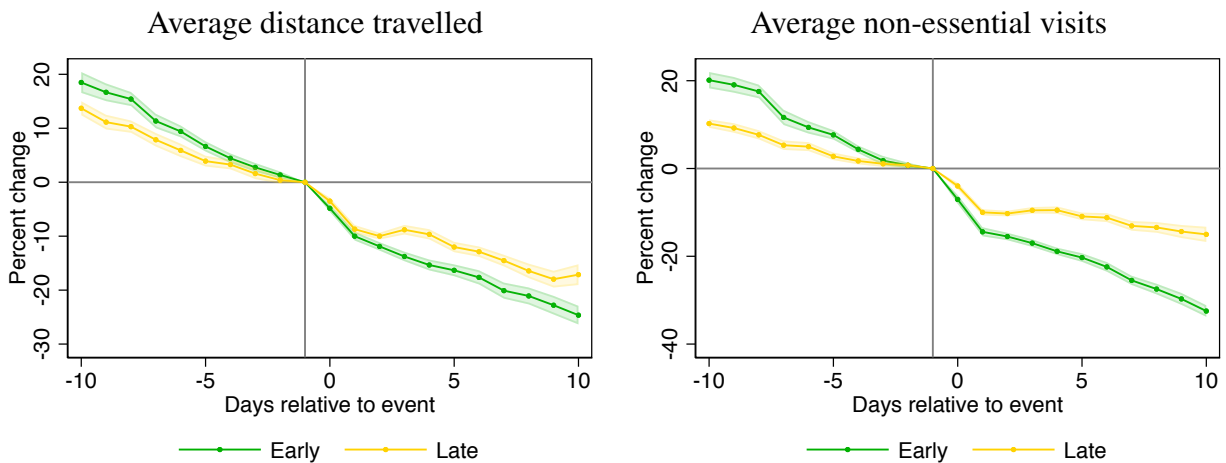
By top and bottom income quartile



By 2016 presidential vote share

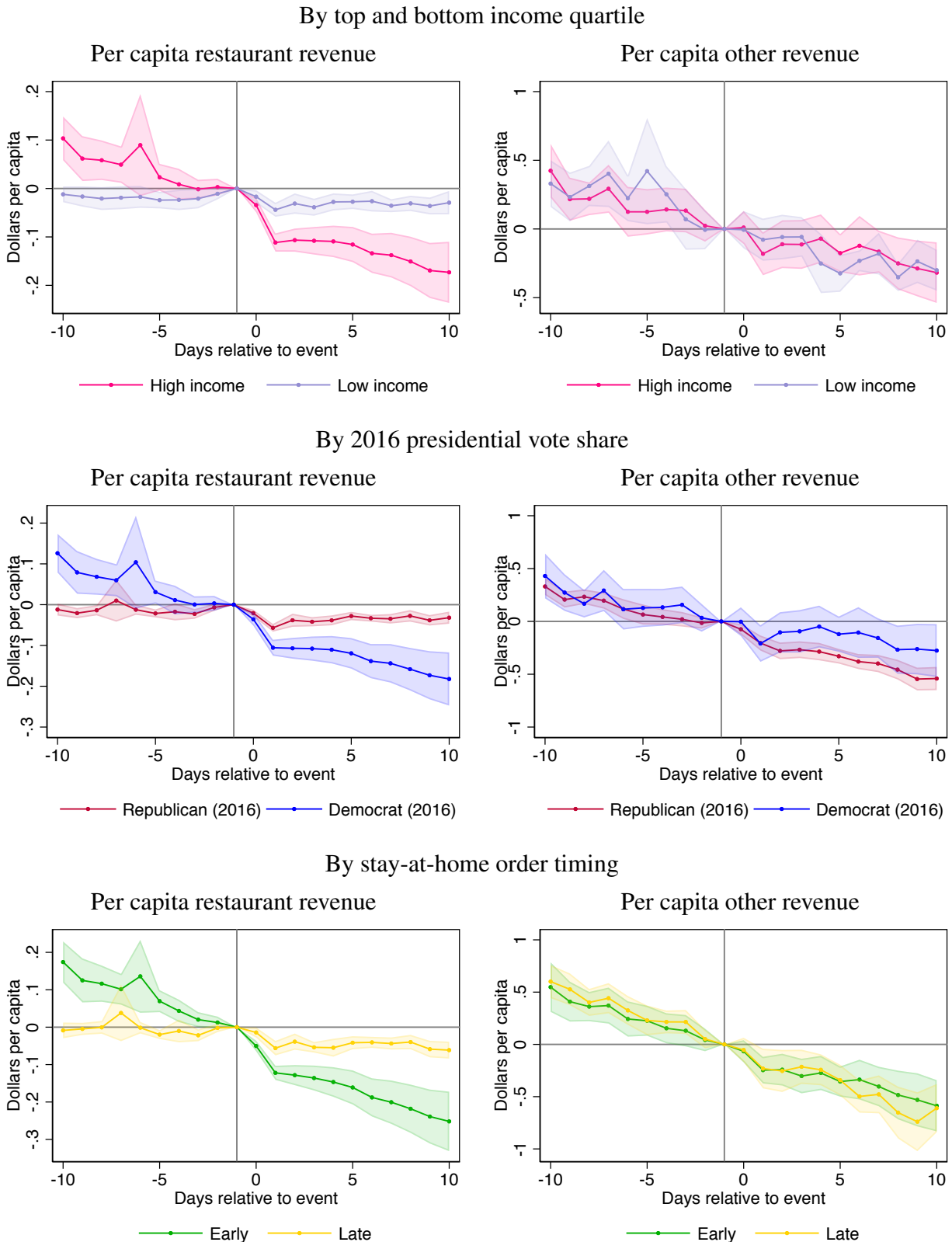


By stay-at-home order timing



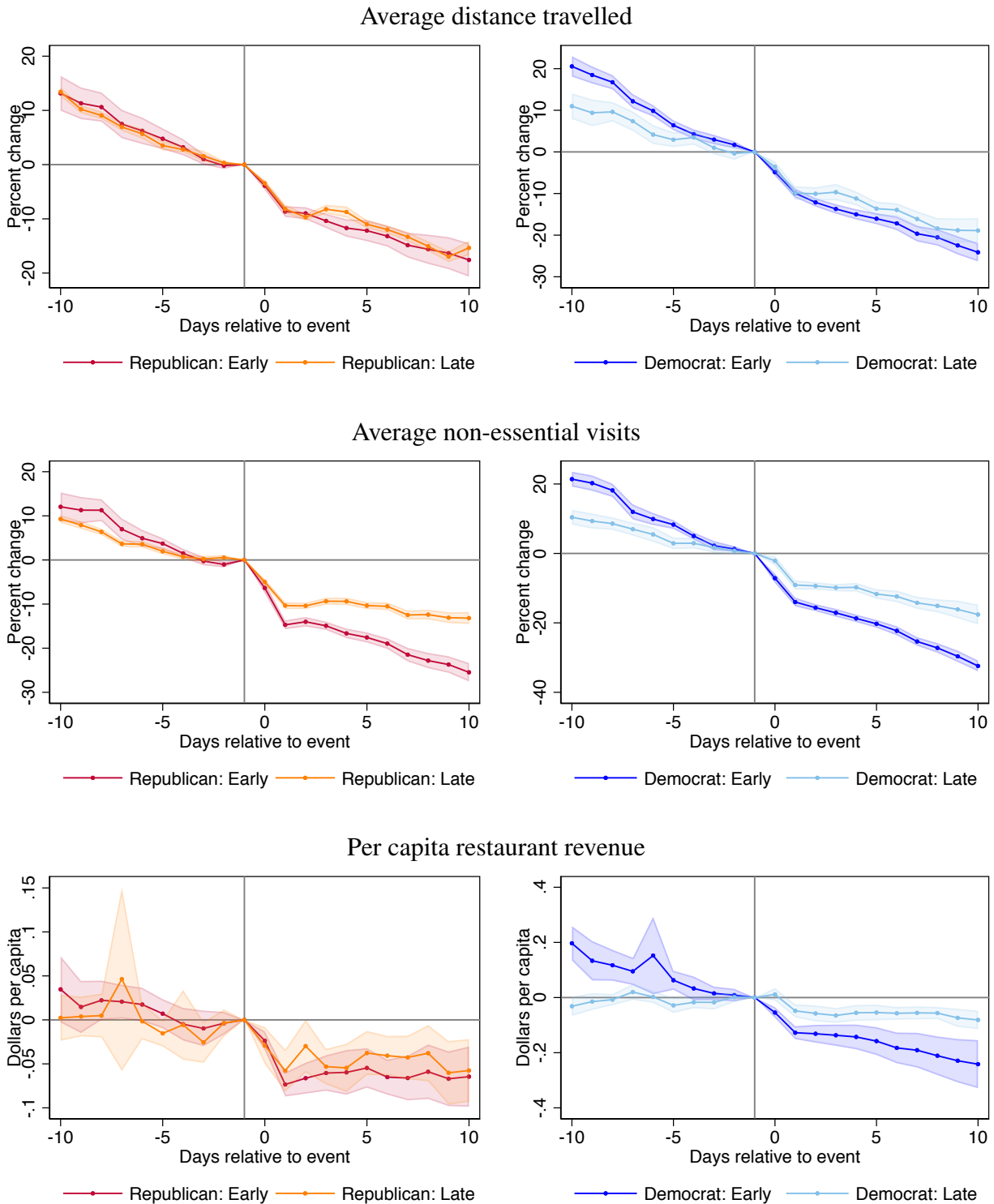
Notes: Data at the county-day level. Plotted are coefficients on event time dummies from a regression which also includes date and county fixed effects; weighted by county-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Mobility outcomes derived from Unacast data.

Figure 10: Womply in event time: by county characteristics



Notes: Data at the county-day level. Plotted are coefficients on event time dummies from a regression which also includes date and county fixed effects; weighted by county-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Per capita revenue outcomes derived from Womply's panel of small businesses.

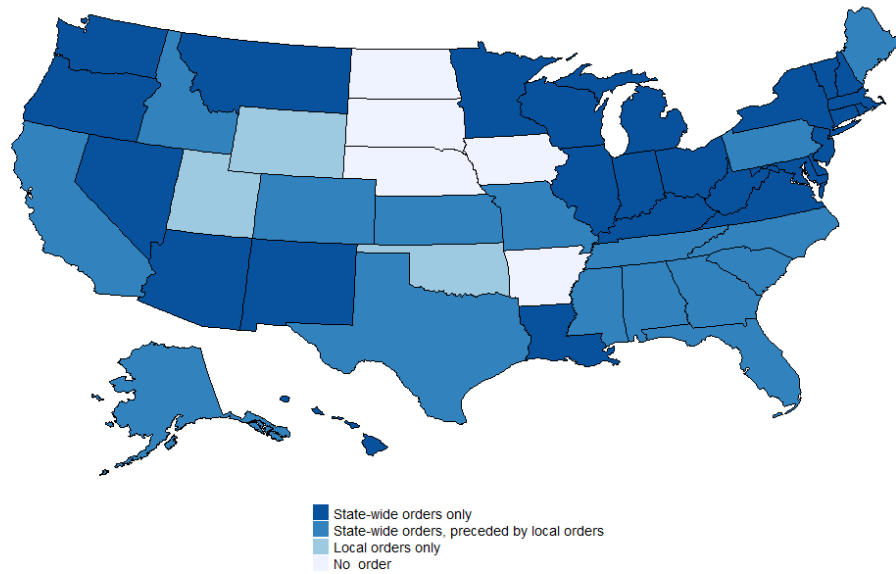
Figure 11: Unacast in event time: by timing and politics



Notes: Data at the county-day level. Plotted are coefficients on event time dummies from a regression which also includes date and county fixed effects; weighted by county-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Mobility outcomes derived from Unacast data. Per capita revenue outcomes derived from Womply's panel of small businesses.

A Appendix: For Online Publication

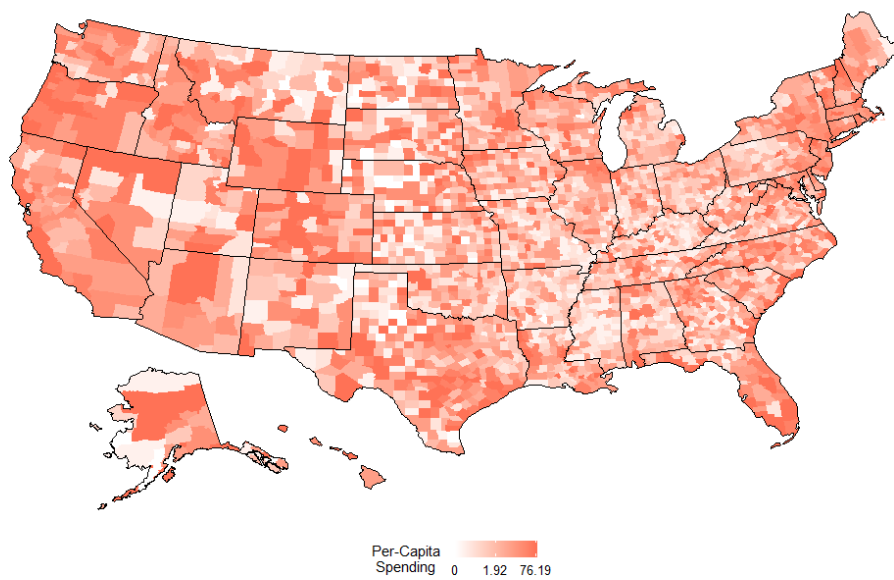
Figure A1: Variation in geographic coverage of stay-at-home orders



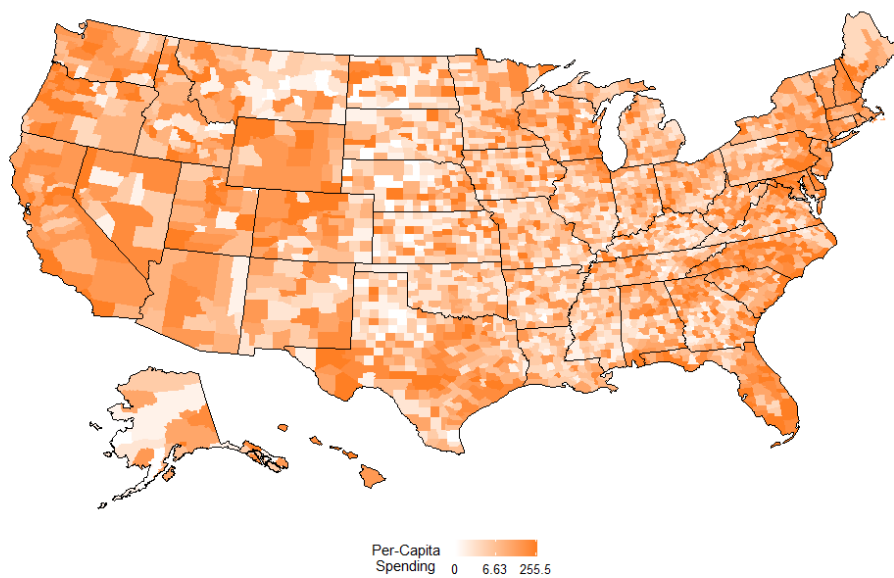
Notes: Data shown through April 7.

Figure A2: Daily per capita revenue (Womply)

Per capita restaurant revenue

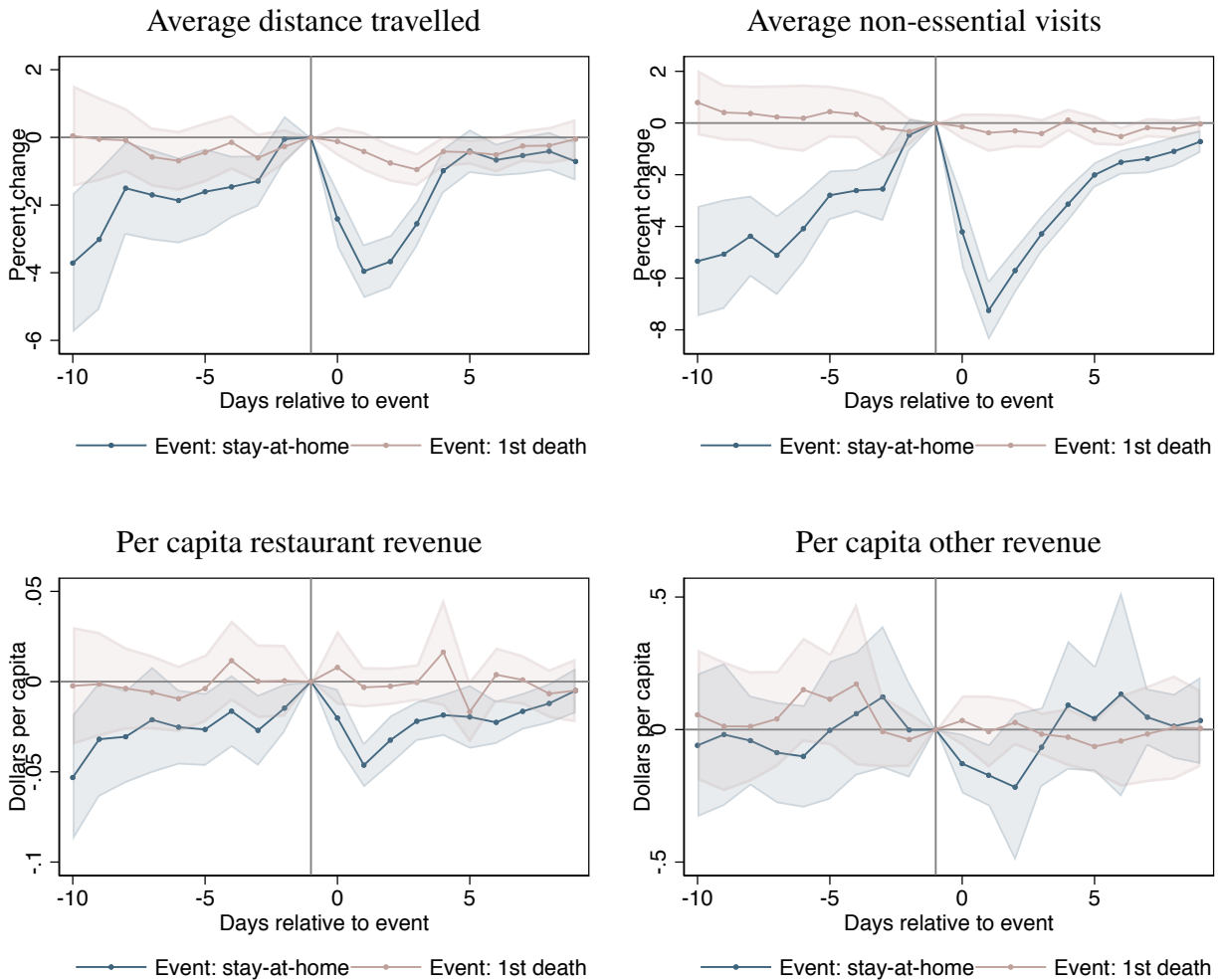


Per capita other revenue



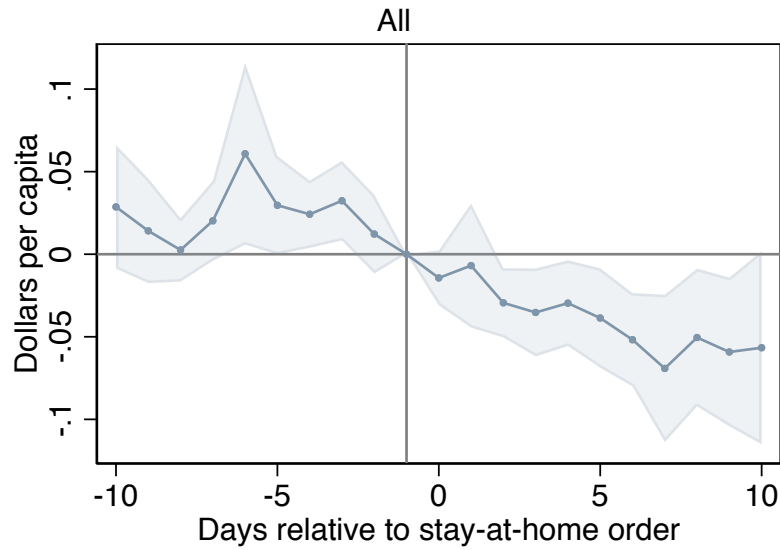
Notes: Per capita restaurant and other revenue derived from Womply's panel of small businesses, from March 1 through March 7.

Figure A3: Effect of stay-at-home orders on mobility and revenue: adding state-by-date fixed effects



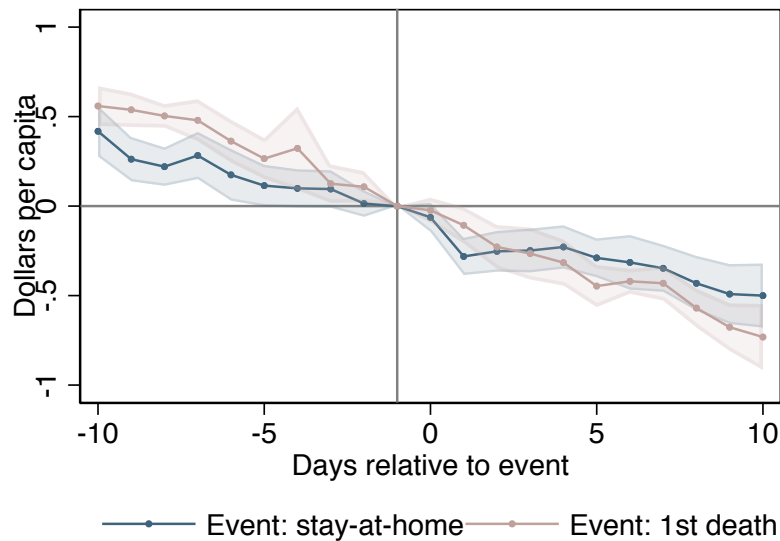
Notes: Data at the county-day level; only states with within state variation in the timing of stay-at-home orders are included. Plotted are coefficients on event time dummies from a regression which also includes date, county, and state-by-date fixed effects; weighted by county-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Mobility outcomes derived from Unacast data. Per capita revenue outcomes derived from Womply's panel of small businesses.

Figure A4: Second Measure in event time: all sectors



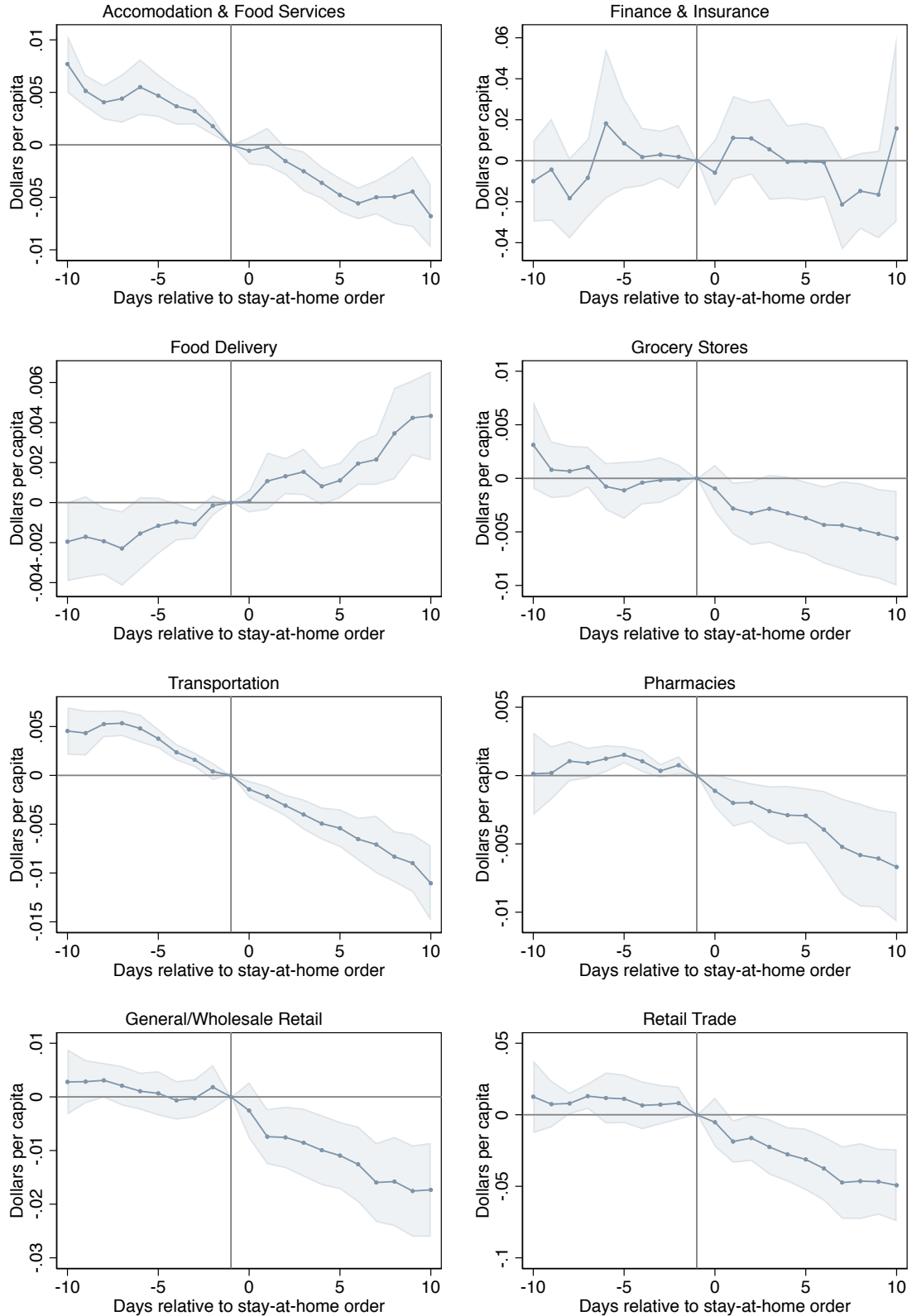
Notes: Data at the state-day level. Plotted are coefficients on event time dummies from a regression which also includes date and state fixed effects, weighted by state-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the date >50% of the state population covered was by a stay-at-home order. Only states with at least 5 days of post-event data are included (event time 0-4). Outcome is total per capita consumer spending at Second Measure's panel of large firms.

Figure A5: Womply in event time: all sectors



Notes: Data at the county-day level. Plotted are coefficients on event time dummies from a regression which also includes date and county fixed effects, weighted by state-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the effective date of the stay-at-home order. Outcome is total per capita revenue derived from Womply's panel of small businesses.

Figure A6: Large business revenue in event time (Second Measure): state-level switches only



Notes: Data at the state-day level. Plotted are coefficients on event time dummies from a regression which also includes date and state fixed effects, weighted by state-level population in 2018. Standard errors are clustered by state. Date 0 in event time is defined as the date >50% of the state population was covered by a stay-at-home order. Only states where state-level stay-at-home orders were not preceded by local stay-at-home orders are included; only states with at least 5 days of post-event data included (event time 0-4). Consumer spending data derived from Second Measure panel of large firms.

Table A1: Summary statistics: Womply

Summary Statistics: Daily Total Spending by County, Womply

March 1st - 7th 2020

Sector	Avg.	Med.	10th %	90th %	S.D.	Aggregated
Arts and Entertainment Businesses	1,799	0	0	2,394	12,804	Other
Auto Sales Businesses	13,894	0	0	29,910	81,247	Other
Auto Services	14,700	1,927	0	33,256	52,348	Other
Educational Institutions	20,856	0	0	23,378	163,609	Other
Health and Beauty Businesses	8,261	516	0	17,323	33,765	Other
Healthcare and Medical Centers	32,108	895	0	50,104	236,407	Other
Local Services	41,392	1,227	0	63,358	246,259	Other
Lodging Places	7,354	97	0	11,627	41,581	Other
Online Businesses	324	0	0	0	4,621	Other
Parking Businesses	1,698	0	0	0	29,074	Other
Pet Services	8,223	0	0	17,620	34,212	Other
Professional Services	39,755	848	0	46,555	271,846	Other
Public Services and Government Places	10,834	0	0	8,835	135,041	Other
Religious Organizations	454	0	0	204	4,534	Other
Retail and Wholesale Businesses	49,480	4,028	0	92,504	245,209	Other
Sports and Recreation Places	10,034	0	0	14,817	82,887	Other
Transportation Businesses	2,391	0	0	1,681	61,887	Other
Bars and Lounges	2,177	0	0	3,498	11,672	Restaurant
Food and Beverage Shops	16,326	1,277	0	28,988	66,538	Restaurant
Quick Serve Food and Beverage Businesses	4,430	27	0	9,244	18,382	Restaurant
Restaurants	32,491	3,813	0	60,623	150,230	Restaurant
Overall	318,981	31,584	2,120	603,418	1,294,875	

Notes: Data are county-level revenue totals from Womply's panel of small businesses.

Table A2: Summary statistics: Womply

Summary Statistics: Daily Per Capita Spending by County, Womply

March 1st - 7th 2020

Sector	Avg.	Med.	10th %	90th %	S.D.	Aggregated
Arts and Entertainment Businesses	0.010	0.000	0.000	0.019	0.058	Other
Auto Sales Businesses	0.088	0.000	0.000	0.239	0.421	Other
Auto Services	0.120	0.070	0.000	0.284	0.203	Other
Educational Institutions	0.081	0.000	0.000	0.160	0.564	Other
Health and Beauty Businesses	0.037	0.017	0.000	0.101	0.068	Other
Healthcare and Medical Centers	0.149	0.031	0.000	0.371	0.731	Other
Local Services	0.194	0.043	0.000	0.473	0.917	Other
Lodging Places	0.079	0.002	0.000	0.144	0.407	Other
Online Businesses	0.002	0.000	0.000	0.000	0.016	Other
Parking Businesses	0.003	0.000	0.000	0.000	0.044	Other
Pet Services	0.052	0.000	0.000	0.156	0.104	Other
Professional Services	0.176	0.027	0.000	0.414	0.682	Other
Public Services and Government Places	0.049	0.000	0.000	0.099	0.355	Other
Religious Organizations	0.002	0.000	0.000	0.001	0.011	Other
Retail and Wholesale Businesses	0.275	0.148	0.000	0.593	0.823	Other
Sports and Recreation Places	0.062	0.000	0.000	0.101	0.458	Other
Transportation Businesses	0.013	0.000	0.000	0.013	0.314	Other
Bars and Lounges	0.013	0.000	0.000	0.034	0.041	Restaurant
Food and Beverage Shops	0.106	0.043	0.000	0.259	0.277	Restaurant
Quick Serve Food and Beverage Businesses	0.032	0.001	0.000	0.095	0.062	Restaurant
Restaurants	0.212	0.141	0.000	0.466	0.319	Restaurant
Overall	1.753	1.198	0.254	3.523	2.410	

Notes: Data are county-level revenue totals from Womply's panel of small businesses, divided by county-level population counts in 2018. Summary statistics are population-weighted.

Table A3: Summary statistics: Second Measure

Summary Statistics: Daily Total Spending by State, Second Measure

March 1st - 7th 2020

Sector	Avg.	Med.	10th %	90th %	S.D.
Accommodation & Food Services	267,285	121,865	24,203	680,095	402,567
Arts, Entertainment & Recreation	32,095	7,747	874	97,594	74,109
Construction	227	0	0	539	744
Educational Services	6,858	2,343	423	18,794	14,326
Finance & Insurance	1,223,929	420,278	88,617	2,633,392	2,219,999
Food Delivery	78,448	29,414	5,308	173,684	130,287
General/Wholesale Retail	541,518	251,096	53,821	1,265,064	786,951
Health Care & Social Assistance	13,538	2,234	253	25,949	63,563
Hotel Booking	80,044	31,143	7,347	190,835	122,073
Information	619,282	243,833	54,261	1,354,120	985,690
Manufacturing	18,965	8,091	1,469	51,256	27,901
Other Services (Except Public Administration)	35,459	11,861	2,032	96,967	63,294
Professional, Scientific & Technical Services	12,438	4,775	824	33,659	21,711
Real Estate, Rental & Leasing	39,176	14,015	2,090	95,218	73,270
Retail Trade	1,990,611	829,308	202,078	5,030,892	2,987,202
Transportation	144,213	57,579	11,603	348,065	229,094
Utilities	6,158	200	0	6,800	27,616
Wholesale Trade	3,719	762	0	9,706	7,879
Grocery Stores	260,434	84,189	6,790	584,145	504,669
Pharmacies	61,595	21,996	3,750	139,131	110,720
Amazon	228,085	97,789	23,709	541,323	337,132
Overall	4,572,446	1,760,789	447,913	10,693,218	7,217,757

Notes: Notes: Data are state-level consumer spending totals from Second Measure's panel of consumer spending at large businesses (representing spending by roughly 1% of U.S. consumers). Second Measure data are divided into 21 categories. 17 of those categories are non-overlapping and based on NAICS code sectors. The remaining four: wholesale trade, grocery stores, pharmacies, and Amazon, are categories that we construct ourselves by hand-collecting firms and combining them into groups. For example, the Pharmacy sector contains CVS, Wallgreens, Rite Aid, and a handful of smaller pharmacies.

Table A4: Summary statistics: Second Measure

Summary Statistics: Daily Per Capita Spending by State, Second Measure

March 1st - 7th 2020

Sector	Avg.	Med.	10th %	90th %	S.D.
Accommodation & Food Services	0.036	0.030	0.014	0.069	0.021
Arts, Entertainment & Recreation	0.004	0.002	0.001	0.007	0.005
Construction	0.000	0.000	0.000	0.000	0.000
Educational Services	0.001	0.001	0.000	0.002	0.001
Finance & Insurance	0.143	0.117	0.045	0.260	0.096
Food Delivery	0.009	0.008	0.003	0.017	0.006
General/Wholesale Retail	0.078	0.075	0.028	0.128	0.041
Health Care & Social Assistance	0.001	0.001	0.000	0.003	0.002
Hotel Booking	0.010	0.009	0.004	0.018	0.006
Information	0.079	0.072	0.029	0.138	0.046
Manufacturing	0.003	0.002	0.001	0.005	0.002
Other Services (Except Public Administration)	0.005	0.003	0.001	0.010	0.004
Professional, Scientific & Technical Services	0.002	0.001	0.000	0.003	0.002
Real Estate, Rental & Leasing	0.005	0.004	0.001	0.010	0.005
Retail Trade	0.263	0.232	0.108	0.437	0.146
Transportation	0.019	0.016	0.006	0.035	0.015
Utilities	0.001	0.000	0.000	0.001	0.002
Wholesale Trade	0.000	0.000	0.000	0.001	0.001
Grocery Stores	0.028	0.018	0.005	0.072	0.027
Pharmacies	0.007	0.006	0.002	0.014	0.005
Amazon	0.032	0.028	0.012	0.056	0.018
Overall	0.581	0.494	0.222	1.011	0.321

Notes: Per capita spending numbers divide the Second Measure panel of state-level daily spending by category (representing roughly 1% of U.S. consumers) by state-level population counts from 2018. In a future draft, we will use sample weights to make Second Measure data representative of consumer spending at their panel of large businesses. Second Measure data are divided into 21 categories. 17 of those categories are non-overlapping and based on NAICS code sectors. The remaining four: wholesale trade, grocery stores, pharmacies, and Amazon, are categories that we construct ourselves by hand-collecting firms and combining them into groups. For example, the Pharmacy sector contains CVS, Wallgreens, Rite Aid, and a handful of smaller pharmacies.