Quantifying trade-offs between economic recovery and lives saved during the COVID-19 pandemic

Quantifying trade-offs between economic recovery and lives saved during the COVID-19 pandemic

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Abstract

Shutdown policies, including business closures and stay-at-home orders, were popular government responses to control the COVID-19 epidemic. In this paper, I estimate the impact of shutdown policies on COVID-19 spread and economic recovery. I find that business closures were effective at slowing disease spread; however, they were often implemented by states at sub-optimal times. I also demonstrate that overall small business activity “bounced back” quickly after reopening. The cost of shutdowns falls from $41 million per life saved to $489 thousand. Sectors explicitly targeted by shutdowns continue underperforming versus open counties even after reopening.

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I Introduction

The COVID-19 pandemic of 2020 was a once-in-a-lifetime event whose long-term economic impacts remain to be understood. In response to increased virus spread within the United States, local and state governments enacted various shutdown policies in an attempt to control virus spread and limit COVID-19 deaths. These shutdown policies included business closures and stay-at-home orders, as well as restrictions on travel, self-quarantine requirements, and bans on large gatherings. While total shutdowns were implemented within the first few weeks of lockdowns, scholars and policy makers quickly noticed severe economic issues associated with total lockdowns. (Allcott et al. (2020), Porter and Tankersley (2020)). Thus, it is essential to understand how significant a trade-off exists between economic recovery and COVID-19 spread, and to what degree shutdown orders mitigated this trade-off. In this paper, I aim to analyze three types of shutdown measures – partial business closures (including limited capacity), full business closures (defined as closing all non-essential businesses), and stay-at-home orders. Assessing these, I perform regressions to understand which policies were most effective at controlling the virus, and what economic spillover effects were associated with each policy. I also consider temporal spillover effects through a two-period model, in which I use the length of shutdowns in the present period to project economic activity and COVID-19 deaths in the following period.

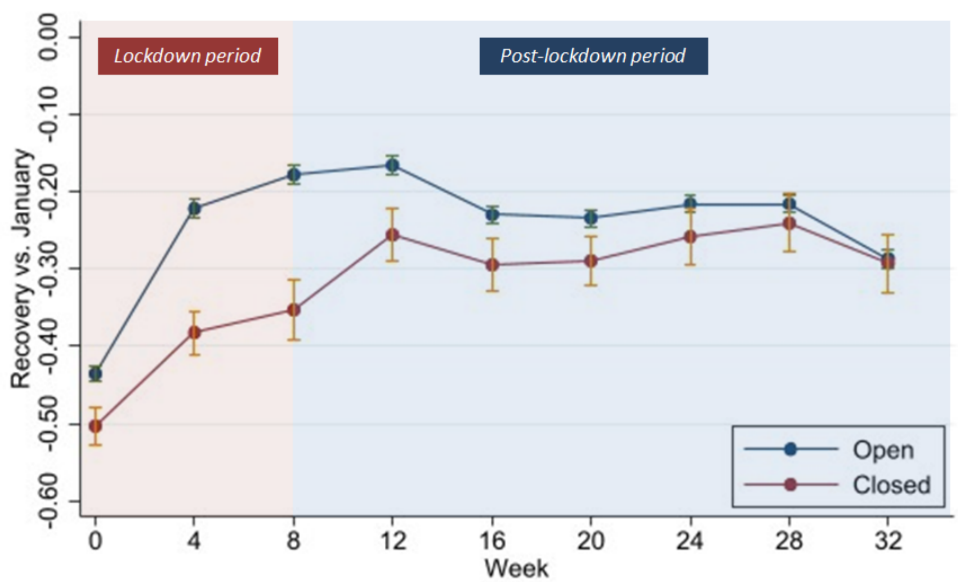
Researchers have already studied the effects of government policies on COVID-19 spread (Hartl et al., 2020) as well as the impact of shutdowns on economic recovery (Andersen et al. (2020), Balla-Elliott et al. (2020), Bartik et al. (2020)). Recent work by Barrot et al. (2020) estimates the cost of lives saved during shutdown periods. My work builds on this growing body of literature by accounting for intertemporal effects, where economic activity in one period may increase COVID-19 spread in subsequent periods and vice versa.

To do this, I first introduce a lead-lag structure to relate COVID-19 spread and economic activity across time periods. This model must necessarily be dynamic – as economic activity may spread the virus, and prevalence of COVID-19 in a community may discourage economic activity. The model I employ in this paper is informed by medical literature and draws on a simplified SIRD model (see Allcott et al. (2020)). While Alcott et al model intertemporal COVID-19 spread versus shutdown measures, I perform original analysis by associating these variables with small business activity. I find that a county's business activity within its first four weeks is positively correlated with its per-capita COVID-19 death rate increase in all subsequent periods. At the same time, death spikes in all subsequent periods were not significantly correlated with changes in economic behavior. This surprising finding suggests that some degree of "behavior setting" occurred in these first four weeks, regardless of changes in underlying COVID-19 risk.

The lead-lag structure also provides insights into the effectiveness of shutdown measures on economic recovery and on disease spread. Primarily, I find that all shutdown measures have a clear effect on limiting COVID-19 spread during the time they are implemented, yet they also tend to mildly increase disease spread during the period of reopening. In all, this results in a net savings of lives. Each additional day of total business shutdowns during the first 12 weeks was associated with a .58 percentage point lower death rate of COVID-19 in-period and .12 percentage point higher death rate over the next 20 weeks. Furthermore, the lower in-period death rate induces a lower death rate in subsequent periods as well (as there are fewer potential spreaders). When accounting for in-period and subsequent effects, I estimate an additional 28 days of business closures within the first 12 weeks saves 12,995 lives. Of the three shutdown measures considered, I observe that full business closures were most effective at limiting COVID-19 deaths, followed by partial business closures, followed by stay-at-home orders.

Economically, I observe that the effects of shutdowns are more muted at 32 weeks: while longer shutdowns are negatively correlated with recovery in the period they are in place, they are positively correlated with future recovery. This suggests that closed counties were able to rebound economically once they reopened, even though their shutdowns limited disease spread. For example, each additional day of total business shutdowns during the first 12 weeks was associated with a .085 percentage point fall in economic activity per day in-period, and a .057 percentage point per-day recovery over the next 20 weeks. This translates to an overall economic cost of $141 billion, though this cost diminishes as I extend the window of observation. Overall, I find evidence indicating a general economic convergence occurred between open and closed counties, while COVID-19 death rates remained lower in more-shutdown counties. This broad phenomenon is illustrated in Figures 1 and 2. By 32 weeks, open and closed counties are performing near-identically in economic terms. However, closed counties see much lower rates of spread within the same period.

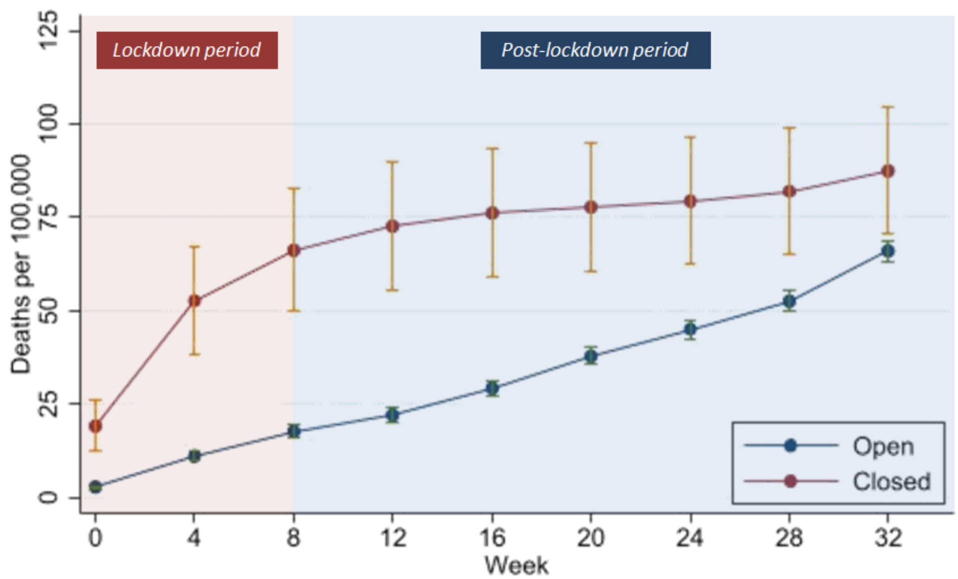
Figure 1: Convergence in Small Business Recovery



Notes: Small business revenues vs. January averages, April 13 - November 25, 2020. "Closed" counties are those that remained under full business shutdown through June 8 (8 weeks, 68 counties). "'Open" counties reopened sometime before June 8 (829 counties)

The economic convergence may partly result from regression to mean, but even if this occurs, it signifies a broader factor is at play. It is plausible that closed counties were better poised to "build back better," though economic convergence may also stem from the failure of open counties to spur long-run economic recovery during their open periods. While the reasons for this convergence remain unclear, my work clearly demonstrates that an economic convergence occurred while a epidemiological convergence did not.

Figure 2: Convergence in COVID-19 deaths



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Notes: COVID-19 deaths per 100,000, April 13 - November 25, 2020. "Closed" counties are those that remained under full business shutdown through June 8 (8 weeks, 68 counties). "Open" counties reopened sometime before June 8 (829 counties)

In general, I find that the cost of shutdowns diminished as the pandemic continued. While costly at the start, I note a hundredfold decrease in cost per life saved by the end of the 32-week period. This is calculated from counterfactual analysis estimating the impact of 28 additional days of shutdown at different points in the recovery. In the first four weeks, I estimate fully shutting businesses in all counties would have cost $325 billion and saved 7,975 lives, translating to a cost per life of $40.7 million. However, if this month-long shutdown occurred at a later point within the 32-week period, I calculate its net cost at $18.9 billion for 38,720 lives saved, implying a cost per life saved of $489 thousand. When contrasted with the value of a statistical life, estimated at around $10 million per life (Kniesner et al., 2012), this work suggests a steep premium was paid for lives saved at the start of the pandemic. Furthermore, it suggests that counties could have more efficiently saved lives had they shutdown later. This finding aligns well with anecdotal evidence from countries like Israel and Germany that enacted second and third-wave shutdowns. While these shutdowns were vastly unpopular, they seem to have more effectively controlled disease spread (Lubell (2020), Neuman (2021)).

I caution that this model does not account for diminishing returns to lockdowns. Longer lockdowns may become less effective as firms and consumers begin to ignore government regulations. My results hint at this fact, as longer stay-at-home orders (a less enforeceable policy) are *positively* associated with COVID-19 spread, suggesting some degree of noncompliance occurs. Furthermore, my approximations do not consider excess deaths caused by shutdowns (e.g. undiagnosed cancers), nor do they adjust for excess lives saved by shutdowns (e.g. traffic accidents). Regardless, these factors do not contradict my principal finding; namely, that shutdowns became much more affordable as the pandemic continued.

These results suggest that many states mistimed their shutdowns during the pandemic. Shutdowns at the start of the pandemic, when general case counts were low, had small effects on overall death numbers in-period. After these places reopened, their COVID-19 death rate picked up again, meaning absolute health savings were minimal. At the same time, these long shutdowns had serious negative in-period effects on business recovery. Shutdowns occurring later in the 32-week period appear to have smaller impact on business activity, likely because of temporal spacing – it is easier for a business to weather two one-month shutdowns than one two-month shutdown. Had shutdowns occurred later in the pandemic, they would likely have prevented more infections and impacted business activity less. Together, these factors make the cost of shutdowns fall dramatically.

Finally, I investigate the sector-specific effects of shutdowns. Using data from SafeGraph Inc., I conduct novel analysis that tracks weekly visitors to full-service restaurants, personal care services (PCS, including beauty parlors, barber shops, and nail salons) and supermarkets. Anecdotal evidence suggested that informal activity occurred in some of these sectors during shutdown periods (Peiser (2020), Bieler (2020)). Because SafeGraph data tracks foot traffic to these businesses, I use it to identify the magnitude of informal activity in these sectors. Among PCS, I estimate that visitor counts to businesses recovered between 10 and 20 percentage points during the first month in states where all PCS were closed by executive order, numbers which might be overlooked in business's reported revenues. This result confirms SafeGraph's unique ability to monitor informal economic activity. Beyond this, my analysis reveals a continued divergence between open and closed counties in sectors targeted by shutdowns. An additional month of shutdowns leaves restaurant visitor counts 4-5% lower than open counties at the end of 32 weeks; PCS visitor counts also drop by 1-3% in the same period. In contrast, supermarkets (an "essential business") did not see their visitor counts diverge between open and closed counties, suggesting that the effects of shutdowns were localized to specific sectors. After applying a lead-lag structure, I observe both negative in-period and future correlations, suggesting that a "downward spiral" affects targeted sectors. Targeted sectors suffered severe, specific, and lasting declines from shutdown policies. This result should caution any policy implications we draw from overall small business analysis, as overall economic metrics may belie sector-specific pain.

I.a Overview of Data Providers

Much of the data used in this project comes from publicly available repositories assembled by the Opportunity Insights Team. These include Womply, which tracks small business recovery, and New York Times COVID-19 daily death and case counts. Other publicly available datasets include the Oxford COVID-19 Government Response Tracker, which records daily shutdown measures in all states, and the U.S. Census, which reports overall population and GDP for each county.

Additionally, I use data from SafeGraph, Inc. to explore the sector-by-sector effects of these shutdowns. This data is normally private; however, it was made freely accessible to researchers during the COVID-19 pandemic. In this study, I limit my attention to three specific sectors: full-service restaurants, personal care services (PCS), and supermarkets. Together, these three provide a representative sample of different types of business activity. Both restaurants and PCS were designated as "non-essential" businesses in most US states, and thus required to shut down. Supermarkets were universally understood to serve essential functions. Demand for these sectors is both frequent and consistent, with the average patron visiting these types of establishments with some degree of regularity, but generally at most once per day. Third, these industries are often location-dependent. This is most obviously true for PCS and supermarkets, where much of the working capital needed for business services (e.g. heat lamps, wash basins, freezers) are not easily movable. Even though many restaurants expanded their delivery capabilities through mobile providers (UberEats, DoorDash, etc.), these programs still require drivers to physically pick up food from a restaurant. Thus, the number of unique visitors to each of these sector is a good proxy of that sector's overall success. At the same time, tracking visitors accounts for any potential informal activity that may have occurred during the pandemic.

To compile this data, I assemble a novel data set that assesses county-level recovery along various dimensions. The dataset and documentation are fully available on GITHUB.

Womply Small Business Revenue Womply is "a company that aggregates data from several credit card processors to provide analytical insights to small businesses and other clients." (Chetty et al., 2020). This firm provided the Opportunity Insights team with raw data which remains private. However, the Opportunity Insights team does publicly publish a filtered version of this data on their website. This data set records county-level small business revenue transactions versus a January baseline in percent terms. While this presentation prevents me from knowing the total revenue figures for each county, I am still able to use these values for analysis. Because these values are relative, though, I opt to use relative values for other pertinent variables in my analysis. The process of converting these relative values back into absolute effects is the subject of Section III of this paper.

New York Times Cases and Deaths The *New York Times* publishes the total COVID-19 cases and deaths per 100,000 people for each county in the U.S. These values were transformed to calculate log cases and log deaths per capita using the formula $\log(COV + 1)$. Because many counties recorded no deaths for a significant period of the year, the addition of 1 ensured that the logarithm would not be unreasonably skewed by large negative values.[1]

While deaths per 100,000 may not fully capture the severity of a COVID-19 epidemic, they are one of the most reliable metrics. Due to the large number of asymptomatic carriers, case counts are driven not just by COVID-19 spread, but also by factors such as health infrastructure, test availability, and testing time. These factors lend a degree of imprecision to all COVID-19 case reports (Larson et al. (2020), Nishiura et al. (2020)) . Similarly, tracking the percent of positive cases in a county may not be as effective. The amount of per-county testing varied significantly across regions, and it is critical that I don't confuse a lowering in actual COVID-19 spread with a rise in "worried-well" testing (Chatterjee et al., 2020). For these reasons. deaths per 100,000 are used as the principal data metric in this project, with cases per 100,000 serving as a secondary met-

[1] The function $\log(COV + 1)$ is invertible on $[0,\infty)$, which means this transformation preserves information. It also means that care must be taken when converting log numbers per capita back into absolute cases or deaths. In Section III, I take special care during this process.

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SafeGraph Ltd. SafeGraph is a third-party geospatial data platform that collects and sells location data from millions of Americans on their economic activity. SafeGraph data is frequently sold to advertisers, but it was made freely available to institutional researchers during the COVID-19 pandemic at safegraph.com. This data, fully anonymized, is collected from Apple and Android devices via telecommunications companies, and is exclusively from users who enable the "Share My Location" on their devices. This limits overall recorded visits (as some users disable this feature on their phone), and potentially overrepresents older demographics (who, ostensibly, are less tech-savvy and thus less likely to opt out). Still, there is little reason to assume the fraction or demographics of users who opt out of location sharing differs across times or geographies. Thus the data set is still informative. From these users, SafeGraph tracks unique visitors to over 3 million establishment every week. This allows me to limit visits by owners and employees, who I expect to visit an establishment multiple times per week.

Each of the over three million points of interest (POIs) that SafeGraph tracks is identified with a unique key, as well as general information on the POI's business sector (NAICS code) and geographic location. National trends of assorted sectors are displayed in Figure 4. In this analysis, I focus on three sectors: full-service restaurants, personal care services (PCS), and supermarkets. These sectors were chosen because they are illiquid, locally provided, and highly represented in SafeGraph data. Additionally, these three sectors were affected differently by state shutdown orders – restaurants were often closed for long periods, PCS were often closed at the start of the pandemic but reopened at limited capacity later, and supermarkets were never fully closed.

In these three sectors, I limit myself to POIs tracked by SafeGraph on and after December 31, 2019. All other businesses were excluded. Since SafeGraph constantly adds POIs to their dataset, this ensures the consistency of my sample.

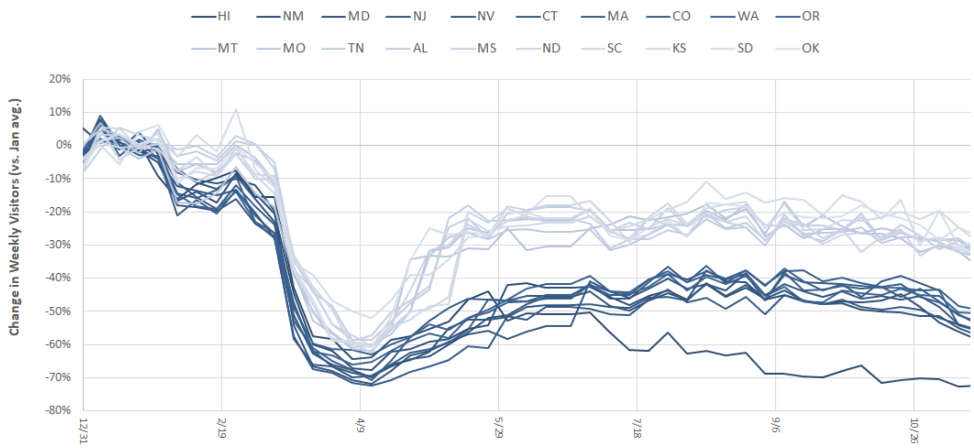
Because SafeGraph tracks physical visits to establishments, it offers an in-depth look at behavior that is somewhat separate from economic activity. During the COVID-19 pandemic, SafeGraph provides an excellent proxy to measure consumer willingness to travel outside, whereas overall business revenue also includes e-commerce and delivery orders. Thus, when trying to understand how people's travel patterns impacts virus spread, SafeGraph is a valuable source for analysis.

I aggregate SafeGraph visitor counts across business sectors and counties for the weeks beginning December 31, 2019 and ending November 25, 2020 (48 weeks).
After aggregation, I clean the data further. For each sector, I compute each region's average January visitors, using the same methodology as Chetty et al. For each sector, counties averaging fewer than 100 visitors per week in all three sectors were removed from the sample. I calculated *weekly %PCS Visitors* by comparing weekly visits in a given week against the region's January average. The decision to use percent recovery is in line with Chetty et al and corrects for population-dependent effects. Figures 3 and 4 illustrate general trends within SafeGraph data. In Figure 3, I chart %PCS visitors for each state, and observe a convergence between the weeks of March 3 and April 13. After April 13 (when states begin to reopen), we witness a clear divergence in PCS outcomes across states. Moreover, I note that some recovery occurs in all states during the first 4 weeks following April 13 – including states that had officially closed all PCS. This is clear evidence of informal activity, as many states (California, New York) required PCS establishments to remain closed well into June, yet still reported an increase in visitors. The bottom 10 states in Figure 3, all of whom closed PCS establishments past May 11, still saw visitors recover on average by 10.3%. Thus, I conclude that these visitor counts account for some measure of informal activity.

This result corroborates high-profile anecdotal stories of this phenomena (Bieler (2020), Peiser (2020)). In Figure 4, I plot %visitor recovery at the national level across different sectors. This figure shows that certain sectors were impacted more severely by

COVID-19, with non-essential discretionary spending (casinos, bowling alleys, amusement parks) being hit the most severely. In contrast, high-demand essential businesses, like convenience stores and supermarkets, were comparatively more protected from overall declines. Even so, all sectors ended in November significantly lower than their January averages, suggesting that a certain number of visitors have still not returned to their general outgoing behaviors.

Figure 3: PCS Visitor Recovery by State, top and bottom quintiles

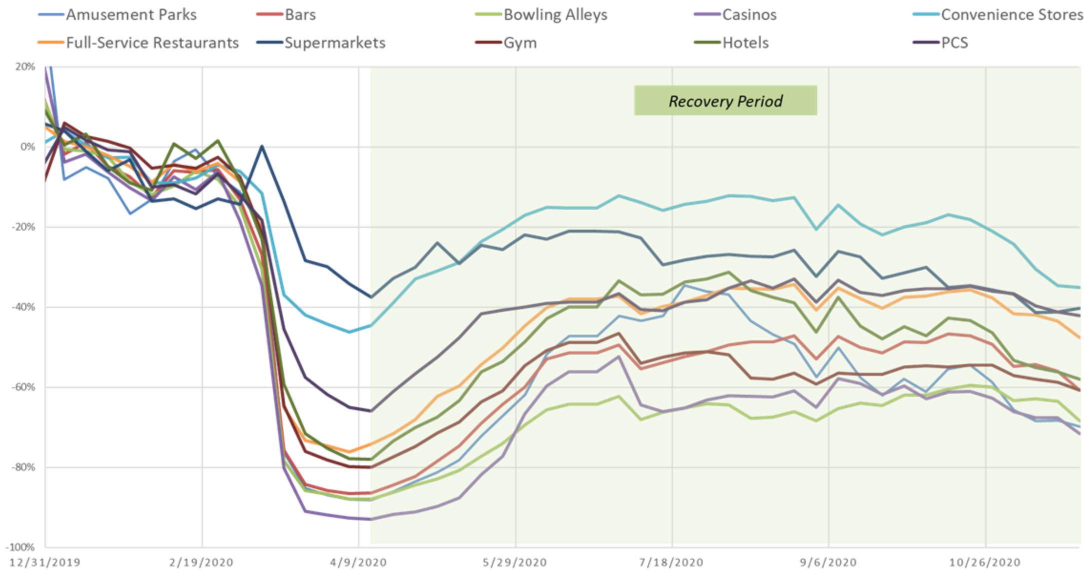


Notes: Percent recovery versus January averages in PCS visitors, state level (including Washington, D.C.). The top 10 and bottom 10 states are displayed, based on outcomes on November 25, 2020. Source: author's elaboration on SafeGraph data.

After aggregation, visitor patterns for 887 counties were represented in the data, encompassing a region with a population of 278 million people and a combined GDP in 2019 of $16.9 trillion.

Oxford COVID-19 Government Response Tracker The Oxford COVID-19 Government Response Tracker (OxCGRT) is a publicly available data set compiled by researchers at the University of Oxford that tracks shutdown policies across countries during the pandemic. Additionally, and most relevant to this project, OxCGRT records these policies by day for all 50 U.S. states. The severity scales that OxCGRT are broad, but they still clearly group states. For example, their scale measuring workplace closings uses a four-point scale: 0 (no closure), 1 (recommended closing), 2 (required closing for some workplaces), and 3 (required closing for all-but-essential workplaces). I use OxCGRT data to determine three counts for each state that measure shutdown severity. For each state, I consider time horizons ranging from 4 weeks to 32 weeks. In each window, I record the number of days when all non-essential businesses are closed, days where businesses are at least partially closed (which include days of full shutdowns), and days where citizens

Figure 4: National Visitor Recovery by Sector



Notes: Percent recovery versus January averages in assorted sectors, national level. Source: author's elaboration on SafeGraph data.

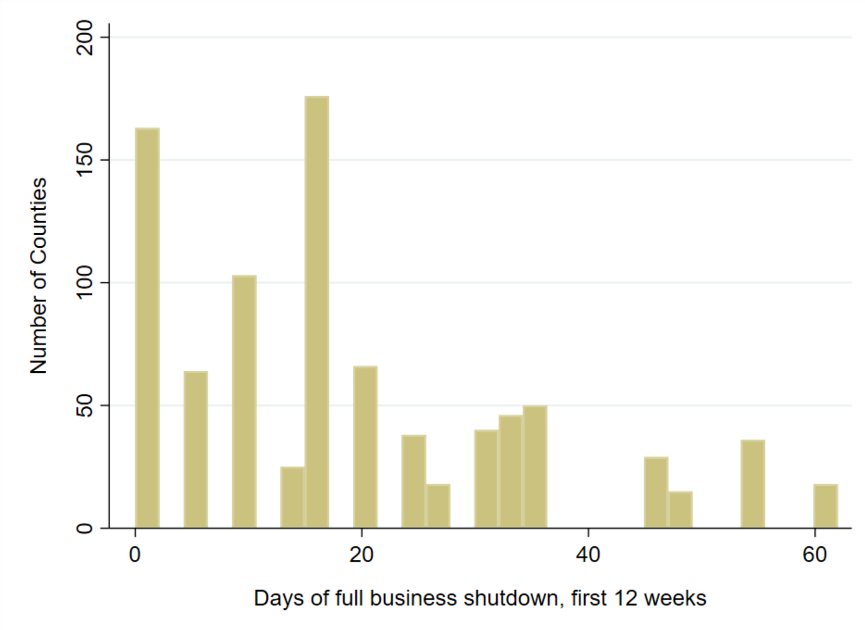
are required to stay at home. Histogram distributions of these three variables at 12 weeks are shown in Figures 5, 6, and 7, respectively.

U.S. Federal Agency Data on Population and GDP The United States government freely publishes county-level statistics through a variety of federal agencies. Most essential to this project are county-level GDP, in adjusted 2019 dollars (available from the Bureau of Economic Advisors), and 2019 county-level population estimates (from the Bureau of Labor Statistics).

I.b Paper Structure

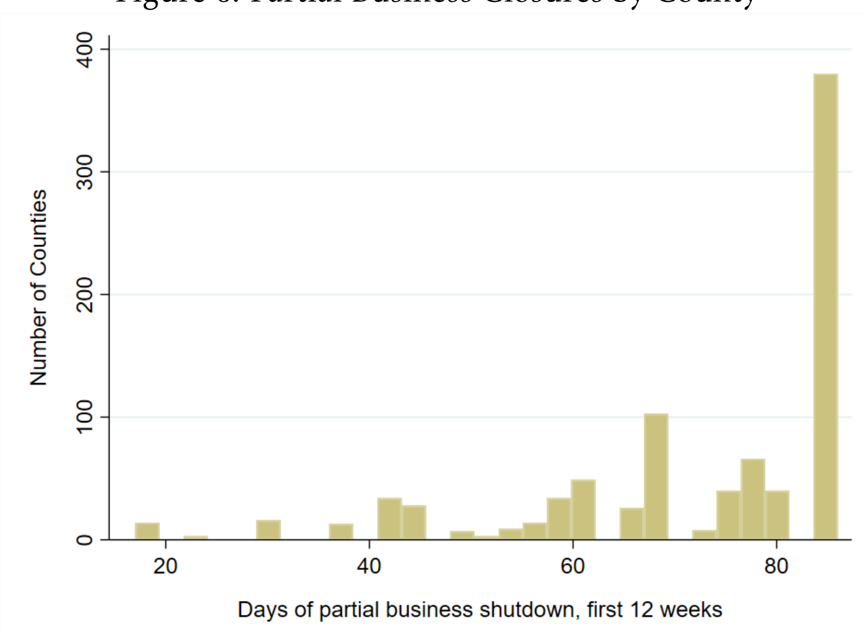
The remainder of the paper is structured as follows. Section II analyzes the effects of shutdown policies on business recovery and COVID-19 deaths, demonstrating differences across sectors and industries. Section III considers shutdown effects on the economy as a whole, generating counterfactuals to estimate the cost per life saved during lockdowns. Section IV concludes.

Figure 5: Full Business Closures by County



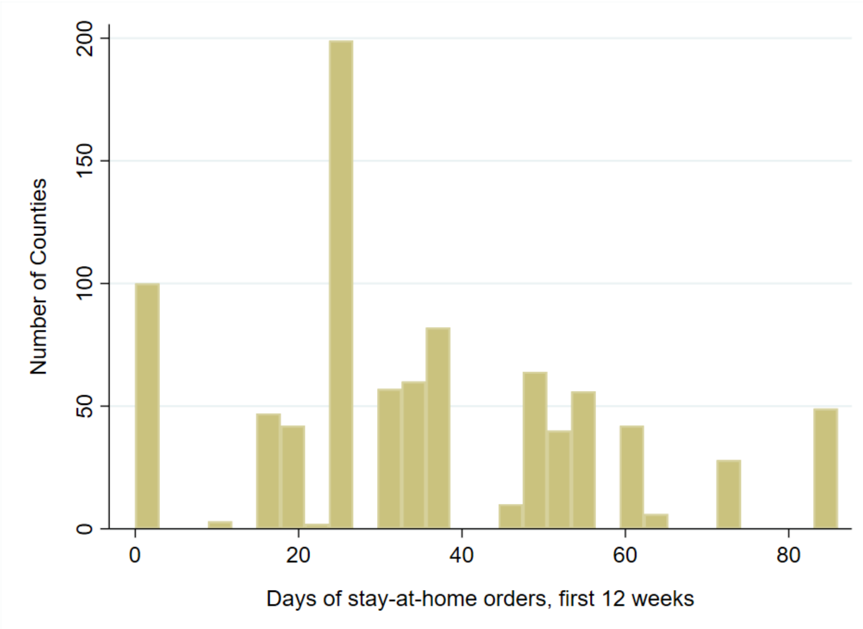
Notes: County-level histogram counting days of full non-essential business closures between April 13, 2020 and July 8, 2020 (12 weeks). Source: Author's elaboration on OxCGRT data.

Figure 6: Partial Business Closures by County



Notes: County-level histogram counting days of partial non-essential business closures (e.g. 25% capacity) between April 13, 2020 and July 8, 2020 (12 weeks). Source: Author's elaboration on OxCGRT data.

Figure 7: Stay-at-home orders by County



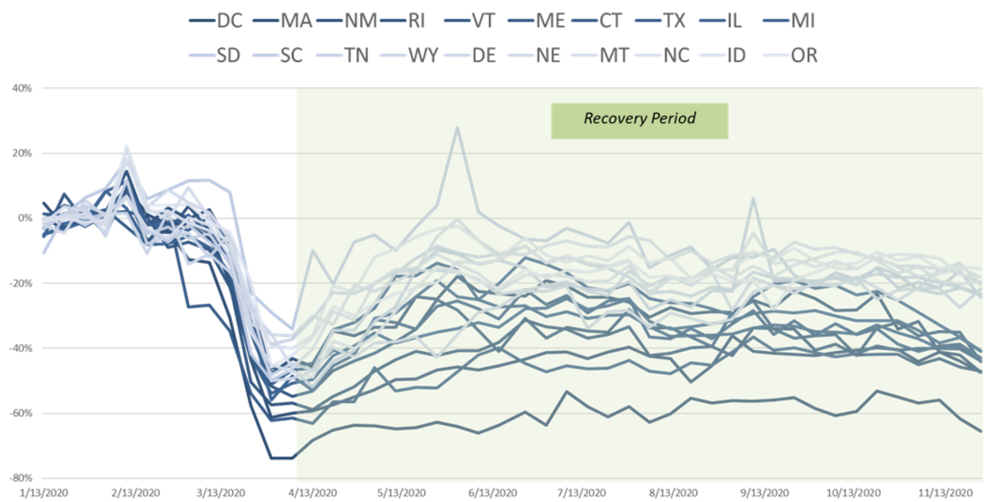
Notes: County-level histogram counting days of mandatory stay-at-home orders between April 13, 2020 and July 8, 2020 (12 weeks). Source: Author's elaboration on OxCGRT data.

II Determining Intertemporal Relations between Shutdowns, Business Activity, and COVID-19 Spread

II.a Overview

My initial analysis explores the relationships the relationships between COVID-19 spread, business recovery, and shutdown orders at the county-level. While concerns over county-level variation are traditionally quite difficult to reconcile, a unique global trend significantly simplifies the work. Specifically, I note that April 13 marks a national low point, both in terms of visitors counts and small business recovery. This pattern exists across different sectors (Figure 4) and at the state level (Figure 8). Furthermore, all U.S. states (except South Dakota) were at least partially locked down through April 18. For these reasons, I argue that April 13 is justified as the "start" of the recovery period across all variables. Time-series data stretches until November 25, 2020, thus, the "recovery period" I study is the 32-week (226-day) period between April 13, 2020 and November 25, 2020.

Figure 8: Small Business Recovery by State, top and bottom quintiles



Notes: Percent small business recovery versus January averages at the state level (including Washington, D.C.). The top 10 and bottom 10 states are displayed, based on outcomes on November 25, 2020. Source: author's elaboration on Womply data.

II.b Developing a Lead-lag structure

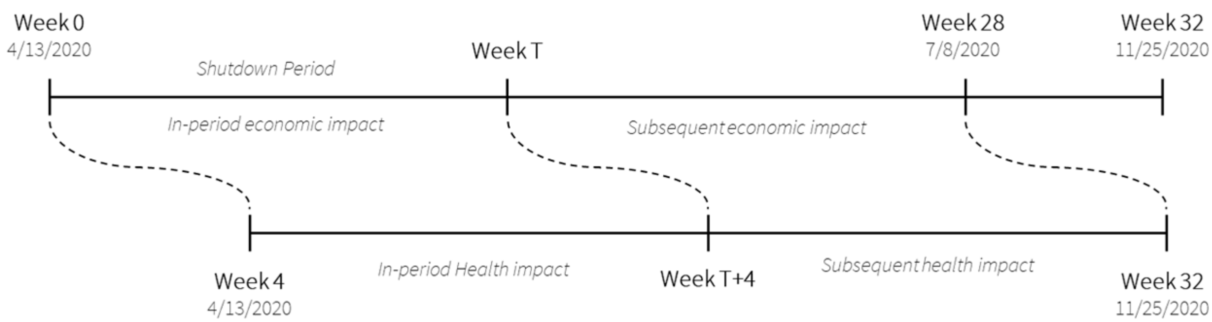
To better interpret this data, I introduce a lead-lag cycle informed by medical literature. Other researchers have used similar models to model COVID-19, e.g. the SIRD-model used by Allcott et al. (2020), which classifies individuals into susceptible, infected, recovered, and deceased categories. While the disease process is envisioned as a chain leading from exposure to infection, subsequent hospitalization, and ultimately death, for this project I am most concerned with the time between initial exposure and death. The mean time between first exposure to COVID-19 and reported deaths is roughly four weeks, with 95% of deaths occurring between 3 and 5 weeks. (Cummings et al. (2020), Weerahandi et al. (2021), Guan et al. (2020)), Lauer et al. (2020)) [2]. Additionally, the time-to-death

[2] There is generally a 4-7 day period between exposure and infection, a day period, a 17-21 lag between infection and death, and a 1-2 day lag in reporting deaths.

has not decreased over the course of the pandemic – although better treatments have ensured that fewer people die from the virus, the average time between exposure and death has not changed significantly over the course of the pandemic (Weerahandi et al. (2021), Tenforde et al. (2020)). All this suggests that there is a roughly 4-week lag between first exposure to COVID-19 and subsequent death.

This 4-week lag structure implies that virus-spreading behavior today (including in-person business activity) will only be realized in *next month's* death counts. In this vein, today's death numbers are reflective of last month's activity. Thus in-period economic effects of shutdowns occur in sync with shutdown decisions, but health effects occur 4 weeks later. This relation is summarized in Figure 9, and is essential in creating a lead-lag structure to test the interactions between COVID-19 spread and economic activity.

Figure 9: Lead-Lag Depiction

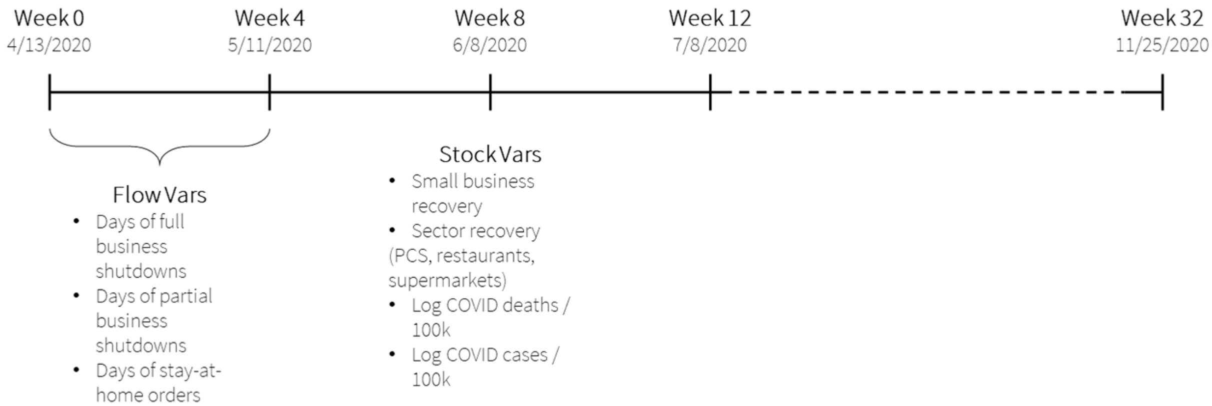


Notes: The lag between infection and death means health impacts occur at a different time versus economic impacts. Shutdowns within the period 0 to T weeks feels in-period economic effects synchronously; health impacts are felt approximately 4 weeks after policy decisions occur. Subsequent effects also obey this 4-week delay.

Because my overall sample time is 32 weeks, I break it into eight 4-week blocks, recording small business recovery (Womply), sector recovery (SafeGraph), COVID-19 cases and deaths per 100,000 (New York Times), and shutdown severity metrics (OxCGRT) for each block. An explanation of these variables is in Table A.1, and the chronological placement of these variables (as well as their classification as either stock variables or flow variables) is shown in Figure 10.

For convenience, I use the adjectives "past" and "future" as follows: at a point in

Figure 10: Overview of Data Points



Notes: Distinction between stock and flow variables. For further information, refer to Table A.1.

time T, my past includes all data up to point T; my future refers to the change in a variable between week T and week 32 (the end of the sample). When discussing shutdowns, "in-period" refers to the window of time in which a shutdown occurs. The "subsequent" period refers to the window of time between the end of the shutdown and the end of the sample.

II.c Intertemporal Analysis

II.c.i Shutdowns and In-period Business Activity

Lockdown policies limited business activity, either explicitly (via business closures) or implicitly (via stay-at-home orders). What remains is to quantify the magnitude and effectiveness of these policies. Intuitively, this correlation should be negative – if businesses are not allowed to operate or if customers are not allowed to go out, overall business activity should decrease.

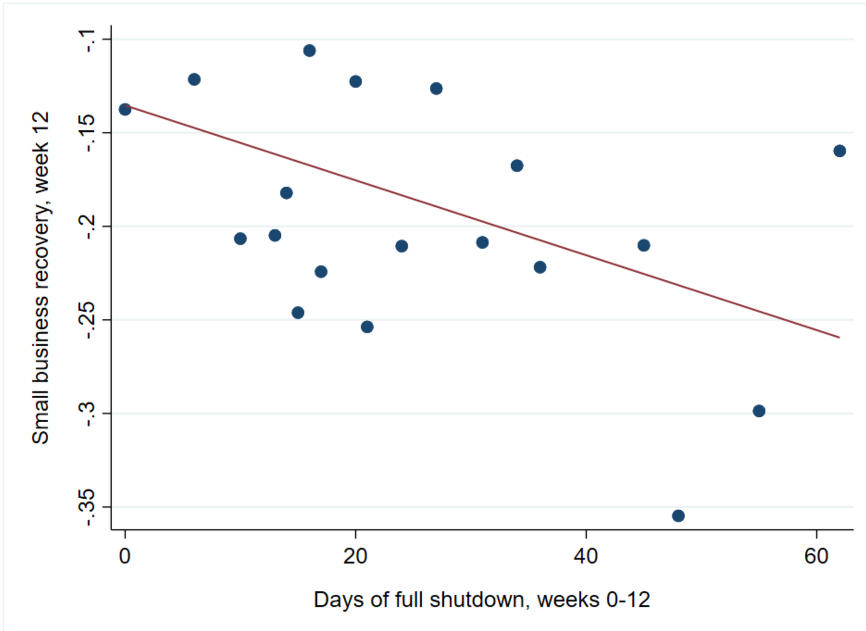
To test this hypothesis, I employ the following regression model:

$$SB_{T,i} - SB_{0,i} = \alpha + \beta_0^{SB} SB_{0,i} + \beta_t^{COV} \log(COV_{0,i} + 1) + \gamma SHUT_{32,s} + \epsilon_i \tag{1}$$

where $SB_{T,i}$ refers to *Small Business Recovery* at time T, $\log(COV_{T,i} + 1)$ refers to *log COVID-19 Deaths* at time T, and $SHUT_{32,s}$ comprises the state-level array of shutdown indicators – *Days Partially Closed*, *Days Fully Closed*, and *Days Stay-at-home* between weeks 0 and 32. The sample covers 877 counties over the 32-week period between April 13 and November 25, 2020. Counties are indexed by i, states are indexed by s. The regression employs robust standard errors. While clustering at the state-level might be tempting, this approach is less desirable given the high degree to which first-wave stay-at-home orders and business shutdowns were directed from the state level. Similarly, it is improper to include state fixed effects as this would lead to autocorrelation errors.

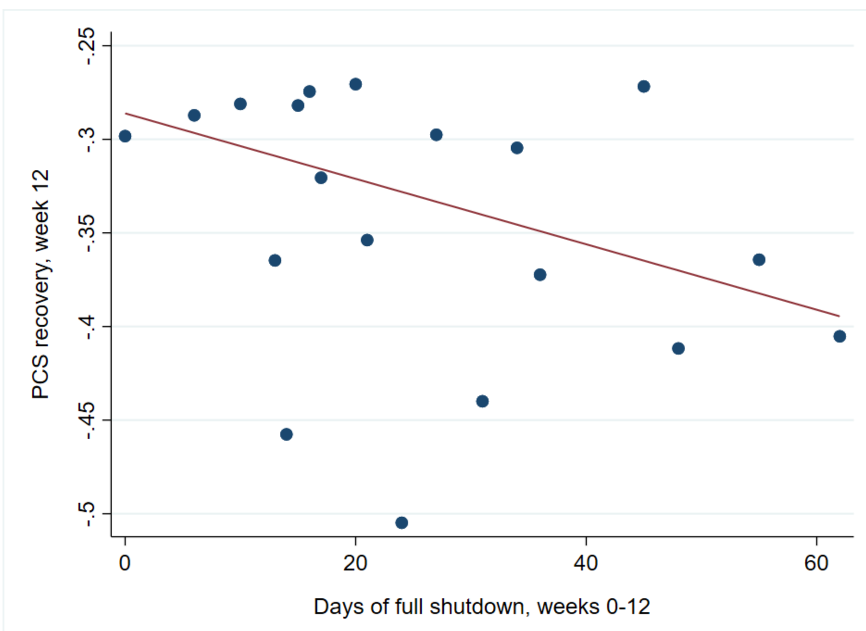
The estimates of this regression model are shown in Table A.2 and Figure 11. As we observe, longer shutdowns at the start of the recovery period are negatively correlated with business recovery, though this effect seems to dampen as time horizons expand. Figure 11 shows this relation at the 12-week mark, where effects are still felt. In Figures 12 through 14 and Tables A.3 through A.5, I repeat the regression in (1) but substitute sector recoveries (from SafeGraph) in PCS, restaurants, and supermarkets for small business recoveries. Again, we see a clear negative trend, demonstrating the impact of business closures on business activity.

Figure 11: Full Business Shutdowns and Small Business Recovery



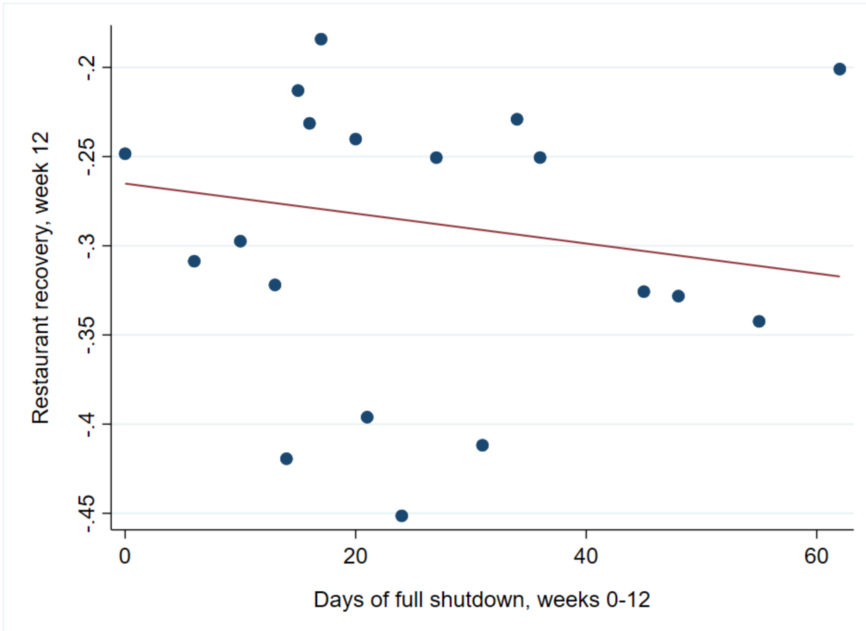
Notes: Bin scatter of *Days Fully Closed* versus *Small Business Recovery*, weeks 0-12.

Figure 12: Full Business Shutdowns and PCS Recovery



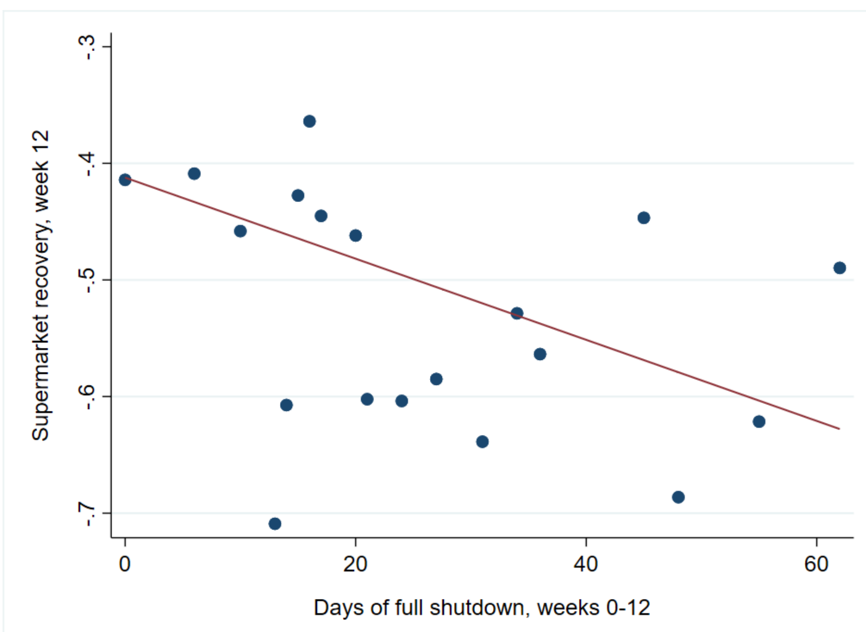
Notes: Binned scatter of *Days Fully Closed* versus *PCS Visitor Recovery*, weeks 0-12.

Figure 13: Full Business Shutdowns and Restaurant Recovery



Notes: Binned scatter of *Days Fully Closed* versus *Restaurant Recovery*, weeks 0-12.

Figure 14: Full Business Shutdowns and Supermarket Recovery



Notes: Binned scatter of *Days Fully Closed* versus *Restaurant Recovery*, weeks 0-12.

II.c.ii Shutdowns, COVID-19 Spread, and Future Business Activity

While it is relatively uncontroversial to argue that shutdowns limit business activity while they are in effect, the longer-run economic impacts are less understood. One train of thought suggests that shutdowns lead to a ”downward economic spiral” – economically damaged areas aren’t able to catch up once they reopen, meaning counties with longer lockdowns should also see slower recoveries. At the same time, a countervailing hypothesis argues that closed counties can “build back better” after reopening. Under this hypothesis, labor markets are relatively elastic, and both demand and supply return quickly once permitted by law, so closed counties catch up to open counties relatively quickly. I test which of these hypotheses – “downward spiral” or “build back better” is better supported by the data.

I also test if COVID-19 spread impacts people’s behavior. If this is the case, I expect a negative relation between COVID-19 increases and economic recovery: if people see high COVID-19 numbers today, they will be more likely stay home more. Similarly, places with low COVID-19 should feel safer, and thus people will be more willing to go out.

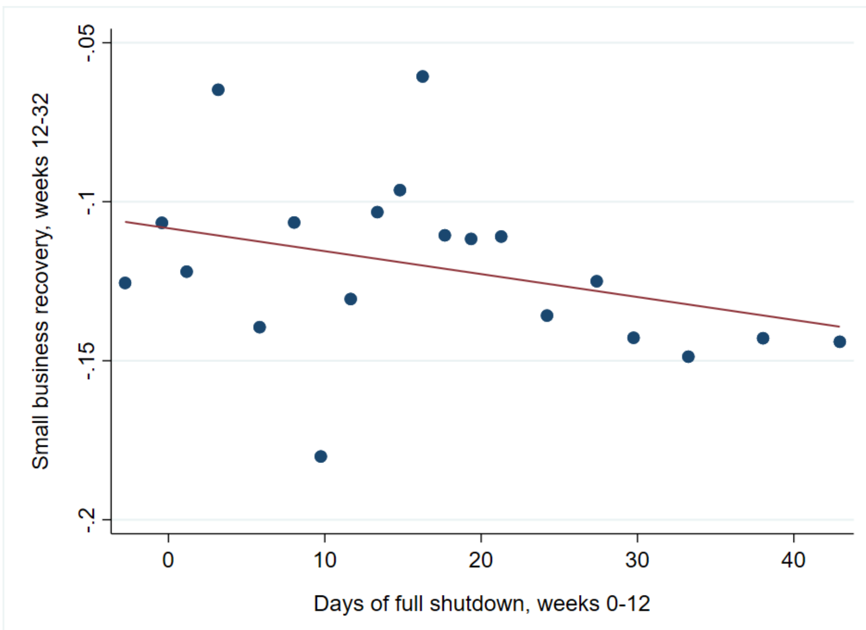
To assess these hypotheses, I employ the following regression model for each period T (Week 4, Week 8, etc.) in the sample:

$$SB_{32,i} - SB_{T,i} = \alpha + \sum_{t=0}^{T} \beta_t^{SB} SB_{t,i} + \sum_{t=0}^{T-1} \beta_t^{COV} \log(COV_{t,i} + 1) + \delta CASE_{(T-4),i}^{T} + \gamma SHUT_{T,s} + \epsilon_i \quad (2)$$

The quantity $SB_{32,i} - SB_{T,i}$ captures a county’s future economic recovery past point T, conditioning on a county’s past economic and epidemiological history. For example, when analyzing the economic recovery between weeks 12 and 32, this entails regressing each county’s week 12 history (in both economic and epidemiological terms) against its change between weeks 12 and 32. As before, SHUT refers to the three-column state-level array of shutdown variables. The presence of $CASE_{(T-4),i}^{T}$ – a two-column array of *log*

COVID-19 Cases in weeks T and $T-4$ – controls for potential behavior shifts due to recent disease spread. This measure accounts for recent COVID-19 spread, which will not appear in death rates at time T (due to the 4-week lag). The sample covers 877 counties over the 32-week period between April 13 and November 25, 2020. The regression employs heteroskedasticity-robust standard errors. The estimates of these regression models are detailed in Table A.6 and Figure 15, and they capture the relation between a county's past and its future.

Figure 15: Full Business Shutdowns and Future Small Business Recovery

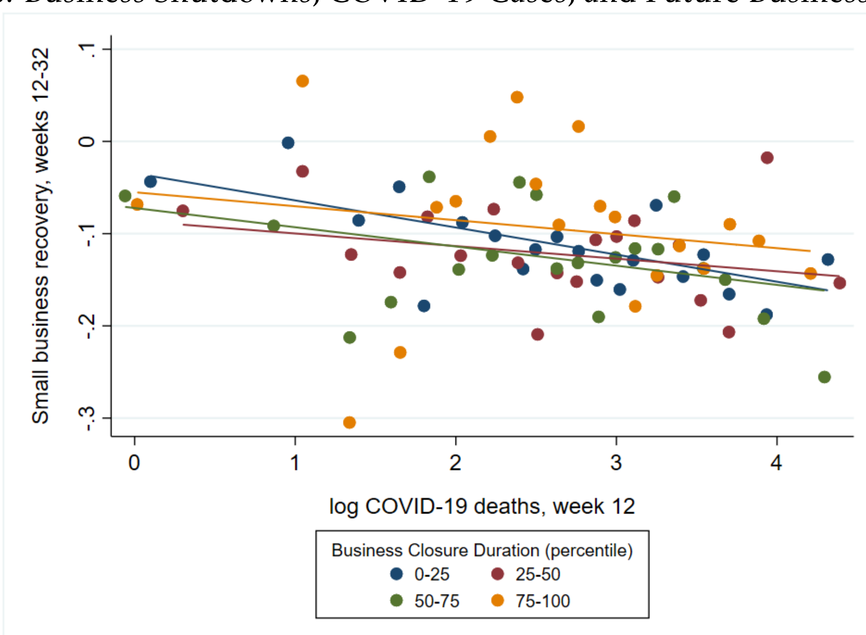


Notes: Bin scatter of *Days Fully Closed* (Weeks 0-12) versus change in *Small Business Recovery*, weeks 12-32. Controls: log *COVID-19 deaths*, week 12; log *COVID-19 cases*, weeks 8 and 12. Two states specifically, New York and Maryland (54 counties). When these states are removed from the sample, the slope is less significant. A bin scatter with these states included is depicted in Figure A.1.

Table A.6 illustrates a few trends. First, there is a negative correlation between a county's starting COVID-19 rate and its long-term recovery, suggesting that places with more underlying COVID-19 saw slower recoveries. Second, I observe a positive correlation between shutdown length and future recovery. This supports the "build back better" hypothesis. This effect may be driven by outlier effects, however. Indeed, Figure 15 demonstrates a sharper negative correlation between small business recovery and shutdown length once two outlier states are removed. Thus, there is also evidence in support of the ”downward spiral” hypothesis.

In Figure 16, I assess the interaction between small business recovery against COVID-19 deaths. Specifically, I contrast COVID-19 deaths at week 12 – a reflection of behavior at week 8 – against small business recovery from week 12 onward. In effect, this studies an 8-week change overall. I separate counties at the 25th, 50th, and 75th percentiles by duration of total shutdown. Additionally, I control for the increase in COVID-19 cases between weeks 8 and 12, as before. We notice that all quartiles display a negative trend, suggesting that places with more COVID-19 recovered more slowly, independently of shutdown lengths.

Figure 16: Business Shutdowns, COVID-19 Cases, and Future Business Recovery



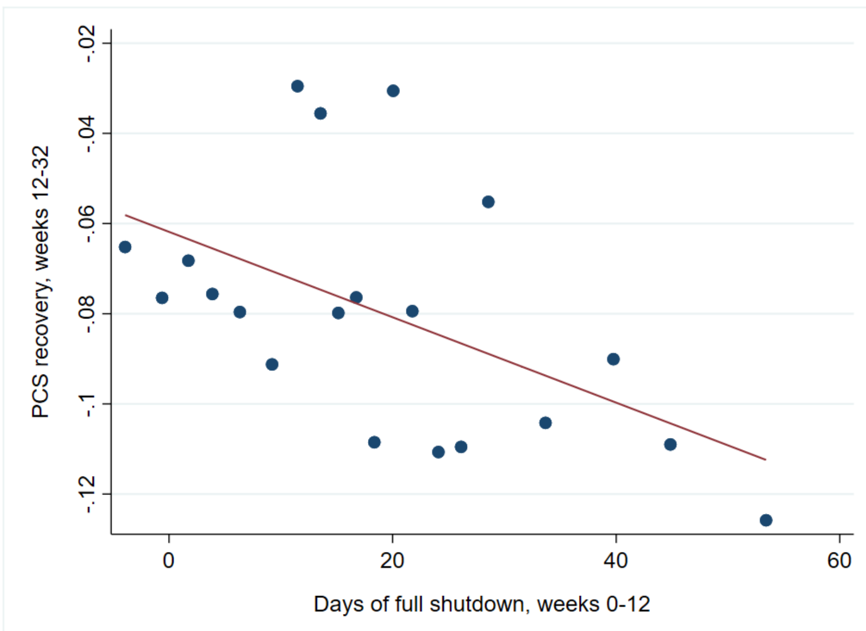
Notes: Binned scatter comparing log *COVID-19 deaths*, week 12, and change in *Small Business Recovery*, weeks 12 through 32. Counties are separated into quartiles by duration of business closures. Controls: log *COVID-19 cases*, weeks 12 and 16.

I repeat the regression technique in (2), substituting SafeGraph sector data for small business recovery. The specific formulation of this regression model is:

$$SEC_{32,i} - SEC_{T,i} = \alpha + \sum_{t=0}^{T} \beta_t^{SEC} SEC_{t,i} + \sum_{t=0}^{T-1} \beta_t^{COV} \log(COV_{t,i}+1) + \delta CASE_{(T-4),i}^{T} + \gamma SHUT_{T,s} + \epsilon_i \quad (3)$$

SEC represents the specific sector analyzed, either *Restaurants*, *PCS*, or *Supermarkets*. The estimates of this regression for full-service restaurants, PCS, and supermarkets are shown in Tables A.7, A.8, and A.9, respectively; 12-week full shutdown regressions are illustrated in Figures 17, 18, and 19.

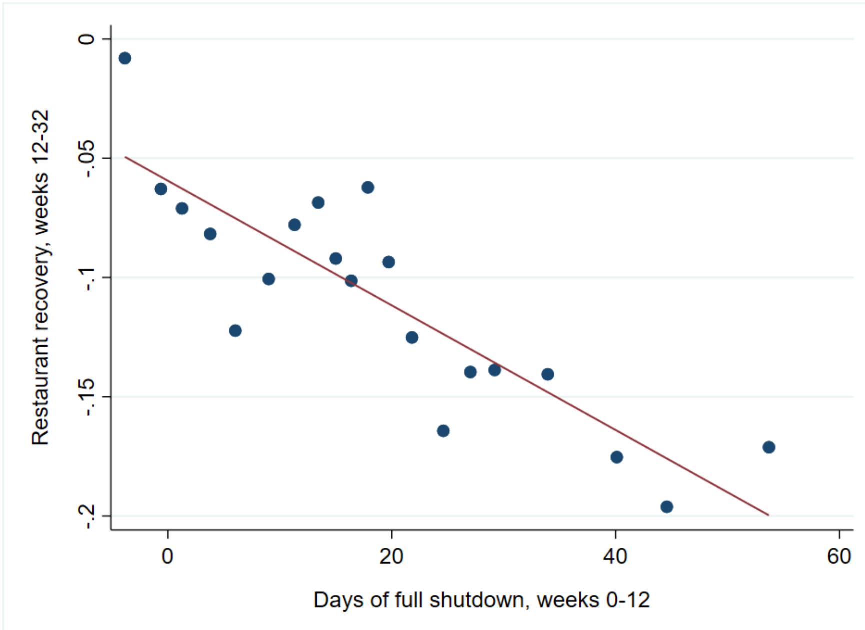
Figure 17: Full Business Shutdowns and Future PCS Recovery



Notes: Binned scatter of *Days Fully Closed* (Weeks 0-12) versus change in *PCS Recovery*, weeks 12-32. Controls: log *COVID-19 deaths*, week 12; log *COVID-19 cases*, weeks 8 and 12.

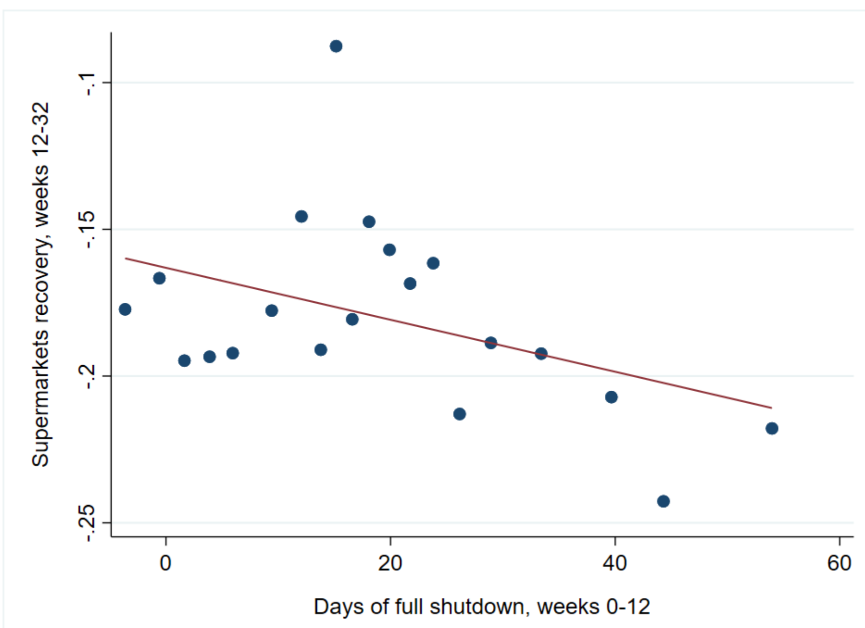
The patterns identified above are only partially repeated throughout these secondary regressions. Starting COVID-19 death rates were also negatively correlated with long-term restaurant recovery, but were not significantly associated with either PCS recovery or supermarket recovery. Furthermore, there is a divergence in shutdown effects by sector. Partial and full shutdowns were negatively associated with PCS and restaurant recovery, while they were positively associated with supermarket recovery. This pattern

Figure 18: Full Business Shutdowns and Future Restaurant Recovery



Notes: Binned scatter of *Days Fully Closed* (Weeks 0-12) versus change in *Restaurant Recovery*, weeks 12-32. Controls: log *COVID-19 deaths*, week 12; log *COVID-19 cases*, weeks 8 and 12.

Figure 19: Full Business Shutdowns and Future Supermarket Recovery



Notes: Binned scatter of *Days Fully Closed* (Weeks 0-12) versus change in *Supermarket Recovery*, weeks 12-32. Controls: log *COVID-19 deaths*, week 12; log *COVID-19 cases*, weeks 8 and 12.

is expected, as restaurants and PCS were sectors that were explicitly closed during shutdown orders, whereas supermarkets remained open. More surprisingly, we observe that stay-at-home orders are positively correlated with restaurant recovery but are negatively correlated with both PCS recovery and supermarket recovery. This finding is unusual and comparatively weak, so it may result from grouping all three shutdown indicators together. In all, these regressions suggest that both hypotheses of economic recovery are in play: while untargeted portions of the economy seem to follow the "build back better" hypothesis, targeted sectors seem to fall into a downward spiral despite shutdowns lifting.

II.c.iii Shutdowns and In-period COVID-19 Spread

I now turn to shutdowns as a method of slowing COVID-19 spread. By closing down places where people congregated, lockdown policies sought to slow disease spread and save lives. If shutdowns are effective at slowing of spread rate, they should reduce COVID-19 death rates. I also expect that the efficacy of shutdown measures will vary with their enforceability. For example, business closures are more enforceable that stay-at-home orders; thus, they should also be more effective.

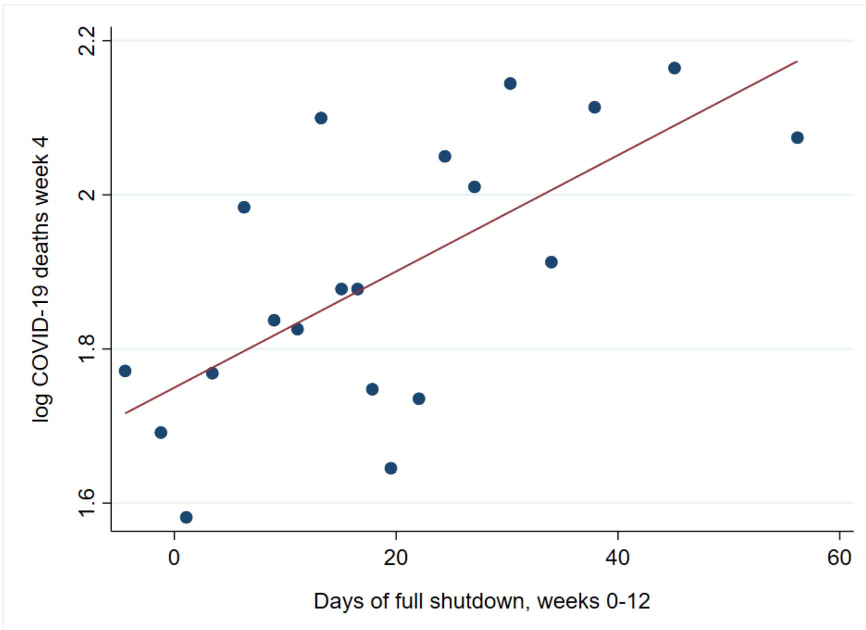
To test these hypotheses, I employ the following regression model:

$$\Delta \log(COV_{t,i}+1)|_4^{(T+4)} = \alpha + \beta_0^{SB} SB_{0,i} + \beta_t^{COV} \log(COV_{0,i}+1) + \delta CASE_{0,i} + \gamma SHUT_{T,s} + \epsilon_i \quad (4)$$

Note the 4-week delay between shutdown policies and deaths (as detailed in Figure 9 – because of the lag structure of infection, infections prevented on a given day are not realized in terms of death saved until 4 weeks later. Additionally, I condition on a county's recent COVID-19 cases. As Figure A.2 shows, these numbers are sharply correlated with one another, so it is appropriate to control for this effect.

The estimates of this regression are shown in Table A.10 and Figure 20. As we observe, longer shutdowns at the start of the recovery period are negatively correlated with COVID-19 spread. This effect seems to dampen, though, as time horizons expand. Figure 20 shows this relation at the 12-week mark, where effects are still felt.

Figure 20: Past COVID-19 deaths and Shutdown Duration



Notes: Binned scatter comparing *Days Fully Closed*, weeks 0-12, with log *COVID-19 deaths*, week 4. Week 4 death counts precede shutdown effects given the 4-week lag. Controls: log *COVID-19 cases*, week 0.

II.c.iv Shutdowns, Past Business Activity, and Future COVID-19 Deaths

I consider the impact of early-stage actions on COVID-19 spread. Effective shutdowns should slow spread beyond the period in which they are employed. Most directly, if shutdowns shrink the total infected population, we expect exponential returns as future generations of the population also avoid infection. Secondary effects of shutdowns may also slow the rate of infection, and longer shutdowns may lead to some degree of "behavior fixing", where individuals are successfully conditioned to avoid disease-spreading interactions. Should this conditioning persist after reopening, the overall rate of infection may decrease. Finally, I test whether business activity is a associated with future COVID-19 spread. If this is the case, visits to businesses in one week should correspond to increases in COVID-19 deaths 4 weeks later. To assess these hypotheses, I employ the following regression model for each period T in the sample:

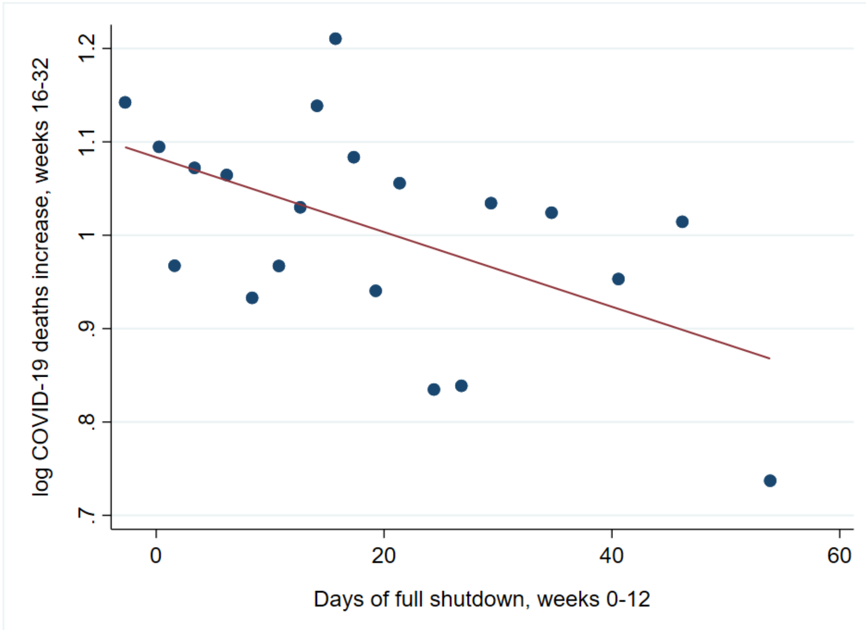
$$\Delta \log(COV_{t,i}+1)|_T^{32} = \alpha + \sum_{t=0}^{T} \beta_t^{COV} \log(COV_{t,i}+1) + \sum_{t=0}^{T} \beta_t^{SB} SB_{t,i} + \delta CASE_{(T-4),i}^{T} + \gamma SHUT_{32,s} + \epsilon_i \tag{5}$$

Through this process, I relate the future increase in COVID-19 deaths to a county's history (in both economic and epidemiological terms), controlling for COVID-19 trajectory and shutdown severity.] As always, regressions employ heteroskedasticity-robust errors. Note that, due to the 4-week lag, these samples only span 28 weeks.

Two patterns are salient from these regressions, displayed in Table A.11. First, I note that shutdown policies are negatively associated with COVID-19 death rates. Figure 21 illustrates this, depicting the negative correlation between shutdown length at 12 weeks and future COVID-19 spread. While partial and full shutdowns are negatively correlated with death rates, as expected, it is surprising that stay-at-home orders are positively correlated with future COVID-19 death rates. This supports the hypothesis that stay-at-home orders are less enforceable and thus less effective. I postulate that this lack of enforceability conditions citizens to be less law-abiding in general, eschewing other policies that reduce spread as well.

The second finding of this regression establishes a link between business activity and future COVID-19 deaths. This correlation surprisingly does not follow a lead-lag structure. Instead, activity between weeks 0 and 4 is strongly and positively predictive of future COVID-19 deaths throughout the entire period. This provides more evidence in support of the "behavior-fixing" hypothesis, as it suggests individuals decided on behavior policies at some point in the first 4 weeks of the recovery, and future COVID-19 spread

Figure 21: Shutdown Duration and Future COVID-19 deaths

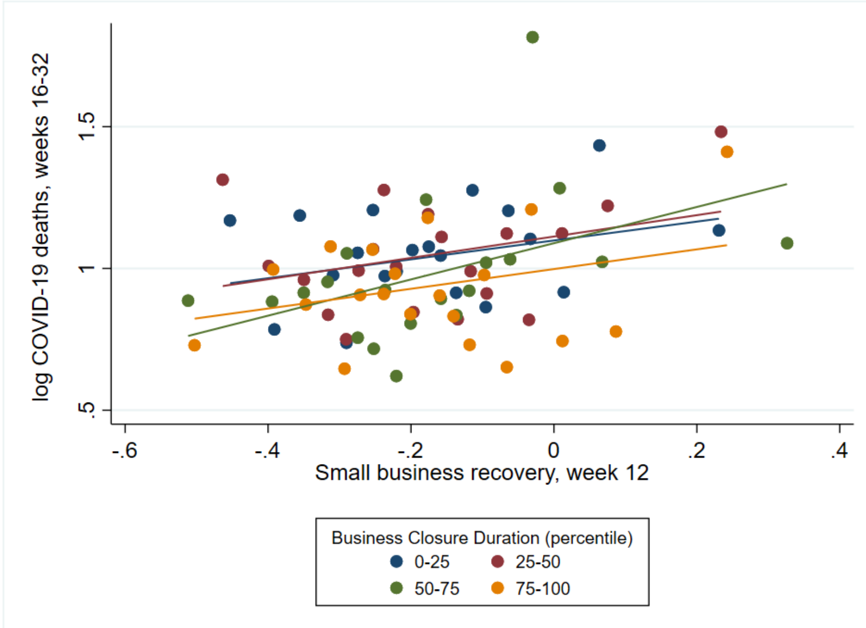


Notes: Binned scatter comparing *Days Fully Closed*, weeks 0-12, with change in log *COVID-19 deaths*, weeks 16-32. There is a four-week delay between the end of shutdowns and future deaths. Controls: log *COVID-19 cases*, weeks 12 and 16.

was partially determined by these initial choices. This is detailed in Figure 22, where I contrast small business activity at week 12 against COVID-19 death increases from week 16 onward. As before, I separate counties at the 25th, 50th, and 75th percentiles by duration of total shutdown. Additionally, I control for the increase in COVID-19 cases between weeks 12 and 16. We notice that all quartiles display a positive trend, indicating that places with more small business activity also saw greater COVID-19 case spread in the subsequent period.

All of these estimates persist across analogous regressions. In Tables A.12, A.13, and A.14, respectively, I perform the analysis in (5) but substitute SafeGraph numbers small for business recovery data, analyzing full-service restaurants, PCS, and supermarkets, respectively. The specific formulation is:

Figure 22: Business Shutdowns, Business Recovery, and Future COVID-19 Cases,



Notes:Binned scatter comparing *Small Business Recovery*, week 12, and change in log *COVID-19 deaths*, weeks 16 through 32. Counties are separated into quartiles by duration of business closures. Controls: log *COVID-19 cases*, weeks 12 and 16.

$$\Delta \log(COV_{t,i}+1)|_T^{32} = \alpha + \sum_{t=0}^{T} \beta_t^{COV} \log(COV_{t,i}+1) + \sum_{t=0}^{T} \beta_t^{SEC} SEC_{t,i} + \delta CASE_{(T-4),i}^{T} + \gamma SHUT_{32,s} + \epsilon_i \tag{6}$$

If anything, the trends noted above become more robust in certain sectors. Activity in restaurants and PCSs during the first eight weeks correlates with long-term COVID-19 death increases, compared to the four-week significance of supermarkets and general small businesses. This may be because PCSs and dine-in restaurants are close-contact, service-based industries, making them excellent transmission locations for COVID-19. Furthermore, these sectors were closed in some counties, meaning places where visitors increased more must also have had other sectors open.

I also observe similar trends in shutdown severity measures. Partial and full shutdowns were negatively associated with recovery in all three sectors, while longer stay-at-home orders were positively associated with recovery.

II.d Key Takeaways

I summarize the key findings of my research in Table 1. From this analysis, I conclude that state-level policies had clear impacts on both COVID-19 spread and business recovery.

Full shutdowns are associated with greater business recovery overall, although they are associated with severe negative effects in targeted sectors (restaurants, PCS). Supermarkets were not significantly affected by this. Additionally, they were negatively correlated with COVID-19 death increases, suggesting that lockdowns significantly checked disease spread.

Partial shutdowns displayed the same trends as full shutdowns, although the effects were smaller in magnitude. These effects were also longer lasting than those of full shutdowns, though this may be because most full shutdowns occurred exclusively at the start of the recovery period, while partial occurred throughout.

Stay-at-home orders are associated with lower business activity and higher COVID-19 fatality rates in the future, an observation that may stem from stay-at-home orders being less enforceable. However, this may also be due to heavy overlap between stay-at-home orders and business closures.

The patterns I observe are more reliable when considering COVID-19 spread: business activity at the start of the pandemic spread the virus. Shutdowns that prevented this activity also slowed virus spread. The first four weeks of recovery were essential in setting the tone of a county's recovery, suggesting some degree of behavior fixing occurred in these early weeks. Higher COVID-19 death rates at week 0 were associated with slower business recovery across sectors. Greater business activity during the first four weeks (and during the first eight-weeks in high-risk sectors) was associated with long-term increases in COVID-19 deaths

These results, taken together, suggest that government policies played an important role in affecting economic activity and COVID-19 spread through two pathways. Primarily, shutdown orders closed businesses and reduced COVID-19 spread during the period in which they were enacted. Secondarily, these orders seem to have had some effect in setting people's behaviors after orders were relaxed or lifted. While economic recovery rebounded in all counties, clear discrepancies in COVID-19 death rates suggest that shutdowns impacted people's behavior. As evidenced by the positive correlation between stay-at-home order length and COVID-19 death rates, long, severe, shutdown measures may inspire ignorance of all guidelines or over-risky behavior after reopening, suggesting that policy makers faced a difficult choice in deciding how stringent their shutdown policies should be.

Moving forward, I attempt to quantify the potential costs or savings of government interventions in preventing COVID-19 deaths.

Table 1: Summary of Part II Results

Dependent variable	**Regression variable**			
In-period Economic Recovery	SB	PCS	Restaurants	Supermarkets
Baseline COVID-19	–	–	–	–
Shutdown Policies	–	–	–	–
In-period COVID-19 deaths				
Baseline Economic Activity	+	N/A	N/A	N/A
Shutdown Policies	–	N/A	N/A	N/A
Future Economic recovery				
Starting COVID-19	–	–	X	X
Partial Business Closures	+	–	–	+
Full Business Closures	+	–	–	X
Stay-at-home orders	+	+	–	–
Future COVID-19 deaths				
Economic Activity, weeks 0-4	+	+	+	+
Partial Business Closures	–	–	–	–
Full Business Closures	–	–	–	–
Stay-at-home orders	+	+	+	+

Notes: Signs of significant coefficients in regressions from Part II. + denotes a positive correlation at the 10% level; – denotes a negative correlation, X denote a lack of significant correlation.

III Estimating Cost per Life Saved of Business Closures

III.a Overview

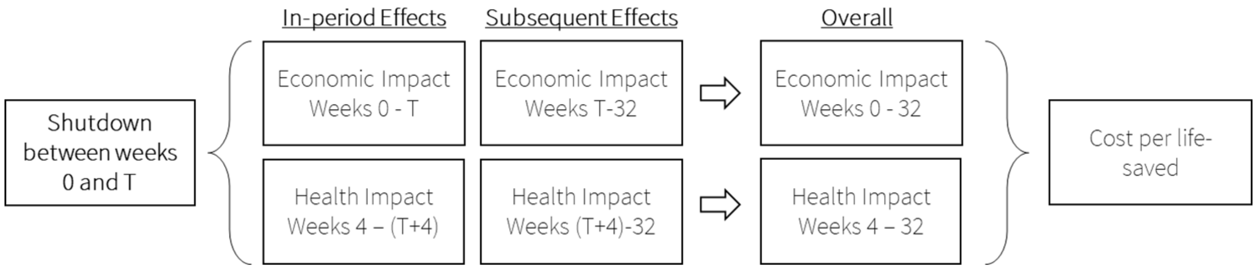
Up to this point, I have considered three shutdown policies: partial business closures, full business closures, and stay-at-home orders. In this section, I restrict my focus solely to full business closures as I work to quantify the cost of shutdown. There are two reasons for this decision. First, full business closures are more extreme measures compared to partial business closures, allowing for better understanding of policy impacts. Moreover, my analysis in Part II demonstrates how business closures are a more significant correlate of recovery than stay-at-home orders.

For business closures, I consider the counterfactual questions, "Had all counties kept businesses closed for 28 more days during the first T weeks, what would the economic impact have been at 32 weeks? How many COVID-19 deaths would have been prevented by the end of the same period?" The answers to these counterfactuals will enable me to estimate cost per life saved.

III.b Quantifying Shutdown Costs

Using the estimated coefficients from regression models in the preceding section, I estimate the overall costs of shutdowns. In general, the goals of this section are illustrated in Figure 23. Critically, I estimate both in-period and out-of-period effects of shutdowns, as these have been shown to be significant. For an additional 28 days of shutdown within the first T weeks, I estimate both in-period and subsequent-period effects on health and economic outcomes. These values are used to estimate the cost per life saved at different points throughout the pandemic.

Figure 23: Overview of Part III Estimations



Notes: Regression coefficients from Part II are used to estimate the cost per life saved of an additional 28 days of full business closure within the first T weeks of the pandemic.

III.b.i Economic Impact

Using the coefficients obtained from regressions 1, I estimate in-period GDP impacts using a simple arithmetic approximation. Subsequent-period effects are specified by the regression model (2) in Part II. To obtain in-period coefficient estimates I slightly modify (1) to model in-period effects. Specifically, my in-period regression model is:

$$SB_{T,i} - SB_{0,i} = \alpha + \beta_0^{SB} SB_{0,i} + \beta_t^{COV} \log(COV_{0,i} + 1) + \gamma SHUT_{T,s} + \epsilon_i \tag{7}$$

Thus, I modify the regression model so that my shutdown indicators also reflect the period of study. The coefficients on *Days Fully Closed* are recorded in Tables 2 through 5.

I then translate these coefficients to GDP impacts. To start, I assume that small business revenue tracks well with GDP, i.e., a 20% decrease in small business revenue is equally associated with a 20% decrease in GDP. Next, I assume that GDP is uniformly accumulated throughout the year. While imprecise, these assumption lets me use annual county-level GDP statistics from BEA to approximate impact. Because some counties remained closed for large swaths of any given period, the incremental time spent closed for each county is: $\widehat{DAYS}_i = \min\{28, 7 \cdot (T - DAYS\_CLOSED_i)\}$.

Under these assumptions, the counterfactual impact of closing for up to 28 more days during the 226-day (32 week period) is:

$$SB\ Cost = \sum_{i \in C} \frac{226}{365} \cdot \widehat{DAYS}_i \cdot (\gamma^{SB}_{0,T} + \gamma^{SB}_{T,32}) \cdot GDP_i \tag{8}$$

The results of these calculations are detailed in Table 2. In general, I assess that these counties would have lost between 1 and 8 billion dollars in GDP had they locked down in the first 16 weeks. Beyond this, my results suggest that that locking down *saved* money long term. We should be somewhat skeptical of this result, however, as these terms have large associated standard errors. That said, this extreme prediction underscores the long-run economic convergence between open and closed counties. This convergence suggests that negative economic shocks were mitigated over subsequent months, reducing the initial burden that closed counties suffered.

Table 2: Shutdowns and Overall Small Business Recovery

	In-Period	Subsequent Period	Daily Impact	28-day impact	GDP COST (Billions USD)
4 Weeks	-0.0031***	-0.0002	-0.0033	-9.2%	324.9
8 Weeks	-0.0002***	0.0004	-0.0014	-3.9%	327.1
12 Weeks	-0.0009***	0.0004	-0.0006	-1.5%	141.0
16 Weeks	-0.0008***	0.0005*	-0.0003	-0.9%	81.1
20 Weeks	-0.0002	0.0005*	0.0002	0.7%	-61.0
24 Weeks	-0.0004	0.0004	0.0000	0.1%	-6.1
28 Weeks	-0.0000	0.0003*	0.0003	0.8%	-71.0
32 Weeks	-0.0000		-0.0000	-0.2%	18.9

Notes: Row headings (*T lives*) list impacts of 28 days of additional shutdown on small business recovery. The incremental effects of one additional day of closure in weeks 0 through T (*In-period*) and in weeks T through 32 (*Subsequent Period*). *Daily Impact* calculates the sum of *In-period* and *Subsequent Period*. *28-day impact* multiplies *Daily Impact* by 28. *GDP COST* calculates the impact of closure on GDP, using equation 8. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

III.b.ii Sector-specific Impact

I can also determine the sector-specific impact of additional business closures. Specifically, I aim to quantify the percentage impact of 28 days of additional business closures on overall industry performance. Because I do not convert percentage changes into absolute numbers, I simply perform the calculation $28 \cdot (\gamma_{0,T}^{SEC} + \gamma_{T,32}^{SEC})$ using coefficients from the regressions from Part III. The results of these summations are shown in Tables 4 through 5.

Table 3: Shutdowns and Overall PCS Recovery

	In-Period	Subsequent Period	Total	28-day impact
4 Weeks	-0.0034***	-0.0002	-0.0036	-10%
8 Weeks	-0.0009***	-0.0003	-0.0012	-3%
12 Weeks	-0.0004	-0.0004	-0.0008	-2%
16 Weeks	-0.0003	-0.0006**	-0.0009	-3%
20 Weeks	-0.0004	-0.0006**	-0.0010	-3%
24 Weeks	-0.0005	-0.0006***	-0.0011	-3%
28 Weeks	-0.0005	-0.0004*	-0.0009	-2%
32 Weeks	-0.0005*		-0.0005	-1%

Notes: Row headings (*T lives*) list impacts of 28 days of additional shutdown on PCS recovery. The incremental effects of one additional day of closure in weeks 0 through T (*In-period*) and in weeks T through 32 (*Subsequent Period*). *Daily Impact* calculates the sum of *In-period* and *Subsequent Period*. *28-day impact* multiplies *Daily Impact* by 28. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Here, I emphasize the divergence between targeted and untargeted sectors. Supermarkets, as an essential business, would have emerged from a longer shutdown marginally ahead of their January baseline. This supports the hypothesis that non-targeted sectors were able to "build back better". In contrast, targeted sectors like restaurants and PCS would have born the brunt of shutdown impacts. PCS visits are estimated to fall between 1 and 3 %; restaurant decreases are in the range of 1% to 5%.

Table 4: Shutdowns and Overall Restaurant Recovery

	In-Period	Subsequent Period	Daily Impact	28-day impact
4 Weeks	-0.003***	-0.002***	-0.0048	-13%
8 Weeks	-0.002**	-0.001***	-0.0031	-9%
12 Weeks	0.0006	-0.0012***	-0.0007	-2%
16 Weeks	0.0005	-0.0008***	-0.0002	-1%
20 Weeks	0.0006	-0.0009***	-0.0003	-1%
24 Weeks	-0.0008**	-0.0006***	-0.0014	-4%
28 Weeks	-0.0014***	-0.0002**	-0.0016	-5%
32 Weeks	-0.0014***		-0.0014	-4%

Notes: Row headings (*T lives*) list impacts of 28 days of additional shutdown on restaurant recovery. The incremental effects of one additional day of closure in weeks 0 through T (*In-period*) and in weeks T through 32 (*Subsequent Period*). *Daily Impact* calculates the sum of *In-period* and *Subsequent Period*. *28-day impact* multiplies *Daily Impact* by 28. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Shutdowns and Overall Supermarket Recovery

	In-Period	Subsequent Period	Daily Impact	28-day impact
4 Weeks	-0.0006***	0.0005	-0.0001	-0.3%
8 Weeks	-0.0001	0.0002	0.0001	0.2%
12 Weeks	0.0004	-0.0001	0.0003	0.9%
16 Weeks	0.0004	0.0000	0.0004	1.1%
20 Weeks	0.0003	0.0000	0.0003	0.8%
24 Weeks	0.0001	0.0000	0.0001	0.3%
28 Weeks	0.0004	-0.0001	0.0003	0.8%
32 Weeks	0.0001		0.000117	0.3%

Notes: Row headings (*T lives*) list impacts of 28 days of additional shutdown on supermarket recovery. The incremental effects of one additional day of closure in weeks 0 through T (*In-period*) and in weeks T through 32 (*Subsequent Period*). *Daily Impact* calculates the sum of *In-period* and *Subsequent Period*. *28-day impact* multiplies *Daily Impact* by 28. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

III.b.iii Lives Saved

I repeat the above process to assess decreases in log COVID-19 deaths. The coefficients are obtained from regression (4) and a modified version of (5):

$$\Delta \log(COV_{t,i}+1)|_{T}^{32} = \alpha + \sum_{t=0}^{T} \beta_t^{COV} \log(COV_{t,i}+1) + \sum_{t=0}^{T} \beta_t^{SB} SB_{t,i} + \delta CASE_{(T-4),i}^{T} + \gamma SHUT_{(T-4),s} + \epsilon_i \tag{9}$$

Note the 4-week lag between the end of the shutdown and the beginning of the "subsequent deaths" period. Once coefficients are obtained, the process of converting them to absolute numbers is more complicated. [3]

Once this is done, I project COV_i^*, the projected new COVID-19 deaths. I use the following formulas to calculate the projected lives save by shutting down:

$$Lives\ Saved = \sum_i (COV_i - COV_i^*) \tag{10}$$

The results of this approximation are detailed in Table 6. Since the effects of a 32-week shutdown are not observed in this sample, I approximate it using a logarithmic fit (Figure A.3), which predicts 38,962 lives saved from a 28-day closure.

My findings suggest that longer shutdowns in the first few months of recovery would have had small effects on long-term death rates, while later shutdowns project many more lives saved.

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[3] The specific formula is

$$COV_i^* = \max\left\{0, \exp\left\{\log(COV_{i,32}+1) + \widehat{DAYS} * (\gamma_{0,T}^{COV} + \gamma_{T,32}^{COV})\right\} - 1\right\}$$

This reverses the $\log(COV+1)$ transformation applied to death counts. Furthermore, the presence of the max function is necessary to ensure counties cannot record negative numbers of COVID-19 deaths.

Table 6: Shutdowns and Overall COVID-19 spread

	In-Period	Subsequent Period	Total	Lives Saved
4 Weeks	-0.0007	-0.0044**	-0.0050	7,975
8 Weeks	-0.0029***	0.0010	-0.0019	4,619
12 Weeks	-0.0058***	0.0012	-0.0046	12,995
16 Weeks	-0.0087***	0.0006	-0.0081	26,333
20 Weeks	-0.0097***	-0.0000	-0.0097	34,839
24 Weeks	-0.0091***	0.0002	-0.0089	36,454
28 Weeks	-0.0076***		-0.0076	36,548

Notes: Row headings (*T lives*) list impacts of 28 days of additional shutdown on log COVID-19 deaths. The incremental effects of one additional day of closure in weeks 4 through T+4 (*In-period*) and in weeks T+4 through 32 (*Subsequent Period*) - note the 4-week lag stemming from the lead-lag structure. *Daily Impact* calculates the sum of *In-period* and *Subsequent Period*. *28-day impact* multiplies *Daily Impact* by 28. *Lives Saved* uses Equation 10 to estimate lives saved. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

III.b.iv Calculating Cost per Life Saved

I now estimate the cost per life saved by dividing the cost of shutting down by the number of lives saved. The results of this are displayed in Table 7. Note that estimates past week 16 are more dubious, given the lack of statistical correlation between full business closures and business recovery. Despite this, a clear pattern emerges. Shutdowns within the first few months of the recovery were costly, perhaps even prohibitively so. Estimated at over $40 million per life saved, my estimate exceeds calculations performed by Barrot et al. (2020) who estimate this amount at $6 million per life saved. For reference, the US Department of Health and Human Services values the average life at $9.6 million (2016), and the OECD appraises a life at $3.5 million (2012). While my numbers are larger than other numbers in the literature, the high absolute cost suggests a premium was placed on saving lives from COVID-19 at the start of the pandemic.

However, equally notable is the dramatic reduction in COVID-19 cost due to the strong long-term recoveries of closed counties. By Week 16, the cost per life falls to $3 million. A projection of lives saved at Week 32 estimates even lower to $489 thousand per life saved. [4] While these numbers should be subjected to further scrutiny, and certainly discounted due to the infrequency of full business closures past 16 weeks, the trend is unmistakable. Due to long-run convergence in economic recoveries, costs per life saved fall precipitously. One interpretation of these results might be as follows: counties might have overzealously shut down at the start of the pandemic, but this phenomenon was equally matched by laxness after reopening. This error in shutdown timing led to significant inefficiency. Later-stage business closures might have saved lives at small economic cost.

Table 7: Cost of Shutdowns per Life Saved

	GDP COST (Billions USD)	Lives Saved	Cost per Life (USD Millions)
4 Weeks	324.9	7,975	40.74
8 Weeks	327.1	4,619	70.81
12 Weeks	141.0	12,995	10.85
16 Weeks	81.1	26,333	3.08
20 Weeks	-61.0	34,839	-1.75
24 Weeks	-6.1	36,454	-0.17
28 Weeks	-71.0	36,548	-1.94
32 Weeks	18.9	38,720†	0.49

Notes: *GDP Cost* is repeated from Table 2, *Lives Saved* is repeated from Table 6. *Cost per Life* is calculated as *GDP COST*/*Lives Saved*. †COVID-19 lives saved at 32 weeks estimated by logarithmic approximation, see Figure A.

IV Interpretation and Future Research

This research has three key takeaways. First, I show how SafeGraph data provides a reliable way to view sector-by-sector trends within economics, especially when these trends include informal activity. Until now, SafeGraph data has been primarily used to study household movement, but this research demonstrates that it can also be used to under-

[4] In weeks 20 through 28, I observe negative economic costs – suggesting that shutdowns actually *saved* money. However, due to large standard errors on these coefficients, I advise caution with these values. The values at 16 weeks are perhaps the most reliable result, as small business recovery is significant both in-period and in the subsequent period. This time mark also evenly splits the sample.

stand firm behavior at the granular level. This work can easily be expanded to study other industries, for example, hotels and convenience stores, as well as the recovery period past November 25, 2020.

Second, this research highlights the decreasing cost of shutdowns. As a whole, I observe that shutdown measures were most effective when they prevented large absolute numbers of infections, while a general convergence in economic outcomes regardless of shutdown policy suggests that lockdowns were not as damaging on long-run economic performance as might have been anticipated. The average county was able to "build back better" after it was shut down. Together, the convergence of economic recovery and the low reduction of deaths from COVID-19 suggest that lockdowns at the start of the pandemic were especially costly, but lockdowns later on were a cost-effective method of saving lives. My specific estimates are admittedly rough, so it may be advantageous to fine-tune the model's calculations, for example, by including excess deaths from shutdowns or by adjusting for the median age of COVID-19 victims in each county. It may also be revealing to explore potential underlying omitted variables, including each county's underlying health capacity or its populace's trust in science.

Third, my analysis of the specific industries targeted by shutdown policies reveals a concerning counter-trend. Even though overall small business activity converged across counties, targeted industries saw visitor declines grow even more severe after lockdowns were lifted. In effect, these targeted industries continued on a "downward spiral" from which they have yet to escape. This observation is important, and policy makers should consider the severe effects of shutdowns on targeted sectors as well as the general benefits of shutdowns when making the decision to shut down.

References

Allcott, H., Boxell, L., Conway, J., Ferguson, B., Gentzkow, M., and Goldman, B. (2020). Economic and health impacts of social distancing policies during the coronavirus pandemic. *Available at SSRN 3610422*.

Andersen, A. L., Hansen, E. T., Johannesen, N., and Sheridan, A. (2020). Pandemic, shutdown and consumer spending: Lessons from Scandinavian policy responses to COVID-19. *arXiv preprint arXiv:2005.04630*.

Balla-Elliott, D., Cullen, Z. B., Glaeser, E. L., Luca, M., and Stanton, C. T. (2020). Business reopening decisions and demand forecasts during the COVID-19 pandemic. Technical report, National Bureau of Economic Research.

Barrot, J.-N., Grassi, B., and Sauvagnat, J. (2020). Estimating the costs and benefits of mandated business closures in a pandemic.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, 117(30):17656–17666.

Bieler, D. (2020). Ben Roethlisberger chided by Pennsylvania governor for putting himself 'in harm's way' with haircut. *The Washington Post*, 19.

Chatterjee, S. S., Vora, M., Malathesh, B. C., and Bhattacharyaa, R. (2020). Worried well and COVID-19: re-emergence of an old quandary. *Asian journal of psychiatry*.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., et al. (2020). Real-time economics: A new platform to track the impacts of COVID-19 on people, businesses, and communities using private sector data. *NBER Working Paper*, 27431.

Cummings, M. J., Baldwin, M. R., Abrams, D., Jacobson, S. D., Meyer, B. J., Balough, E. M., Aaron, J. G., Claassen, J., Rabbani, L. E., Hastie, J., et al. (2020). Epidemiology, clinical course, and outcomes of critically ill adults with COVID-19 in New York City: a prospective cohort study. *The Lancet*, 395(10239):1763–1770.

Guan, W.-j., Ni, Z.-y., Hu, Y., Liang, W.-h., Ou, C.-q., He, J.-x., Liu, L., Shan, H., Lei, C.-l., Hui, D. S., et al. (2020). Clinical characteristics of coronavirus disease 2019 in China. *New England journal of medicine*, 382(18):1708–1720.

Hartl, T., Wälde, K., and Weber, E. (2020). Measuring the impact of the German public shutdown on the spread of COVID-19. *Covid economics*, 1:25–32.

Kniesner, T. J., Viscusi, W. K., Woock, C., and Ziliak, J. P. (2012). The value of a statistical life: Evidence from panel data. *Review of Economics and Statistics*, 94(1):74–87.

Larson, T., Culbreath, K., Chavez, D., Larson, R., Crossey, M., and Grenache, D. G. (2020). Modeling SARS-CoV-2 positivity using laboratory data: timing is everything. *Clinical chemistry*, 66(7):981–983.

Lauer, S. A., Grantz, K. H., Bi, Q., Jones, F. K., Zheng, Q., Meredith, H. R., Azman, A. S., Reich, N. G., and Lessler, J. (2020). The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. *Annals of internal medicine*, 172(9):577–582.

Lubell, M. (2020). Israel imposing third national COVID-19 lockdown.

Neuman, S. (2021). 'Basically in a new pandemic,' says Merkel, as Germany extends lockdown. *National Public Radio*.

Nishiura, H., Kobayashi, T., Miyama, T., Suzuki, A., Jung, S.-m., Hayashi, K., Kinoshita, R., Yang, Y., Yuan, B., Akhmetzhanov, A. R., et al. (2020). Estimation of the asymptomatic ratio of novel coronavirus infections (COVID-19). *International journal of infectious diseases*, 94:154.

Peiser, J. (2020). GOP slams Nancy Pelosi for her indoor haircut in San Francisco, where that's still banned. *The Washington Post*.

Porter, E. and Tankersley, J. (2020). Shutdown spotlights economic cost of saving lives. *New York Times*, 24.

Tenforde, M. W., Kim, S. S., Lindsell, C. J., Rose, E. B., Shapiro, N. I., Files, D. C., Gibbs, K. W., Erickson, H. L., Steingrub, J. S., Smithline, H. A., et al. (2020). Symptom duration and risk factors for delayed return to usual health among outpatients with COVID-19 in a multistate health care systems network—United States, March–June 2020. *Morbidity and Mortality Weekly Report*, 69(30):993.

Weerahandi, H., Hochman, K. A., Simon, E., Blaum, C., Chodosh, J., Duan, E., Garry, K., Kahan, T., Karmen-Tuohy, S. L., Karpel, H. C., et al. (2021). Post-discharge health status and symptoms in patients with severe COVID-19. *Journal of general internal medicine*, pages 1–8.

A Additional Tables and Figures

Table A.1: Overview of Variables

Name	Description
ECONOMIC INDICATORS	
Small Business Recovery	% Small business revenue vs. January average. Source: Womply
PCS Visitor Recovery	% PCS Visitors vs. January average. Source: SafeGraph
Restaurant Visitor Recovery	% Restaurant Visitors vs. January average. Source: SafeGraph
Supermarket Visitor Recovery	% Supermarket Visitors vs. January average. Source: SafeGraph
HEALTH INDICATORS	
log *COVID-19 Deaths*	log of total deaths per 100,000. Source: NYT
log *COVID-19 Cases*	log of total cases 100,000. Source: NYT
SHUTDOWN INDICATORS	
Days Fully Closed	Days of state-mandated full business closures (level 3 and above, according to OxCGRT benchmarks)
Days Partially Closed	Days of state-mandated partial business closures (level 2 and above, according to OxCGRT benchmarks)
Days Stay-at-home	Days of state-mandated stay-at-home orders Source: OxCGRT benchmarks

Notes: SafeGraph sector-specific data is the arithmetic average of the three week block surrounding each point estimate; e.g. Week 4 is the average of reported values for weeks 3, 4, and 5.

Table A.2: Shutdowns and In-period % Small Business Recovery

	4 Weeks	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks	28 Weeks	32 Weeks
Small Business Baseline	0.911***	0.680***	0.583***	0.562***	0.529***	0.521***	0.472***	0.418***
	(0.038)	(0.045)	(0.047)	(0.040)	(0.041)	(0.046)	(0.047)	(0.043)
log COVID Baseline	-1.288***	-3.154***	-0.606	-0.908*	-0.790	-1.186**	-1.632***	-2.164***
	(0.426)	(0.508)	(0.570)	(0.491)	(0.530)	(0.588)	(0.606)	(0.574)
Days Partially Closed	0.209	0.170**	0.042	-0.018	0.005	-0.005	-0.013	0.002
	(0.320)	(0.070)	(0.030)	(0.017)	(0.013)	(0.010)	(0.010)	(0.008)
Days Fully Closed	-0.314***	-0.186***	-0.091***	-0.086***	-0.024	-0.036	-0.006	-0.006
	(0.042)	(0.033)	(0.035)	(0.032)	(0.034)	(0.033)	(0.032)	(0.027)
Days Stay-at-home	-0.074	-0.022	0.004	0.032*	0.045***	0.015	0.013	0.006
	(0.054)	(0.029)	(0.024)	(0.018)	(0.016)	(0.011)	(0.010)	(0.009)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.553	0.375	0.237	0.263	0.195	0.197	0.164	0.141

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in small business revenue recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Shutdowns and In-period PCS Visits

	4 Weeks	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks	28 Weeks	32 Weeks
PCS Baseline	1.058***	0.990***	0.735***	0.686***	0.629***	0.632***	0.608***	0.563***
	(0.044)	(0.062)	(0.065)	(0.066)	(0.081)	(0.076)	(0.080)	(0.068)
log COVID Baseline	-1.021***	-1.708***	-0.248	0.088	0.069	-0.582	-0.862	-1.440***
	(0.336)	(0.591)	(0.540)	(0.569)	(0.656)	(0.602)	(0.647)	(0.555)
Days Partially Closed	0.202	-0.109	-0.142***	-0.102***	-0.071***	-0.057***	-0.035***	-0.034***
	(0.214)	(0.091)	(0.029)	(0.020)	(0.016)	(0.012)	(0.009)	(0.008)
Days Fully Closed	-0.339***	-0.098***	-0.046	-0.030	-0.042	-0.050	-0.058	-0.055**
	(0.038)	(0.032)	(0.029)	(0.036)	(0.045)	(0.042)	(0.041)	(0.026)
Days Stay-at-home	-0.171***	-0.004	0.032	-0.001	-0.046***	-0.046***	-0.032***	-0.020**
	(0.044)	(0.029)	(0.023)	(0.019)	(0.016)	(0.012)	(0.011)	(0.008)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.546	0.334	0.225	0.187	0.147	0.181	0.164	0.19

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in PCS visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks $T$and $T-4$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Shutdowns and In-period % Restaurant Visits

	4 Weeks	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks	28 Weeks	32 Weeks
Restaurant Baseline	1.302***	1.168***	0.880***	0.841***	0.771***	0.816***	0.900***	1.085***
	(0.047)	(0.098)	(0.141)	(0.153)	(0.124)	(0.071)	(0.065)	(0.061)
log COVID Baseline	-1.370***	-3.564***	-2.924**	-2.129	-1.946*	-1.494***	-1.619***	-1.042***
	(0.347)	(0.939)	(1.299)	(1.329)	(1.048)	(0.542)	(0.421)	(0.395)
Days Partially Closed	-0.157	-0.090	-0.155***	-0.120***	-0.066***	-0.050***	-0.029***	-0.020***
	(0.170)	(0.084)	(0.046)	(0.034)	(0.019)	(0.009)	(0.007)	(0.006)
Days Fully Closed	-0.280***	-0.173***	0.047	0.047	0.054	-0.089**	-0.146***	-0.139***
	(0.041)	(0.065)	(0.092)	(0.101)	(0.081)	(0.039)	(0.022)	(0.017)
Days Stay-at-home	-0.059	0.021	0.097**	0.081**	0.014	0.002	0.011	0.026***
	(0.036)	(0.041)	(0.040)	(0.033)	(0.018)	(0.012)	(0.010)	(0.007)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.5	0.198	0.068	0.058	0.072	0.234	0.325	0.411

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in restaurant visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5: Shutdowns and In-period Supermarket Visits

	4 Weeks	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks	28 Weeks	32 Weeks
Supermarket Baseline	2.045***	1.905***	1.806***	1.732***	1.722***	1.715***	1.739***	1.752***
	(0.020)	(0.036)	(0.054)	(0.063)	(0.053)	(0.048)	(0.049)	(0.044)
log COVID Baseline	-0.072	0.110	-0.643	-0.745	-0.435	-0.449	-0.377	-0.109
	(0.185)	(0.442)	(0.677)	(0.704)	(0.594)	(0.518)	(0.531)	(0.501)
Days Partially Closed	-0.108	-0.121**	-0.090***	0.006	0.039**	0.029***	0.035***	0.023***
	(0.097)	(0.049)	(0.033)	(0.023)	(0.015)	(0.010)	(0.009)	(0.007)
Days Fully Closed	-0.056***	-0.011	0.038	0.032	0.023	-0.001	0.038	0.011
	(0.020)	(0.026)	(0.040)	(0.044)	(0.039)	(0.032)	(0.025)	(0.019)
Days Stay-at-home	-0.014	0.037*	0.042	0.040*	0.026*	0.021*	-0.026***	-0.017**
	(0.020)	(0.022)	(0.027)	(0.023)	(0.015)	(0.012)	(0.009)	(0.007)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.955	0.811	0.627	0.567	0.604	0.657	0.641	0.686

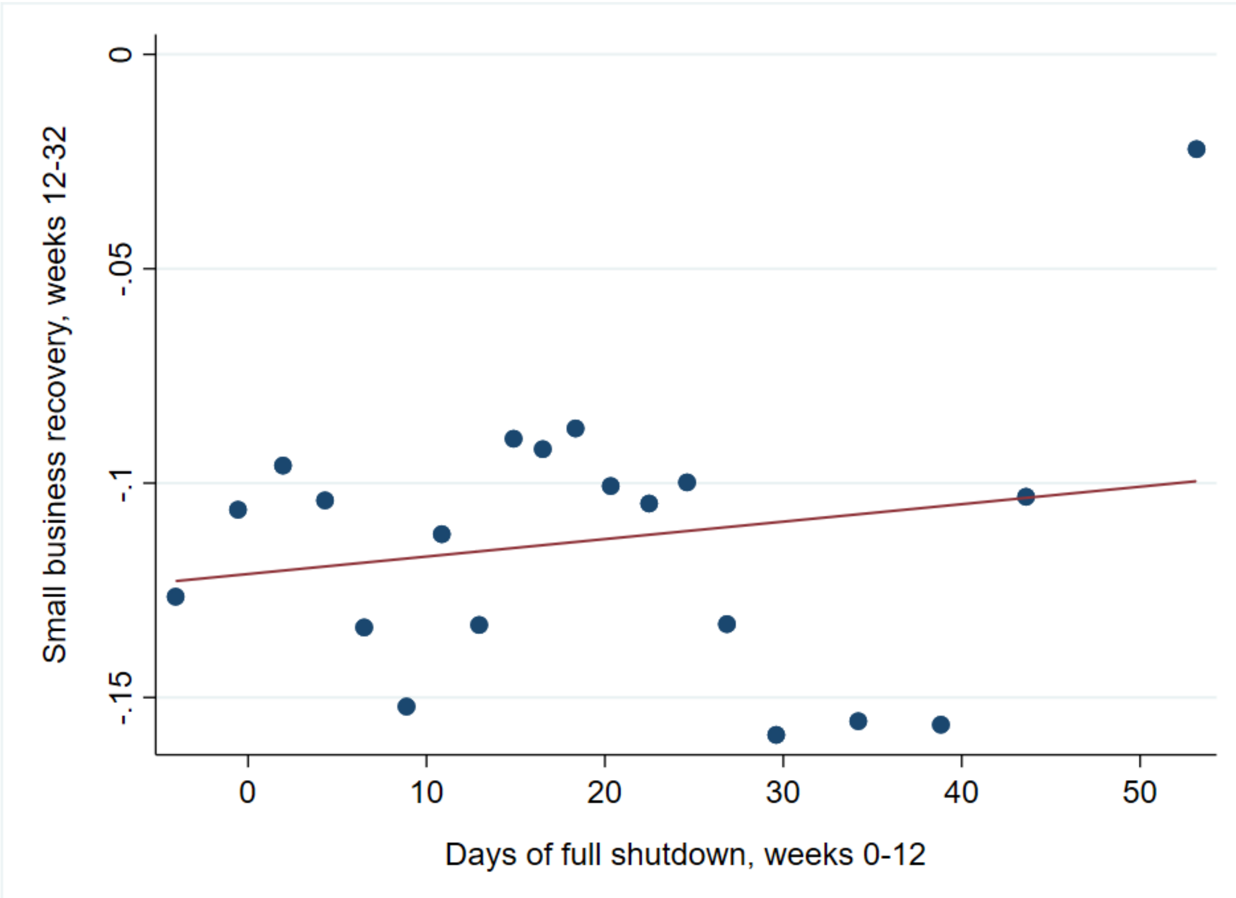
Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in supermarket visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6: COVID-19 Spread and % Subsequent Small Business Recovery

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
SB Baseline	-0.582***	0.245***	0.122*	0.093	0.033	-0.002	-0.024	-0.023
	(0.043)	(0.071)	(0.063)	(0.059)	(0.060)	(0.054)	(0.046)	(0.042)
SB Revenue: Week 4		-0.803***	-0.110**	-0.128***	-0.120***	-0.091**	-0.054	-0.024
		(0.056)	(0.048)	(0.045)	(0.043)	(0.039)	(0.034)	(0.030)
SB Revenue: Week 8			-0.409***	0.291***	0.201***	0.168***	0.090**	0.062*
			(0.053)	(0.073)	(0.066)	(0.057)	(0.042)	(0.037)
SB Revenue: Week 12				-0.568***	0.180**	0.033	0.027	0.012
				(0.068)	(0.074)	(0.063)	(0.051)	(0.047)
SB Revenue: Week 16					-0.540***	0.245***	0.051	-0.004
					(0.079)	(0.077)	(0.066)	(0.060)
SB Revenue: Week 20						-0.548***	0.224***	0.144***
						(0.049)	(0.050)	(0.048)
SB Revenue: Week 24							-0.469***	0.257***
							(0.050)	(0.052)
SB Revenue: Week 28								-0.536***
								(0.053)
log COVID Baseline	-2.164***	-3.363***	-1.298	-1.403	-1.588*	-1.486*	-1.286*	-0.716
	(0.574)	(1.217)	(0.993)	(1.000)	(0.937)	(0.833)	(0.771)	(0.716)
log COVID Week 4		1.197	0.579	0.013	0.627	0.792	0.461	-0.235
		(0.947)	(1.743)	(1.736)	(1.625)	(1.473)	(1.311)	(1.187)
log COVID Week 8			0.106	0.263	-0.560	-1.139	-0.550	0.321
			(1.382)	(2.299)	(2.160)	(1.957)	(1.612)	(1.552)
log COVID Week 12				-0.253	-0.116	0.552	-0.090	-0.775
				(1.984)	(2.223)	(1.972)	(1.648)	(1.604)
log COVID Week 16					0.332	0.246	1.598	2.484
					(1.184)	(2.101)	(1.832)	(1.665)
log COVID Week 20						-0.435	-1.180	-2.313
						(1.707)	(2.193)	(2.391)
log COVID Week 24							-0.511	0.156
							(1.593)	(2.915)
log COVID Week 28								-0.211
								(1.844)
Time Spent Partially Closed	0.002	0.004	0.015**	0.017**	0.017***	0.014**	0.013**	0.013***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)
Time Spent Fully Closed	-0.006	0.021	0.052**	0.052**	0.052**	0.043**	0.034*	0.031*
	(0.027)	(0.027)	(0.023)	(0.022)	(0.021)	(0.021)	(0.019)	(0.017)
Time w/ Mandatory Stay-at-home orders	0.006	0.004	0.013*	0.012*	0.007	-0.004	0.000	0.001
	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.181	0.389	0.290	0.251	0.192	0.224	0.188	0.235

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in small business revenue recovery between weeks 0 and *T*. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.1: Full Business Shutdowns and Future Small Business Recovery



Notes: Binned scatter of *Days Fully Closed* (Weeks 0-12) versus change in *Small Business Recovery*, weeks 12-32. Controls: log *COVID-19 deaths*, week 12; log *COVID-19 cases*, weeks 8 and 12. Unlike Figure 15, this graphic includes outlier counties in New York and Maryland (54 counties).

Table A.7: COVID-19 Spread and Subsequent % PCS Recovery

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
pcs Baseline	-4.37e-01***	5.63e-02	-1.89e-02	-1.27e-02	1.97e-02	2.52e-02	-2.72e-02	-4.83e-02
	(0.068)	(0.080)	(0.081)	(0.080)	(0.071)	(0.065)	(0.056)	(0.043)
pcs Revenue: Week 4		-5.37e-01***	2.03e-01***	2.10e-01***	1.34e-01***	1.05e-01**	7.05e-02*	6.43e-02**
		(0.046)	(0.066)	(0.062)	(0.048)	(0.043)	(0.038)	(0.030)
pcs Revenue: Week 8			-6.38e-01***	1.73e-01*	1.64e-01**	8.51e-02	4.66e-02	2.94e-02
			(0.070)	(0.097)	(0.064)	(0.064)	(0.044)	(0.032)
pcs Revenue: Week 12				-7.67e-01***	-3.29e-01***	-4.62e-02	-2.36e-02	4.75e-02
				(0.079)	(0.094)	(0.088)	(0.077)	(0.066)
pcs Revenue: Week 16					-3.36e-01***	-7.92e-03	7.23e-02	-3.15e-02
					(0.099)	(0.095)	(0.077)	(0.066)
pcs Revenue: Week 20						-4.56e-01***	5.40e-02	-1.03e-02
						(0.055)	(0.068)	(0.043)
pcs Revenue: Week 24							-4.32e-01***	1.49e-01***
							(0.081)	(0.057)
pcs Revenue: Week 28								-3.70e-01***
								(0.057)
log COVID Baseline	-1.44e-02***	-9.13e-03	-2.78e-03	-4.56e-03	-6.82e-03	-8.47e-03	-4.94e-03	-6.17e-04
	(0.006)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)
log COVID Week 4		-1.88e-03	-2.05e-03	-2.46e-03	-4.61e-03	-4.58e-03	-8.02e-03	-9.68e-03
		(0.007)	(0.013)	(0.013)	(0.011)	(0.009)	(0.008)	(0.007)
log COVID Week 8			-2.18e-03	-6.12e-03	1.24e-02	7.86e-03	1.09e-02	2.35e-04
			(0.010)	(0.020)	(0.017)	(0.016)	(0.016)	(0.015)
log COVID Week 12				4.05e-03	-3.96e-02**	-3.06e-02*	-2.54e-02	-5.12e-03
				(0.015)	(0.019)	(0.017)	(0.016)	(0.016)
log COVID Week 16					3.31e-02***	1.04e-02	8.60e-03	1.35e-02
					(0.011)	(0.021)	(0.018)	(0.017)
log COVID Week 20						2.32e-02	-7.13e-03	-1.47e-02
						(0.017)	(0.022)	(0.017)
log COVID Week 24							2.93e-02**	-3.71e-04
							(0.014)	(0.015)
log COVID Week 28								1.98e-02*
								(0.012)
Time Spent Partially Closed	-3.36e-04***	-2.10e-04***	-1.39e-04*	-1.19e-04*	-4.05e-05	-4.29e-05	2.03e-05	-2.75e-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Spent Fully Closed	-5.54e-04**	-4.47e-05	-1.73e-04	-1.86e-04	-4.31e-04**	-4.17e-04**	-4.61e-04**	-3.08e-04*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time w/ Mandatory Stay-at-home orders	-1.96e-04**	-2.58e-04***	-1.92e-04***	-1.82e-04***	-1.37e-04**	-3.01e-05	3.49e-05	3.02e-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3.40e-02	-1.06e-01**	-1.66e-01***	-1.45e-01***	-1.78e-01***	-1.83e-01***	-2.02e-01***	-1.61e-01***
	(0.043)	(0.042)	(0.044)	(0.045)	(0.039)	(0.037)	(0.035)	(0.029)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.100	0.257	0.344	0.337	0.336	0.390	0.308	0.268

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in PCS visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rate in weeks 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.8: COVID-19 Spread and Subsequent Restaurant Recovery

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
Restaurant Visitors Baseline	0.085	0.200**	0.206**	0.214**	0.180**	0.084	-0.031	0.050
	(0.061)	(0.098)	(0.090)	(0.091)	(0.085)	(0.073)	(0.059)	(0.042)
Restaurant Visitors: Week 4		-0.368***	0.613***	0.525***	0.432***	0.467***	0.371***	0.202***
		(0.055)	(0.057)	(0.070)	(0.073)	(0.066)	(0.056)	(0.049)
Restaurant Visitors: Week 8			-0.986***	0.192***	0.479***	0.424***	0.139**	0.151***
			(0.037)	(0.073)	(0.083)	(0.085)	(0.067)	(0.058)
Restaurant Visitors: Week 12				-1.117***	-0.751***	-0.547***	-0.444***	-0.333***
				(0.048)	(0.099)	(0.127)	(0.091)	(0.062)
Restaurant Visitors: Week 16					-0.558***	0.066	0.173	0.112*
					(0.077)	(0.177)	(0.132)	(0.064)
Restaurant Visitors: Week 20						-0.711***	-0.132	0.046
						(0.109)	(0.105)	(0.046)
Restaurant Visitors: Week 24							-0.156**	-0.094
							(0.079)	(0.081)
Restaurant Visitors: Week 28								-0.160**
								(0.076)
log COVID Baseline	-1.042***	-0.677	-0.391	-0.270	-0.163	-0.149	-0.519	-0.056
	(0.395)	(0.558)	(0.591)	(0.586)	(0.581)	(0.556)	(0.399)	(0.320)
log COVID Week 4		0.225	-1.339	-1.382	-1.009	-0.999	0.019	0.187
		(0.432)	(1.073)	(1.059)	(1.032)	(0.964)	(0.747)	(0.663)
log COVID Week 8			1.418	1.897	2.466	2.121	0.523	-0.016
			(0.896)	(1.669)	(1.688)	(1.691)	(1.021)	(0.893)
log COVID Week 12				-0.404	-1.375	-0.322	-0.683	-0.117
				(1.275)	(1.735)	(1.715)	(1.031)	(0.918)
log COVID Week 16					-0.044	-3.857*	-1.838	-1.005
					(0.991)	(2.171)	(1.501)	(1.096)
log COVID Week 20						3.744**	-0.032	0.003
						(1.806)	(1.494)	(1.198)
log COVID Week 24							3.688***	1.235
							(1.137)	(1.420)
log COVID Week 28								0.883
								(1.025)
Time Spent Partially Closed	-0.020***	-0.001	-0.000	-0.002	-0.004	-0.001	0.009***	0.000
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.003)
Time Spent Fully Closed	-0.139***	-0.080***	-0.080***	-0.067***	-0.055***	-0.060***	-0.046***	-0.018**
	(0.017)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.011)	(0.009)
Time w/ Mandatory Stay-at-home orders	0.026***	-0.004	-0.004	-0.002	0.001	0.002	0.011**	0.008***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.003)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.128	0.210	0.779	0.892	0.913	0.875	0.679	0.453

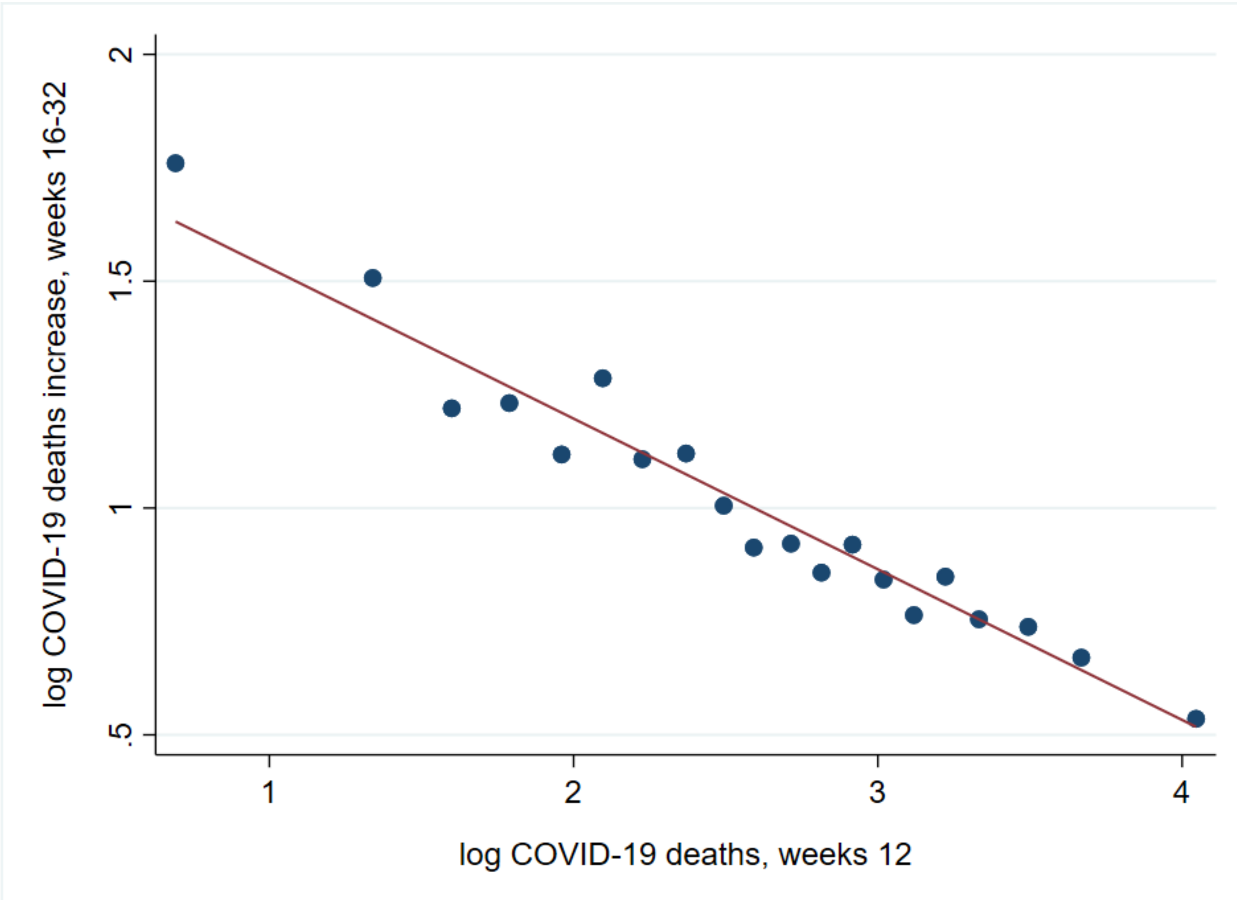
Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in restaurant visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.9: COVID-19 Spread and % Subsequent Supermarket Recovery

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
Supermarket Visitors Baseline	0.752***	1.313***	1.689***	1.896***	1.473***	1.469***	1.175***	0.333***
	(0.044)	(0.210)	(0.210)	(0.213)	(0.205)	(0.198)	(0.165)	(0.092)
Supermarket Visitors: Week 4		-0.786***	-0.277*	-0.239	-0.116	-0.259**	-0.247**	0.033
		(0.100)	(0.143)	(0.147)	(0.128)	(0.117)	(0.097)	(0.057)
Supermarket Visitors: Week 8			-0.666***	-0.164	0.175	-0.077	-0.082	-0.043
			(0.080)	(0.134)	(0.133)	(0.120)	(0.102)	(0.047)
Supermarket Visitors: Week 12				-0.637***	-0.971***	-0.107	-0.031	-0.149**
				(0.073)	(0.153)	(0.155)	(0.147)	(0.065)
Supermarket Visitors: Week 16					0.119	0.010	0.035	0.157**
					(0.111)	(0.171)	(0.164)	(0.068)
Supermarket Visitors: Week 20						-0.343***	0.090	0.004
						(0.091)	(0.100)	(0.047)
Supermarket Visitors: Week 24							-0.378***	-0.045
							(0.064)	(0.039)
Supermarket Visitors: Week 28								-0.149***
								(0.025)
log COVID Baseline	-0.109	0.536	0.353	0.699	0.340	0.045	0.247	0.191
	(0.501)	(0.910)	(0.940)	(0.913)	(0.791)	(0.748)	(0.730)	(0.345)
log COVID Week 4		-0.595	0.383	-0.111	0.081	1.039	0.366	-0.294
		(0.693)	(1.779)	(1.719)	(1.425)	(1.395)	(1.378)	(0.657)
log COVID Week 8			-0.918	1.173	1.893	-0.359	-0.701	-0.045
			(1.458)	(2.454)	(2.397)	(2.131)	(2.000)	(0.875)
log COVID Week 12				-1.706	-3.592	-2.321	-0.870	-0.481
				(1.883)	(2.405)	(2.041)	(1.964)	(0.803)
log COVID Week 16					1.282	0.969	1.351	0.261
					(1.054)	(1.852)	(1.687)	(0.890)
log COVID Week 20						0.994	-1.677	0.002
						(1.441)	(1.950)	(1.099)
log COVID Week 24							1.926	0.124
							(1.420)	(1.336)
log COVID Week 28								1.080
								(0.952)
Time Spent Partially Closed	0.023***	0.024***	0.025***	0.020***	0.008	0.007	0.007	-0.006**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.003)
Time Spent Fully Closed	0.011	0.017	0.010	-0.005	0.006	0.001	0.008	-0.010
	(0.019)	(0.019)	(0.018)	(0.018)	(0.016)	(0.015)	(0.014)	(0.008)
Time w/ Mandatory Stay-at-home orders	-0.017**	-0.018**	-0.022***	-0.019***	-0.023***	-0.024***	-0.027***	0.000
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.288	0.171	0.314	0.504	0.571	0.388	0.248	0.230

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in supermarket visitor recovery between weeks 0 and T. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in week 0. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.2: Past and Future COVID-19 Deaths



Notes: Binned scatter of the change in log *COVID-19 deaths*, weeks 16-32, versus its baseline at week 12. Controls: log *COVID-19 cases*, weeks 12 and 16.

Table A.10: Shutdowns and In-period COVID-19 Spread

	4 Weeks	8 Weeks	12 Weeks	16 Weeks	20 Weeks	24 Weeks	28 Weeks
Small Business Baseline	0.001	0.003*	0.003*	0.005***	0.006***	0.007***	0.008***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
log COVID Baseline	-0.205***	-0.286***	-0.366***	-0.419***	-0.442***	-0.459***	-0.488***
	(0.019)	(0.023)	(0.030)	(0.034)	(0.035)	(0.035)	(0.037)
Days Partially Closed	-0.003	0.000	0.001	0.002	0.001	0.000	-0.001***
	(0.009)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	-
Days Fully Closed	-0.001	-0.003***	-0.006***	-0.009***	-0.010***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Days Stay-at-home	0.001	0.000	-0.002	0.001	0.001	0.001*	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	-
# Observations	887	887	887	887	887	887	887
R-Squared	0.159	0.172	0.233	0.312	0.398	0.463	0.565

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in log COVID-19 deaths in the first affected T weeks - i.e., between weeks 4 and $T+4$, due to the lead-lag structure of COVID-19 spread. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks 0 and 4. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.11: % Small Business Recovery and Subsequent COVID-19 Spread

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
SB Baseline	0.005***	-0.004	-0.004	-0.001	0.001	0.001	0.002	0.000
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
SB Revenue: Week 4		0.010***	0.010***	0.006***	0.002	0.002	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
SB Revenue: Week 8			0.000	0.001	-0.000	0.000	0.001	-0.000
			(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
SB Revenue: Week 12				0.000	0.000	0.001	-0.002	-0.001
				(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
SB Revenue: Week 16					0.002	0.002	0.001	0.001
					(0.002)	(0.002)	(0.002)	(0.001)
SB Revenue: Week 20						-0.002	-0.001	-0.002**
						(0.001)	(0.001)	(0.001)
SB Revenue: Week 24							0.000	0.000
							(0.001)	(0.001)
SB Revenue: Week 28								0.001
								(0.001)
log COVID Baseline	-0.625***	0.052	0.029	0.024	-0.005	0.008	0.019	-0.005
	(0.025)	(0.044)	(0.038)	(0.032)	(0.029)	(0.024)	(0.020)	(0.014)
log COVID Week 4		-0.693***	0.028	-0.021	-0.001	-0.012	-0.036	-0.002
		(0.045)	(0.070)	(0.058)	(0.051)	(0.046)	(0.040)	(0.026)
log COVID Week 8			-0.689***	0.081	0.023	0.071	0.082*	0.018
			(0.065)	(0.093)	(0.073)	(0.059)	(0.049)	(0.034)
log COVID Week 12				-0.659***	0.024	-0.016	-0.030	-0.000
				(0.082)	(0.075)	(0.054)	(0.044)	(0.030)
log COVID Week 16					-0.514***	-0.117	-0.043	-0.014
					(0.054)	(0.083)	(0.066)	(0.040)
log COVID Week 20						-0.325***	-0.085	0.030
						(0.088)	(0.094)	(0.060)
log COVID Week 24							-0.152*	-0.040
							(0.085)	(0.084)
log COVID Week 28								-0.138
								(0.092)
Time Spent Partially Closed	-0.001***	-0.001**	-0.001**	-0.001***	-0.001***	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Spent Fully Closed	-0.003**	-0.003**	-0.002**	-0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Time w/ Mandatory Stay-at-home orders	0.001**	0.001***	0.001***	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.489	0.700	0.720	0.731	0.653	0.591	0.522	0.531

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in log COVID-19 deaths in the first affected T weeks - i.e., between weeks 4 and $T+4$, due to the lead-lag structure of COVID-19 spread. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks T and $T-4$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.12: % PCS Visits and Subsequent COVID-19 Spread

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
PCS Baseline	0.011***	0.000	-0.001	0.002	0.004	0.003	0.004**	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
PCS Visitors: Week 4		0.012***	0.010***	0.004*	-0.000	-0.001	-0.003**	-0.001
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
% PCS Visitors: Week 8			0.004**	0.006***	0.005***	0.005***	0.003*	0.000
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
% PCS Visitors: Week 12				-0.001	-0.000	0.001	0.002	0.002
				(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
PCS Visitors: Week 16					-0.000	-0.003	-0.002	-0.001
					(0.002)	(0.002)	(0.002)	(0.002)
PCS Visitors: Week 20						0.002	0.001	0.001
						(0.001)	(0.002)	(0.001)
PCS Visitors: Week 24							-0.000	-0.001
							(0.002)	(0.001)
PCS Visitors: Week 28								0.001
								(0.001)
log COVID Baseline	-0.628***	0.041	0.019	0.020	-0.002	0.011	0.022	-0.003
	(0.023)	(0.040)	(0.034)	(0.030)	(0.027)	(0.023)	(0.019)	(0.014)
log COVID Week 4		-0.688***	0.023	-0.022	-0.005	-0.016	-0.040	-0.001
		(0.044)	(0.069)	(0.055)	(0.049)	(0.045)	(0.039)	(0.026)
log COVID Week 8			-0.684***	0.048	0.014	0.056	0.065	0.007
			(0.064)	(0.090)	(0.072)	(0.057)	(0.047)	(0.033)
log COVID Week 12				-0.627***	0.051	0.011	-0.018	0.009
				(0.080)	(0.075)	(0.054)	(0.043)	(0.029)
log COVID Week 16					-0.532***	-0.116	-0.033	-0.008
					(0.054)	(0.084)	(0.066)	(0.041)
log COVID Week 20						-0.342***	-0.100	0.023
						(0.090)	(0.093)	(0.061)
log COVID Week 24							-0.152*	-0.034
							(0.085)	(0.082)
log COVID Week 28								-0.151*
								(0.091)
Time Spent Partially Closed	-0.001***	-0.000	-0.000	-0.001***	-0.001***	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Spent Fully Closed	-0.002*	-0.003**	-0.002**	-0.001	0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Time w/ Mandatory Stay-at-home orders	0.001*	0.001***	0.001***	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.495	0.708	0.731	0.739	0.663	0.601	0.531	0.533

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in log COVID-19 deaths in the first affected T weeks - i.e., between weeks 4 and $T+4$, due to the lead-lag structure of COVID-19 spread. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks T and $T-4$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.13: % Restaurant Visits and Subsequent COVID-19 Spread

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
Restaurant Baseline	0.020***	-0.000	-0.005	0.003	0.005	0.002	0.003	0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)
Restaurant Visitors: Week 4		0.014***	0.023***	0.008**	0.002	0.002	-0.001	0.002
		(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Restaurant Visitors: Week 8			-0.006***	0.003	0.000	-0.001	-0.004	-0.004*
			(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Restaurant Visitors: Week 12				-0.003	-0.002	0.006	0.008**	0.006**
				(0.002)	(0.004)	(0.004)	(0.004)	(0.003)
Restaurant Visitors: Week 16					0.001	-0.007**	-0.005	-0.004*
					(0.002)	(0.003)	(0.003)	(0.002)
Restaurant Visitors: Week 20						0.004*	-0.001	0.001
						(0.002)	(0.002)	(0.002)
Restaurant Visitors: Week 24							0.005***	0.004
							(0.002)	(0.003)
Restaurant Visitors: Week 28								-0.003
								(0.002)
log COVID Baseline	-0.612***	0.057	0.008	0.020	-0.007	0.006	0.016	-0.008
	(0.023)	(0.041)	(0.035)	(0.032)	(0.029)	(0.024)	(0.020)	(0.013)
log COVID Week 4		-0.682***	0.018	-0.021	-0.007	-0.016	-0.033	-0.000
		(0.044)	(0.069)	(0.058)	(0.051)	(0.047)	(0.041)	(0.026)
log COVID Week 8			-0.654***	0.075	0.036	0.059	0.056	0.013
			(0.064)	(0.091)	(0.073)	(0.060)	(0.051)	(0.034)
log COVID Week 12				-0.648***	0.036	0.016	-0.018	0.002
				(0.081)	(0.077)	(0.056)	(0.047)	(0.032)
log COVID Week 16					-0.533***	-0.142*	-0.041	-0.021
					(0.056)	(0.083)	(0.067)	(0.040)
log COVID Week 20						-0.318***	-0.068	0.039
						(0.090)	(0.095)	(0.061)
log COVID Week 24							-0.165*	-0.048
							(0.087)	(0.076)
log COVID Week 28								-0.136
								(0.084)
Time Spent Partially Closed	-0.001***	-0.000	-0.000	-0.001***	-0.001***	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Spent Fully Closed	-0.002*	-0.003**	-0.002**	-0.001	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Time w/ Mandatory Stay-at-home orders	0.001**	0.001*	0.001*	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.506	0.719	0.741	0.735	0.650	0.589	0.525	0.536

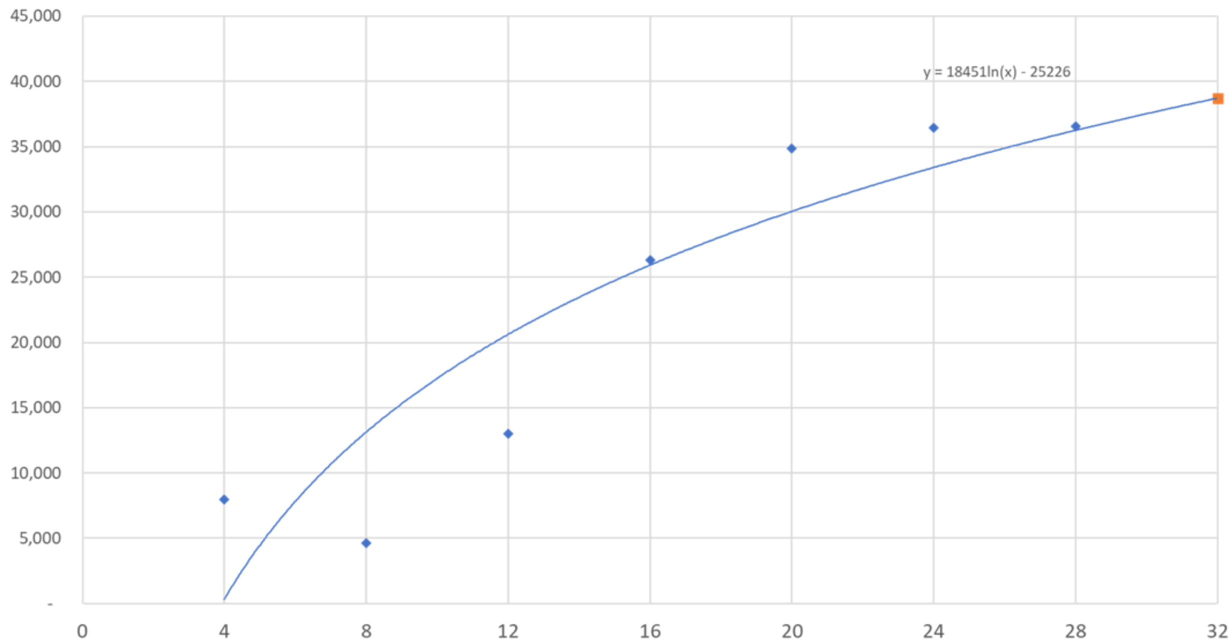
Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (*T Weeks*) describe the increase in log COVID-19 deaths in the first affected T weeks - i.e., between weeks 4 and $T+4$, due to the lead-lag structure of COVID-19 spread. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks T and $T-4$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.14: % Supermarket Visits and Subsequent COVID-19 Spread

Time frame	Weeks 0-32	Weeks 4-32	Weeks 8-32	Weeks 12-32	Weeks 16-32	Weeks 20-32	Weeks 24-32	Weeks 28-32
Supermarket Baseline	0.015***	-0.007	-0.019**	-0.012	-0.003	-0.003	-0.004	-0.002
	(0.002)	(0.008)	(0.009)	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)
Supermarket Visitors: Week 4		0.012***	0.026***	0.016***	0.010*	0.005	0.005	0.003*
		(0.004)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)
Supermarket Visitors: Week 8			-0.010***	-0.001	-0.002	-0.002	0.000	-0.002
			(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
Supermarket Visitors: Week 12				-0.004*	-0.003	0.002	0.001	0.004
				(0.002)	(0.004)	(0.005)	(0.004)	(0.002)
Supermarket Visitors: Week 16					0.002	-0.003	-0.003	-0.005*
					(0.003)	(0.004)	(0.004)	(0.003)
Supermarket Visitors: Week 20						0.003	0.003	0.005**
						(0.002)	(0.003)	(0.002)
Supermarket Visitors: Week 24							-0.001	-0.001
							(0.002)	(0.002)
Supermarket Visitors: Week 28								-0.001
								(0.001)
log COVID Baseline	-0.599***	0.058	0.038	0.024	-0.000	0.007	0.015	-0.006
	(0.024)	(0.041)	(0.034)	(0.030)	(0.027)	(0.023)	(0.019)	(0.013)
log COVID Week 4		-0.713***	0.035	0.005	0.013	0.002	-0.024	0.012
		(0.043)	(0.067)	(0.056)	(0.050)	(0.046)	(0.040)	(0.027)
log COVID Week 8			-0.713***	0.066	0.028	0.057	0.066	0.004
			(0.063)	(0.089)	(0.071)	(0.058)	(0.048)	(0.035)
log COVID Week 12				-0.680***	0.006	-0.009	-0.025	0.003
				(0.082)	(0.076)	(0.055)	(0.045)	(0.031)
log COVID Week 16					-0.523***	-0.110	-0.027	-0.008
					(0.054)	(0.085)	(0.068)	(0.041)
log COVID Week 20						-0.347***	-0.086	0.032
						(0.091)	(0.093)	(0.060)
log COVID Week 24							-0.174**	-0.043
							(0.085)	(0.078)
log COVID Week 28								-0.152*
								(0.091)
Time Spent Partially Closed	-0.001***	-0.000	-0.000	-0.001***	-0.001***	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Spent Fully Closed	-0.001	-0.003**	-0.002**	-0.001	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Time w/ Mandatory Stay-at-home orders	0.001***	0.001***	0.002***	0.001**	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# Observations	887	887	887	887	887	887	887	887
R-Squared	0.513	0.711	0.731	0.741	0.663	0.595	0.525	0.537

Notes: OLS regressions, heteroskedastically-robust standard errors reported in parentheses. *Days Fully Closed* is the number of days a county was under full shutdown within the 32-week period; *Days Partially Closed* is the number of days a county was under partial shutdown; *Days Stay-at-home* is the number of days a county had mandatory stay-at-home orders in place. Column headings (T *Weeks*) describe the increase in log COVID-19 deaths in the first affected T weeks - i.e., between weeks 4 and $T+4$, due to the lead-lag structure of COVID-19 spread. *Baseline* refers to week 0 values of independent variables. All analysis controls for COVID-19 case rates in weeks T and $T-4$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.3: Logistic Approximation of Lives Saved



Notes: Given predicted lives saved for weeks 0-28 from Table 6, lives saved at week 32 were calculated via logarithmic fit. The fit model was found to be $Lives\_Saved = 18451\log(Weeks) - 25226$.