The Impact of Shutdown Policies on Unemployment During a Pandemic

Ed Kong
Daniel Prinz

May 2020

"All the News That's Fit to Print"

The New York Times

Late Edition

Today, clouds giving way to some sunshine, morning rain, high 63. **Tonight,** clear early, increasing clouds late, low 44. **Tomorrow,** rain, high 52. Weather map appears on Page B16.

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JOB LOSSES SOAR; U.S. VIRUS CASES TOP WORLD

VICTOR J. BLUE FOR THE NEW YORK TIMES

Since the coronavirus descended on Brooklyn Hospital Center three weeks ago, the staff has handled over 800 potential cases.

New Data Shows Staggering Toll of Outbreak

This article is by ***Ben Casselman, Patricia Cohen*** *and* ***Tiffany Hsu.***

More than three million people filed for unemployment benefits last week, sending a collective shudder throughout the economy that is unlike anything Americans have experienced.

The alarming numbers, in a report released by the Labor Department on Thursday, provide some of the first hard data on the economic toll of the coronavirus pandemic, which has shut down whole swaths of American life faster than government statistics can keep track.

Just three weeks ago, barely 200,000 people applied for jobless benefits, a historically low number. In the half-century that the government has tracked applications, the worst week ever, with 695,000 so-called initial claims, had been in 1982.

Thursday's figure of nearly 3.3 million set a grim record. "A large part of the economy just collapsed," said Ben Herzon, executive director of IHS Markit, a business data and analytics firm.

The numbers provided only the first hint of the economic cataclysm in progress. Even comparatively optimistic forecasters expect millions more lost jobs, and with them foreclosures, evictions and bankruptcies. Thousands of businesses have closed in response to the pandemic, and many will never reopen. Some economists say the decline in gross domestic product this year could rival the worst years of the Great Depression.

And there was fresh evidence on Thursday of the relentless course of the virus itself. Cases in the United States now exceed 80,000, the most of any nation, even China and Italy, according to a New York Times database. More than 1,000 deaths across the country have been linked to the virus.

At least 160 million people na-

Continued on Page A17

Labeling Regions by Risk

President Trump told governors he planned to classify counties according to the danger of coronavirus infection. Page A11.

Under Trump, Unfilled Posts Hinder Action

By JENNIFER STEINHAUER and ZOLAN KANNO-YOUNGS

WASHINGTON — Of the 75 senior positions at the Department of Homeland Security, 20 are either vacant or filled by acting officials, including Chad F. Wolf, the acting secretary who recently was unable to tell a Senate committee how many respirators and protective face masks were available in the United States.

The National Park Service, which like many federal agencies is full of vacancies in key posts, tried this week to fill the job of a director for the national capital region after hordes of visitors flocked to see the cherry blossoms near the National Mall, creating a potential public health hazard as the coronavirus continues to spread.

At the Department of Veterans Affairs, workers are scrambling to order medical supplies on Amazon after its leaders, lacking experience in disaster responses, failed to prepare for the onslaught of patients at its medical centers.

Ever since President Trump came into office, a record high turnover and unfilled jobs have emptied offices across wide sections of the federal bureaucracy. Now, current and former administration officials and disaster experts say the coronavirus has exposed those failings as never be-

Continued on Page A11

Online Class With No Way To Get There

By NIKITA STEWART

Allia Phillips was excited about picking up an iPad from her school in Harlem last week. She did not want to miss any classes and hoped to land on the fourth-grade honor roll again.

On Monday, the first day that New York City public schools began remote learning, the 10-year-old placed her iPad on a tray she set up over her pillow on a twin bed in a studio that she shares with her mother and grandmother inside a homeless shelter on the Upper West Side.

And then, Allia saw nothing.

"I went downstairs to find out that they don't have any internet," said Kasha Phillips-Lewis, Allia's mother. "You're screwing up my daughter's education. You want to screw me up? Fine. But not my daughter's education."

The Department of Education, which runs the largest school system in the country with more than 1.1 million students, began attempting to teach all students through remote learning this week because schools were closed to slow the spread of the coronavirus.

Shuttering the vast system, which includes 1,800 schools, was a serious challenge for the city, and the large-scale, indefinite school closures are uncharted territory, altering the lives and rou-

Continued on Page A16

Courage at a Brooklyn Hospital, At the Front of an Invisible War

By SHERI FINK

With Supplies Waning, Workers Soldier On

It was not even 9 in the morning and Dr. Sylvie de Souza's green N95 mask, which was supposed to form a seal against her face, was already askew.

In freezing rain on Monday, she trudged in clogs between the emergency department she chairs at the Brooklyn Hospital Center and a tent outside, keeping a sharp eye on the trainee doctors, nurses and other staff members who would screen nearly 100 walk-in patients for the coronavirus that day.

Inside her E.R., more than a dozen people showing signs of infection waited for evaluation in an area used just a few weeks ago for stitches and casts. Another dozen lay on gurneys arranged one in front of the next, like a New York City car park. One man on a ventilator was waiting for space in the intensive care unit.

Minutes before paramedics wheeled in a heart attack patient, Dr. de Souza pointed to beds reserved for serious emergencies, separated by a newly constructed wall from the suspected virus cases. "This is our safe area," she told a reporter. Then she corrected herself: "This is thought to be safe." There was really no way

Continued on Page A14

No Crowd, but I'll Take You Out to the Ballgame

By DAN BARRY

A Fan Writes a Fantasy for Opening Day

Professional baseball greeted a new season this afternoon with an Opening Day game for the ages, an extra-inning masterpiece that vividly unfolded on the sun-dappled field of the imagination. The crack of the bat could almost be heard, the blur of white almost seen, the communal joy nearly felt.

From the moment the first batter tipped his helmet — and a bird flew out — to the walk-off home run by a faltering pinch-hitter, this 11-inning affair redefined what constitutes a perfect game. No one cared about the outcome; the distraction was reward enough.

Don't misunderstand: This game between the New York Gothams and the Cincinnati Greens mattered, but in ineffable ways beyond the columns of wins and losses. It mattered so much that complaints about baseball's slow pace yielded to the universal wish that this game would last forever.

"I could've played into the night," said the redeemed Gothams left fielder Sammy Sosa, who missed part of last season after sneezing so hard that he strained a ligament in his back. "I didn't

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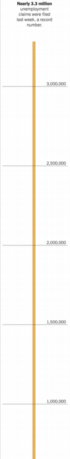

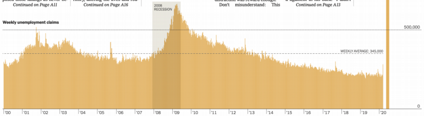

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  - Framework: unemployment expectations
- Only a small share of increased UI claiming is a direct effect of NPIs
  - Large-gatherings bans, school closures, public health emergencies have no direct effect

Contributions and Literature

1. Estimate effect of 6 different NPIs on Google search volume
2. Show how to translate Google search volume estimates into UI claims estimates
3. Jointly estimate different effect sizes across multiple policies

- Work on NPIs: Baek et al. (2020), Lin and Meissner (2020), Correia et al. (2020)
- Labor markets during the COVID-19 pandemic: Bartik et al. (2020*a*), Kahn et al. (2020), Dingel and Neiman (2020), Mongey et al. (2020), Coibion et al. (2020)
- Broader literature on economic activity: Lewis et al. (2020), Baker et al. (2020*b*), Bartik et al. (2020*b*), Hassan et al. (2020), Baker et al. (2020*a*)
- Macro models: Atkeson (2020), Bethune and Korinek (2020), Eichenbaum et al. (2020), Jordà et al. (2020), Glover et al. (2020), Guerrieri et al. (2020), Krueger et al. (2020), Ludvigson et al. (2020), Rampini (2020)
- Economics work using Google Trends: Stephens-Davidowitz and Varian (2015) Baker and Fradkin (2017), Goldsmith-Pinkham and Sojourner (2020)

Background

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- Can cause wide spectrum of disease: mild illness, moderate and severe pneumonia, respiratory failure, and death
- 1.19 million cases and 68,551 deaths have been reported in the U.S.

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  There is significant policy and timing variation across states

Data

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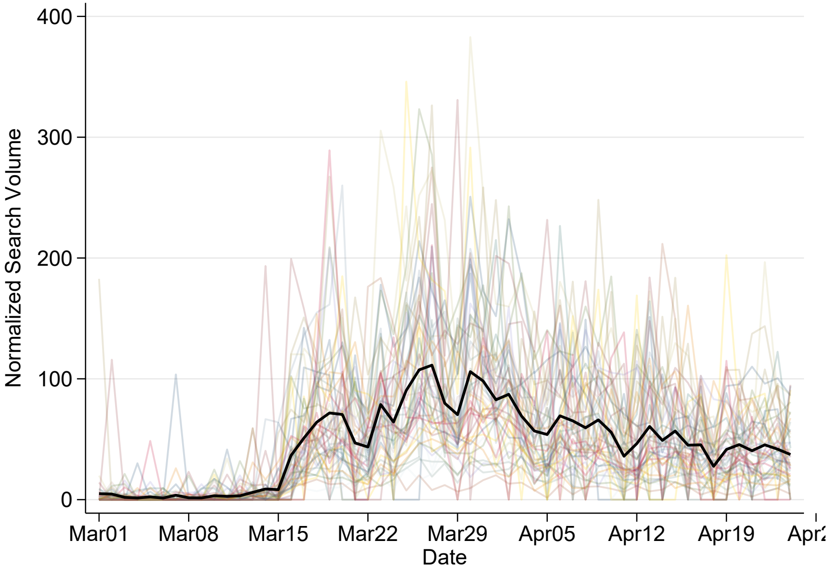
- We download data through API 100 times to account for sampling variation

Evolution of Google Search Volume for Claiming Unemployment Insurance

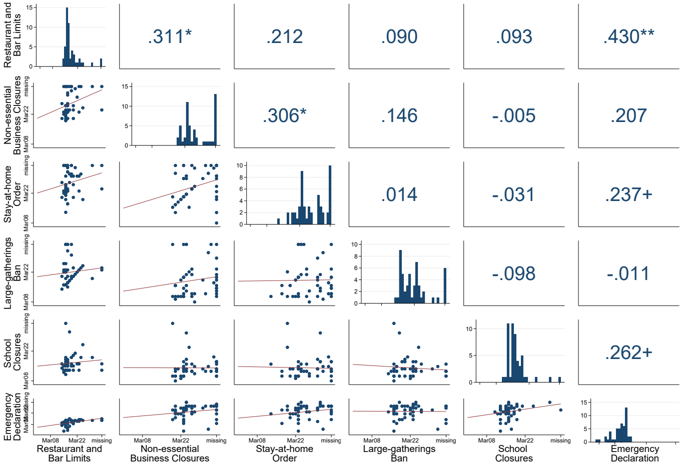


NPI Timing Data

- Use Kaiser Family Foundation data on NPI dates by states
- Dates for six NPIs:
  - Restaurant and bar limitations
  - Non-essential business closures
  - Stay-at-home orders
  - Large-gatherings bans
  - School closures
  - Emergency declarations
- If multiple announcements, use first

Map: Restaurant Limitation | Map: Business Closure | Map: Stay Home
Map: Gatherings Ban | Map: School Closure | Map: Health Emergency

States Not Implementing Same Policies At Same Time



+ p < .1, * p < .05, ** p < .01

▸ Map: Restaurant Limitation ▸ Map: Business Closure ▸ Map: Stay Home

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Other Data

- Confirmed COVID-19 cases and deaths from *JHU Dashboard*
- National UI claims from *Department of Labor*
- Industry employment shares from *QCEW* and *ACS*
- State level UI by industry from MA, NY, and WA state governments

Empirical Strategy

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- But we don't see evidence of delayed effects

Single-Policy Event Study

$$S_{it} = \sum_{\tau=-7}^{6} \gamma_\tau \times 1\{r = \tau\} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{1}$$

- S_{it}: Google search volume in state i and date t
- r: days relative to the date the policy was announced ($r = 0$)
- α_i: state FE
- α_t: calendar date FE
- γ_τ: coefficient of interest, differential increase in search volume relative to $r = -1$ on relative day τ
- Normalize $\gamma_{\tau=-1} = 0$
- Bin periods before and after into $\tau = -7$ and $\tau = 6$.
- Cluster standard errors at the state level

Multiple-Policy Event Study

$$S_{it} = \sum_{p \in \mathcal{P}} \sum_{\tau=-7}^{6} \eta_{p,\tau} \times 1\{r(p) = \tau\} + \alpha_i + \alpha_t + \nu_{it} \tag{2}$$

- S_{it}: Google search volume in state i and date t,
- $\mathcal{P}$: set of included policies
- $r(p)$: days relative to the date that policy p was announced $(r = 0)$
- α_i: state FE
- α_t: calendar date FE
- $\eta_{p,\tau}$: coefficient of interest, differential increase in search volume for policy p relative to $r(p) = -1)$ on relative day τ, controlling for the time-varying effects of the other policies in $\mathcal{P}$
- Normalize $\eta_{p,\tau=-1} = 0$ for all policies p
- Bin periods before and after into $\tau = -7$ and $\tau = 6$.
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Alternative Approach: Difference-in-Differences

Compare early and late states (based on first NPI in state)

$$S_{it} = \alpha + \delta \times 1\{\text{Early Adopter}\} \times 1\{\text{Post}\} + \beta \times 1\{\text{Early Adopter}\} + \xi_t + \mu_{it}, \quad (3)$$

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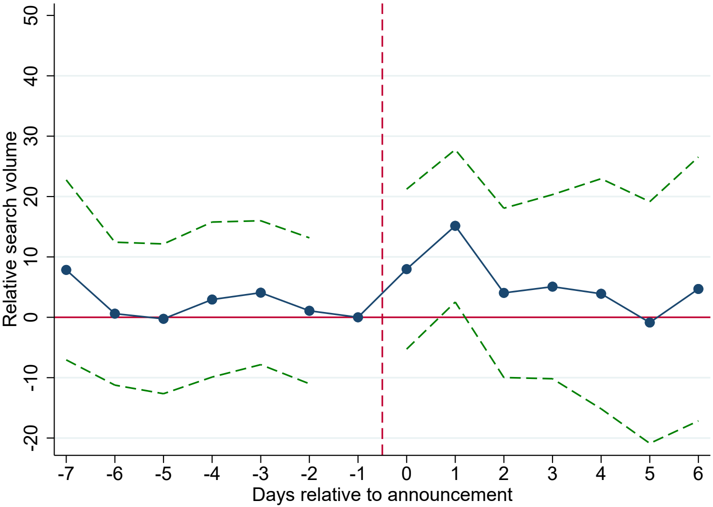
- Case study of food services industry

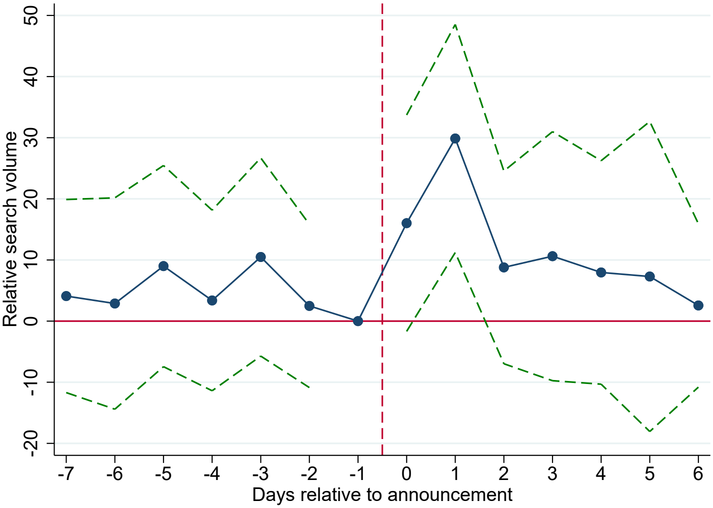
Results

Event Study: Restaurant and Bar Limitations



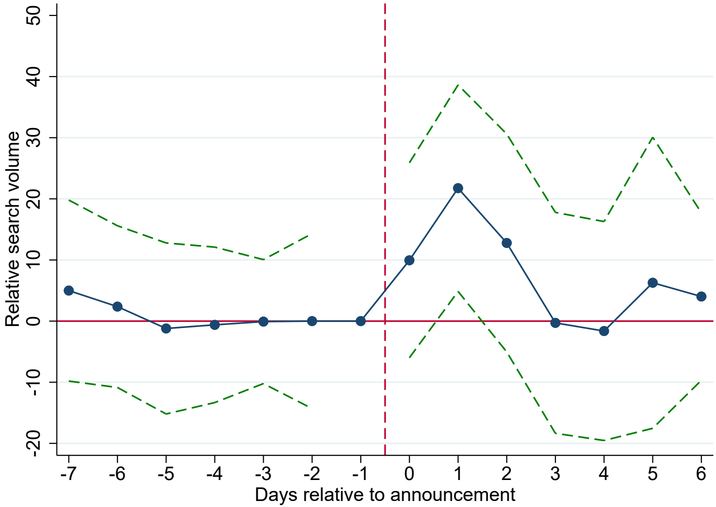
▸ Alternative Specifications

Event Study: Non-Essential Business Closures



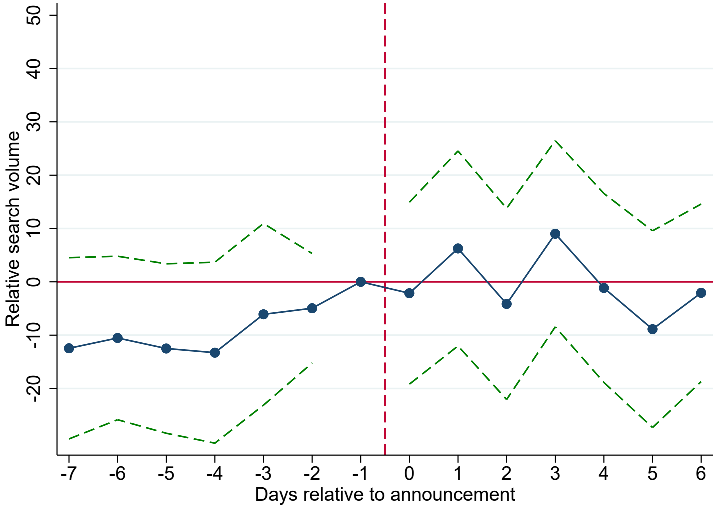
Alternative Specifications

Event Study: Stay-at-Home Orders



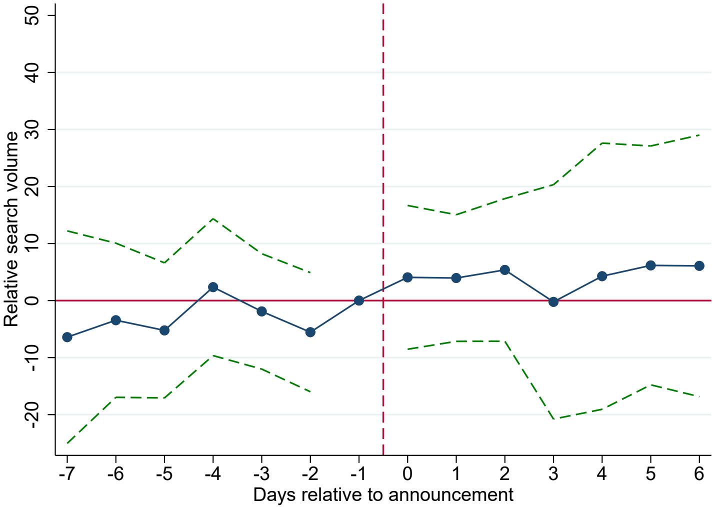
Alternative Specifications

Event Study: Large-Gatherings Bans



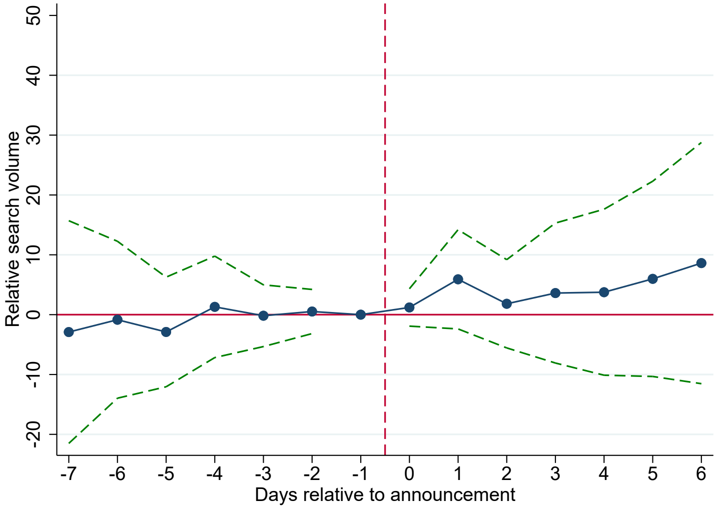
▸ Alternative Specifications

Event Study: School Closures



Alternative Specifications

Event Study: Public Health Emergencies



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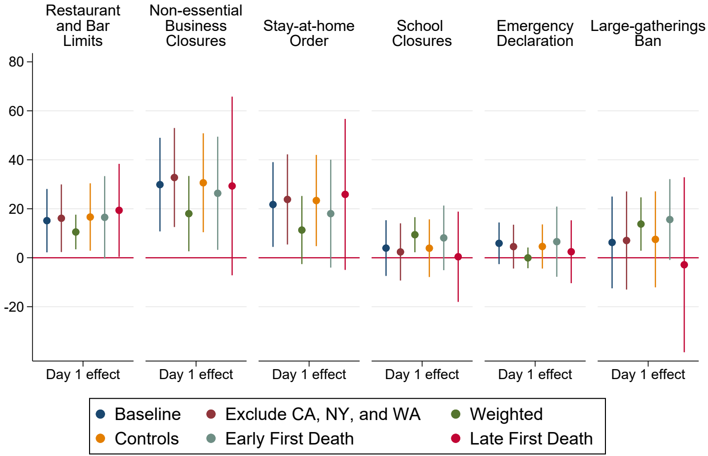
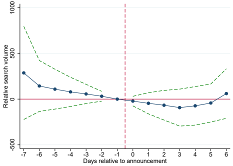
Robustness: Alternative Specifications



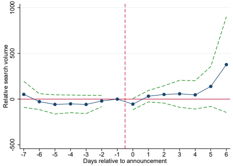
Event Studies: Restaurant Limitation
Event Studies: Business Closure
Event Studies: Stay Home
Event Studies: Gatherings Ban
Event Studies: School Closure
Event Studies: Health Emergency

Robustness: Epidemiological Outcomes

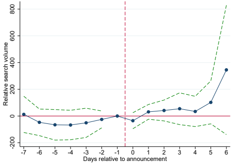
Case Growth



(a) Restaurant Limitations

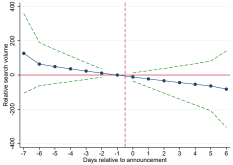


(b) Non-Essential Business Closures

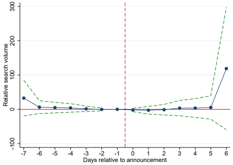


(c) Stay-at-Home Orders

Deaths



(d) Restaurant Limitations



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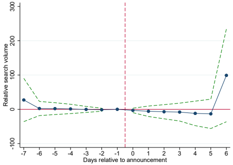
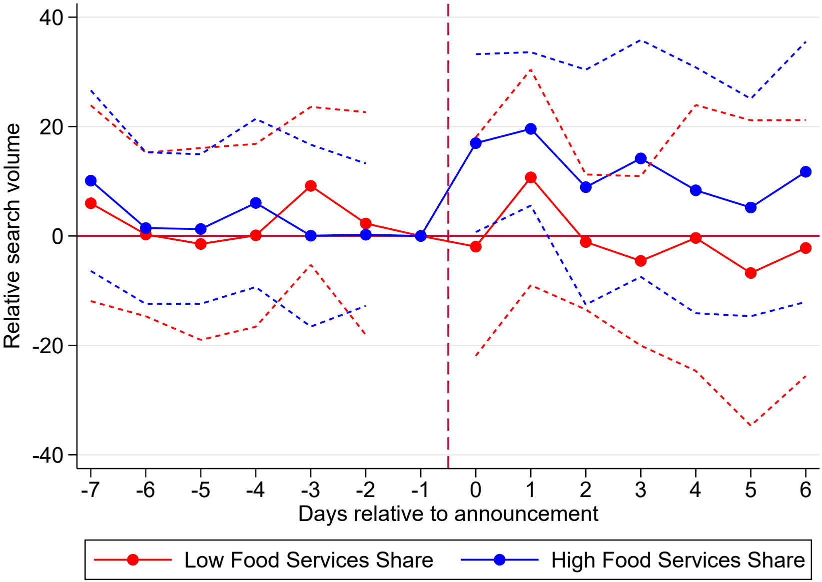
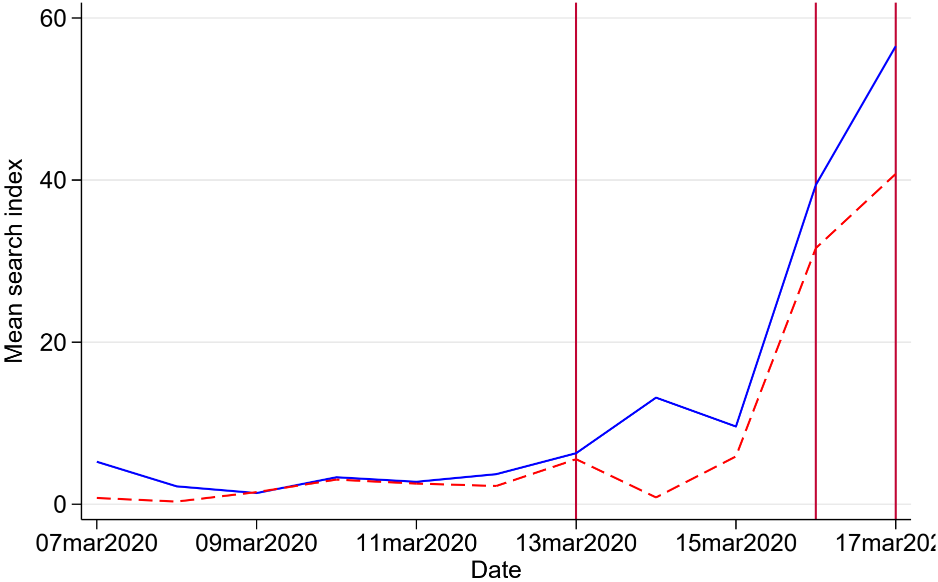


(f) Stay-at-Home Orders

Case Study: Food Servies



Difference-in-Differences



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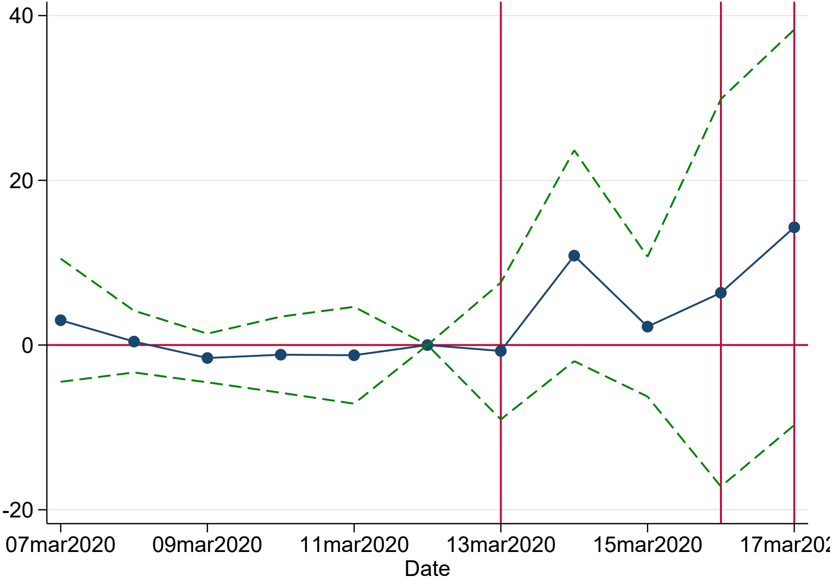

Estimating Policy Effects

Estimating Policy Effects with Proxy Outcomes

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  - Directly tests relevance of the proxy S
- Drawbacks:
  - Requires data on U sometimes not available

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- Benefits:
  - Requires minimal data on the outcome variable U
- Drawbacks:
  - Requires defining and estimating $\mathcal{P}$ (but can define p of interest and everything else)
  - Relevance of proxy is not directly tested

Application to UI Claiming

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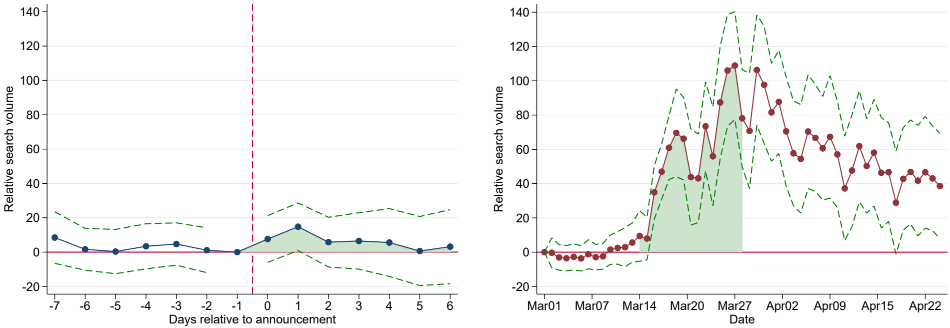
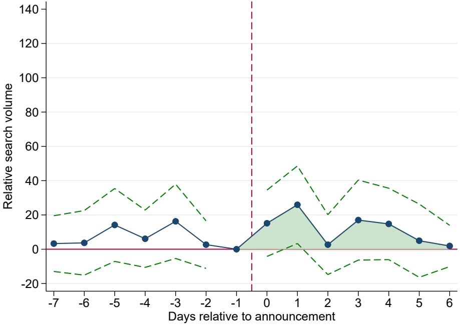
- Assume all increase in UI from March 14-28 is due directly to NPIs or other pandemic effects
- Compare integral under event study estimates to integral under overall time trend:

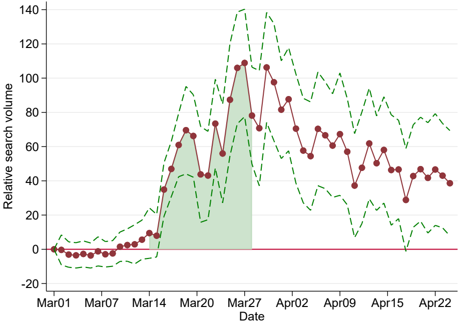
$$\text{Share of UI claims caused by NPI} = \frac{I_{NPI}}{I_{NPI} + I_{\alpha,t1,t2}} \tag{5}$$

Quantitative UI Estimates: Restaurant and Bar Limitations

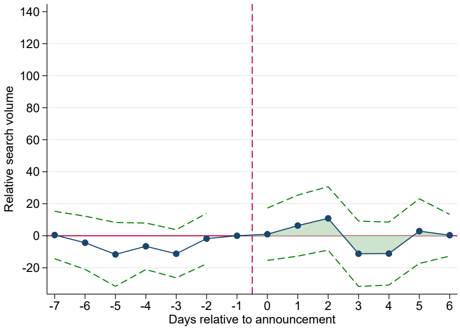


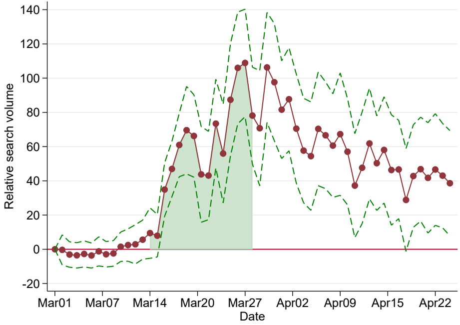
Quantitative UI Estimates: Non-Essential Business Closures





Quantitative UI Estimates: Stay-at-Home Orders





Quantitative UI Estimates: Stay-at-Home Orders

Between March 14 and 28, share of total UI claims due to

- restaurant limitations: 4.3%
- non-essential business closures: 8.4%
- stay-at-home orders: 0%

Discussion

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- Overall small share of UI claims direct consequence of NPIs

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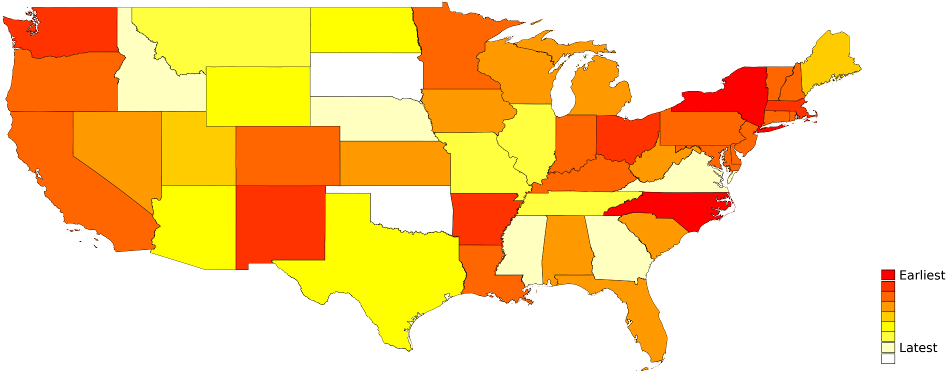
- Some NPIs don't directly increase UI claims but could slow spread of virus

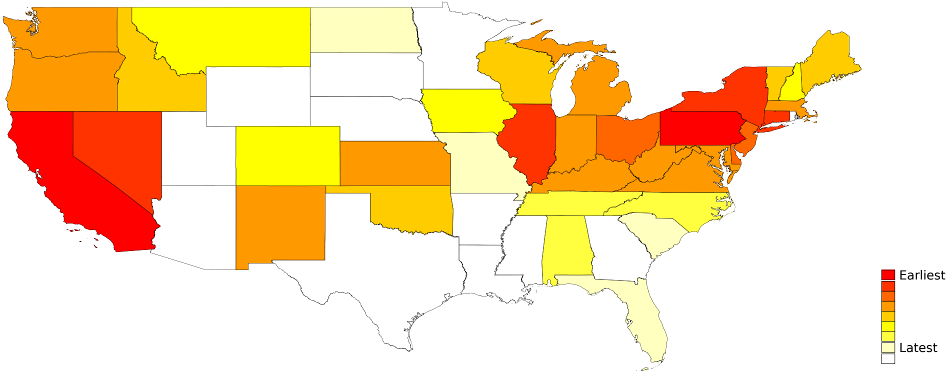
Thank You!

Geographic Distribution of NPI Adoption: Restaurant and Bar Limitations



◂ NPI Correlations ◂ NPI Timing Data

Geographic Distribution of NPI Adoption: Non-Essential Business Closures



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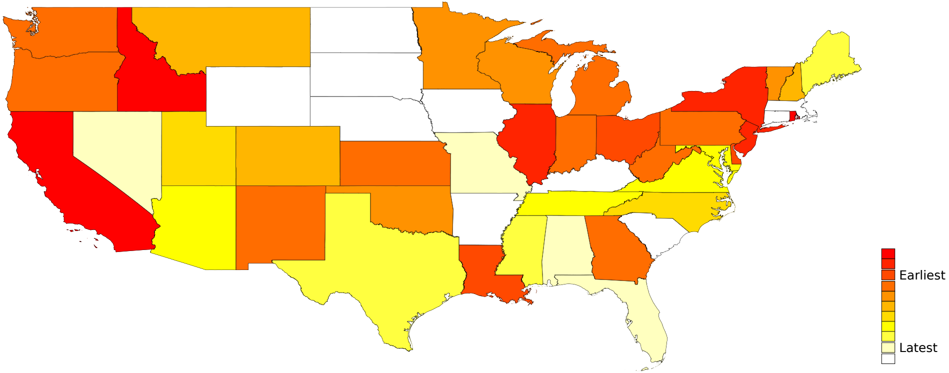

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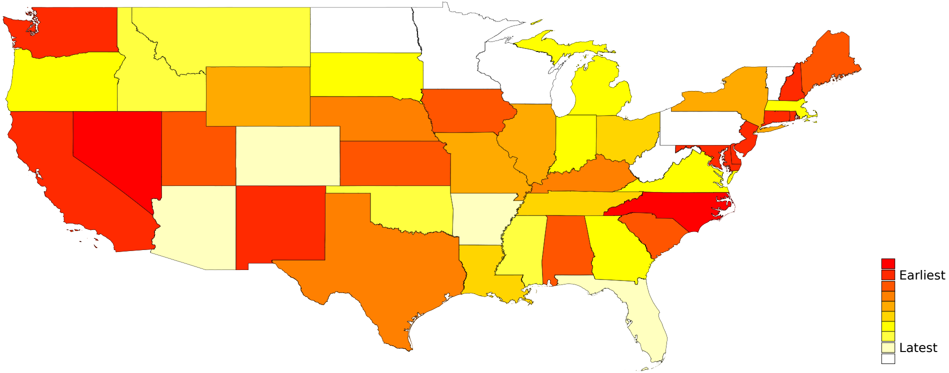
Geographic Distribution of NPI Adoption: Large-Gatherings Bans



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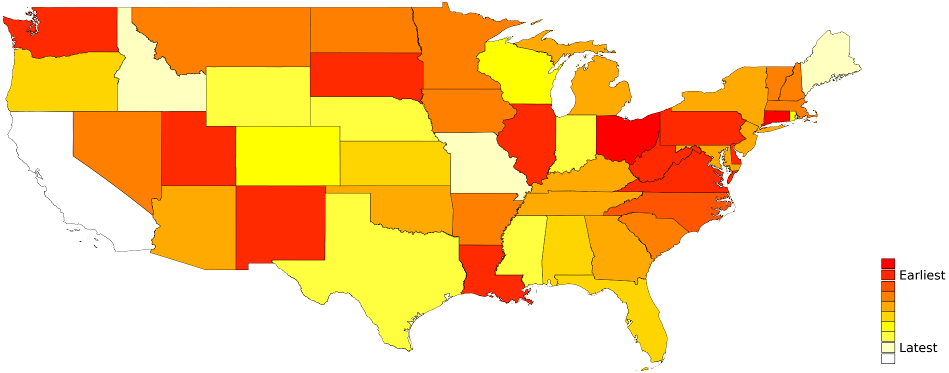
Geographic Distribution of NPI Adoption: School Closures



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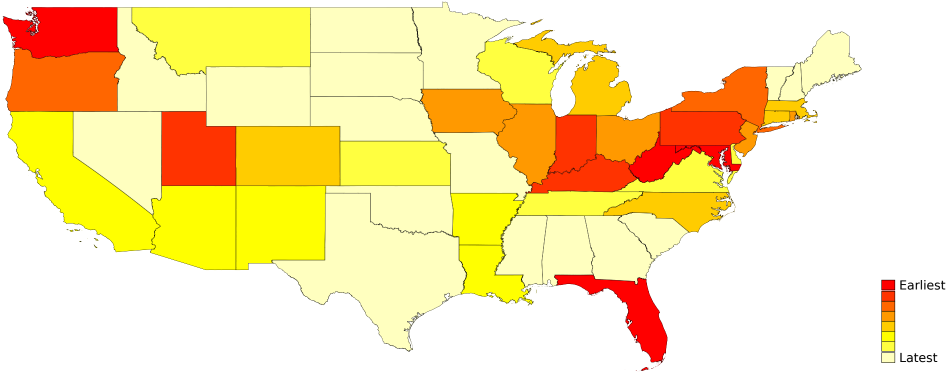
Geographic Distribution of NPI Adoption: Public Health Emegencies



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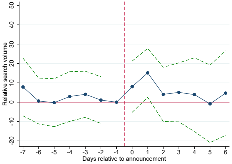
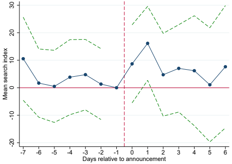
Robustness: Restaurant and Bar Limitations



(a) Main Specification



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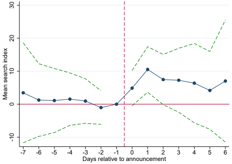

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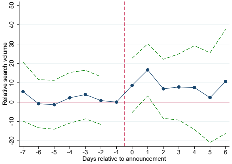

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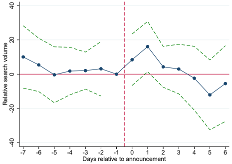
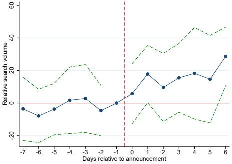


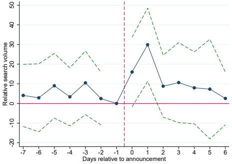
(e) Early First Death



(f) Late First Death

◂ Main Estimate ◂ Robustness Summary

Robustness: Non-Essential Business Closures



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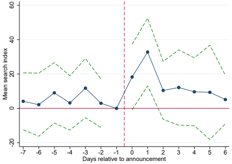

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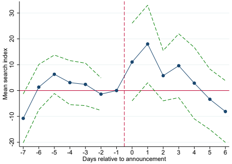

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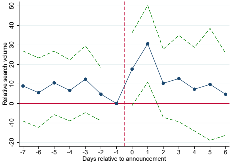

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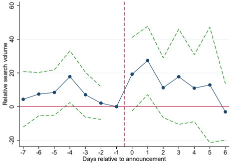

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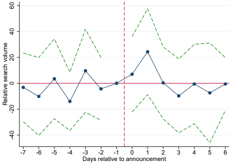

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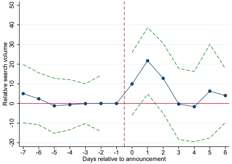

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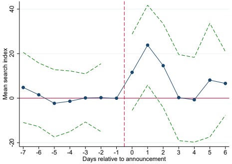

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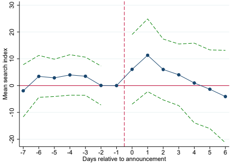

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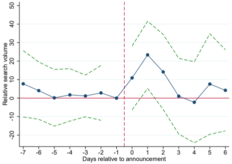

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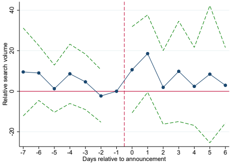

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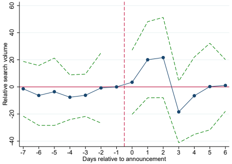

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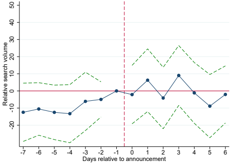

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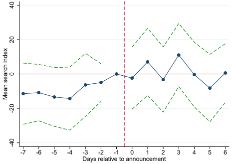

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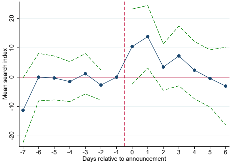

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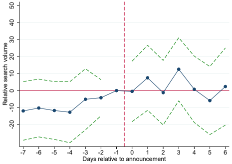

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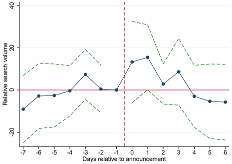

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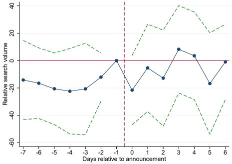

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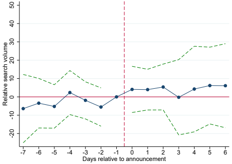
Main Estimate Robustness Summary

Robustness: School Closures



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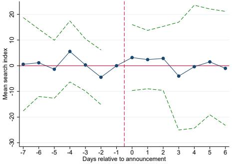

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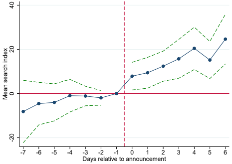

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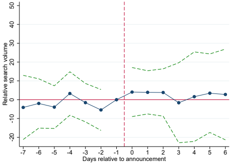

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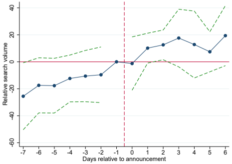

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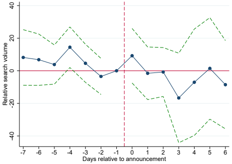

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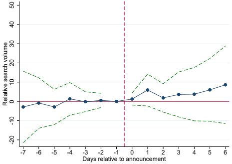
◂ Main Estimate ◂ Robustness Summary

Robustness: Public Health Emergencies



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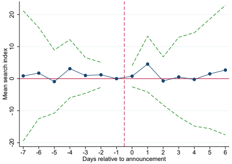

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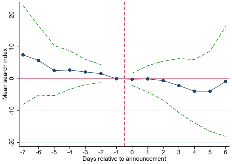

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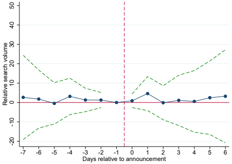

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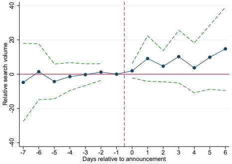

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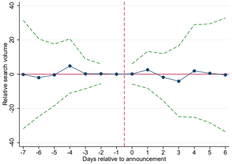

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