The Impact of Shutdown Policies on Unemployment During a Pandemic

Ed Kong
Daniel Prinz

May 2020
JOB LOSSES SOAR; U.S. VIRUS CASES TOP WORLD

New Data Shows Staggering Toll of Outbreak

Under Trump, Unfilled Posts Hinder Action

Online Class With No Way To Get There

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

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

Weekly unemployment data

New York, Friday, March 27, 2020

$3.00
In March 2020...
In March 2020...

- COVID-19 cases and deaths took off
In March 2020...

- COVID-19 cases and deaths took off
- States announced NPIs
In March 2020...

- COVID-19 cases and deaths took off
- States announced NPIs
- UI claiming skyrocketed
Impact of NPIs on UI?

Want to disentangle effects of NPIs from other things happening.

Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?

Use high-frequency Google search data.

Use KFF database on NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, public health emergency.

State-day variation in NPIs.

Translate search volumes into estimates of UI claiming.

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.
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
- Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
- Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?
- Use high-frequency Google search data
Want to disentangle effects of NPIs from other things happening

Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?

Use high-frequency Google search data

Use KFF database on NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, public health emergency
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
- Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?
- Use high-frequency Google search data
- Use KFF database on NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, public health emergency
- State-day variation in NPIs
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
- Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?
- Use high-frequency Google search data
- Use KFF database on NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, public health emergency
- State-day variation in NPIs
- Translate search volumes into estimates of UI claiming
  - Framework: unemployment expectations
Impact of NPIs on UI?

- Want to disentangle effects of NPIs from other things happening
- Fiscal externality matters for policy: what NPIs reduce virus spread without much externality?
- Use high-frequency Google search data
- Use KFF database on NPIs: restaurant and bar limitations, non-essential business closures, stay-at-home orders, large-gatherings bans, school closures, public health emergency
- State-day variation in NPIs
- Translate search volumes into estimates of UI claiming
  - 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
   ▶ Broader literature on economic activity: Lewis et al. (2020), Baker et al. (2020b), Bartik et al. (2020b), Hassan et al. (2020), Baker et al. (2020a)
Background
COVID-19 Pandemic in the U.S.
COVID-19 Pandemic in the U.S.

- Spread to U.S. January 2020
- Highly infectious: $R_0 = 2.2 - 2.7$ (or higher)
- Symptoms: fever, cough, shortness of breath, difficulty breathing, chills, muscle pain, headache, sore throat, and new loss of taste or smell
- 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.
COVID-19 Pandemic in the U.S.

- Coronavirus disease 2019 (COVID-19): infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
- Spread to U.S. January 2020

1.19 million cases and 68,551 deaths have been reported in the U.S.
COVID-19 Pandemic in the U.S.

- Coronavirus disease 2019 (COVID-19): infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
- Spread to U.S. January 2020
- Highly infectious: $R_0 = 2.2-2.7$ (or higher)
COVID-19 Pandemic in the U.S.

- Coronavirus disease 2019 (COVID-19): infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
- Spread to U.S. January 2020
- Highly infectious: $R_0=2.2-2.7$ (or higher)
- Symptoms: fever, cough, shortness of breath, difficulty breathing, chills, muscle pain, headache, sore throat, and new loss of taste or smell
COVID-19 Pandemic in the U.S.

- Coronavirus disease 2019 (COVID-19): infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
- Spread to U.S. January 2020
- Highly infectious: $R_0 = 2.2 - 2.7$ (or higher)
- Symptoms: fever, cough, shortness of breath, difficulty breathing, chills, muscle pain, headache, sore throat, and new loss of taste or smell
- Can cause wide spectrum of disease: mild illness, moderate and severe pneumonia, respiratory failure, and death
COVID-19 Pandemic in the U.S.

- Coronavirus disease 2019 (COVID-19): infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
- Spread to U.S. January 2020
- Highly infectious: $R_0=2.2-2.7$ (or higher)
- Symptoms: fever, cough, shortness of breath, difficulty breathing, chills, muscle pain, headache, sore throat, and new loss of taste or smell
- 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.
Non-Pharmaceutical Interventions

Currently no vaccine or specific treatment exists for COVID-19

U.S. states and cities have adopted NPIs

We study six:

- Restaurant and bar limitations
- Non-essential business closures
- Stay-at-home orders
- Large-gatherings bans
- School closures
- Emergency declarations

There is significant policy and timing variation across states
Non-Pharmaceutical Interventions

- Currently no vaccine or specific treatment exists for COVID-19
Non-Pharmaceutical Interventions

- Currently no vaccine or specific treatment exists for COVID-19
- U.S. states and cities have adopted NPIs
Non-Pharmaceutical Interventions

- Currently no vaccine or specific treatment exists for COVID-19
- U.S. states and cities have adopted NPIs
- We study six:
  - Restaurant and bar limitations
  - Non-essential business closures
  - Stay-at-home orders
  - Large-gatherings bans
  - School closures
  - Emergency declarations

There is significant policy and timing variation across states
Non-Pharmaceutical Interventions

- Currently no vaccine or specific treatment exists for COVID-19
- U.S. states and cities have adopted NPIs
- We study six:
  - Restaurant and bar limitations
  - Non-essential business closures
  - Stay-at-home orders
  - Large-gatherings bans
  - School closures
  - Emergency declarations

There is significant policy and timing variation across states
Data
Google Search Data
Google Search Data

- Google Trends releases data on search volumes
Google Search Data

- Google Trends releases data on search volumes
- Search term: “file for unemployment”
Google Search Data

- Google Trends releases data on search volumes
- Search term: “file for unemployment”
- Published search volumes are relative, we normalize to highest point in California
Google Search Data

- Google Trends releases data on search volumes
- Search term: “file for unemployment”
- Published search volumes are relative, we normalize to highest point in California
- 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

Restaurants and Bars Limits

Mar08  Mar22  missing

Non-essential Business Closures

Mar08  Mar22  missing

Stay-at-home Order

Mar08  Mar22  missing

Large Gatherings Ban

Mar08  Mar22  missing

School Closures

Mar08  Mar22  missing

Emergency Declaration

Mar08  Mar22  missing

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

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

Map: Gatherings Ban  Map: School Closure  Map: Health Emergency
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
Firms and workers internalize the effects of NPIs on their future employment prospects. Firms make layoff decisions based on how NPIs affect future conditions. 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020). Implies workers change Google search behavior immediately in response to the NPI. Concern: under- or over-reaction to NPI policies. Only a problem if bias is different compared to other causes of search volume. Still a problem if NPIs cause future layoffs and these are not internalized, and other searches are caused by actual layoffs. But we don’t see evidence of delayed effects.
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects *future* conditions
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects future conditions
  - 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)

Concern: under- or over-reaction to NPI policies
- Only a problem if bias is different compared to other causes of search volume
- Still a problem if NPIs cause future layoffs and these are not internalized, and other searches are caused by actual layoffs
- But we don’t see evidence of delayed effects
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects *future* conditions
  - 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)
- Implies workers change Google search behavior immediately in response to the NPI
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects future conditions
  - 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)
- Implies workers change Google search behavior immediately in response to the NPI
- Concern: under- or over-reaction to NPI policies
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects *future* conditions
  - 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)
- Implies workers change Google search behavior immediately in response to the NPI
- Concern: under- or over-reaction to NPI policies
- Only a problem if bias is different compared to other causes of search volume
Firms and workers internalize the effects of NPIs on their future employment prospects.

Firms make layoff decisions based on how NPI affects future conditions:
- 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)

Implies workers change Google search behavior immediately in response to the NPI.

Concern: under- or over-reaction to NPI policies.

Only a problem if bias is different compared to other causes of search volume.

Still a problem if NPIs cause future layoffs and these are not internalized, and other searches are caused by actual layoffs.
Conceptual model

- Firms and workers internalize the effects of NPIs on their future employment prospects
- Firms make layoff decisions based on how NPI affects future conditions
  - 72% of small businesses expect to re-open in December 2020 if the pandemic lasts 1 month, 47% if 4 months (Bartik et al., 2020b)
- Implies workers change Google search behavior immediately in response to the NPI
- Concern: under- or over-reaction to NPI policies
- Only a problem if bias is different compared to other causes of search volume
- Still a problem if NPIs cause future layoffs and these are not internalized, and other searches are caused by actual layoffs
- But we don’t see evidence of delayed effects
Single-Policy Event Study

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

- **\( S_{it} \):** Google search volume in state \( i \) and date \( t \)
- **\( r \):** days relative to the date the policy was announced (\( r = 0 \))
- **\( \alpha_i \):** state FE
- **\( \alpha_t \):** calendar date FE
- **\( \gamma_{\tau} \):** coefficient of interest, differential increase in search volume relative to \( r = -1 \) on relative day \( \tau \)
- 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

\[ S_{it} = \sum_{p \in \mathcal{P}} \sum_{\tau=6}^{6} \eta_{p,\tau} \times 1 \{ r(p) = \tau \} + \alpha_i + \alpha_t + \nu_{it} \]  

- \( S_{it} \): 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 \( (r = 0) \)
- \( \alpha_i \): state FE
- \( \alpha_t \): 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 \( \tau \), 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 \( \tau = 6 \).
- Cluster standard errors at the state level
Alternative Approach: Difference-in-Differences

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

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

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of deaths
- Divide into early and late first death states
- Show not related to epidemiological events (case growth, deaths)
- Difference-in-differences comparing early vs late adopters
- Case study of food services industry
Robustness

- Exclude CA, WA, NY
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of death
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of death
- Divide into early and late first death states
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of death
- Divide into early and late first death states
- Show not related to epidemiological events (case growth, deaths)
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of death
- Divide into early and late first death states
- Show not related to epidemiological events (case growth, deaths)
- Difference-in-differences comparing early vs late adopters
Robustness

- Exclude CA, WA, NY
- Weight states by total employment
- Control for case growth and number of death
- Divide into early and late first death states
- Show not related to epidemiological events (case growth, deaths)
- Difference-in-differences comparing early vs late adopters
- 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
Event Study: Public Health Emergencies

Relative search volume

Days relative to announcement

Alternative Specifications
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

(d) Restaurant Limitations
(e) Non-Essential Business Closures
(f) Stay-at-Home Orders
Case Study: Food Services

Days relative to announcement

Low Food Services Share

High Food Services Share
Difference-in-Differences

<table>
<thead>
<tr>
<th>Date</th>
<th>Early closures</th>
<th>Late/no closures</th>
</tr>
</thead>
<tbody>
<tr>
<td>07mar2020</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>09mar2020</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>11mar2020</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>13mar2020</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>15mar2020</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>17mar2020</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Mean search index

Graph showing the comparison of early closures and late/no closures from 07 March 2020 to 17 March 2020.
Alternative Approach: Difference-in-Differences
Estimating Policy Effects
Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Typical process:

- Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_U, \theta_S$.
- Estimate causal effect $\gamma_p$ of policy $p$ on $S$.
- Feed $\hat{\gamma}_p$ through estimated relationship $\hat{\theta}_U, \hat{\theta}_S$.

Benefits:
- Works for any set of policies
- Works for any relationship between $U$ and $S$
- Directly tests relevance of the proxy $S$

Drawbacks:
- Requires data on $U$ sometimes not available
Estimating Policy Effects with Proxy Outcomes

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Typical process:

1. Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_{U,S}$.
Estimating Policy Effects with Proxy Outcomes

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Typical process:
1. Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_{U,S}$.
2. Estimate causal effect $\gamma_p$ of policy $p$ on $S$.

Benefits:
- Works for any set of policies
- Works for any relationship between $U$ and $S$
- Directly tests relevance of the proxy $S$

Drawbacks:
- Requires data on $U$ sometimes not available
Estimating Policy Effects with Proxy Outcomes

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Typical process:

1. Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_{U,S}$.
2. Estimate causal effect $\gamma_p$ of policy $p$ on $S$.
3. Feed $\hat{\gamma}_p$ through estimated relationship $\hat{\theta}_{U,S}$.

Benefits:

- Works for any set of policies
- Works for any relationship between $U$ and $S$
- Directly tests relevance of the proxy $S$

Drawbacks:

- Requires data on $U$ sometimes not available
Estimating Policy Effects with Proxy Outcomes

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Typical process:
1. Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_{U,S}$.
2. Estimate causal effect $\gamma_p$ of policy $p$ on $S$
3. Feed $\hat{\gamma}_p$ through estimated relationship $\hat{\theta}_{U,S}$

Benefits:
- Works for any set of policies
- Works for any relationship between $U$ and $S$
- Directly tests relevance of the proxy $S$
Estimating Policy Effects with Proxy Outcomes

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

▶ Typical process:
  1. Estimate relationship between outcome of interest $U$ and proxy $S$, parameterized by $\theta_{U,S}$.
  2. Estimate causal effect $\gamma_p$ of policy $p$ on $S$.
  3. Feed $\hat{\gamma}_p$ through estimated relationship $\hat{\theta}_{U,S}$.

▶ Benefits:
  ▶ Works for any set of policies
  ▶ Works for any relationship between $U$ and $S$
  ▶ Directly tests relevance of the proxy $S$

▶ Drawbacks:
  ▶ Requires data on $U$ sometimes not available
Approach we use

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

▶ Our approach

1. Assume a function such that $F(S)$ is proportional to $U$
2. Assume we can estimate $\gamma_p$ for a set of policies $P$ that fully accounts for $U$
3. Multiply $\tilde{U}$ by Share of $\tilde{U}$ caused by NPI = $\hat{\gamma}_p \sum_{k \in P} \hat{\gamma}_k$ (4)

Benefits:

▶ Requires minimal data on the outcome variable $U$

Drawbacks:

▶ Requires defining and estimating $P$ (but can define $p$ of interest and everything else)
▶ Relevance of proxy is not directly tested
Approach we use

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

- Our approach
  1. Assume a function such that $F(S)$ is proportional to $U$
Approach we use

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

▶ Our approach

1. Assume a function such that $F(S)$ is proportional to $U$
2. Assume we can estimate $\gamma_p$ for a set of policies $\mathcal{P}$ that fully accounts for $U$

▶ 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
Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Our approach

1. Assume a function such that $F(S)$ is proportional to $U$
2. Assume we can estimate $\gamma_p$ for a set of policies $\mathcal{P}$ that fully accounts for $U$
3. Multiply $\tilde{U}$ by

$$\text{Share of } \tilde{U} \text{ caused by NPI} = \frac{\hat{\gamma}_p}{\sum_{k \in \mathcal{P}} \hat{\gamma}_k}$$

(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)
Approach we use

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

Our approach

1. Assume a function such that $F(S)$ is proportional to $U$
2. Assume we can estimate $\gamma_p$ for a set of policies $P$ that fully accounts for $U$
3. Multiply $\tilde{U}$ by

$$\text{Share of } \tilde{U} \text{ caused by NPI} = \frac{\hat{\gamma}_p}{\sum_{k \in P} \hat{\gamma}_k}$$

(4)

Benefits:

- Requires minimal data on the outcome variable $U$
Approach we use

Goal: estimate causal effect $\beta_p$ of policy on the overall change in $U$ over time (call this $\tilde{U}$, known) using proxy $S$.

- **Our approach**
  1. Assume a function such that $F(S)$ is proportional to $U$
  2. Assume we can estimate $\gamma_p$ for a set of policies $P$ that fully accounts for $U$
  3. Multiply $\tilde{U}$ by
     \[
     \text{Share of } \tilde{U} \text{ caused by NPI} = \frac{\hat{\gamma}_p}{\sum_{k \in P} \hat{\gamma}_k} \quad (4)
     \]

- **Benefits:**
  - Requires minimal data on the outcome variable $U$

- **Drawbacks:**
  - Requires defining and estimating $P$ (but can define $p$ of interest and everything else)
  - Relevance of proxy is not directly tested
Application to UI Claiming

Assume UI claims proportional to search volume (area under curve)

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:

\[
\text{Share of UI claims caused by NPI} = \frac{\int_{t_1}^{t_2} I_{\text{NPI}} \, dt}{\int_{t_1}^{t_2} I_{\alpha} \, dt}
\]
Application to UI Claiming

- Assume UI claims proportional to search volume (area under curve)
Application to UI Claiming

- Assume UI claims proportional to search volume (area under curve)
- Assume all increase in UI from March 14-28 is due directly to NPIs or other pandemic effects
Application to UI Claiming

- Assume UI claims proportional to search volume (area under curve)
- 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:

$$\text{Share of UI claims caused by NPI} = \frac{I_{NPI}}{I_{NPI} + I_{\alpha,t1,t2}}$$  \hspace{1cm} (5)
Quantitative UI Estimates: Non-Essential Business Closures

[Graph showing relative search volume over days relative to announcement date, with a peak around March 27 and a decline thereafter.]

[Graph showing the progression of events with dates from March 1 to April 22, marked with significant days such as Mar01, Mar07, Mar14, Mar20, Mar27, Apr02, Apr09, Apr15, Apr22.]
Quantitative UI Estimates: Stay-at-Home Orders

Diagram showing relative search volume over days relative to announcement and dates.
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

Overall small share of UI claims direct consequence of NPIs

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

- Overall small share of UI claims direct consequence of NPIs
Discussion

- Overall small share of UI claims direct consequence of NPIs
- 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
Geographic Distribution of NPI Adoption: Large-Gatherings Bans
Geographic Distribution of NPI Adoption: Public Health Emergencies

- **Earliest**
- **Latest**

NPI Correlations

NPI Timing Data
Robustness: Restaurant and Bar Limitations

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted
(d) Controls
(e) Early First Death
(f) Late First Death
Robustness: Non-Essential Business Closures

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted
(d) Controls
(e) Early First Death
(f) Late First Death
Robustness: Stay-at-Home Orders

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted
(d) Controls
(e) Early First Death
(f) Late First Death
Robustness: Large-Gatherings Bans

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted

(d) Controls
(e) Early First Death
(f) Late First Death
Robustness: School Closures

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted

(d) Controls
(e) Early First Death
(f) Late First Death
Robustness: Public Health Emergencies

(a) Main Specification
(b) Exclude CA, NY, and WA
(c) Weighted

(d) Controls
(e) Early First Death
(f) Late First Death