The Impact of COVID-19 on Small Business Activity: Real-Time Estimates With Homebase Data

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- BLS and Census data by industry & estab size is published only with considerable delay and only at annual or quarterly frequency.

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- Match Homebase records with info on business activity from **Google**, **Facebook**, and **Safegraph** to distinguish openings & closings from other entry & exits (sample churn)
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  - benchmark to pre-pandemic official data from QCEW and BED / BDS
  - estimate small business employment *taking into account* business openings and closings
- Exploit high-frequency nature of data to estimate effects of Paycheck Protection Program (PPP) and Pandemic Unemployment Compensation (PUC) on small business activity.

Homebase data, matching, and estimation

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- **Novelty of our work:** Use Homebase establishment name & lat-lon/address to
  1. Match to **Safegraph** Places of Interest (POIs)

     $\Rightarrow$ NAICS industry codes

     $\Rightarrow$ weekly visits to businesses from cell phone pings
  2. Match to **Google Places** and **Facebook (CrowdTangle)**

     $\Rightarrow$ infer closing and new openings from Google closed tag and Facebook posting history

Matching Sample Open/Close

Benchmarking and estimation

- **Benchmarking:**
  - HB establishments may have different propensity to be closings / openings than in population
  - adjust opening and closing rates so as to fit pre-pandemic BED/BDS birth and death rates

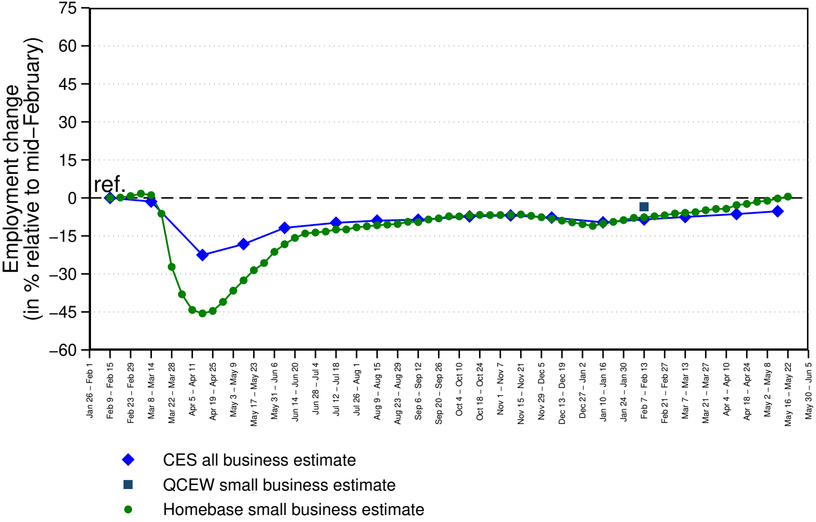
▸ Benchmarking to BED/BDS

- **Estimation:**
  - build weekly estimate of small business employment for each of the four service sectors
  - uses weights to make estimates representative of QCEW
  - similar to CES estimator but directly takes into account openings and closings

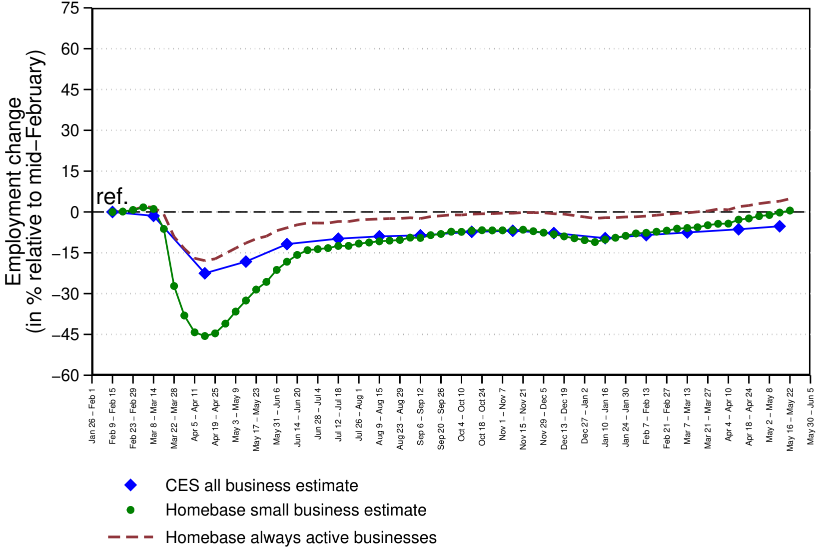
  $\Rightarrow$close fit of resulting HB small biz employment estimates with QCEW counterparts for 2019

▸ Estimator ▸ 2019 QCEW comparison

#1: Larger initial decline and stronger recovery of small biz employment



#2: Distinguishing closings & openings from other exits & entry is key



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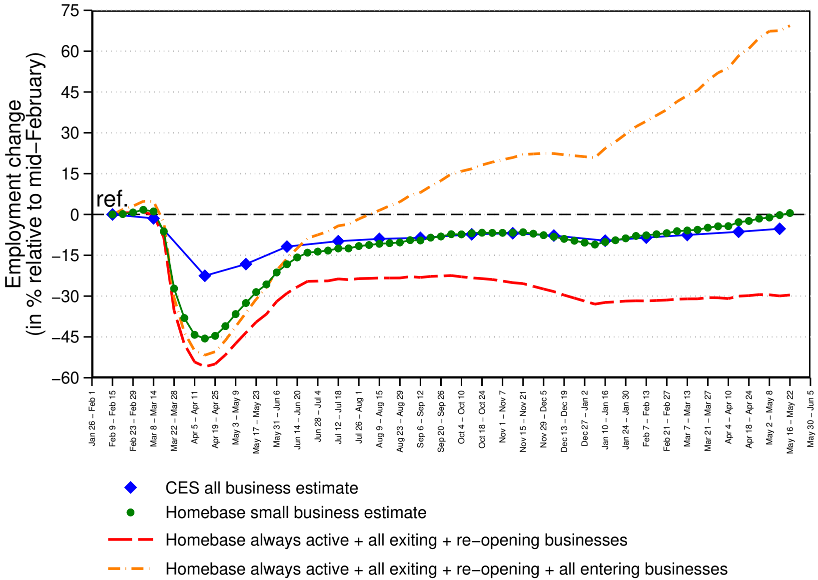
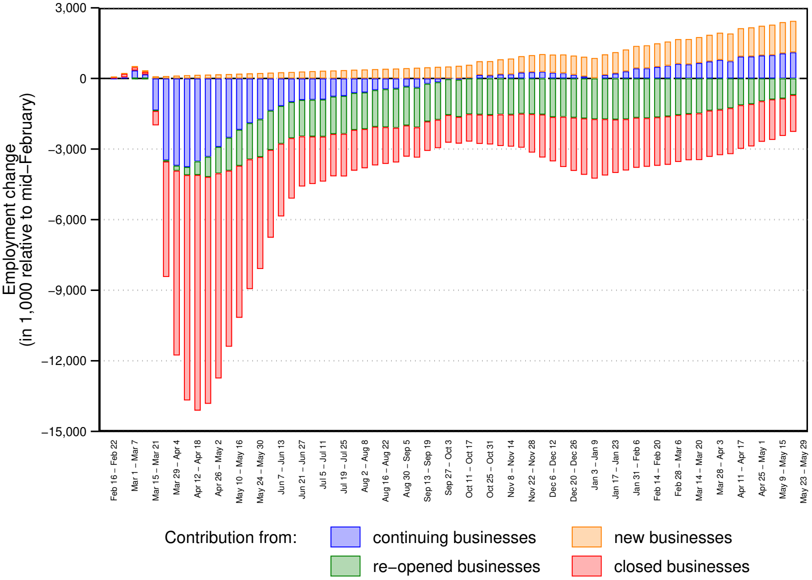
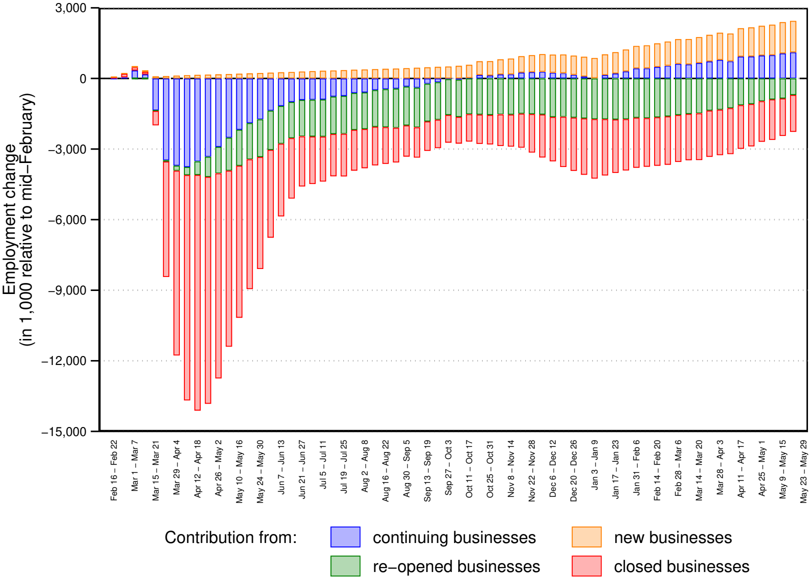


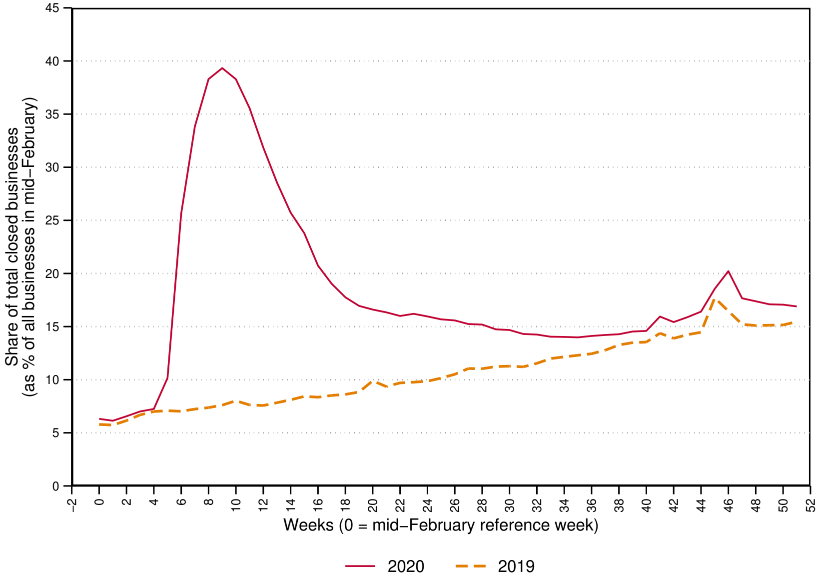
#3: Closings drive initial contraction and subsequent rebound...



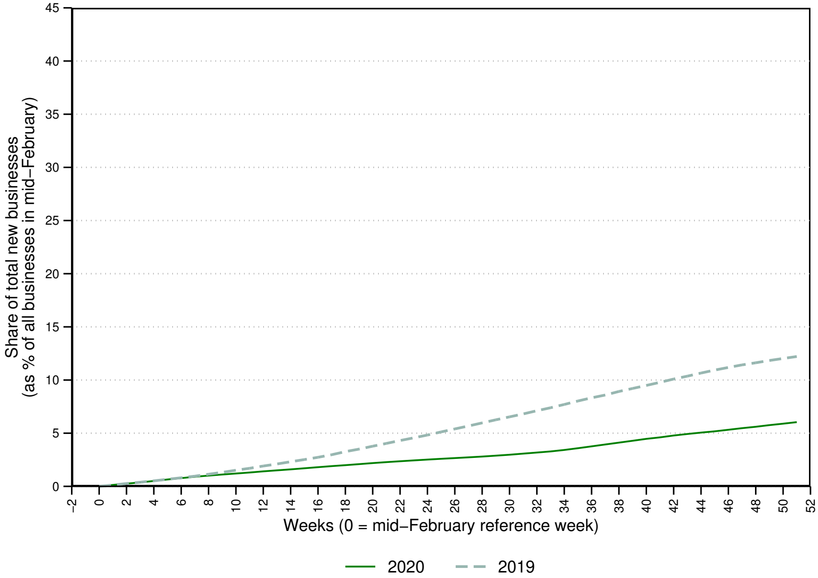
...new openings & job gains by continuing businesses drive recovery



Cumulative closings after 1 year are similar to pre-pandemic



Cumulative new openings after 1 year are about 50% of pre-pandemic



Additional results

- Average weekly hours fell only briefly in beginning of pandemic and then fully recovered.

▸ Avg weekly hours

- Businesses primarily recalled previous workers to ramp employment back up – new hiring rates from June 2020 onward are similar to one year earlier.

▸ Hiring and recalls

- Excess turnover rates from June 2020 onward are similar to one year earlier.

▸ Excess turnover

#4: Using data to assess effect of Federal pandemic response

- Two prominent policies of 2020 CARES Act that likely affected small businesses:

  (1) Paycheck Protection Program (PPP): loans to businesses with < 500 employees

  (2) Pandemic Unemployment Comp (PUC): $600 of additional weekly UI

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- **Exploit local variations in timing and extent of PPP and PUC**

  $\Rightarrow$ high-frequency / detailed geography data, including on closings and openings, is key

Paycheck Protection Program (PPP)

- \$669 billion in **conditionally forgivable loans to businesses** with $<$ 500 employees
  - First round: \$349 billion; started on April 3 and exhausted on April 16, 2020
  - Second round: \$320 billion authorized on April 24 and started on April 27, 2020
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- Similar to Doniger and Kay (2021), measure difficulty in obtaining PPP loan by share of loans in beginning of second round relative to loans just before exhaustion of first round

$$sharePPPdelayed_c = \frac{(loans\,April\,26 - May\,2)_c}{(loans\,April\,12 - May\,2)_c}$$

County-level regression for PPP loan delay

- Regress county c – week t outcome on county c share of delayed PPP loans

$$y_{c,t} = \sum_{t=1}^{57} \beta_t \left[1(week = t) \times sharePPPdelayed_c \right] + \mathbf{X}'_{\mathbf{c,t}} \gamma + \phi_t + \mu_c + \varepsilon_{c,t}$$

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  - county Covid case & death rates, NPIs, change in school visits, max temperature
  - county average household income interacted with weekly fixed effect

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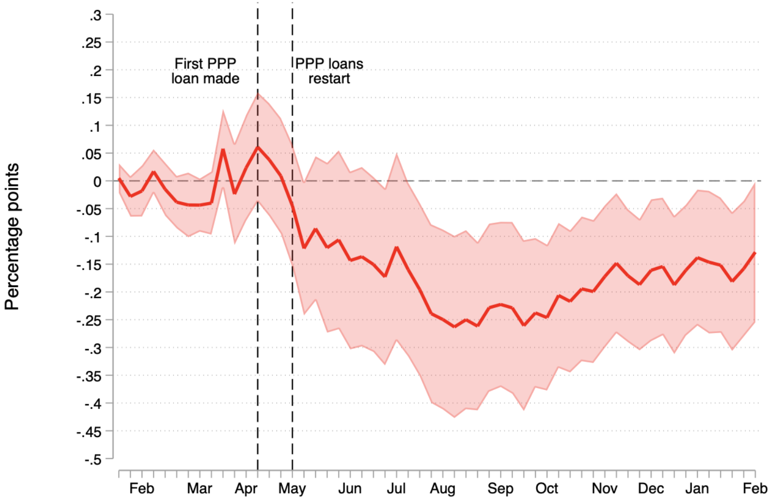
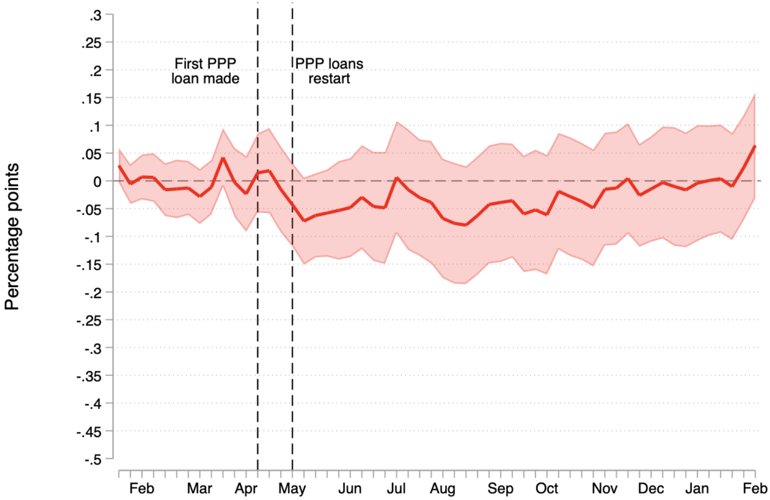
- Controls
  - county Covid case & death rates, NPIs, change in school visits, max temperature
  - county average household income interacted with weekly fixed effect
- Identifiying assumption: $E[sharePPPdelayed_c, \varepsilon_{c,t} | \mathbf{X}_{c,t}, t, c] = 0$
  - $sharePPPdelayed_c$ exogenous to changes in business behavior during pandemic
  - $sharePPPdelayed_c$ not correlated with other omitted local differences

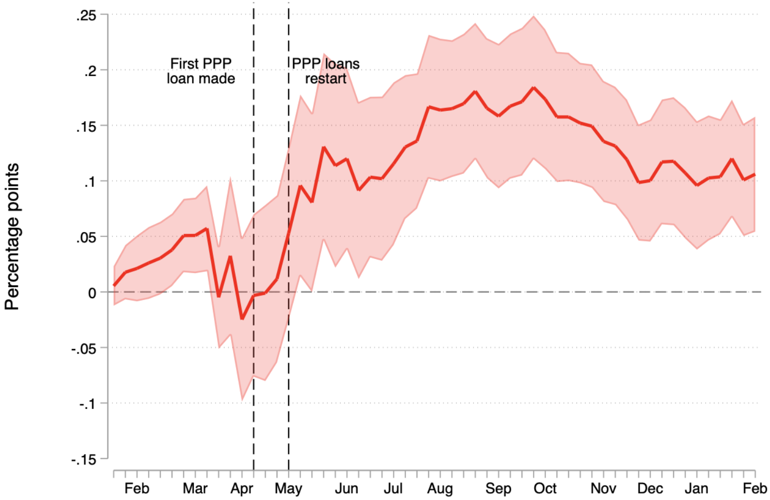
Counties with more PPP delays experience lower small biz employment



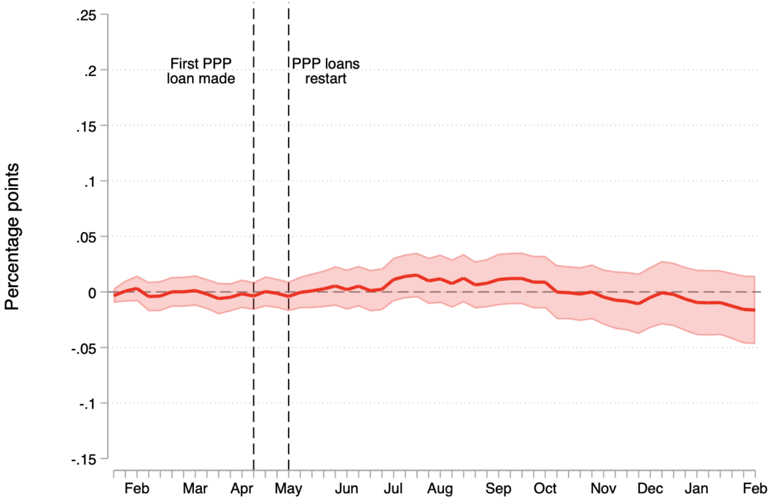
Effect on continuously active businesses is modest



Most of the effect comes from permanent closings



PPP delays did not affect new openings



Pandemic Unemployment Compensation (PUC)

- \$600 of additional weekly UI benefits from April through end of July 2020
  - increased median replacement rate to 145%, with UI $>$ pre-pandemic earnings for 2/3 of likely recipients (Ganong et al., 2020)
  - no discernible disincentive effects (e.g. Dubé, 2021; Finamor and Scott, 2021; Marinescu et al, 2021) but large consumer spending effects (Ganong et al., 2021)

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- We exploit (wide) dispersion of \$600 PUC relative to pre-pandemic earnings across counties, using similar research design as for PPP loan delay.
- **Main result:** counties where PUC is **more** generous relative to pre-pandemic earnings experience **stronger** recovery of small business activity
  - business closings (smaller) & new openings (larger) play important role
  - suggests that stimulative effect of PUC in slack local labor markets dwarfed possible disincentive effects

▸ FPUC results

Conclusion

- **Novelty:** Estimate small business employment *taking into account* closings / openings.

  $\Rightarrow$ distinguishing closings / openings from sample churn matters importantly

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- **Key results:**

  1. Small businesses have recovered larger share of lost jobs than larger businesses.
  2. Closings and openings are main driver of results.
  3. PPP and PUC significantly mitigated negative effects of pandemic.

Appendix

Literature measuring employment impact of COVID-19

- **Studies using Homebase:** Bartik et al. (2020), Dvorkin and Bharadwaj (2020), Finamor and Scott (2021), Granja et al. (2020)...
- **Studies using other real-time data:** Bick and Blandin (2020), Cajner et al. (2020), Chetty et al. (2020), Coibon et al. (2020), Dalton et al. (2020), Kahn et al. (2020)...
- **Studies on business closings and new openings:** Crane et al. (2020), Cajner et al. (2020), Dalton et al. (2020), Haltiwanger et al (2020), ...
- **Studies estimating employment impact of PPP and UI benefits:** Bartik et al. (2020), Chetty et al. (2020), Doniger and Kay (2020), Dube (2021), Finamor and Scott (2021), Ganong et al. (2021), Granja et al. (2020), Marinescu et al. (2021)...

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Matching with Safegraph

- Safegraph contains approx 6.5 million places of interest (POIs) where customers can spend time and money.
  - many in-person service businesses; e.g. restaurants, retail stores, and grocery stores are all examples of POIs
  - detailed geo-location, name, NAICS-6, visits derived from cell-phone devices
- Match HB establishment records by name, address / GPS coordinates to Safegraph POIs.
  - Clean up HB name and address data and match to Google Places for additional name info and GPS coordinates
  - Merge (exactly) by name and GPS coordinates and then name and address
  - Fuzzy match by name and address
- Keep only merges and high quality matches

Match statistics with Safegraph for 2020 sample

	Base sample		New entrants	
	#	%	#	%
Merge on name and GPS coordinates	25,565	50.9	8,468	32.1
Merge on name and address	1,899	3.8	851	3.2
Match on name and address	5,891	11.7	2,757	10.4
Merge on name and zip code	4,209	8.4	1,281	4.9
Merge on name and city	530	1.1	449	1.7
Merge on name and state	2,335	4.7	1,855	7.0
Match on name and zip code	1,299	2.6	975	3.7
Match on name and city	1,344	2.7	1,474	5.6
Match on name and state	6,278	12.5	7,387	28.0
Others	831	1.7	912	3.5
Total	50,181	100	26,409	100

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Comparison with Placekey match algorithm

Our algorithm		Placekey	
Match method	Matches	Matches	No Matches
Exact merge on name and either full address or lat/lon	28,036	26,676	1,360
Fuzzy match on name and either full address or lat/lon	5,943	5,581	362
Exact merge and fuzzy match on name and zip-code	4,159	3,988	276
Exact merge and fuzzy match on name + city	648	462	186
Exact merge and fuzzy match on name + state	11,100	4,915	6,185
Low quality match	827	351	476
Total	**50,818**	**41,973**	**8,845**

Back

Base sample, exits, and new entrants

	2019		2020	
Base sample	38,911	(100%)	50,250	(100%)
- active in mid-Feb	35,339	(91%)	46,317	(92%)
- temporarily inactive in mid-Feb	3,572	(9%)	3,933	(8%)
Exits without return	14,232	(37%)	17,662	(35%)
New entrants	25,997	(67%)	16,788	(33%)

NAICS industry codes

	# estab.	# workers
44-45 Retail trade	7,819	66,354
441- Motor Vehicle and Parts Dealers		
442- Furniture and Home Furnishings Stores		
443- Electronics and Appliance Stores		
444- Building Material and Garden Equipment and Supplies Dealers		
445- Food and Beverage Stores		
446- Health and Personal Care Stores		
447- Gasoline Stations		
448- Clothing and Clothing Accessories Stores		
451- Sporting Goods, Hobby, Musical Instrument, and Book Stores		
452- General Merchandise Stores		
453- Miscellaneous Store Retailers		
61-62 Education and Health Services	5,362	54,167
611- Educational Services		
621- Ambulatory Health Care Services		
622- Hospitals		
623- Nursing and Residential Care Facilities		
624- Social Assistance		
71-72 Leisure & Hospitality	28,093	344,730
711- Performing Arts, Spectator Sports, and Related Industries		
712- Museums, Historical Sites, and Similar Institutions		
713- Amusement, Gambling, and Recreation Industries		
721- Accommodation		
722- Food Services and Drinking Places		
81 Other Services	3,877	30,239
811- Repair and Maintenance		
812- Personal and Laundry Services		
813- Religious, Grantmaking, Civic, Professional, and Similar Organizations		
Total	46,305	495,488

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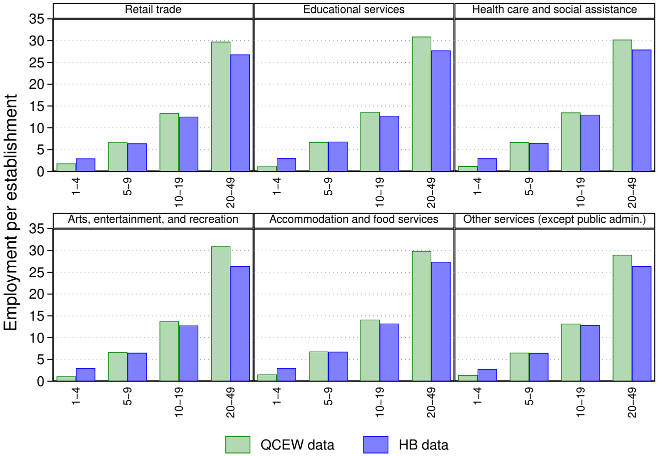
Geographical distribution of HB and QCEW establishments

	2019			2020		
	HB base sample		QCEW small estab.	HB base sample		QCEW small estab.
	#	%	%	#	%	%
Alaska, Hawaii, Oregon, Washington	2,056	5.4	4.9	2,623	5.2	4.9
California	6,226	16.3	21.5	8,068	16.1	21.7
Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming	3,292	8.6	6.1	4,341	8.7	6.2
Iowa, Kansas, Minnesota, Missouri, North Dakota, Nebraska, South Dakota	2,363	6.2	6.5	3,152	6.3	6.5
Illinois, Indiana, Michigan, Ohio, Wisconsin	4,415	11.6	11.4	5,903	11.8	11.3
Texas	3,484	9.1	6.4	4,692	9.4	6.4
Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, Tennessee	2,914	7.6	7.6	3,957	7.9	7.6
Connecticut, Massachusetts, Maine, New Hampshire, Rhode Island, Vermont	1,239	3.2	5.7	1,636	3.3	5.6
New York	1,534	4.0	6.1	2,002	4.0	6.0
Pennsylvania, New Jersey, Delaware	2,071	5.4	6.5	2,604	5.2	6.5
District of Columbia, Maryland, Virginia	1,818	4.8	5.4	2,281	4.5	5.3
Georgia, North Carolina, South Carolina	3,502	9.2	6.0	4,589	9.1	6.1
Florida	3,287	8.6	5.9	4,333	8.6	5.9
Total	38,201	100	100	50,181	100	100

Back

Average employment by establishment size



Back

Estimating closings from Google & Facebook info

Locations $l \in i$ that exit HB in week t and return in week $t+n \Rightarrow l \in \mathrm{C}_{i,t}$

Estimating closings from Google & Facebook info

Locations $l \in i$ that exit HB in week t and return in week $t+n \Rightarrow l \in \mathrm{C}_{i,t}$

Locations $l \in i$ that exit HB in week t without return

1. If matched to **Google Places** and tagged "closed" $\Rightarrow l \in \mathrm{C}_{i,t}$
2. Else if matched to **CrowdTangle** with unique Facebook address and regular posts while active in HB
   - if regular posts stop after exit from HB $\Rightarrow l \in \mathrm{C}_{i,t}$
   - if regular posts continue after exit from HB $\Rightarrow l \notin \mathrm{C}_{i,t}$
3. Else, $l \in \mathrm{C}_{i,t}$ with probability equal to proportion of closings obtained in step 2
4. Adjust resulting $p(close|exit)$ such that for 2019, we fit BED death rate by sector-size

Estimating closings from Google and Facebook info

	2019		2020	
	#	%	#	%
Exiting locations that do not reopen	13,627	100	25,615	100
- Google closed	2,678	19.7	3,031	11.8
- Not Google-closed and matched to FB	396	2.91	2,532	9.88
- Estimated as closed from FB posts	108	0.79	811	3.17
% of exiting locations closed	41.6		40.1	

Estimating openings from Facebook info

Locations $l \in i$ that exited HB in week $t - n$ and return in week $t \Rightarrow l \in \mathrm{R}_{i,t} \subseteq \mathrm{O}_{i,t}$

Estimating openings from Facebook info

Locations $l \in i$ that exited HB in week $t-n$ and return in week $t \Rightarrow l \in \mathrm{R}_{i,t} \subseteq \mathrm{O}_{i,t}$

Locations $l \in i$ that enter HB in week t for the first time

1. If matched to **CrowdTangle** with unique Facebook address and regular posts while active in HB
   - if no posts prior to mid-Feb reference period $\Rightarrow l \in \mathrm{N}_{i,t} \subseteq \mathrm{O}_{i,t}$
   - if posts prior to mid-Feb reference period $\Rightarrow l \notin \mathrm{O}_{i,t}$
2. Else, $l \in \mathrm{N}_{i,t} \subseteq \mathrm{O}_{i,t}$ with probability equal to proportion of closings obtained in step 2
3. Adjust resulting $p(open|entry)$ such that for 2019, we fit BED birth rate by sector-size

Alternative Safegraph estimator Back

Benchmarking to official BLS / Census data

- Business Employment Dynamics (BED) = longitudinally linked estabs from QCEW
  - quarterly opening/closing and birth/death rates by industry but not size class
- Business Dynamics Statistics (BDS) = longitudinally linked estabs from Census BR
  - annual entry and exit rates by industry and size class but stops in 2018

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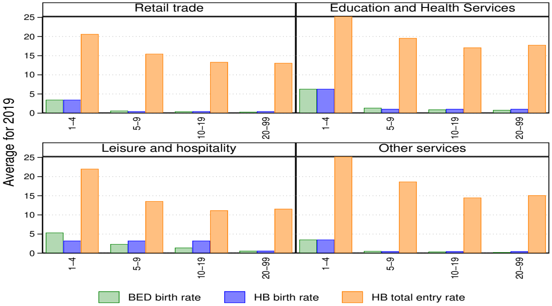
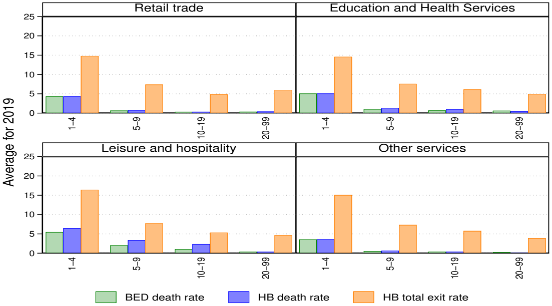
- Benchmarking:
  - combine BED and BDS to create quarterly birth & death rates by industry and size class
  - compute quarterly equivalents implied by HB data
  - adjust estimated closing and new opening probabilities for 2019 so as to fit BED birth and death rates

Benchmarking to BED / BDS birth and death rates



(a) Birth rates



(b) Death rates

Back

Estimating weekly employment

- Employment estimator for given sector

$$\widehat{E}_t = \widehat{E}_{t-1} \times \frac{\sum_i \omega_i \left(\hat{e}_{it}^{\mathrm{A}_{i,t}} + \hat{e}_{it}^{\mathrm{O}_{i,t}} \right)}{\sum_i \omega_i \left(\hat{e}_{it-1}^{\mathrm{A}_{i,t}} + \hat{e}_{it-1}^{\mathrm{C}_{i,t}} \right)}$$

  - $\hat{E}_0$ = CES estimate from mid-February 2020 (reference week)
  - ω_i = QCEW-HB sampling weight for industry-size-geography cell i
  - $\hat{e}_{it}^{\mathrm{A}_{i,t}}$ = employment of establishments $\mathrm{A}_{i,t}$ active in HB in both week t and $t-1$
  - $\hat{e}_{it}^{\mathrm{O}_{i,t}}$ = employment of establishments $\mathrm{O}_{i,t}$ newly opening or reopening in week t
  - $\hat{e}_{it-1}^{\mathrm{C}_{i,t}}$ = employment of establishments $\mathrm{C}_{i,t}$ closing temporarily or permanently in week t

Estimating weekly employment

- Employment estimator for given sector

$$\widehat{E}_t = \widehat{E}_{t-1} \times \frac{\sum_i \omega_i \left(\hat{e}_{it}^{\mathrm{A}_{i,t}} + \hat{e}_{it}^{\mathrm{O}_{i,t}} \right)}{\sum_i \omega_i \left(\hat{e}_{it-1}^{\mathrm{A}_{i,t}} + \hat{e}_{it-1}^{\mathrm{C}_{i,t}} \right)}$$

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  - $\hat{e}_{it-1}^{\mathrm{C}_{i,t}}$ = employment of establishments $\mathrm{C}_{i,t}$ closing temporarily or permanently in week t
- Similar to CES estimator except that we directly incorporate closings and openings

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Importance of adjusting for sample churn

t	0	1	2	3	
estab. A	6	5	7	8	in sample continuously
estab. B	4	3	$\cdots$	$\cdots$	in sample for $t = 0, 1$
estab. C	$\cdots$	5	8	9	in sample for $t = 1, 2, 3$
estab. D	10	2	0	0	closing in $t = 2$
estab. E	0	0	3	7	opening in $t = 2$

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Suppose that $\hat{E}_0 = 100$. Our employment estimator yields:

$$\hat{E}_1 = 100 \times \frac{5+3+2}{6+4+10} = 100 \times \frac{10}{20} = 50 \quad \ldots vs \;\; 100 \times \frac{5+3+5+2}{6+4+10} = 75 \;\; \textit{with sample churn}$$

$$\hat{E}_2 = 50 \times \frac{7+8+3}{5+5+2} = 50 \times \frac{18}{12} = 75 \quad \ldots vs \;\; 75 \times \frac{7+8+3}{5+3+5+2} = 90 \;\; \textit{with sample churn}$$

$$\hat{E}_3 = 75 \times \frac{8+9+7}{7+8+3} = 75 \times \frac{24}{18} = 100 \quad \ldots vs \;\; 75 \times \frac{8+9+7}{7+8+3} = 120 \;\; \textit{with sample churn}$$

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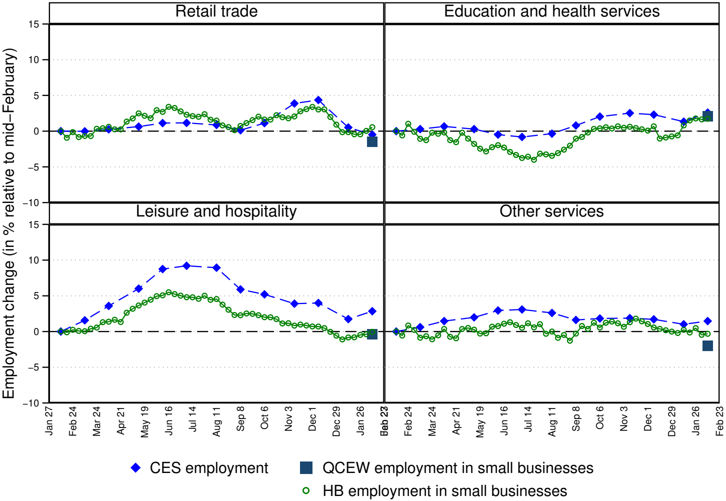
Comparison to 2019 CES estimates and QCEW



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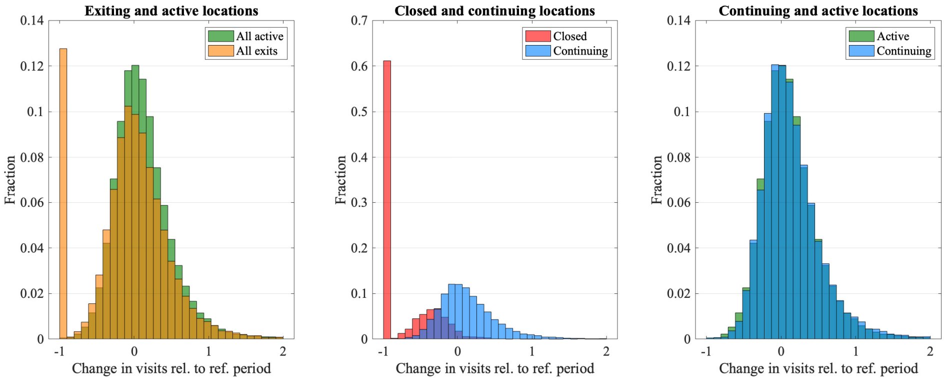
Alternative estimation approach with Safegraph data

- Estimate closings using changes in visits from Safegraph Weekly Patterns data
- Estimate new openings using appearance in Safegraph historical Core Places files

Alternative estimation approach with Safegraph data

- Estimate closings using changes in visits from Safegraph Weekly Patterns data
- Estimate new openings using appearance in Safegraph historical Core Places files
- Challenges:
  - For small businesses (especially in malls, multi-story buildings) visits data often very noisy
  - Safegraph Core Places updates not only due to birth / death but also improvements in algorithm, better data

Estimating closings from Safegraph visits



Example: Change in Safegraph visits distributions 2020-2021 in Leisure & Hospitality sector

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Estimating small business dynamics

Establishment closings, reopenings and new openings

$$rate(\mathrm{I}_t) = \frac{\sum_i \omega_i \hat{n}_{it}^{\mathrm{I}_{i,t}}}{\sum_i \omega_i \left(\hat{n}_{i0}^{\mathrm{A}_{i,1}} + \hat{n}_{i0}^{\mathrm{C}_{i,1}} \right)}$$

- $\hat{n}_{it}^{\mathrm{I}_{i,t}}$ = count of establishments in industry-size-geography cell i that
  - closed in week t ($\mathrm{I}_{i,t} = \mathrm{C}_{i,t}$),
  - or reopened in week t ($\mathrm{I}_{i,t} = \mathrm{R}_{i,t}$),
  - or newly opened in week t ($\mathrm{I}_{i,t} = \mathrm{N}_{i,t}$)
- $\hat{n}_{i0}^{\mathrm{A}_{i,1}} + \hat{n}_{i0}^{\mathrm{C}_{i,1}}$ = count of active establishments in mid-Feb reference week

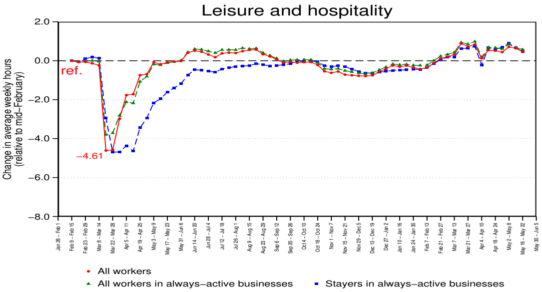
Average weekly hours

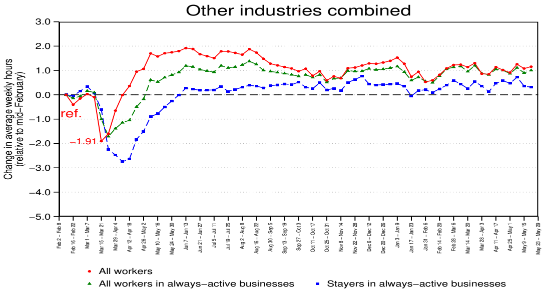
$$\widehat{AWH}_t = \widehat{AWH}_{t-1} \times \frac{\left(\sum_i \omega_i wh_{it}\right) / \left(\sum_i \omega_i e_{it}\right)}{\left(\sum_i \omega_i wh_{it-1}\right) / \left(\sum_i \omega_i e_{it-1}\right)}, \tag{1}$$

We construct estimates based on three different groups of workers:

1. All workers employed across all establishments in week t
2. All workers employed in establishments that have remained open continuously throughout the entire sample
3. Workers who remained employed continuously in establishments that have remained open continuously

Average weekly hours recovered quickly





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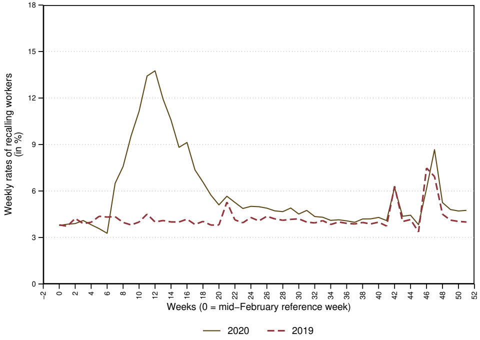
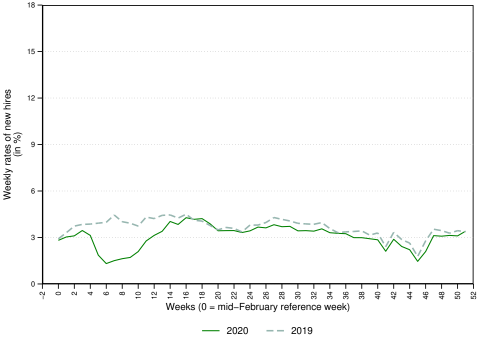
Businesses primarily recalled workers to ramp employment back up





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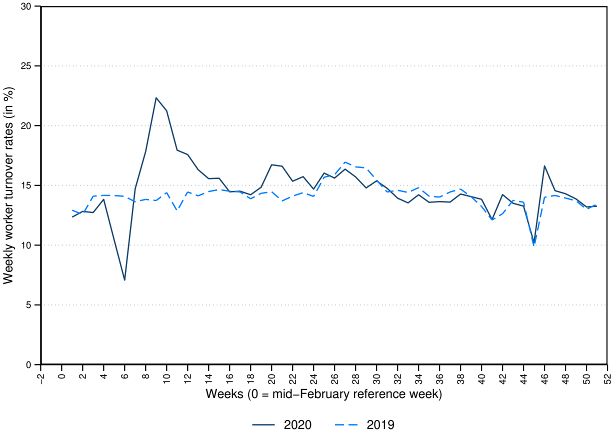
Excess turnover from June 2020 forward similar to one year earlier



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County-level regression for relative generosity of FPUC UI benefits

- Regress establishment (or county) i – week t outcome on county c generosity of PUC

$$y_{c,t} = \sum_{t=0}^{57} \beta_t \left[1(week = t) \times \triangle UIrate_c \right] + \mathbf{X}'_{\mathbf{c},\mathbf{t}} \gamma + \phi_t + \mu_c + \varepsilon_{c,t}$$

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- Identifiying assumption: $E[\triangle UIrate_c, \varepsilon_{c,t} | X_{i,t}, t, c] = 0$
  - $\triangle UIrate_c$ exogenous to changes in business behavior during pandemic
  - $\triangle UIrate_c$ does not account for other omitted local differences in impact of pandemic

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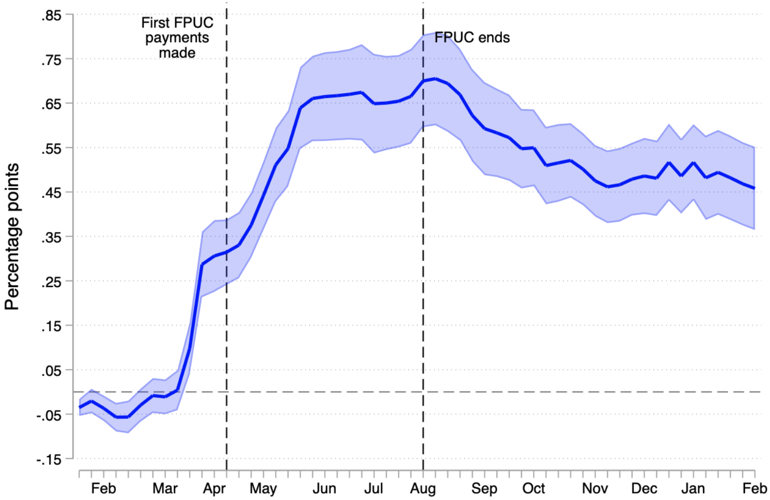
- Workers' earnings and therefore $\triangle UIrate_c$ may proxy for local affluence (e.g. urban vs rural) and therefore impact of pandemic (see Chetty et al., 2020).

PUC persistently increases small business employment



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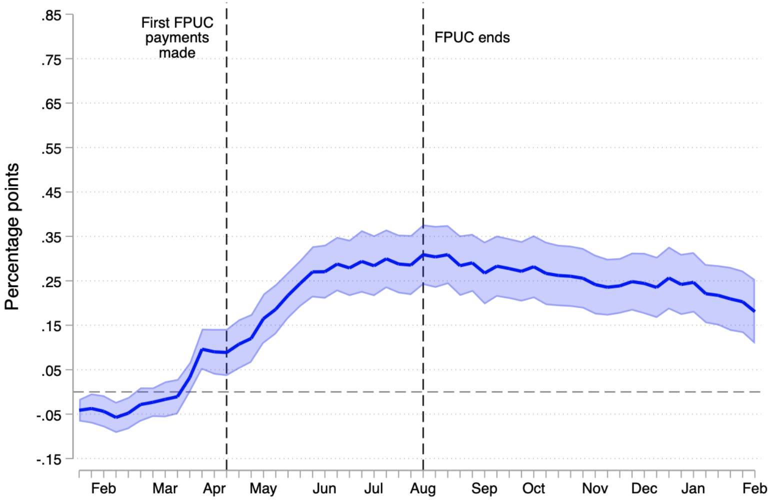
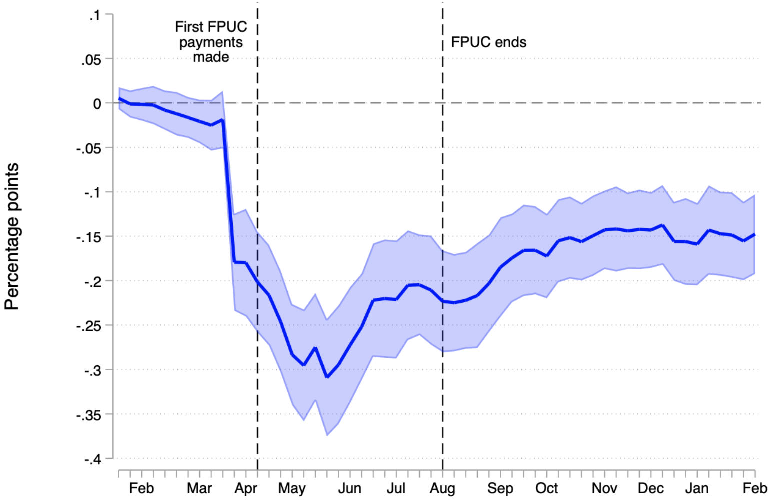
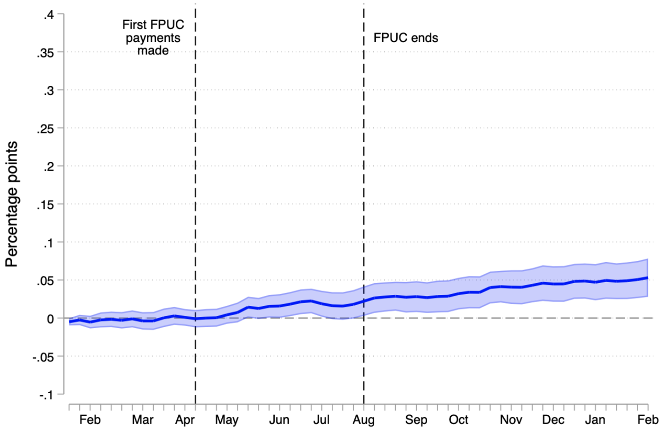


PUC accelerates return of temporarily closed businesses



PUC stimulates new openings



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