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

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Introduction

- Financial resilience is a known issue for households
- Resilience is also an important concept for businesses
    - Important to understand how well a business sustain an unexpected expense or loss in revenue
    - Firm resilience has strong implications for workers
- Impacts of the Covid-19 pandemic and corresponding government response provides an opportunity to study resilience of businesses in the U.S.

Introduction

- COVID-19 pandemic hits the US in early 2020
  - Widespread cases and deaths, especially in Northeast and Midwest
  - Large losses of jobs and small businesses Employment
- Most state governments react by issuing restrictions on activity
  - Duration and intensity of these restrictions were quite varied across states and time State Stringencies
- Job losses and business closures in this time made these restrictions controversial

Business Closures

Research Questions

- How resilient are firms in the U.S. to prolonged restrictions in doing business?
  - How long can firms weather conditions without laying off workers? Without shutting down entirely?
  - Are layoffs and business failures being driven by stay-at-home orders, or are they stemming directly from the pandemic?
- How do county restrictions impact spillovers of economic activity into neighboring counties?
- Strategy: difference-in-difference specification that exploits similarities in neighboring counties combined with discontinuous government restrictions

Preview of Results - Resilience

- Presence of stay-at-home order associated with a large and immediate drop in open small businesses in the affected county
  - Effect persists well after end of order, peaking at 10 weeks after implementation
  - Acceleration of shutdowns after 8 weeks
- Negative effects also present in employment, but at lower magnitudes

Preview of Results - Spillovers

- The presence of a stay-at-home order in either county in a county-pair results in large reductions in movement in both directions
  - $\mathit{Visitors}_{closed \rightarrow open} \downarrow$
  - $\mathit{Visitors}_{open \rightarrow closed} \downarrow$
- No evidence for a directional spillover from closed to open county
- Reduced spillovers in neighbor county pairs which lie in different commute zones

Roadmap

- Literature
- Data & Identification
- Resilience
    - Two Approaches / Specifications
        - Event Study
        - Broader Difference-in-Difference
    - Results
- Spillovers
    - Data
    - Empirical Specification
    - Results
- Conclusion

Literature Review

- Financial and Economic Resilience
  - Farrell and Wheat (2018), Ahrens and Ferry (2020), Danisman (2021)
  - Piccolo and Pinto (2021), Giroud and Mueller (2017)
    Contribution: Studying resilience by looking at timing of firm closures and layoffs
- Impacts of the Covid-19 Pandemic/Restrictions
  - Chetty et. al (2021), Cortes and Forsythe (2020), Kurmann, Lalé, and Ta (2022)
  - Spiegel and Tookes (2021), Amuedo-Dorantes et. al (2020)
    Contribution: Estimate impact of Covid-19 restrictions on immediate and longer-run firm closures
- Economic Spillovers
  - Elenev et. al (2021), Bernstein et. al (2019), Chalermpong (2004), Bronars and Lott Jr. (1998)
    Contribution: Look at role of commute zone in county-to-county spillovers

Data

- Stay-at-Home Orders from Spiegel and Tookes (2021)
    - County level data on the start and end dates of various lockdown measures from Spiegel and Tookes (2021)
- Main Outcome Variables
    - Womply weekly data on percentage change in open small businesses relative to January 2020 in each county[1]
        - Small business determined by SBA revenue thresholds
    - BLS monthly data on total non-government employment in each county
        - Also normalize based on January 2020 for consistency

Other Data

[1] Sourced from Opportunity Insights

Covid Restrictions in the United States

- Federal restrictions limited to restrictions on international arrivals
- Domestic restrictions such as stay-at-home orders and mask mandates largely issued at state and local level
- Stay-at-home orders in place in most counties in the early stages of the pandemic
  - People often still permitted to leave home for things like individual exercise
  - In most cases, all non-essential businesses required to close

Identification Strategy

- Focus on county pairs that lie on state borders since most of the variation in stay-at-home order policies is at the state level Map
- Exploit similarity in neighboring counties to take advantage of differences in government response despite similar pandemic levels Evidence

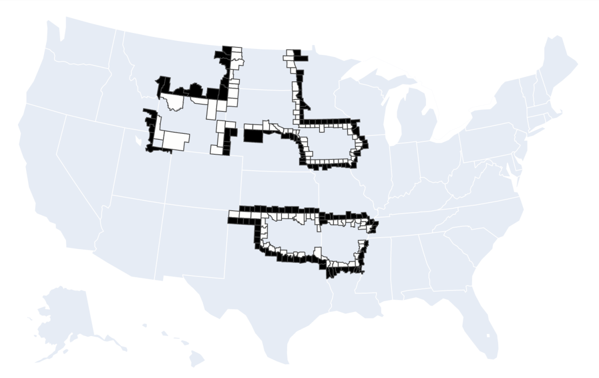
Identification Challenges

- **Problem:** Covid-19 restrictions are issued to combat the underlying pandemic
- **Solution:** Repeat analysis removing 5 most populous counties as in Spiegel and Tookes (2021)
  - Most stay-at-home orders issued at state level
  - Restrictions likely issued in response to pandemic in the largest counties in the state
  - Can treat issued stay-at-home order in other counties as random
- **Problem:** Stay-at-home orders may cause economic spillovers and bias results
- **Solution:** Perform main analysis on county-pairs lying in different commute zones
  - Counties in the same commute zone are likely to be more connected and prone to spillovers

First Approach: Event Study

- One challenge with studying stay-at-home orders is that most counties implemented them
- Most of the variation is in the duration and timing of stay-at-home orders
- The only true controls are the ones which were never under a stay-at-home order
- To get the most precise treatment / control distinction, start with county pairs where one county implemented one stay-at-home order and its neighbor across a state border never implemented a stay-at-home order

Event Study Sample



- Counties in black were under 1 stay-home-order in 2020, white counties were under none

Merchants Sample

Event Study Specification (Merchants)

$$\Delta Merchants_{i,i_n,t} = \sum_{j=-5, j\neq -1}^{23} \beta_j Event_{j,i,i_n,t} + \gamma \mathbf{X}_{i,i_n,t} + \nu_{i,i_n} + \mu_t + \epsilon_{i,i_n,t}$$

- i and i_n index counties and their neighbors, t indexes weeks
- $Merchants_{i,i_n,t}$ is the percentage change in open small businesses relative to January 2020, i.e.:

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

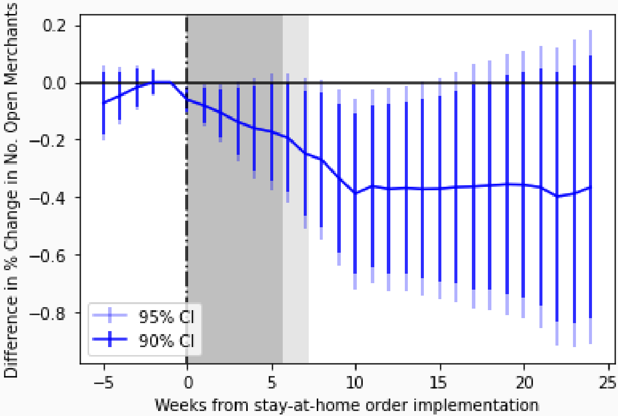
- $Event_J$ are indicators for j periods after the implementation of the stay-at-home order by the "closed" county
- ν and μ are county-pair and time fixed effects, respectively
- Standard errors are clustered at state-pair level

Balance Table

Table 1: Pre-Pandemic Balance Table

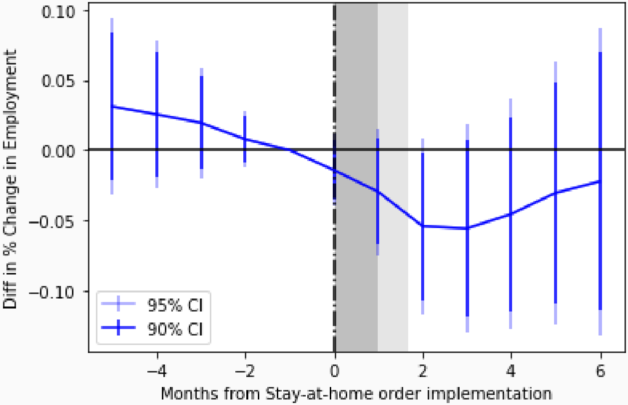
	Merchants Sample			Employment Sample		
	Treated	Control	p-value	Treated	Control	p-value
Merchants	0.014	0.030	0.321	-	-	-
Employment	-	-	-	1.000	1.001	0.657
% Food Services	0.124	0.130	0.661	0.102	0.101	0.889
Bank Branches	40.531	43.843	0.261	67.475	61.583	0.054*
Avg. DEM Share	0.348	0.344	0.896	0.303	0.325	0.088*
Population	80609	45169	0.027**	28255	22812	0.156

Event Study Results (Merchants)



Without top 5 counties

Event Study Results (Employment)



Without top 5 counties

Second Approach: More general Difference-in-Difference specification

- Previous setup defines a experiment with once treated treatment counties bordering never treated control counties
    - At significant cost to sample size
- Much of variation in stay-at-home order policies is given by duration of the order (where both counties in the pair had one stay-at-home order)
- I use a second specification that looks more granular differences in implementation of stay-at-home orders

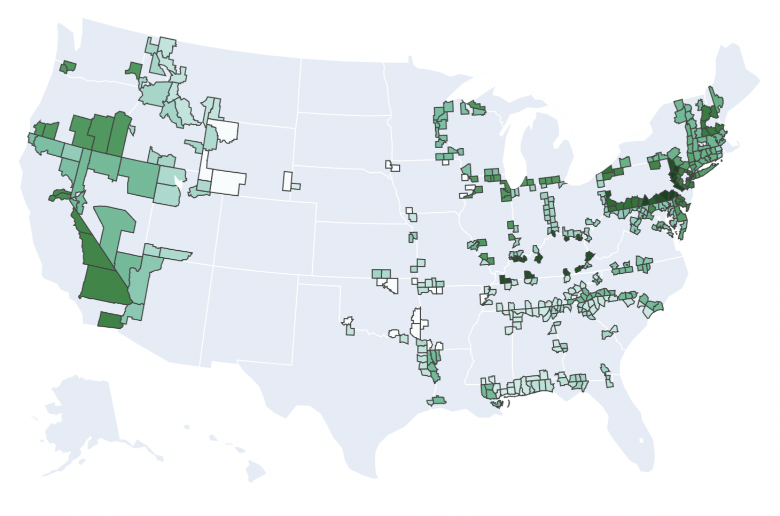
Difference-in-Difference Specification (Merchants)

- For firm survival results, main WLS specification is given by:

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

  - where i, i_n represent a county pair, t time (in weeks)
  - $\Delta SAH_{i,i_n,t}$ is the difference in stay-at-home policy between i and i_n during time t
  - $\mathbf{X}$ is a vector of controls
  - ν and μ are county-pair and time fixed effects
  - Standard errors are clustered at state-pair level

Difference-in-Difference Sample (Merchants)



Difference in Difference Results (Merchants)

	$\Delta Merchants_t$	
	(1)	(2)
ΔSAH_{t+4}	-0.0209	-0.0105
	(0.0144)	(0.0121)
ΔSAH_{t+2}	-0.0075	0.0045
	(0.0086)	(0.0060)
ΔSAH_t	-0.0441**	-0.0477***
	(0.0187)	(0.0091)
ΔSAH_{t-2}	-0.0239*	-0.0161*
	(0.0132)	(0.0086)
ΔSAH_{t-4}	-0.0091	-0.0081
	(0.0091)	(0.0075)
ΔSAH_{t-6}	0.0003	0.0045
	(0.0067)	(0.0055)
ΔSAH_{t-8}	-0.0150**	-0.0129***
	(0.0059)	(0.0048)
ΔSAH_{t-10}	-0.0062	-0.0053
	(0.0046)	(0.0078)
$\Delta NewDeathRate_t$	-0.0081**	0.0007
	(0.0039)	(0.0050)
R-squared	0.7325	0.7130
R-squared Adj.	0.7232	0.7025
Observations	12142	8245
County-Pair FE	Yes	Yes
Week FE	Yes	Yes
Top 5 Dropped	No	Yes

*Significance codes: *: 0.1, **: 0.05, ***: 0.01*

Difference in Difference Results (Employment)

	$\Delta Employment_t$	
	(1)	(2)
ΔSAH_{t+2}	0.0053	0.0027
	(0.0051)	(0.0038)
ΔSAH_{t+1}	0.0048	0.0043
	(0.0105)	(0.0064)
ΔSAH_t	-0.0074	-0.0079
	(0.0089)	(0.0052)
ΔSAH_{t-1}	-0.0107**	-0.0182***
	(0.0044)	(0.0051)
ΔSAH_{t-2}	0.0005	-0.0099*
	(0.0051)	(0.0053)
$\Delta NewDeathRate_t$	0.0002	0.0009
	(0.0020)	(0.0019)
$\Delta NewDeathRate_{t-1}$	-0.0022	-0.0036**
	(0.0018)	(0.0016)
$\Delta NewDeathRate_{t-2}$	-0.0041*	-0.0050**
	(0.0021)	(0.0022)
R-squared	0.5762	0.5449
R-squared Adj.	0.5281	0.4930
Observations	8460	6990
County-Pair FE	Yes	Yes
Month FE	Yes	Yes
Top 5 Dropped	No	Yes

*Significance codes: *: 0.1, **: 0.05, ***: 0.01*

Do Spillover Effects Drive Results?

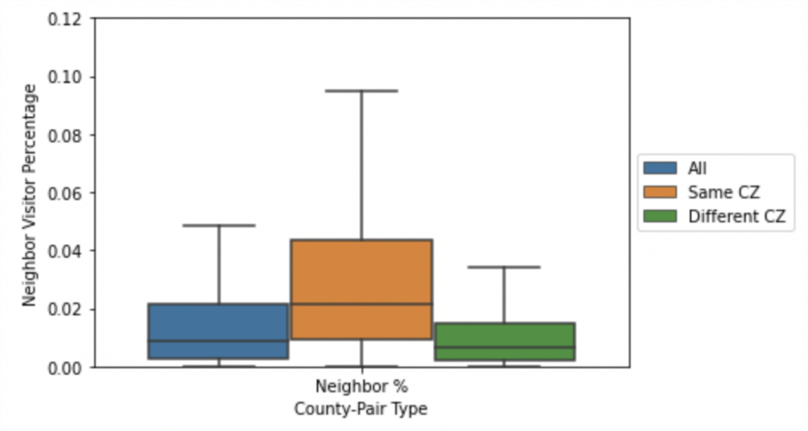
- Part of the difference in counties may be explained by spillover effects
  - If county A is closed and B is open, then some people from county A may take their shopping to county B instead of not shopping at all
  - This will exaggerate the importance of the shutdown on the difference between counties
- Previous results account for possible spillover impacts by restricting sample to neighbor county pairs that do not lie in the same commute zone
- Foot-traffic data allows us to directly estimate spillover affects caused by stay-at-home orders and test the assumption used in the main results

Safegraph Data

- Weekly foot traffic data in various places of interest throughout the United States in 2020
  - Raw data of roughly 200 million observations
- Contains detailed information on visitors such as home census block group
- I drop all observations with less than 5 visits in a week since this data is changed to protect privacy
  - Any establishment with fewer than 5 visitors gets listed as having 5 visitors
- Transformed this data to county-pair level with number of visitors traveling between the two counties in both directions

Neighbor Visitor Percentage by County-Pair Type

- Looking at county pairs, we see that the percentage of visitors that come from the neighboring county is indeed smaller in pairs that are in two different commute zones



Spillovers Specification

- To estimate spillovers effects, I use the following specification

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

- where $y_{i,i_n,t}$ is one of 3 measures of travel between the two counties
    - (1): Visitors (per capita) from county i_n to county i
    - (2): Visitors (per capita) from county i to county i_n
    - (3): Ratio of (1) to (2)

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

- Rel. Closed $\equiv \mathbb{1}\left(\Delta SAH > 0\right)$, Rel. Open $\equiv \mathbb{1}\left(\Delta SAH < 0\right)$

Results on Spillovers - Inter-county Visitors

	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

*Significance codes: *: 0.1, **: 0.05, ***: 0.01*

Other Direction

Results on Spillovers - Visitor Ratio

	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

*Significance codes: *: 0.1, **: 0.05, ***: 0.01*

Discussion and Policy Implications

- Negative effects found on both employment and open small businesses
    - Effects on employment are smaller
    - More evidence that employment was rebounding by year-end than open small businesses
- As discussed in Hubbard and Strain (2021), more non-payroll expense aid may have been beneficial
- In future emergency scenarios, more effort should be made to make sure small businesses in particular have adequate access to financing

Future Work

- Explore the impacts of other NPIs, such as school and restaurant closures and mask mandates on economic outcomes
- Further analysis with other dependent variable data that can identify mechanism behind closures
    - Dun & Bradstreet data on firm financial health
    - Data on bankruptcies instead of closures

Conclusion

- Stay-at-home orders caused increased shutdowns of small businesses
- Many firms were only resilient enough to remain open for 8 weeks after the order began
    - This despite the fact that the duration of these orders was shorter
- Firms quick to resort to layoffs, however county employment recovered faster
- Covid restrictions cause reductions in inter-county travel
    - No evidence of a directional spillover
    - Spillovers reduce in county pairs that lie in different commute zones

Resilience is Insufficient in most American Households

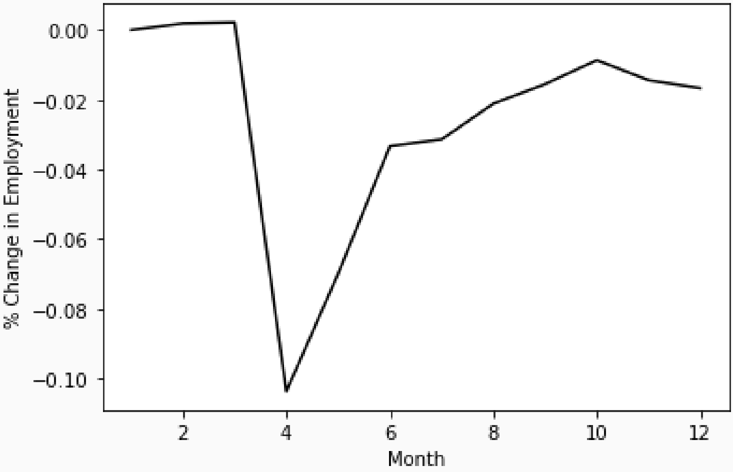
CNN BUSINESS Audio Live TV Log In

Only 39% of Americans can afford a $1,000 emergency expense

By Anna Bahney, CNN Business

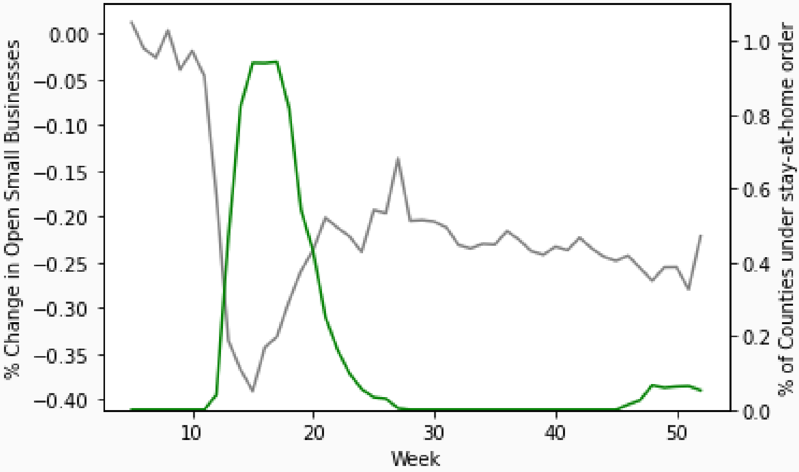
Updated 5:29 PM EST, Mon January 11, 2021

Change in Employment over 2020



Intro

Small Businesses Closures in 2020



Intro

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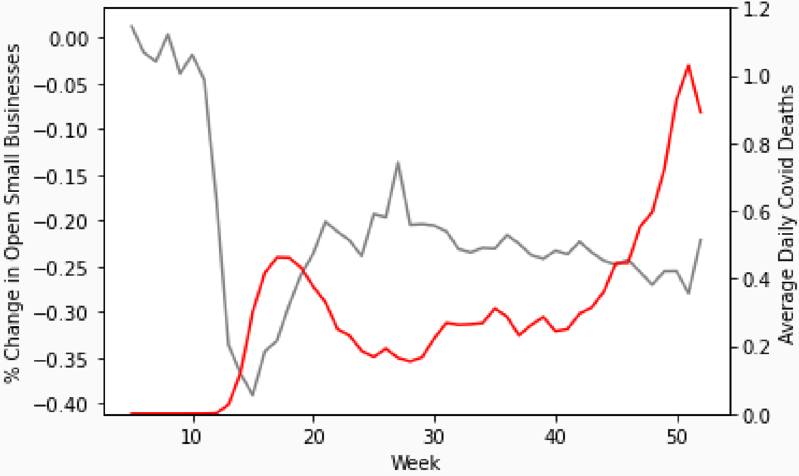
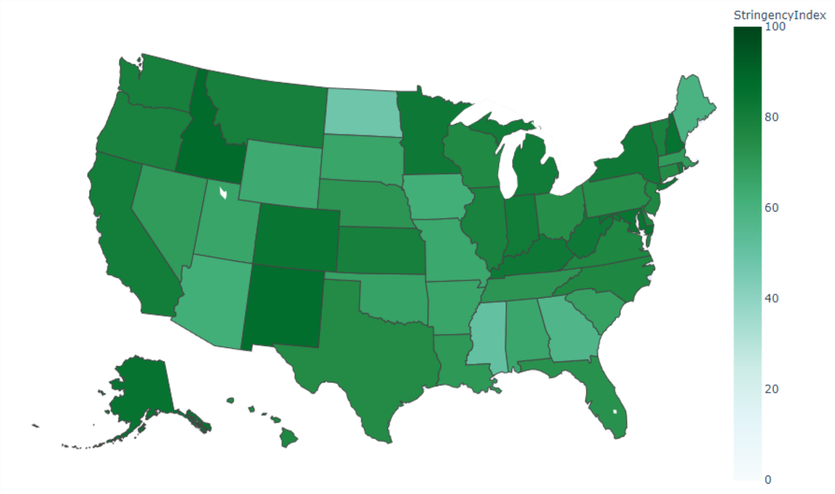
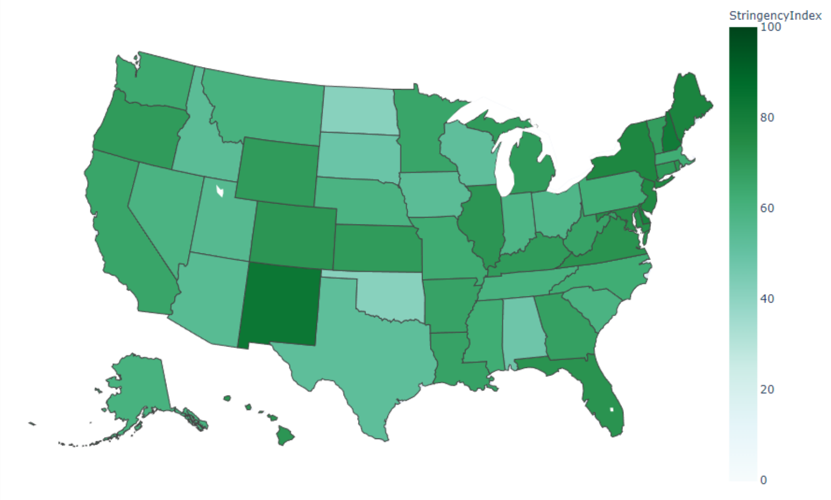


Intro

Stringency Index by State, April 2020



Stringency Index by State, June 2020



Other Data Sources

- County border data from Census' County Adjacency File
- COVID-19 deaths from New York Times[2]
- Commute Zone data from Autor and Dorn (2013)
- Industry composition data from Census' County Business Pattern
- Bank Branches from FDIC
- Political data from MIT Election Lab

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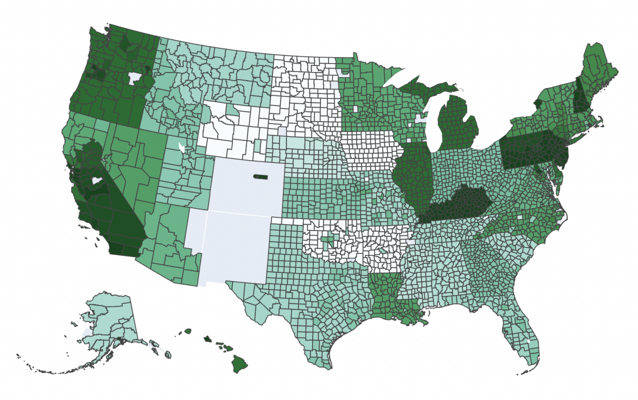
[2] Sourced from Opportunity Insights

County Variation - Days Under Active Stay at Home Order

- There is some variation across different counties in the same state, but most of the variation is across state borders



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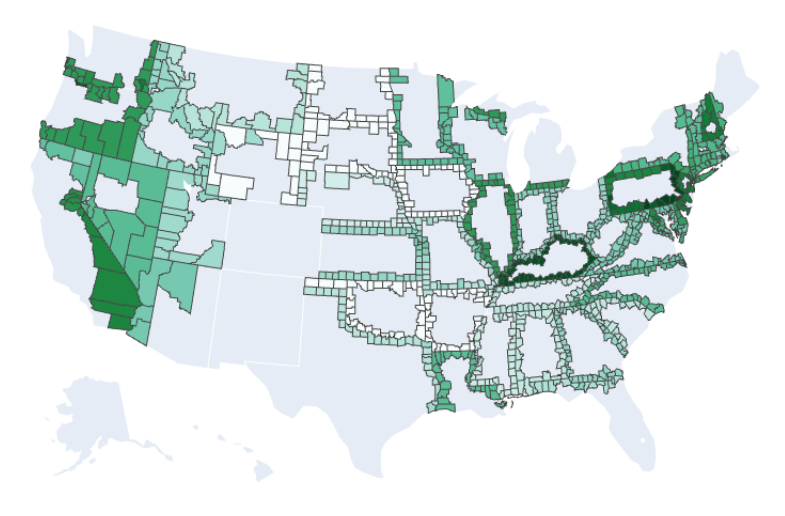
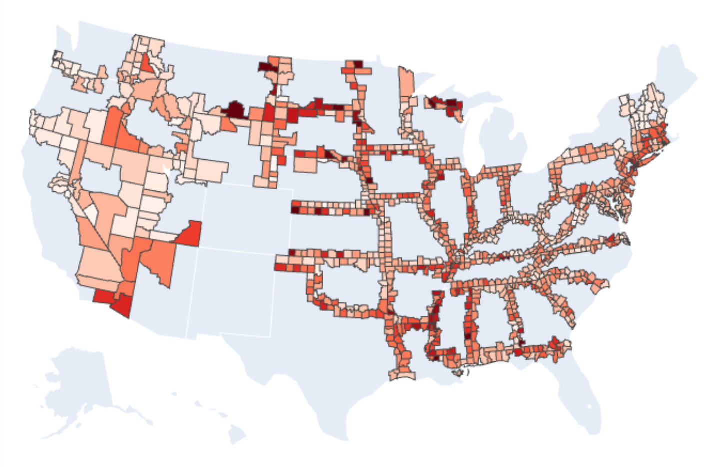
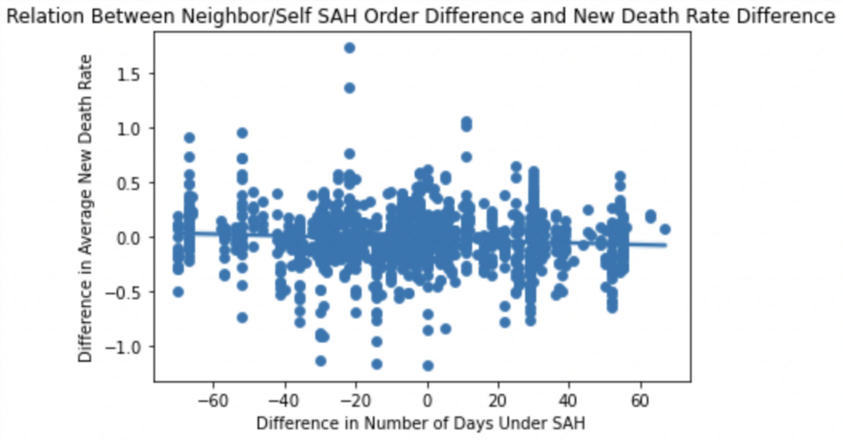
Restrictions Discontinuous at Border



COVID-19 Deaths Not Discontinuous



Deaths Don't Correlate With Stay-at-home Orders in the Sub-sample



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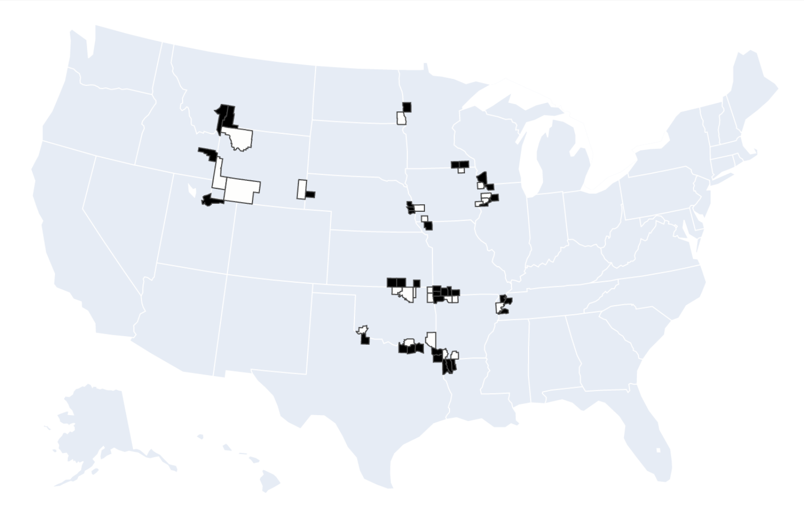
Summary Statistics in All Counties vs Border Counties

	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
% Food Services	0.112	0.115	0.115
# Bank Branches (p.c.)	43.029	43.603	45.322
Population	105424	102558	94596

Event Study Sample (Merchants)



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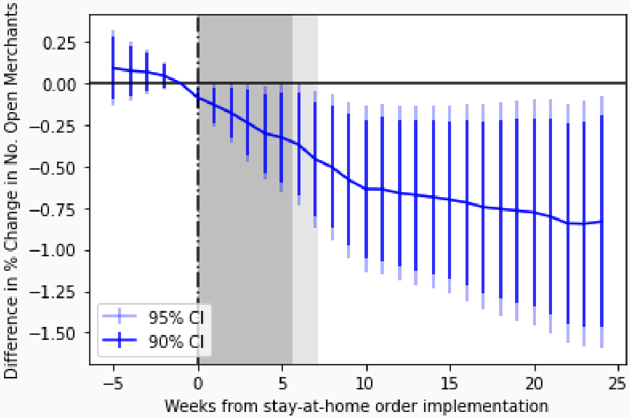
Event Study Results (Merchants) Without Top 5



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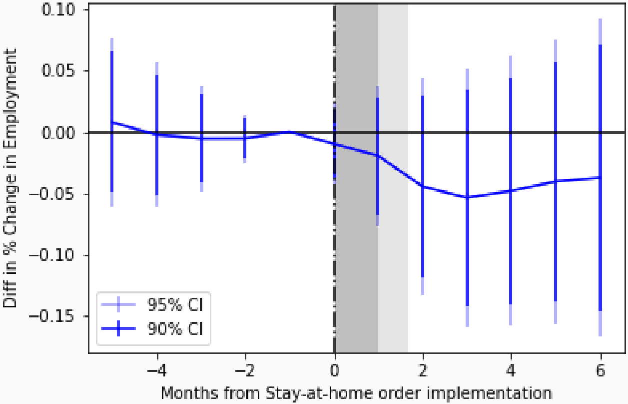
Event Study Results (Employment) Without Top 5



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Spillovers - Self to Neighbor

	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

*Significance codes: *: 0.1, **: 0.05, ***: 0.01*

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