Resilience in U.S. Firms: Evidence from the Covid-19 Pandemic

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Abstract

In this paper, I exploit the Covid-19 pandemic and associated government restrictions as a natural experiment in order to study the resilience of businesses in the United States. I use a border-county identification strategy with data on government restrictions, employment and open small businesses, in order to assess the resilience of small businesses in the United States. In my main results, I find negative impacts of stay-at-home orders on the number of open small merchants. In particular, shutdowns of businesses accelerated 8 weeks after imposition of a stay-at-home order, suggesting that many businesses were only resilient enough to handle adverse conditions for 8 weeks. On average, a county with a stay-at-home order experienced an additional 1.51 percentage points loss in the number of open small businesses, relative to January 2020, 8 weeks later compared to a neighboring county that did not have a stay-at-home order. Firms were quicker to resort to layoffs. On average a county with an active stay at home order in a month experienced an additional 1.19 percentage point loss in employment, relative to January 2020, the following month compared to a neighbor that did not have a stay-at-home order the previous month. I also find that stay-at-home orders caused significant reductions in movement in both directions between neighboring counties.

1 Introduction

Much attention has been paid to the resilience, or lack thereof, of households and governments to unexpected shocks. A survey by bankrate.com finds that just 39% of Americans can afford to

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pay an unexpected \$1000 bill [18]. This is despite the fact that such expenses are not uncommon, with researchers at the Federal Reserve finding that 17% of Americans incurred unexpected medical expenses between \$1000 and \$2000. There is a rich literature examining the resilience of consumers and governments and factors impacting it. Papers such as Klapper and Lusardi (2020) and Hussain et. al (2019) have studied ways to improve consumer financial resilience. Resilience of local governments has likewise been studied in papers such as Ahrens and Ferry (2020) which examines the resilience of English local governments in the wake of Covid-19.

Less attention has been given to the resilience of businesses. Like households, businesses are also subjected to unexpected shocks on both the supply and demand side. This paper aims to contribute to the growing literature on the resilience of businesses to unexpected shocks. Other papers have been written about the resilience of financial markets and resilience of firms by studying cash balances. This paper more directly studies impacts on firm operations, such as remaining open and not resorting to layoffs, as a measure of resilience. How resilient are businesses in the United States to unexpected shocks? How long can firms withstand the expenses associated with unexpected shocks (such as a forced closure) before they are forced to start laying off employees? How long can they remain open at all? In this paper, I exploit variation in state responses to the Covid-19 pandemic to help answer these questions and more.

The Covid-19 pandemic wreaked havoc throughout the world in the early 2020s. At the time of writing, the disease had claimed just under 1 million deaths in the United States alone, and over 6 million deaths worldwide. The damage was not limited to health outcomes. Unemployment in the United States skyrocketed in the initial wave of the pandemic, rising from 3.5% in February to 14.7% in April. Without knowledge of the most effective treatment methods or vaccines, governments throughout the world largely resorted to non-pharmaceutical interventions (NPIs) in order to combat the virus. Some of the most restrictive NPIs used by many states in the U.S. were “Stay-at-Home Orders,” which closed all non-essential businesses from operating and banned many types of gatherings.

The economic hardships faced by many individuals and businesses in this time made many of these NPIs quite controversial. Some argued that public health orders must take into account their impact on the economy and that the “cure” should not be made worse than the disease. Others attributed the economic impact as instead directly stemming from the disease itself and that the economy could not be saved without focusing on reducing the outbreak first. In this paper, I quantify the impacts of the government enacted NPIs versus the impacts of the underlying pandemic itself. To answer this question, I employ a border county strategy in order to look at differences in outcomes caused by differences in government response. My identifying assumption here is that neighboring counties tend to be relatively similar. Specifically, that unobserved factors that may be relevant will also be similar between the two counties.

Another topic that I discuss is in this paper is that of county-to-county economic spillovers. One possible issue with the strategy described above is that there may be spillovers in economic activity between neighboring counties. This may bias results and exaggerate impacts of stay-at-home orders. In order to first mitigate the impact of spillovers, I focus my analysis on neighboring counties that lie in different commute zones as in Autor and Dorn (2013). I then use detailed data on movement between counties during 2020 to show evidence that my assumption about reduced spillovers when counties lie in different commute zones is reasonable. Additionally, I then estimate directly the magnitude (if any) and direction of spillover effects between counties and discuss the implications.

There are three main strands of literature which this paper contributes to. First, this paper contributes to the literature on the resilience of businesses. Piccolo and Pinto (2021) highlight the importance of businesses financial resilience and connect it to other issues such as labor negotiations. Papers such as Farrel and Wheat (2018) have examined the financial resilience of firms in the wake of disasters by using cash balances as a measure of resilience. This paper contributes to the business resilience literature by using the pandemic as a natural experiment to study a specific kind of resilience: the ability of firms to avoid layoffs and shutting down during the challenging conditions created by the pandemic.

Second, the paper also adds to the diverse literature on the economic impacts of the Covid-

19 pandemic. Papers such as Chetty et. al (2021), Crotes and Forsythe (2020), and Deryugina, Shruchkov and Stears (2021) all examine impacts of the pandemic on various kinds of workers. This paper contributes to this literature through studying the county-level employment effects of the pandemic. On the firm side, papers such as Bartik et. al (2019), Bloom, Fletcher and Yeh (2021), Bloom et. al (2021) all examine the effects of the pandemic on firms. This paper contributes to this literature through studying the impacts of the pandemic on firm closures.

A related literature looks at the impact of government restrictions on both economic and health outcomes. Particularly relevant to this paper is Spiegel and Tookes (2021), which examines the impact of various Covid-19 government restrictions on deaths at a county level and contributes a novel data set which has detailed information on county level restrictions throughout the United States. Papers such as Amuedo-Dorantes (2020), Alexander and Karger (2021) and Caselli et. al (2020) examine other impacts of the stay-at-home orders and other NPIs. I contribute to this literature by conducting an event study on the impacts of a stay-at-home order on both employment and business closures as well as a more general difference-in-difference specification.

Third, this paper contributes to the literature on spillovers. Spillovers have been studied in many contexts, such as the impact of gun control legislation as in Bronars and Lott Jr. (1998). Economic spillovers are studied in Bernstein et. al. (2019), which looks at the negative economic impacts of bankruptcies onto neighboring establishments. Economic spillovers created by government actions are examined in papers like Chalermpong (2005) which examines negative spillovers created by a the construction of a highway. Holtz et. al. (2020) and Elenev et. al. (2021) in particular also examine economic spillovers caused by stay-at-home orders. I contribute to the literature examining this by further examining the role of commute zones in spillovers as well as studying directional effects on the ratio of travel in both directions.

The rest of this paper is organized as follows. Section 2 goes through the data used in this project in detail. Section 3 examines the variation in state responses to the pandemic and explains the identification strategy used. Section 4 introduces the first set of specifications and results for the first set research questions on resilience and impacts of the pandemic and stay-at-home orders. Section 5 examines the second set of research questions on economic spillovers. Section 6 concludes.

2 Data

I use several different sources of data in this project which I outline below.

2.1 Main Outcome Variables

My primary research questions look at two different outcomes as proxies for resilience: employment and the number of open small businesses. Specifically, I studied the resilience of firms insofar as avoiding layoffs, and avoiding a shutdown.

Data on the number of businesses is from Womply and accessed via the Opportunity Insights data contributed by Chetty et. al. (2021). The Womply measure of open small businesses is weekly and collected at the county level. It is reported in each county as the percentage change in the number of open small businesses compared to January 2020.

Employment data comes from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages which contains monthly data on employment at the county level. In order to interpret results in a similar manner to the merchants data, I convert the raw employment data to a percentage change as well using January 2020 as a baseline.

Both of these dependent variables are used to study the primary question of the effect of the pandemic and government restrictions on the resilience of firms in the United States. Two different outcomes are used in order to examine resilience in two different settings. Employment data is used to study the effect of the pandemic and government policies on resilience by interpreting resilience as the ability of a firm to withstand conditions without laying off workers. The number of open small businesses is used to study resilience as the ability of firms to remain operational entirely. These variables are chosen as both layoffs and firm failures are major negative outcomes for firms.

2.2 Government Restrictions Data

For this project, I use two measures of government restrictions. The first is the stringency index constructed by researchers at Oxford's Government Response Tracker. The second is data collected on the start and end dates of various NPIs from Spiegel and Tookes (2021).

The stringency index is an ordinal measure of the intensity of a state's collection of NPIs. This includes measures such as stay at home orders, school closures, restaurant capacity constraints, as well as others. It is generated daily at the country level as well as at the state level in the United States throughout the pandemic. For this project, I primarily use the stringency index as motivation for my identification strategy. Table 1 below displays some summary statistics about the stringency index during the time period of interest.

[Table 1]

I also use data on start and end dates of various county level measures from Spiegel and Tookes (2021). This data contains information on when a diverse set of NPIs were enacted and terminated throughout all the counties in the United States. In some cases, start and/or end dates are listed at the state-level instead of county when directives are enacted by the state. For this project, I focus on the usage of stay-at-home orders. Stay-at-home orders were the most stringent level of restrictions enacted by state and local governments in the United States. Unlike other countries, American governments largely did not prevent people from leaving their homes entirely. People were instead instructed to not leave their homes for non-essential reasons. The stay-at-home orders were paired with mandates forcing the closure of non-essential business, such as gyms and movie theaters. Stay-at-home orders were chosen to be studied for this project as they were the most extreme measure taken in the early stages of the pandemic and often thought to have been the one to cause the most economic hardship.

2.3 Neighbor Counties

In order to match counties with their neighbors, I use the County Adjacency File which contains a list of neighboring counties for each county in the United States. I then match counties based on this data to create a list of all county-pairs that share a border. I manually removed some county-pairs that were considered to be neighboring by the county adjacency file but only shared a maritime border in actuality. This included some county-pairs consisting of Eastern Wisconsin and Western Michigan counties, which were labeled as neighbors but are only connected by Lake Michigan. In order to avoid double counting county-pairs, I toss all county-pairs where the main county's FIPS code is larger than its neighbors. For example, in the case of Chemung County, New York (FIPS 36015) and Bradford County, Pennsylvania (42015), the pair (36015, 42015) is kept while (42015, 36015) is tossed. Note that counties may appear in more than one county-pair. Bradford County, PA appears in pairs with both Chemung County, NY and Tioga County, NY.

2.4 Other Controls

Daily data on COVID-19 death rates is taken from the Opportunity Insights project that is also mentioned above. Deaths are used instead of cases as they are likely to have been less under-counted than cases, especially in the early stages of the pandemic where tests were limited to severe cases. The deaths are reported as 7-day averages in order to account for day-of-week trends that are present due to how most health agencies report data.

In order to control for the fact that the pandemic affected different industries in different ways, I use data from the County Business Pattern to control for the percentage of business in each county that are in various NAICS super-sectors. Some industries, such as food services and entertainment are thought to have been especially hindered by the pandemic. As such, counties that have an especially high concentration of these industries may suffer additional losses of businesses and employment independent of their government policies.

Political controls are taken from the Massachusetts Institute of Technology Election Lab as a proxy for the tendency for people in counties to obey restrictions and follow voluntary social-distancing measures. Gollwitzer et. al (2020) find that counties that had more Hillary Clinton voters exhibited more social distancing. Specifically, I use the average two-party vote share received by the Democratic candidate in the 2012 and 2016 presidential elections. Controlling for politics will also help account for differences in propensity for governments to enact restrictions when facing waves of the virus. While governments consider many factors when deciding their policy, one of the most significant concerns for them is their electoral concerns. Support for stringent restrictions became a highly politicized issue, and conservative and conservative-leaning people became far more likely to be opposed to restrictions as the pandemic unfolded. As such, heavily Republican governments were less likely to impose restrictions than their Democratic counterparts.

Access to financing was crucial for businesses during the pandemic. Many small businesses were only able to access the emergency loans by filing applications with their banks. As a proxy for access to financing, I compute the number of bank branches (per capita) using data from the Consumer Financial Protection Bureau. Small businesses in particular are more likely to file applications at a local bank branch.

Lastly, in order to account for the possibility that spillovers drive my main results, I use data from Autor and Dorn (2013) to map counties to commute zones. I then run my main specifications on a set of border counties that do not lie in the same commute zone. I assume here that neighboring counties in different commute zones will have less movement between them, and thus, less spillovers. I discuss this issue in greater detail and show evidence for this assumption in section 5.

2.5 Movement Data

To address my last research question regarding county to county economic spillovers, I use data from Safegraph that contains information on movement in counties throughout the United States. The data has establishment level information on all the people who visit the establishment on a weekly basis. In particular, it contains information on the home census block group of each visitor. I filter out any establishments that had under 5 visits a week, as Safegraph adds noise to establishments with less than 5 visitors to protect privacy. I then transform the establishment level data to convert data on the home census block of visitors into their home county.

I aggregate the establishment data by county. This results in a data set that has the number of visitors from each other county in the United States. I then match neighboring counties to create county-pairs. I then extract the specific number of visitors that come from the neighboring county into the "main" county and vice-versa. To account for population differences, I convert these measure to per-capita measures for the main analysis. I use the number of visitors from a neighbor county as a proxy of "economic spillovers" coming from that county.

3 Identification Strategy

3.1 Variation in Government Actions

My specification relies on the existence of variation in government policies both across counties and over time. As very few restrictions were enacted federally in the first year of the pandemic, much of the decision making was left to state and local authorities. As such, due to differences in policy makers' preferences and politics, in many cases neighboring states imposed different levels of restrictions. To see some of the variation across states, consider Figure 1 below which shows the variation in state measures near the beginning of the first wave of the pandemic.

[Figure 1]

As seen in Figure 1, the intensity of government restrictions is quite varied across states. The first wave of the pandemic in the United States was largely more severe in the midwest and northeast, especially in the New York City area. As seen in the map, many of the darker states are indeed located in the northeast and midwestern regions of the country. Next, consider the situation 2 months later in the map below.

[Figure 2]

As seen in Figure 2, the map is overall much lighter than in Figure 1 as the pandemic was overall much less severe in the country on June 1st compared to April 1st. Most parts of the country were experiencing fewer cases and deaths. However, this was not uniformly true. Some southern states were experiencing higher case counts at this time, labeled by some as the "Summer Surge." As seen in the figures, Georgia is one of the few states which is darker on June 1st than it was on April 1st. Overall, it is seen in the two maps that there is considerable variation in stringency both across states and across time, which will allow studying the economic impacts.

Figure 3 below shows the variation across counties in government restrictions. As the stringency index is a state-level indicator, county level analysis instead uses the data from Spiegel and Tookes (2021) on the durations of stay-at-home orders.

[Figure 3]

As seen in the figure above, there is some county-to-county variation within states. For instance, very northern California counties largely had fewer days under a stay at home order than counties in the rest of the state. Metropolitan Oklahoma City counties enacted a stay-at-home order whereas the rest of the state did not.

However, most of the variation between counties is found across state borders. While many counties did enact county-level orders, in many cases they were similarly timed to state-level orders. Some other counties enacted restrictions at the county level which were later rescinded as part of a statewide policy. For this reason, I conduct my main analysis on neighbor county-pairs that lie in different states.

3.2 Border County Strategy

In order to study the pandemic and government restrictions on resilience, it is necessary to first address endogeneity concerns. Stay-at-home orders are enacted by politicians in conjunction with health departments in response to the pandemic. Unobserved factors may contribute to whether a government enacts an order or not and also impact businesses.

In order to mitigate these concerns, I use a border-county identification strategy. My identifying assumption is that neighboring counties tend to be relatively similar. In particular, the pandemic does not respect borders, as seen in Figure 4 below.

[Figure 4]

As seen in the above figure, Covid-19 deaths do not seem to be distributed with regard to state borders. Rather, deaths are geographically concentrated without respect for borders. A county next to another county with a high Covid-19 death rate is likely to have a high Covid-19 death rate itself, regardless of if its neighbor is in the same state or a different state. This is not the case with Covid-19 restrictions however, as seen in the next figure.

[Figure 5]

Unlike the case with deaths, there are differences across state border in stringency, as many of the orders are created by state governments. Taking the two maps in conjunction shows that the sample of neighboring counties in different states is a sample of counties that had experienced similar levels of the pandemic, but did not necessarily have identical responses to it. This is seen more precisely in Figure 6.

[Figure 6]

As seen in the graph, there is not a strong relationship between the difference in average new death rate in neighboring counties and the difference in average stringency index. The line is nearly flat, confirming that the set of county-pairs has significant variation in the two variables.

By running my empirical specifications using the difference between neighboring counties, I also lessen the impact of unobserved variables. This is because, on average, the difference in unobservables will also be relatively small in neighboring counties, thus reducing the effect they have on the results.

In order to further account for possible endogeneity concerns surrounding stay-at-home orders, I redo my main regressions using a subsample of county pairs where neither county is in the top 5 in their state when ranked by population, similar to Spiegel and Tookes (2021). This is because while stay-at-home orders were not random, they were usually determined at the state level and not controlled by individual counties. States likely considered the needs of their largest counties or population centers when deciding their policies. Smaller counties thus had to implement these orders whether or not their local conditions warranted them. As such, the imposition of stay-at-home orders on these counties can be more plausibly seen as exogenous.

Possible County-to-County Spillovers

Before getting to the methodology, I will first discuss the possibility of county-to-county spillovers. Economic activity is not limited to intra-county consumption. While people will likely mostly visit stores in the same county as their home, people also shop elsewhere in the country, especially in neighboring counties. If a county closes its businesses, there will likely be some people who will take their shopping to a neighboring county, rather than staying at home.

Consider two counties: A and B. Suppose that county A imposes a stay-at-home order and closes all nonessential businesses. In this project I study the impact of this on businesses in county A by looking at the change in difference in employment and the number of open businesses in the two counties. If people in county A increase shopping in county B as a response to the stay-at-home order, then economic indicators in county B will be boosted by these spillovers. This will increase the difference between the two counties and exaggerate the influence of the stay-at-home order on county A alone.

To minimize the impact of spillovers on the main results, I conduct the main analysis on a subset of county-pairs that lie in two different commute zones as defined in Autorn and Dorn (2013). My assumption here is that inter-county economic is reduced in when counties are not in the same commute zone, as they are likely to be less linked by roads and public transport. In section 5, I provide evidence for this assumption and study spillovers in greater detail.

After reducing the sample of counties to only those that neighbor a county in a different state that is not in the same commute zone, I end up with a reduced sample of 923 counties which I use to create pairs. Table 2 presents summary statistics.

[Table 2]

As seen in the table, the reduced sample of border counties with a different commute zone neighbor, is fairly representative of the 2989 counties in the whole sample. Importantly, the average stringency the government restrictions and Covid-19 levels are nearly identical in these counties to the full sample.

4 Empirical Specification and Main Results

My main specifications address the questions about the resilience of businesses in avoiding shutdown and layoffs. I use two different types of specifications to answer these questions. The first type of specification uses an event study that focuses only on neighboring county-pairs where one county implemented one stay-at-home order and its neighbor never issued one. This specification focuses on maximizing the identification by using a tight definition for treated vs. control counties, at the expense of sample size. The second type of specification is a more general difference-in-difference specification, which looks at a larger set of border counties and makes use of neighbor county-pairs where both may have implemented stay-at-home orders, but at different times or for different lengths.

4.1 Event Study Specification - Resilience to Shutdown

I first study business resilience by studying how Covid-19 and its associated restrictions affected the ability of business to stay open. For this specification I utilize the Womply variable which represents the change in number of open small businesses in a county each week relative to January 2020. As my observations are neighboring county-pairs, my dependent variable is the difference between the two counties in the percentage change in the number of open merchants from January 2020. More precisely, suppose the tuple (i, i_n) represents a county-pair where i is the "main" county and i_n is its neighbor. Define t to be the time index, which is weeks for this specification. The dependent variable is then defined as

$$\Delta Merchants_{i,i_n,t} \equiv \frac{\#Merchants_{i,t}}{\#Merchants_{i,Jan2020}} - \frac{\#Merchants_{i_n,t}}{\#Merchants_{i_n,Jan2020}}$$

This means that coefficients from the regression defined below measure the percentage point additional change in the number of open merchants in the "main" county caused by an increase in the associated variable.

In all of the main results, I focus my attention to pairs neighboring counties that lie in different states and are also members of different commute zones. For this specification, I focus only on county-pairs where one county enacted a stay-at-home order only once, and its neighbor never issued a stay-at-home order. This is done to clearly define the treatment as having a stay-at-home order issued, and not have confounding issues associated with further stay-at-home orders in some of the treated counties. This reduces the sample to 62 counties forming 43 county-pairs. In order to avoid double counting pairs as well as keep the "event" consistent for each observation, I keep only the counties where the "main" county is the one which implemented the stay-at-home order. As such, for each county-pair, the "event" being studied is the moment the main county in the pair implements its stay at home order. Figure 7 shows a map of this sample.

[Figure 7]

I weigh the regression specification in order to not have results driven by smaller counties. For the merchants specification, I weigh county-pairs by their combined 2019 populations. The main weighted least squares event study specification for results on open small businesses is thus given by:

$$\Delta Merchants_{i,i_n,t} = \beta_{pre} Event_{pre,i,i_n,t} + \sum_{j=-5, j\neq -1}^{23} \left(\beta_j Event_{j,i,i_n,t}\right) + \beta_{post} Event_{post,i,i_n,t} + \gamma \mathbf{X}_{i,i_n,t} + \nu_{i,i_n} + \mu_t + \varepsilon_{i,i_n,t}$$

The variables $Event_{j,i,i_n,t}$ where $-5 \leq j \leq 23$ and $j \neq -1$ are indicators for the time period of the observation being j weeks after (or $-j$ weeks behind, when j is negative) the time period where county i implemented its stay-at-home order. For example, if county i implemented its stay-at-home order week 3, then $Event_{0,i,i_n,3} = 1$ and $Event_{-2,i,i_n,1} = 1$ as well. As is common in event studies, I drop the period $j = -1$ and treat it as the base period for comparison for each county-pair observation. $Event_{pre}$ and $Event_{post}$ are indicators for being more than 5 weeks before, or more than 23 weeks after, the week the stay-at-home order is implemented in county i.

X is a vector of controls as described in the data section earlier in the paper. One control worth highlighting is $\Delta NDR_{(i,i_n),t}$, which is defined as the difference in 7-day average daily death rates. ν_{i,i_n} and μ_t are county-pair and time fixed effects, respectively.

4.2 Event Study Specification - Resilience to Layoffs

I next study business resilience in terms of a businesses' ability to withstand economic conditions without resorting to layoffs. In this specification, I use monthly data on county level employment. In order to have a similar interpretation to the open merchants specification, I transform the employment data as a percentage change in employment from a baseline. Since the employment data is monthly, in order to have enough lags to verify the lack of a pre-trend, I include the last 3 months of 2019 data in the event study. I then use January 2020 as a baseline for employment. As such, the dependent variable for this specification is similarly defined as

$$\Delta Employment_{i,i_n,t} \equiv \frac{\#Employed_{i,t}}{\#Employed_{i,Jan2020}} - \frac{\#Employed_{i_n,t}}{\#Employed_{i_n,Jan2020}}$$

I weigh observations by combined January 2020 employment. The full weighted least squares specification is given by

$$\begin{aligned}\Delta Employment_{i,i_n,t} = \beta_{pre}Event_{pre,i,i_n,t} + \sum_{j=-4,j\neq-1}^{5}\left(\beta_j Event_{j,i,i_n,t}\right) + \beta_{post}Event_{post,i,i_n,t} \\ + \gamma\mathbf{X}_{i,i_n,t} + \nu_{i,i_n} + \mu_t + \varepsilon_{i,i_n,t}\end{aligned}$$

The variables $Event_{j,i,i_n,t}$ where $-4 \leq j \leq 5$ and $j \neq -1$ are similarly defined to the previous specification with the main difference being t denoting months rather than weeks. The period 1 month before the Event is dropped similar to the last specification as well. $Event_{pre}$ and $Event_{post}$ are indicators for being more than 4 months before, or more than 5 months after, the month the stay-at-home order is implemented in county i.

As in the previous specification, my sample consists of county-pairs where one county issued 1 stay-at-home order and its neighbor issued none. As the employment data is available for a larger set of counties than the Womply open merchants data, my resulting sample is a slightly larger 259 counties and 255 county-pairs. Figure 8 showcases this sample.

[Figure 8]

4.3 Event Study Results - Resilience to Shutdown

[Figure 9]

Figure 9 shows the results of the event study regression using the number of open merchants as the dependent variable. Full results that report all coefficients are available in tabular format in the appendix, table A1. As standard in event studies, it is important to first examine if there are any pretrends. All coefficients before week -1 are insignificant, and we can see there is not much evidence of a pretrend.

Some impacts of the stay-at-order are felt immediately, as there is a significant and negative coefficient beginning the week the stay-at-home order is issued. Recall that the dependent variable is the difference in percentage change of number of small businesses from January 2020 between the county issuing the stay-at-home order and its neighbor. As such, a negative effect is consistent with the idea that stay-at-home orders caused shutdowns of businesses. The presence of some immediate effects are unsurprising as the data includes temporary closures that are to comply with the active stay-at-home order. Longer term effects are more likely driven by economically-driven closures. Indeed, the coefficient remains significant and becomes increasingly negative as the weeks post the event go on. Weeks 8 through 10 appear to have the most significant negative effects, as the coefficient falls the fastest in this range and becomes increasingly significant. 10 weeks after the stay-at-home order was first enacted, the enacting county on average has additional 40 percentage point loss from January 2020 in the number of open small businesses compared to its neighbor that did not enact a stay-at-home order compared to the week before the stay-at-home order took effect. After week 10, the effect seems to wane, as the point estimate remains remarkably flat after this point. Significance wanes after week 10, and the impact of the stay-at-home order is no longer statistically significant 24 weeks after the implementation.

[Figure 10]

Results are quite similar when counties that are among the top 5 most populous in their state are decreased. I find a similar persistent negative effect of the impact of stay-at-home orders on the number of open small businesses in county. Results in this specification are also at a more negative point estimate and remain significant through the end of the horizon.

4.4 Event Study Results - Resilience to Layoffs

[Figure 11]

Figure 11 shows the results of the event study regression using difference in change in employment as the dependent variable. Full regression results are available in appendix table A2. As in the merchants results, there is no evidence of a pretrend before the implementation of the stay-at-home order as all coefficients for months -5 to -2 are not statistically significant.

Unlike the merchants result, the effects of the stay-at-home order are not immediately seen in the results on employment. This is not surprising as the employment data is not affected by temporary closures in the same way the data on open small businesses is. Both the coefficients on the month that the stay-at-home order is enacted and the first month after are negative but insignificant. The strongest effects from the stay-at-home order are seen in month 2 3 after the event occurs, with the coefficients on months 2 negative and significant at the 90% level. On average, 3 months after the order is first enacted, counties that enacted a stay-at-home order see an additional 4.5 percentage point loss in employment since January 2020 compared to its neighbor with no stay-at-home order versus the month before the stay-at-home order went into effect. Effects seem to diminish after the 3 month mark. The point estimates remain negative but start increasing after month 3, and are no longer significant.

[Figure 12]

Figure 12 shows the results of a similar specification as in figure 11 but with the top 5 most populous counties in each state dropped. While statistical significance of the terms after the event is no longer present, we still see the same qualitative story as in figure 11. The evidence for a lack of pretrend is even stronger than in Figure 11 and, while statistical significance is not seen, there is a clear negative trend after the event which is similar to the previous results.

4.5 General Difference-in-Difference Specification - Resilience to Shutdown

I now introduce the specification used for my second set of main results. While the goal of the event study specifications was to define a very precise group of treated and non-treated counties, the goal of these difference-in-difference specifications is to take advantage of a larger group of counties and more types of variation in stay-at-home orders.

I weigh the regression specification in order to not have results driven by smaller counties. For the merchants specification, I weigh county-pairs by their combined 2019 populations. The main weighted least squares specification for results on open small businesses is thus given by:

$$\Delta Merchants_{i,i_n,t} = \sum_{k=-2}^{5} \beta_k \left(\Delta SAH_{i,i_n,t-2k}\right) + \gamma \mathbf{X}_{(i,i_n),t} + \nu_{i,i_n} + \mu_t + \varepsilon_{i,i_n,t}$$

The variable $\Delta SAH_{i,i_n,t}$ is the difference in amount of time under a stay-at-home order between county i and i_n during week t. For example, if county i has a stay-at-home order during the entire week t and county i_n has no stay-at-home order at that time, then $\Delta SAH_{i,i_n,t} = 1$. ΔSAH may be non-integer values if there are weeks partially covered by stay-at-home orders.

As the impacts of the Covid-19 pandemic and its associated government restrictions are not likely to be contemporaneous, I include them in my regression as lags. Specifically, I include lags up to 10 weeks prior to the current date at 2 week intervals. As the data on stay-at-home orders and Covid-19 deaths are highly co-linear from week to week, I drop the odd numbered lags in order to keep the variation between lag terms. I also include two forward lags ($t+2$ and $t+4$) in order to verify that forward terms are not significant. Another reason for including several lags is to absorb the effect of stay-at-home orders causing temporary closures that are merely reflecting compliance with the stay-at-home order. As my dependent variable is simply the number of open small businesses, I am not able to directly distinguish shutdowns induced by economic conditions versus closures to comply with the government action. The nearer-term lags then importantly act to absorb the temporary short-term impact of the stay-at-home orders so that the longer-term lags are more likely to fully have significance driven by permanent, economic closures.

$\mathbf{X}$ is a vector of controls as described in the data section earlier in the paper. ν_{i,i_n} and μ_t represent county-pair and week fixed effects, respectively.

After excluding counties where some data is missing, the final sample consists of 437 counties forming 361 unique county-pairs. Figure 13 below showcases the counties that make up this sample.

[Figure 13]

4.6 General Difference-in-Difference Specification - Resilience to Layoffs

I use lags of stay-at-home order and Covid-19 deaths similar to the previous specification. Since the employment data is monthly, I use 1 and 2 month lags of each. I use a weighted least squares specification using the total employment in the two counties in each pair as the weight for each observation. The specification is given by

$$\Delta Employment_{i,i_n,t} = \sum_{k=-2}^{2} \beta_k \left(\Delta SAH_{i,i_n,t-k}\right) + \gamma \mathbf{X}_{(i,i_n),t} + \nu_{i,i_n} + \mu_t + \varepsilon_{i,i_n,t}$$

The time index t now months in this specification. The independent variables are defined similarly to the previous specification but now at the month level.

4.7 Difference-in-Difference Results - Resilience to Shutdown

[Table 3]

It is important to first discuss the different interpretation of the results in this specification. Whereas the event-study shows the cumulative effect on the dependent variable over time, the coefficients in this regression show the independent effects of differences in explanatory variables at individual time periods. Additionally, as mentioned in the section discussing the specification, there will be a confounding effect caused by temporary shutdowns that are merely to comply with the mandate. This is apparent in this result on the coefficient on the 0-week lag of ΔSAH. While it is highly significant and negative, it is likely heavily driven by temporary closures caused by the stay-at-home order, rather than actual business failures. As such, I focus my attention to longer run effects, specifically the coefficient on the 8-week lag of ΔSAH. The coefficient on this term is significant and negative, similar to findings in the event study specification. On average, a county that has an active stay-at-home order during a full week with a neighbor that does not impose one will have an additional 1.51 percentage points loss in the number of open small businesses relative to January 2020 compared to its neighbor after 8 weeks. Results are similar when reducing the sample to only counties that are not ranked in the top 5 of their state by population. I similarly find a highly significant and negative coefficient of -0.0113 on the 8-week lag of ΔSAH. The nearer term lags of ΔSAH remain significant as well in column 2, but at reduced significance.

Additionally, the contemporaneous coefficient of ΔNDR is significant and negative in column (1), though not column (2). The significance however suggests that even after accounting for impacts of the stay-at-home orders, I cannot fully reject the counterfactual that the pandemic has its own direct negative effects on the economy. This gives some credence to the idea that simply avoiding these non-pharmaceutical interventions would not be sufficient to avoid economic damages to small businesses. Indeed, if the interventions are significantly reducing deaths, undoing them may cause additional harm, rather than improve economic conditions.

4.8 Difference-in-Difference Results - Resilience to Layoffs

[Table 4]

Table 4 contains the results of the regression using the difference in difference specification and difference in change in employment as the dependent variable. As mentioned in the specification section, this specification varies slightly from the previous, with the time unit being months rather than weeks.

I find a significant and negative impact of the stay-at-home orders on employment, similar to the result using the event study specification. On average, a county implementing a stay-at-home order for the duration of a month with a neighbor that does not have any stay-at-home order that month will see an additional 1.19 percentage point loss in employment relative to January 2020 in the following month. It is worth noting here that the significance in the employment specification is on the one month lag term of ΔSAH, whereas it was on the 8 week lag term in the merchants specification. This suggests that on average, businesses' resilience to layoffs was closer to 1 month. This makes sense intuitively, as layoffs are a less severe outcome than going out of business. Additionally, the coefficient remains negative with a more negative value of -0.0163 in the specification without the most populous counties in each state.

I also find a significant and negative coefficient on the 2 month lag term of ΔNDR, showing that there are separate effects from the pandemic itself similar to the results on the number of open merchants. Unlike those, this negative effect on employment is present in both columns of table 4, further giving credibility to the hypothesis that the pandemic has its own direct effects.

5 Discussion on Spillovers

As discussed briefly earlier in the paper, one concern with the main results is that they may be driven by spillovers. Increased travel to neighboring cities caused by stay-at-home orders may cause overestimating of the negative effects of stay-at-home orders. In order to mitigate this issue, the main results discussed so far were all done on county-pairs in which the two counties were part of different commute zones. The assumption is that counties are less connected to neighboring counties if they are not in the same commute zone. This would imply that there is less travel between the two counties, which means less people shopping in neighboring counties and potentially less spillovers associated with stay-at-home orders. In this section, I provide further evidence for this claim and also study county-to-county spillovers due to the pandemic in more detail.

5.1 Movement Between Counties

In order to examine how spillovers may be impacting results, I first look at movement data between counties. I use Safegraph provided data that contains information on visitors to establishments in each county and information on the home census block groups of visitors. I first examine trends in movement and movement between counties by looking at data on weekly visits to establishments in 2020.

[Figure 14]

As seen in figure 14, the number of visitors to establishments sharply dropped around 10 weeks into 2020, coinciding with the first wave of the Covid-19 pandemic. This decrease was seen in both intra- and inter-county visitors to establishments. The black dotted line which represents the percentage of visitors that come from outside the county drops slightly at this time as well, but recovers by week 20 to pre-pandemic levels. It is important to note that weeks 10 through 20 of the year included the heaviest use of stay-at-home orders throughout the United States during the pandemic. Though future waves had higher measured case counts, governments often avoided re-enacting strong NPIs due to their unpopularity. Despite the stringent measures in place during the early wave of the pandemic, figure 14 clearly shows that there was no uptick in the fraction of visits that are inter-county to establishments during this time.

Next, I examine the differences in travel between counties in the same commute zone versus those in different commute zones. In this step I now look at travel between pairs of counties rather than more general inter-county movement. As before, I focus on county-pairs that straddle a state border. Figure 15 shows the distribution of the percentage of visitors in establishments in a county that come from its neighbor county across all the county-pairs in the sample.

[Figure 15]

As seen in the figure, the percentage of visitors that come from the neighboring county in a county-pair varies considerably depending on whether or not the two counties share a commute zone. Across all county-pairs, the average percentage of visitors that come from the neighbor is roughly 2.1%. For county-pairs lying in the same commute zone, this number is around 4.0%, whereas for different commute zone pairs, it is 1.4%. The boxplots show that the distribution as a whole for same commute zone pairs is quite different, as the median county-pair here has a higher neighbor visitor percentage than 75th percentile county-pair in the different commute zone set.From this it is clear that my assumption that counties will have fewer spillovers from neighbors in different commute zones seems reasonable. Next, I show specifically that the spillovers caused by the stay-at-home orders in particular are diminished.

5.2 Estimating Spillovers Specification

I use a similar specification as in difference-in-difference specifications in the main results. First I look at the impacts of stay-at-home orders on movement between counties. Unlike the previous specifications, there are two distinct directions of movement per county-pair that could be impacted by policies and the pandemic: movement from the main county to its neighbor, and movement in the opposite direction. I define two dependent variables for the first set of regressions. As before, county i represents the "main" county and i_n its neighbor in the county-pair. The first variable is visitors traveling from the neighbor county to the main county.

$$Visitors_{i_n \to i,t} \equiv \frac{\#Visitors_{i_n \to i,t}}{Population_{i_n}}$$

Similarly, I define per-capita visitors traveling in the opposite direction as

$$Visitors_{i \to i_n,t} \equiv \frac{\#Visitors_{i \to i_n,t}}{Population_i}$$

Part of the purpose in studying spillover effects is to examine the differences between pairs that share a commute zone versus pairs that do not. As such, unlike previous specifications, I do not remove county-pairs that share a commute zone in this specification. As such, my sample of counties for this specification is the largest yet with 1071 counties and 1160 unique county-pairs. The sample is illustrated in figure 16.

[Figure 16]

It is important to consider that stay-at-home orders may not affect movement between counties in strictly linear ways. Residents of a county may not adjust their travel in the same magnitude when moving from a county with no active policy to one with an active stay-at-home order as they would when moving in the opposite direction. To allow for this, I no longer require the effects of ΔSAH to be linear in nature. In order to estimate spillovers, I use the following specification

$$\begin{aligned} Visitors_{i_n \to i,t} = {} & \beta_1 Rel.Closed_{i,i_n,t} + \beta_2 Rel.Open_{i,i_n,t} \\ & + \beta_3 \left(Rel.Closed_{i,i_n,t} \times DCZ_{i,i_n}\right) + \beta_4 \left(Rel.Open_{i,i_n,t} \times DCZ_{i,i_n}\right) \\ & + \gamma \mathbf{X}_{(i,i_n),t} + \nu_{i,i_n} + \mu_t + \varepsilon_{i,i_n,t} \end{aligned}$$

where

$$RelClosed \equiv \mathbf{1}\left(\Delta SAH_{i,i_n,t} > 0\right) \text{ and } RelOpen \equiv \mathbf{1}\left(\Delta SAH_{i,i_n,t} < 0\right)$$

and

$$DCZ_{i,i_n} \equiv \mathbf{1}\left(i \text{ and } i_n \text{have different commute zones}\right)$$

In plain language, *RelClosed* is an indicator variable that is equal to 1 when the main county in a pair, i, is under a stay-at-home order for a larger portion of week t than its neighbor i_n. Hence, i is *relatively closed* compared to i_n. Likewise, if i_n is more stringent in this time period, ΔSAH will be negative and $RelOpen$ will be equal to 1 since i is *relatively open* compared to i_n. DCZ is an indicator for if counties i and i_n are in the same commute zone. The specification using travel in the opposite direction, i.e. visitors from the main county to its neighbor, is identical on the right hand side.

In addition to directly estimating spillover effects caused by stay-at-home orders, the goal of this section of the paper is also to evaluate the hypothesis used in the main economic results. That is, establishing if spillover effects caused by stay-at-home orders are in fact reduced in county pairs where the two counties lie in separate commute zones. The coefficients of interest here are thereby those on the interactions between $RelClosed$ and DCZ and between $RelOpen$ and DCZ, which are β_3 and β_4 above. Where β_1 and β_2 measure direct spillovers, β_3 and β_4 measure the marginal impact of counties in the pair lying in two separate commute zones on these spillovers. As such, if the hypothesis that these spillovers are mitigated is correct, then β_3 should have the opposite sign of β_1 and β_4 should have the opposite sign of β_2.

5.3 Results on Spillovers

[Table 5]

There are now two separate coefficients for the effects of the stay-at-home order. Somewhat surprisingly, I find large and negative and significant coefficients on both $Rel.Closed$ and $Rel.Open$ in the regression. I find that, on average, a county with an active stay-at-home order will receive 626 fewer visitors per capita from its neighbor which does not have one in a week. Additionally, a county without an active stay-at-home order will also receive an average of 408 fewer visitors per capita from its neighbor which is under a stay-at-home order. On average, the number of visitors from a neighbor county to the main county during a week in this sample is about 1600 visitors per capita, suggesting that this represents between a one fourth and one third reduction of travel in both directions. While the negative coefficient on $Rel.Closed$ is unsurprising and consistent with spillovers from the closed county onto the open one, the coefficient on $Rel.Open$ is not consistent with this theory of spillovers. The negative coefficient on $Rel.Open$ implies that there are negative spillovers from the relatively more closed county onto the less open county as well. If Covid-19 restrictions caused people to shop in neighboring open counties instead, we would expect the coefficient on $Rel.Open$ to be positive. Instead, I find spillovers are negative in both directions. Results are similar in column 2 which is the same specification but without the 5 most populous counties in each state.

Next, I examine the assumption that these spillovers are mitigated if the counties lie in different commute zones. I find positive and significant coefficients on both interaction terms between *DCZ* and the two indicators for the difference in stay-at-home order. As the spillovers in both directions are negative, positive coefficients on the interaction terms means that spillovers caused by the stay-at-home orders are indeed mitigated by the two counties in a pair not being in the same commute zone.

[Table 6]

In table 6, I show results for the same specification as the results in table 5, but changing the direction of movement in the dependent variable. Here the results paint a similar story. The non-linear specification again finds that there are actually negative spillovers in both directions of travel: from the closed county to the open as well as the open county to the closed. I also find highly significant positive coefficients on the interactions between *DCZ* and the stay-at-home order variables in this specification, providing further evidence that different commute zones mitigate spillovers between counties.

The results from tables 5 and 6 clearly show that spillovers from stay-at-home orders in the United States are negative in both directions. Residents in both counties reduce their movement to their neighboring county regardless of if their county is the relatively closed one or the relatively open one. This runs against the idea that consumers in the county under a stay-at-home order would then increase their shopping in a neighboring county. The possibility remains, however, that even though travel is reduced in both directions, it reduces asymmetrically and that stay-at-home orders may increase the *relative* amount of travelers in one direction. To examine this, I introduce a new dependent variable, the ratio of travel in both directions, which is given by

$$VisitorRatio_{i,i_n,t} \equiv \frac{Visitors_{i_n \to i,t}}{Visitors_{i \to i_n,t}}$$

I then rerun the specifications in tables 5 and 6 using this dependent variable. Results from this regression are found in table 7.

[Table 7]

I find no significant coefficients on either $Rel.Closed$ or $Rel.Open$. This provides evidence that the "main" county being less stringent than its neighbor does not affect the composition of travel between the two counties. The previous results show that gross spillovers are negative in both directions as people decrease inter-county travel. The results in table 7 now go further to find no evidence of a "net" spillover between the two counties. The lack of significance on the coefficients on $Rel.Closed$ and $Rel.Open$ show that there is no evidence that travel in one direction dropped more sharply than the other. As there is no evidence of a directional spillover, it makes sense that there is also minimal evidence of the importance of commute zones in this specification. While there is a mildly significant coefficient on $Rel.Closed \times DCZ$ in column 1, this is only significant at the 10% level and is not present in column 2.

6 Conclusion

The Covid-19 pandemic provided a stark reminder of the importance of business resilience. Though many people are already aware of the importance of personal resilience, such as in the way of emergency funds for things like rent, the concept is just as important to businesses. Many firms throughout the country found themselves unready for a prolonged shutdown brought on in March 2020.

In this paper I exploit the Covid-19 pandemic and use a border county identification strategy to study the resilience of firms in the United States. I find that, on average, most layoffs occurred about one month after the implementation of stay-at-home orders and that most business failures occurred 8-10 weeks after. Intuitively it makes sense that firms resort to laying off employees first before they decide to shut down as layoffs are a significantly less severe outcome. This analysis also answers questions about the degree to which stay-at-home orders, versus the pandemic itself, impacted firms and workers throughout the United States. I find that both the pandemic and stay-at-home orders individually contribute to the losses in employment and businesses seen in the country throughout 2020. Ultimately, my paper agrees with the viewpoint that simply "reopening the economy" by revoking stay-at-home orders may not be sufficient to undo the economic damages as some stem from the pandemic itself, regardless of economic restrictions. It is important for policy makers to consider results here alongside other economics literature and public health literature when making considerations on how to implement non-pharmaceutical interventions.

I also show that spillovers in movement are negative in both directions of travel when a county implements a stay-at-home order. Furthermore, there is some evidence that, while spillovers are negative in both directions, there is a directional effect and the composition of travel between two counties is affected. However, spillovers are reduced between counties which do not share a commute zone. While many neighboring governments stressed the importance of coordination to reduce spillovers, it seems that such concerns were slightly overblown as many people reduced inter-county travel when either their own county or their neighbor is under a stay-at-home order.

There are many policy implications from these results, however it should be noted that the complete analysis indicating how the government should proceed in its implementation of stay-at-home orders and other NPIs will also require analysis on impacts on death rates such as in Spiegel and Tookes (2021). While I find that there is a significant harm to businesses caused by stay-at-home orders, careful consideration should be paid to their health benefits as well. Indeed, the results in the regressions in this paper alone imply that if health benefits to stay-at-home orders are large, then they may not have much of a negative economic impact. What is clear from the results here is that economic aid to businesses should be increased and targeted more, such as to places where there are more stringent policies or higher concentrations of restaurants and food services.

As discussed in Hubbard and Strain (2020), more cohesive revenue replacement programs may be appropriate to greater assist firms where non-payroll expenses are more significant. There is some indication in the results in this paper that the effects on business survival were larger than employment losses in magnitude, suggesting that greater assistance in non-payroll expenses could have been beneficial.

I chose to focus this paper on the study of stay-at-home orders as they were the most stringent and controversial type of non-pharmaceutical intervention seen in the United States. It would be interesting if future work in the literature examined how results vary when studying the economic impacts of other types of orders. Mask mandates in particular are thought to be less economically intrusive by many and still effective in reducing the severity of an outbreak. I also study the impact of access to financing via the number of bank branches in a county variable. It would also be interesting if future work examined other measures of access to financing, such as the amount of economic impact emergency loans approved in a county. It would also be valuable to look at other measures of business health as measures of business resilience, such as cash holdings.

References

[1] Ahrens, Thomas, and Laurence Ferry. "Financial resilience of English local government in the aftermath of COVID-19." *Journal of Public Budgeting, Accountin & Financial Management* (2020).

[2] Alexander, Diane, and Ezra Karger. "Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior." *The Review of Economics and Statistics* (2020): 1-25.

[3] Bartik, Alexander W., Marianne Bertrand, Zoe Cullen, Edward L. Glaeser, Michael Luca, and Christopher Stanton. "The impact of COVID-19 on small business outcomes and expectations." *Proceedings of the national academy of sciences* 117, no. 30 (2020): 17656-17666.

[4] Bernstein, Shai, Emanuele Colonnelli, Xavier Giroud, and Benjamin Iverson. “Bankruptcy spillovers.” *Journal of Financial Economics* 133, no. 3 (2019): 608-633.

[5] Bloom, Nicholas, Robert S. Fletcher, and Ethan Yeh. “The impact of COVID-19 on US firms.” No. w28314. *National Bureau of Economic Research* (2021).

[6] Caselli, Francesca, Francesco Grigoli, Weicheng Lian, and Damiano Sandri. “The great lockdown: dissecting the economic effects.” *World Economic Outlook* (2020): 65-84.

[7] Chalermpong, Saksith. “Empirical study of economic spillovers of interstate 105 in Los Angeles county.” *Transportation research record* 1864, no. 1 (2004): 94-102.

[8] Chetty, Raj, John N. Friedman, Nathaniel Hendren, and Michael Stepner. “The economic impacts of COVID-19: Evidence from a new public database built using private sector data.” No. w27431. *National Bureau of Economic Research* (2020).

[9] Cortes, Guido Matias, and Eliza Forsythe. “Heterogeneous Labor Market Impacts of the COVID-19 Pandemic.” *ILR Review* (2020): 00197939221076856.

[10] Danisman, Gamze Ozturk, Ender Demir, and Adam Zaremba. “Financial resilience to the COVID-19 pandemic: The role of banking market structure.” *Applied Economics* 53, no. 39 (2021): 4481-4504.

[11] Elenev, Vadim, Luis E. Quintero, Alessandro Rebucci, and Emilia Simeonova. “Direct and spillover effects from staggered adoption of health policies: Evidence from covid-19 stay-at-home orders.” No. w29088. *National Bureau of Economic Research, 2021.*

[12] Farrell, Diana, and Chris Wheat. “Bend, Don’t Break: Small Business Financial Resilience after Hurricanes Harvey and Irma.” *JPMorgan Chase Institute* (2018).

[13] Gollwitzer, Anton, Cameron Martel, William J. Brady, Philip Pärnamets, Isaac G. Freedman, Eric D. Knowles, and Jay J. Van Bavel. “Partisan differences in physical distancing are

linked to health outcomes during the COVID-19 pandemic." *Nature human behaviour* 4, no. 11 (2020): 1186-1197.

[14] Holtz, David, Michael Zhao, Seth G. Benzell, Cathy Y. Cao, Mohammad Amin Rahimian, Jeremy Yang, Jennifer Allen et al. "Interdependence and the cost of uncoordinated responses to COVID-19." *Proceedings of the National Academy of Sciences* 117, no. 33 (2020): 19837-19843.

[15] Hubbard, R. Glenn, and Michael R. Strain. "Has the Paycheck Protection Program Succeeded?". No. w28032. *National Bureau of Economic Research*, 2020.

[16] Belayeth Hussain, A. H. M., Noraida Endut, Sumonkanti Das, Mohammed Thanvir Ahmed Chowdhury, Nadia Haque, Sumena Sultana, and Khandaker Jafor Ahmed. "Does financial inclusion increase financial resilience? Evidence from Bangladesh." *Development in Practice* 29, no. 6 (2019): 798-807.

[17] Klapper, Leora, and Annamaria Lusardi. "Financial literacy and financial resilience: Evidence from around the world." *Financial Management* 49, no. 3 (2020): 589-614.

[18] Ostrowski, Jeff. "Fewer than 4 in 10 Americans Could Pay a Surprise $1,000 Expense from Savings, Survey Finds." Bankrate, January 11, 2021. https://www.bankrate.com/banking/savings/financial-security-january-2021/.

[19] Piccolo, Alessio, and Roberto Pinto. "Financial Resilience in Labor Negotiations." *Kelley School of Business Research Paper* 2021-22 (2021).

[20] Safegraph Data (to add citation)

[21] Spiegel, Matthew, and Heather Tookes. "Business restrictions and COVID-19 Fatalities." *The Review of Financial Studies* 34, no. 11 (2021): 5266-5308.

Figures and Tables

Table 1: Stringency Index summary statistics from March 2020 to December 2020. The left column shows variation of the stringency index over time across states. The right column shows variation across states in the average stringency index in this time period

	Stringency Index	Stringency Index State Average
N	17085	51
Mean	45.099	45.099
Std. Dev.	21.917	11.190
Min	0	0
25th percentile	35.19	39.993
Median	47.69	45.281
75th percentile	61.11	51.533
Max	87.96	66.452

Figure 1: Stringency Index by state on April 1st, 2020. Darker is more stringent.

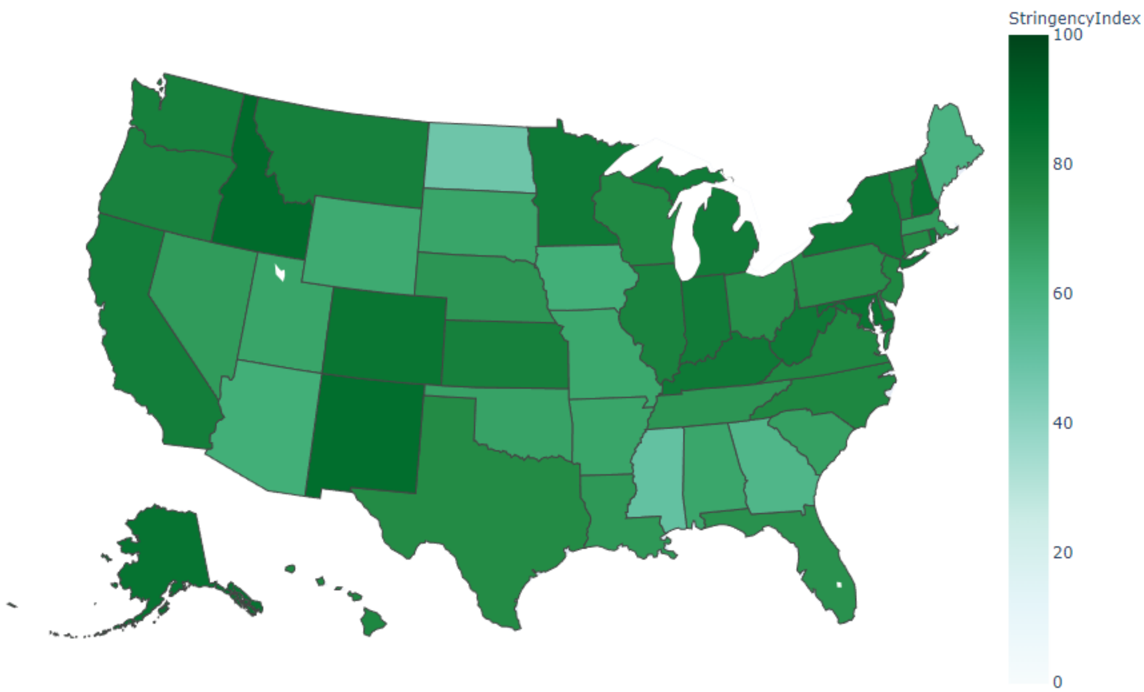

Figure 2: Stringency Index by state on June 1st, 2020.

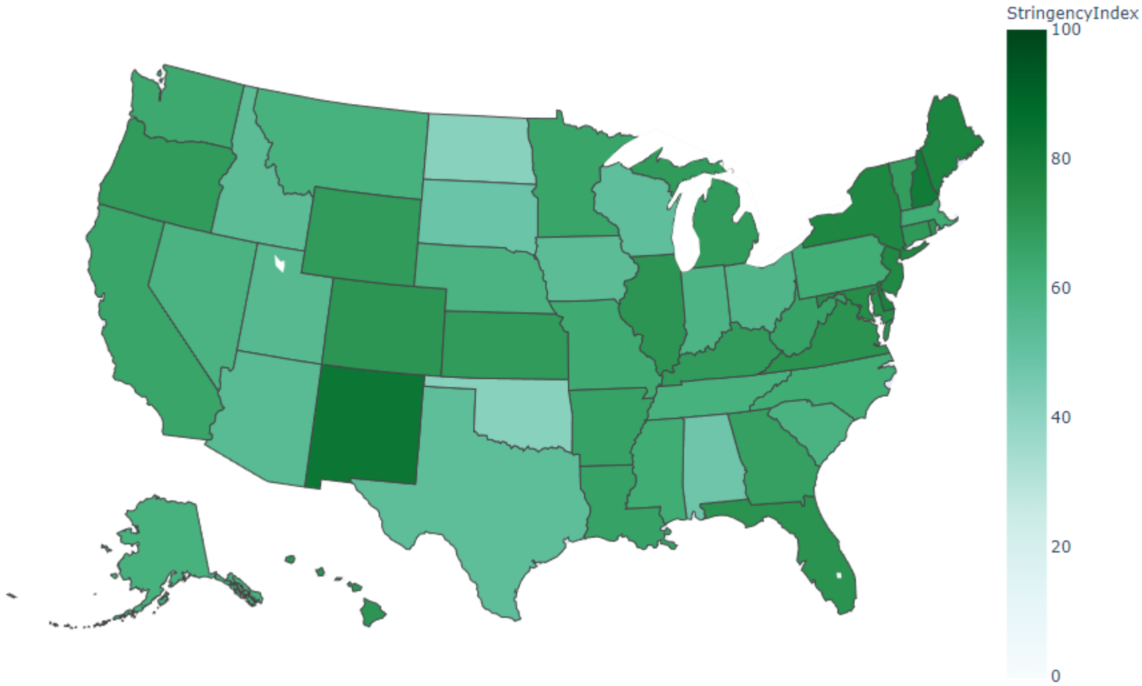

Figure 3: Total number of days under active stay-at-home order by county. Darker counties had more stay-at-home order days. Grayed-out counties and states are grayed-out due to data issues.

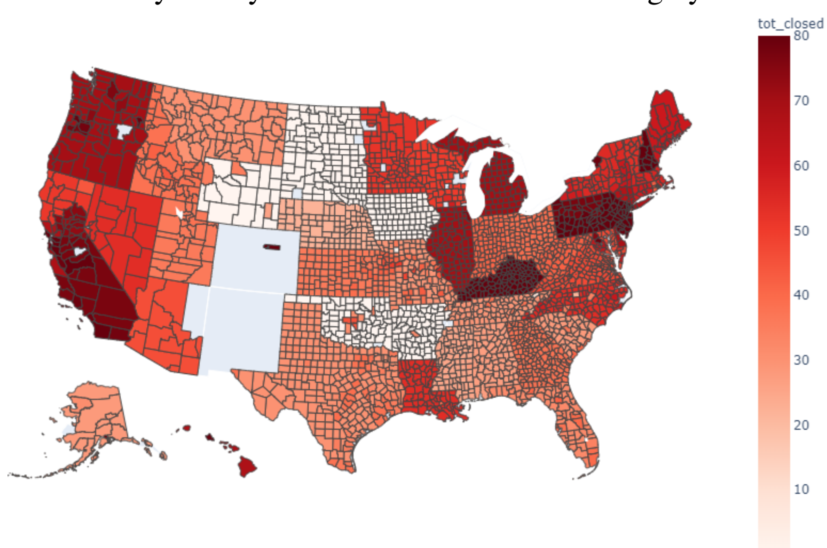

Figure 4: Average Covid-19 death rate by county in 2020. Darker counties experienced more deaths.

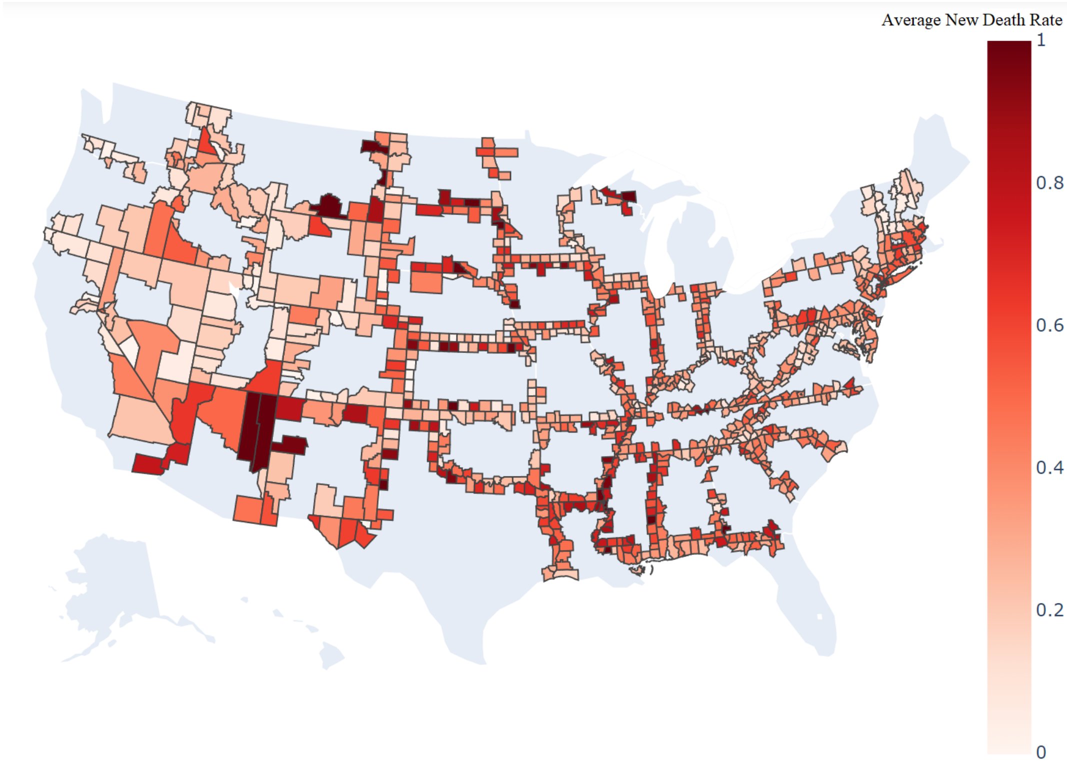

Figure 5: Average Stringency Index by county in 2020. Darker is more stringent.

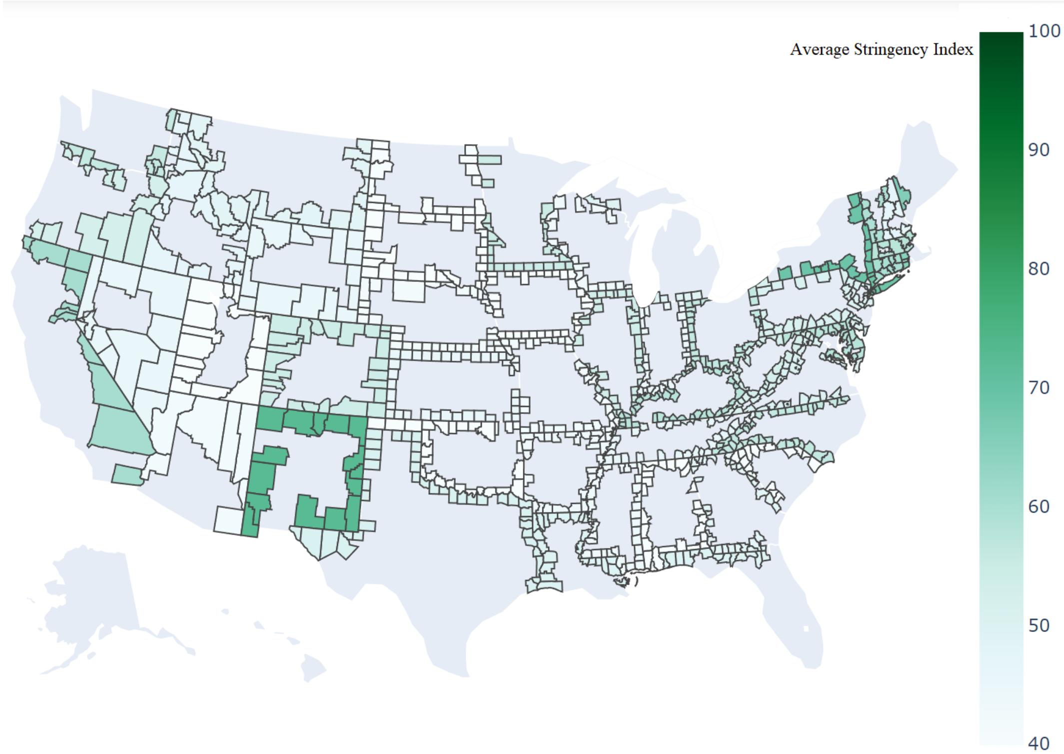

Figure 6: Difference in average 2020 Covid-19 death rate in neighboring counties versus difference in average 2020 stringency index.

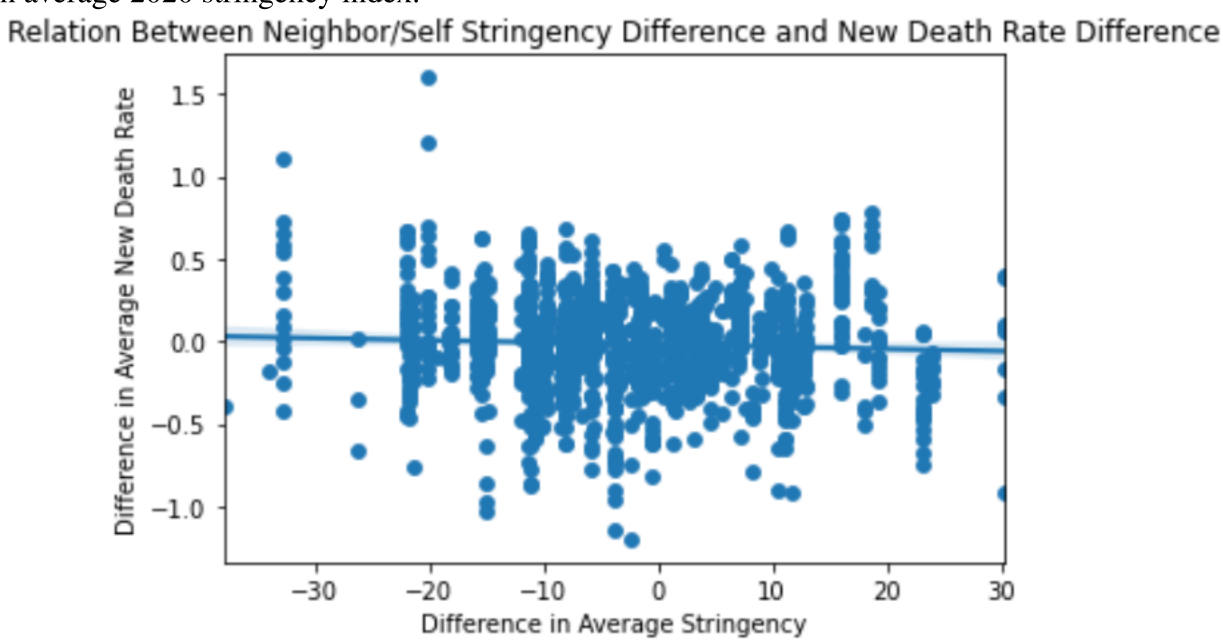

Table 2: Mean values of main variables of interests. Left column is all 2989 counties in the original sample. Middle is reduced sample of only counties on a state border. Right column is further reduced to state border counties whose neighbor is in a different commute zone.

	Full Data	Border Counties	Border Counties with Diff. CZ Neighbor
N	2989	1105	923
Stringency Index	43.821	43.689	43.531
SAH	0.123	0.125	0.123
New Death Rate	0.333	0.328	0.333
Avg. DEM Vote Share	0.359	0.357	0.351
% NAICS 72	0.112	0.115	0.115
# Bank Branches (p.c.)	43.029	43.603	45.322
Population	105423.717	102557.760	94596.339

Figure 7: Counties included in event study regression on number of open merchants. Black counties issued a stay-at-home order in 2020 while white ones did not issue any.

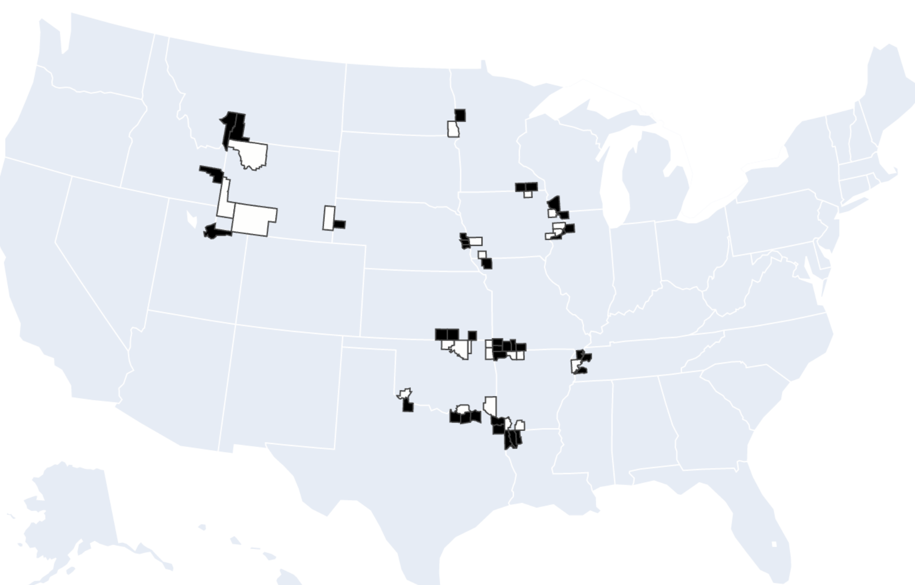

Figure 8: Counties included in event study regression on number of open merchants. Black counties issued a stay-at-home order in 2020 while white ones did not issue any.

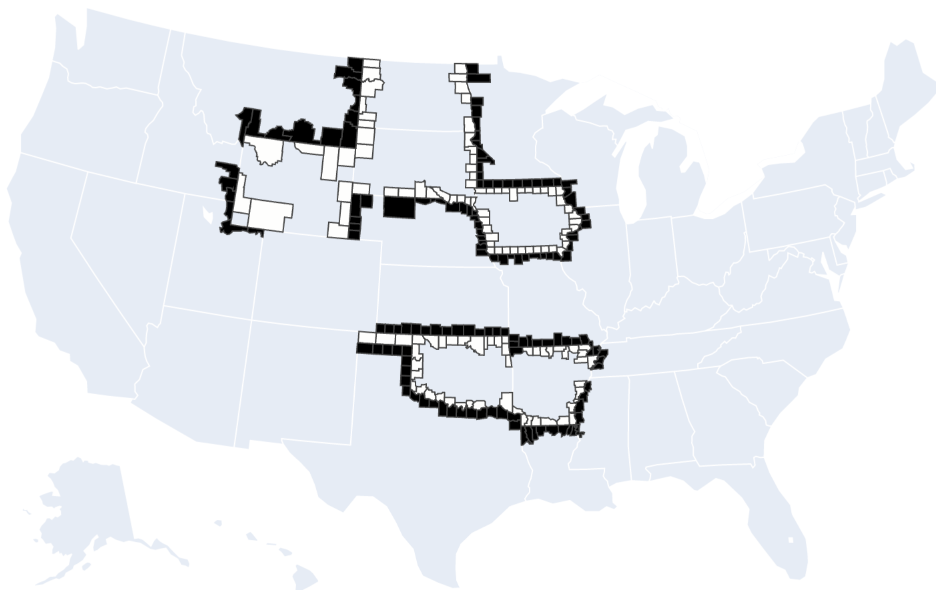

Figure 9: Results from event-study regression on number of open merchants. The y-axis is the difference between county issuing the stay-at-home order and the neighboring county in the percentage change in number of small businesses in each county compared to January 2020. Time is indexed in weeks. Week 0 is the week the stay-at-home order imposing county issued the order. Weeks -6 to -2 are included to examine any pre-trend and Week -1 is dropped as the baseline. Bands show 90% and 95% confidence intervals.

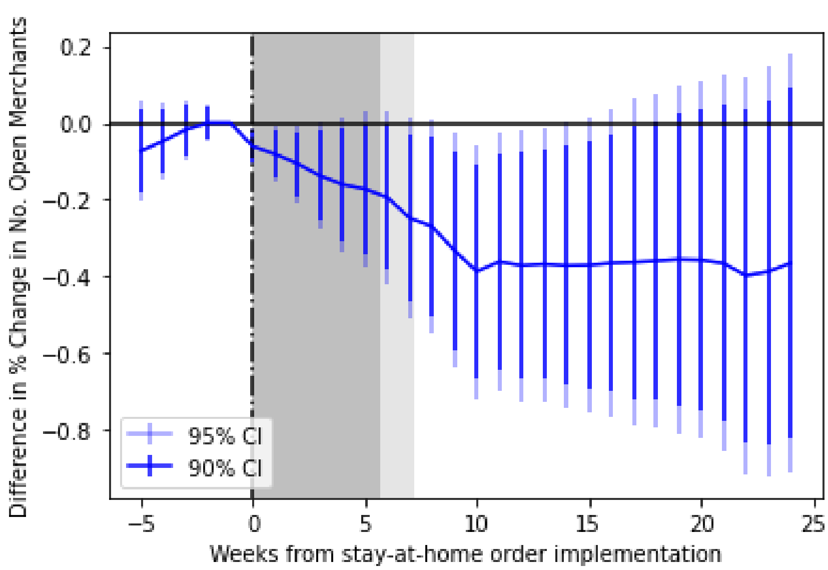

Figure 10: Results from event-study regression on number of open merchants with the top 5 most populous counties in each state dropped. The y-axis is the difference between county issuing the stay-at-home order and the neighboring county in the percentage change in number of small businesses in each county compared to January 2020. Time is indexed in weeks. Week 0 is the week the stay-at-home order imposing county issued the order. Weeks -6 to -2 are included to examine any pre-trend and Week -1 is dropped as the baseline. Bands show 90% and 95% confidence intervals.

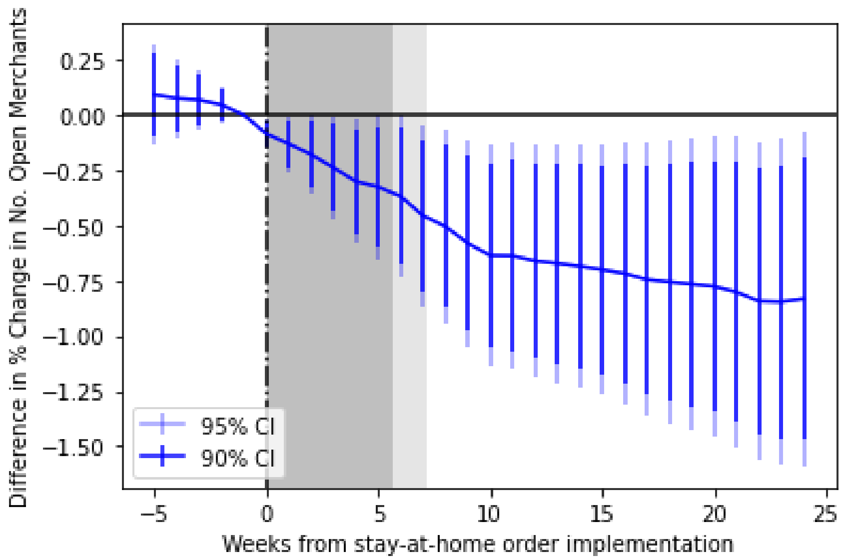

Figure 11: Results from event-study regression on employment. The y axis is the difference between county issuing the stay-at-home order and the neighboring county in the percentage change in employment in each county compared to January 2020. Time is indexed in weeks. Month 0 is the week the stay-at-home order imposing county issued the order. Months -6 to -2 are included to examine any pre-trend and Month -1 is dropped as the baseline. Bands show 90% and 95% confidence intervals.

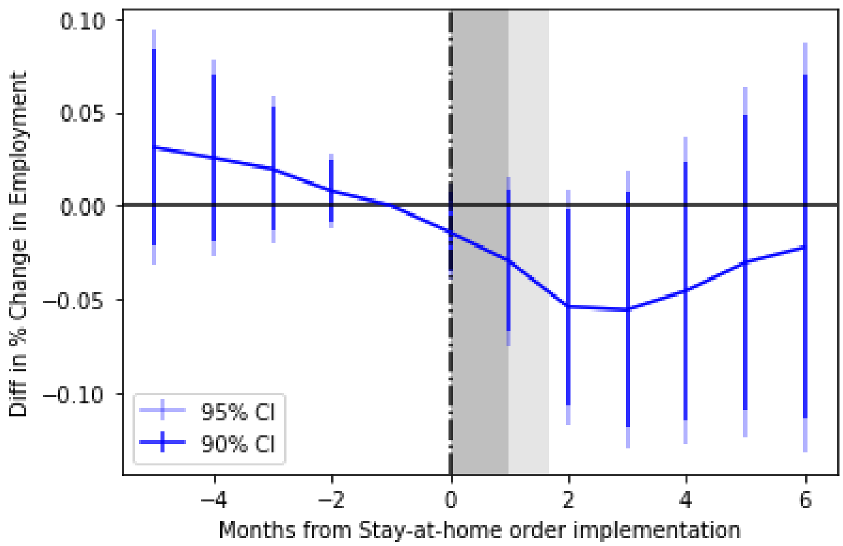

Figure 12: Results from event-study regression on employment with the top 5 most populous counties in each state dropped. The y axis is the difference between county issuing the stay-at-home order and the neighboring county in the percentage change in employment in each county compared to January 2020. Time is indexed in weeks. Month 0 is the week the stay-at-home order imposing county issued the order. Months -6 to -2 are included to examine any pre-trend and Month -1 is dropped as the baseline. Bands show 90% and 95% confidence intervals.

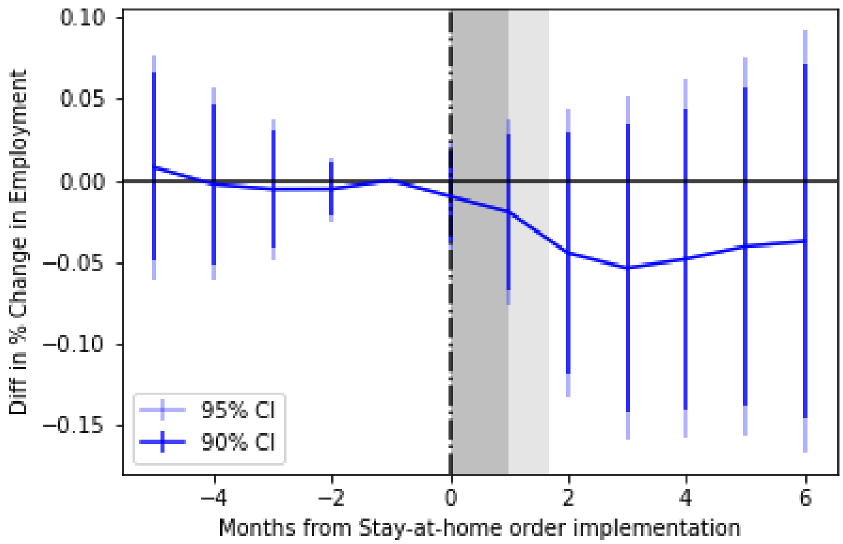

Figure 13: Counties included in the open merchants results

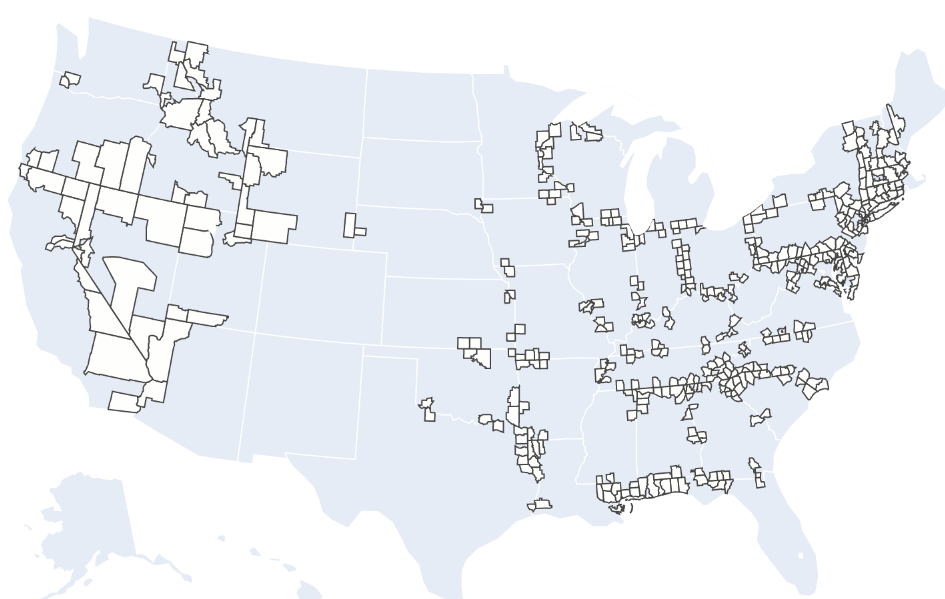

Table 3: Results from difference-in-difference regression on number of open merchants. Variables with a Δ are differences between a county and its neighboring county. Merchants is the percentage change in number of open small businesses at time t in a county versus January 2020. Observations are weighted by combined county-pair 2019 population.

	$\Delta Merchants_t$	
	(1)	(2)
ΔSAH_t	-0.0395***	-0.0353***
	(0.0103)	(0.0089)
ΔSAH_{t-2}	-0.0183***	-0.0106*
	(0.0059)	(0.0058)
ΔSAH_{t-4}	-0.0112**	-0.0115**
	(0.0053)	(0.0053)
ΔSAH_{t-6}	-0.0009	0.0021
	(0.0046)	(0.0054)
ΔSAH_{t-8}	-0.0151***	-0.0113***
	(0.0043)	(0.0041)
ΔSAH_{t-10}	-0.0053	-0.0042
	(0.0038)	(0.0068)
$\Delta NewDeathRate_t$	-0.0067**	0.0016
	(0.0030)	(0.0035)
R-squared	0.7309	0.7095
R-squared Adj.	0.7229	0.7006
Observations	13461	9120
County-Pair FE	Yes	Yes
Week FE	Yes	Yes
Top 5 Dropped	No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 4: Results from difference-in-difference regression on employment. Variables with a Δ are differences between a county and its neighboring county. Merchants is the percentage change in employment at time t in a county versus January 2020. Observations are weighted by combined county-pair January 2020 employment.

	$\Delta Employment_t$	
	(1)	(2)
ΔSAH_t	-0.0053	-0.0131**
	(0.0040)	(0.0057)
ΔSAH_{t-1}	-0.0119***	-0.0163***
	(0.0029)	(0.0035)
ΔSAH_{t-2}	0.0015	-0.0089**
	(0.0044)	(0.0041)
$\Delta NewDeathRate_t$	0.0008	0.0008
	(0.0016)	(0.0012)
$\Delta NewDeathRate_{t-1}$	-0.0015	-0.0016
	(0.0011)	(0.0012)
$\Delta NewDeathRate_{t-2}$	-0.0035**	-0.0040**
	(0.0014)	(0.0016)
R-squared	0.5986	0.5634
R-squared Adj.	0.5612	0.5225
Observations	10152	8388
County-Pair FE	Yes	Yes
Month FE	Yes	Yes
Top 5 Dropped	No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Figure 14: Number of visitors by visitor type in all border counties in the United States by week in 2020. The dotted line is the average percentage of visitors that come from outside the county.

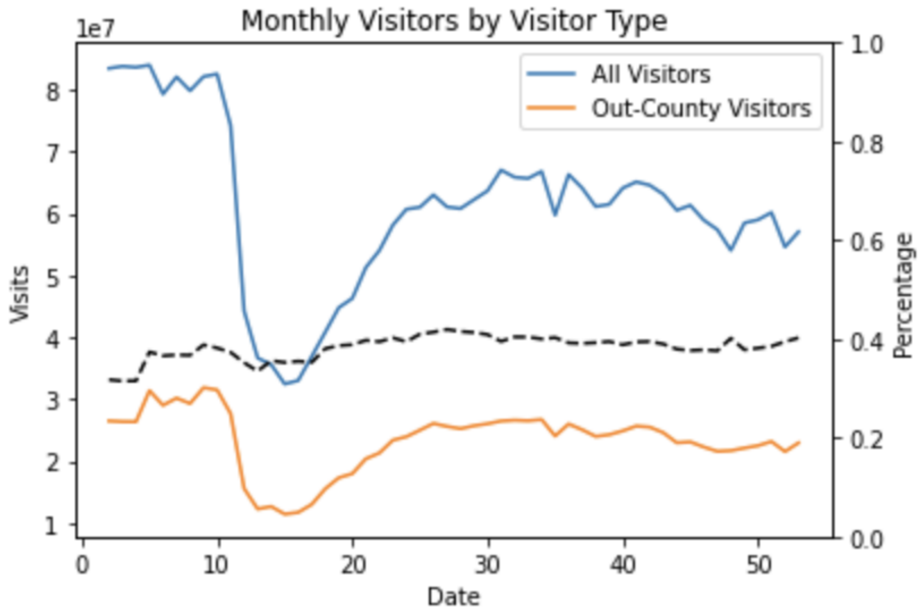

Figure 15: Distribution of percentage of visitors to establishments in the main county in a county-pair that come from the neighbor county. The blue box plot shows the distribution across all county-pairs in the sample. The orange and green box plots show the breakdown when decomposing the sample into county-pairs that lie in the same commute zone and those that lie in different commute zones, respectively.

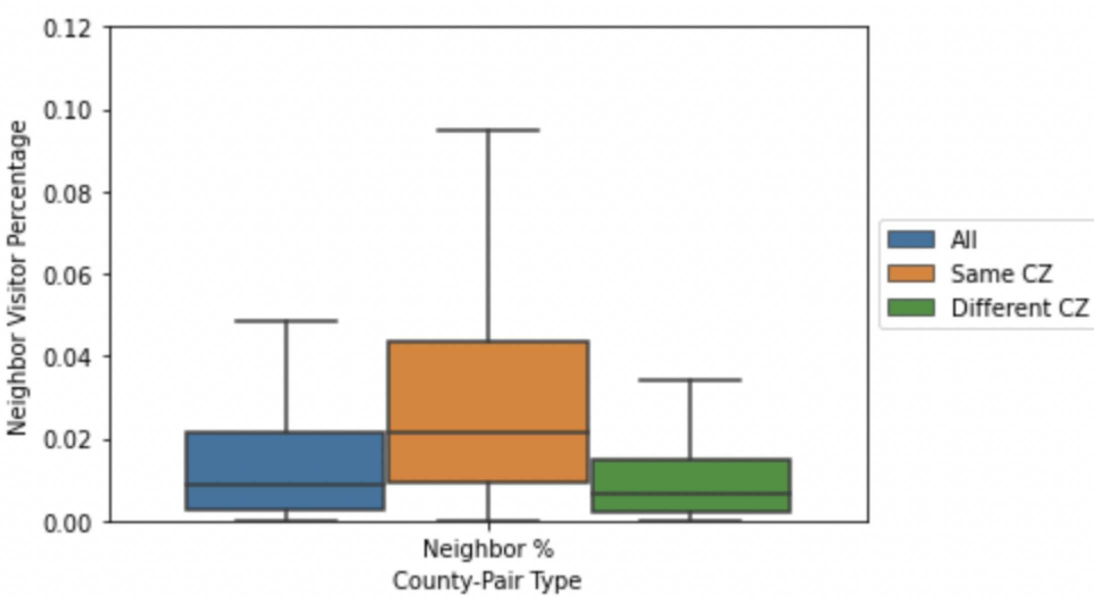

Figure 16: Counties included in the spillovers results.

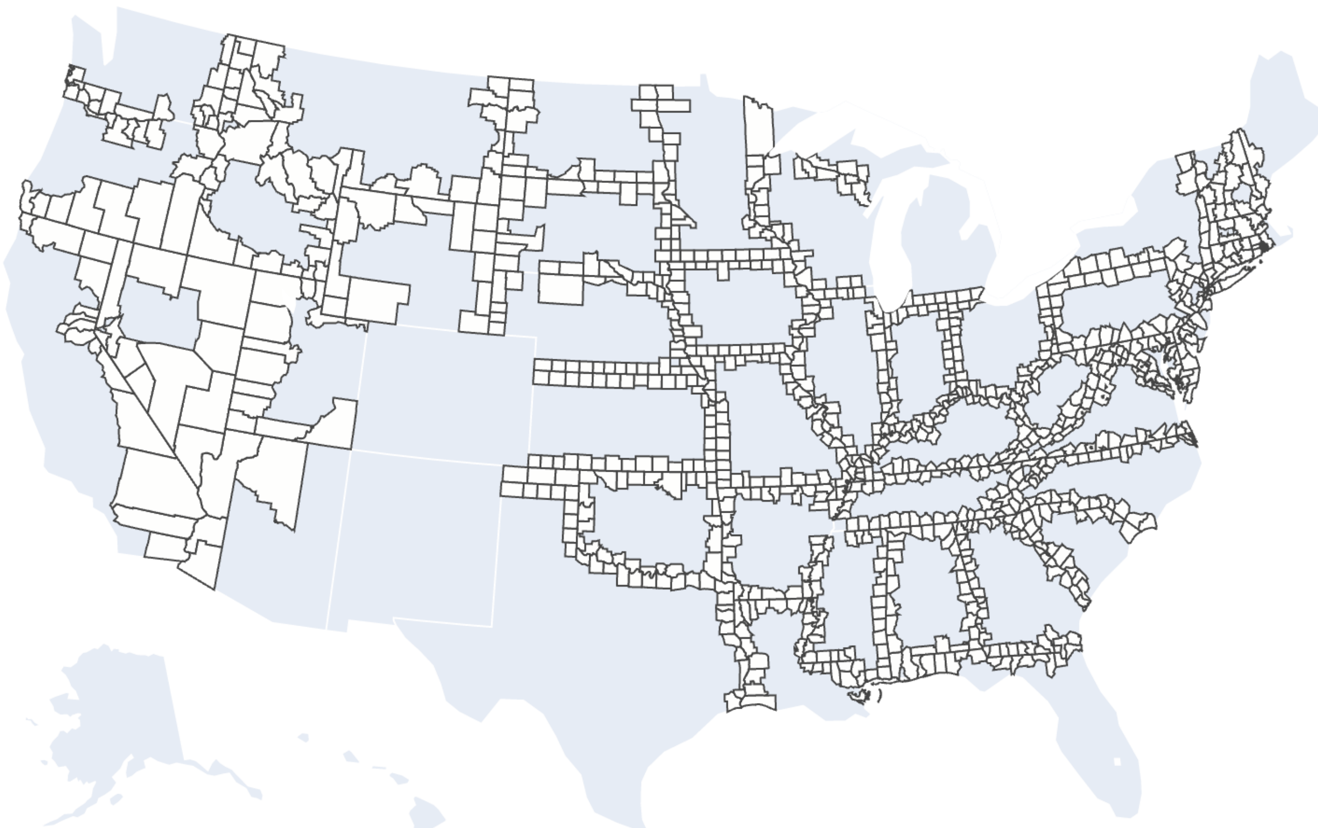

Table 5: Results from difference-in-difference regression on inter-county movement within county-pairs. Observations are weighted by combined county-pair 2019 population. The left two columns use movement from the neighbor county to main county as the dependent variable whereas the right two columns look at the opposite direction. Each dependent variable is used with both the linear specification using stay-at-home order and the non-linear one using indicators for relatively closed or open.

	Neighbor County to Main County Visitors$_t$	
	(1)	(2)
$Rel.Closed_t$	-626.3188***	-407.1668***
	(180.9939)	(131.4806)
$Rel.Open_t$	-408.0482***	-221.2564**
	(154.5871)	(98.5817)
$Rel.Closed_t \times DCZ$	592.5045**	478.5878***
	(236.9369)	(146.4631)
$Rel.Open_t \times DCZ$	438.7342**	230.5418**
	(170.4588)	(114.4471)
R-squared	0.9468	0.9553
R-squared Adj.	0.9457	0.9543
Observations	60318	48722
County-Pair FE	Yes	Yes
Week FE	Yes	Yes
Top 5 Dropped	No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Results from difference-in-difference regression on inter-county movement within county-pairs. Observations are weighted by combined county-pair 2019 population. The left two columns use movement from the neighbor county to main county as the dependent variable whereas the right two columns look at the opposite direction. Each dependent variable is used with both the linear specification using stay-at-home order and the non-linear one using indicators for relatively closed or open.

	Main County to Neighbor County Visitors$_t$	
	(1)	(2)
$Rel.Closed_t$	-170.3127***	-53.8137
	(49.5822)	(43.4909)
$Rel.Open_t$	-268.9482***	-291.2850***
	(63.8029)	(101.7833)
$Rel.Closed_t \times DCZ$	254.0445***	137.5031***
	(56.7189)	(47.5937)
$Rel.Open_t \times DCZ$	283.2866***	223.7066**
	(68.3146)	(107.4454)
R-squared	0.9536	0.9632
R-squared Adj.	0.9526	0.9624
Observations	60318	48722
County-Pair FE	Yes	Yes
Week FE	Yes	Yes
Top 5 Dropped	No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7: Results from difference-in-difference regression on ratio of inter-county movement within county-pairs. Observations are weighted by combined 2019 county-pair population. $N \to S$ and $S \to N$ represent per capita visitors from the neighbor county to the main county and vice-versa, respectively.

	Visitor Ratio_t	
	(1)	(2)
$Rel.Closed_t$	1.9601	-0.7979
	(1.8989)	(0.8034)
$Rel.Open_t$	-2.1420	1.0629
	(1.7743)	(1.3435)
$Rel.Closed_t \times DCZ$	-3.3133*	0.0812
	(1.9739)	(1.0098)
$Rel.Open_t \times DCZ$	-0.2042	-0.9648
	(1.8784)	(1.6484)
R-squared	0.6345	0.6562
R-squared Adj.	0.6265	0.6486
Observations	56778	45370
County-Pair FE	Yes	Yes
Week FE	Yes	Yes
Top 5 Dropped	No	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A1: Event study regression on change in the number of open merchants. Event 0 is the indicator for the period the main county in a pair imposes a stay-at-home order. The time period before this (-1) is dropped.

	Δ Merchants$_{t,Jan2020}$
Event$_{pre}$	0.0403
	(0.0845)
Event$_{-4}$	0.0352
	(0.0662)
Event$_{-3}$	0.0425
	(0.0502)
Event$_{-2}$	0.0322
	(0.0302)
Event	-0.0792***
	(0.0283)
Event$_{1}$	-0.1306**
	(0.0484)
Event$_{2}$	-0.1802**
	(0.0693)
Event$_{3}$	-0.2400***
	(0.0854)
Event$_{4}$	-0.2991***
	(0.1046)
Event$_{5}$	-0.3313**
	(0.1255)
Event$_{6}$	-0.3568**
	(0.1463)
Event$_{7}$	-0.4409**
	(0.1622)
Event$_{8}$	-0.4904***
	(0.1794)
Event$_{9}$	-0.5875***
	(0.1882)
Event$_{10}$	-0.6397***
	(0.2003)
Event$_{11}$	-0.6314***
	(0.2067)
Event$_{12}$	-0.6530***
	(0.2127)
Event$_{13}$	-0.6382***
	(0.2188)
Event$_{14}$	-0.6304***
	(0.2272)
Event$_{15}$	-0.6295**
	(0.2337)
Event$_{16}$	-0.6258**
	(0.2431)
Event$_{17}$	-0.6407**
	(0.2501)
Event$_{18}$	-0.6467**
	(0.2556)
Event$_{19}$	-0.6587**
	(0.2612)
Event$_{20}$	-0.6646**
	(0.2663)
Event$_{21}$	-0.6721**
	(0.2725)
Event$_{22}$	-0.7093**
	(0.2793)
Event$_{23}$	-0.6995**
	(0.2855)
Event$_{post}$	-0.6810**
	(0.2914)
Month-Year FE	Yes
County-Pair FE	Yes
R-squared	0.5922
R-squared Adj.	0.5662
N	2002

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A2: Event study regression on change in employment. Event 0 is the indicator for the period the main county in a pair imposes a stay-at-home order. The time period before this (-1) is dropped.

	Δ Employment$_{t,Oct2019}$
Constant	-0.0229
	(0.0230)
Event$_{pre}$	0.0113
	(0.0237)
Event$_{-4}$	0.0084
	(0.0215)
Event$_{-3}$	0.0068
	(0.0167)
Event$_{-2}$	0.0013
	(0.0085)
Event	-0.0155
	(0.0126)
Event$_{+1}$	-0.0215
	(0.0173)
Event$_{+2}$	-0.0418*
	(0.0228)
Event$_{+3}$	-0.0445*
	(0.0262)
Event$_{+4}$	-0.0354
	(0.0280)
Event$_{+5}$	-0.0218
	(0.0314)
Event$_{post}$	-0.0170
	(0.0341)
Δ New Death Rate	0.0008
	(0.0016)
Month-Year FE	Yes
County-Pair FE	Yes
R-squared	0.6452
R-squared Adj.	0.6218
N	4590

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$