Vacancy Posting, Firm Balance Sheets, and Pandemic Policy Interventions

David Van Dijcke	University of Michigan
Marcus Buckmann	Bank of England
Arthur Turrell	Office for National Statistics
Tomas Key	Bank of England

Economic Statistics Centre of Excellence Annual Conference, May 27, 2022

The views expressed here do not necessarily represent those of the Bank of England or those of the Office for National Statistics. Data copyright Indeed.

Overview

Aim:

- Study the role of firm balance sheets in propagating economic and policy shocks to labour demand during COVID-19 pandemic in the UK

Method:

- Match high-frequency, firm-level job vacancy data to firm balance sheet data
- Exploit natural variation due to three policy interventions in 2020 to disentangle balance sheet channels:
  - Tier restrictions
  - Eat Out to Help Out scheme
  - Bounce Back Loan Scheme

Contribution:

- Find that less leveraged, more financially healthy firms increased vacancies more in response to positive demand and liquidity shocks
  - Complement to well-document results in corporate finance:
    1. Leveraged firms cut employment more in response to negative shocks (Sharpe, 1994; Giroud et al., 2012; Giroud and Mueller, 2017; Chodorow-Reich, 2014)
    2. Credit supply shocks can affect labour demand even in normal times (Aristizábal-Ramırez and Posso, 2021; Benmelech et al., 2021)

Main data sources

Vacancy data

- Largest job postings website in the UK
- $\sim$5.9 million vacancies in 2019, with $\sim$370 thousand manually entered firm names
- Active period, firm, and region of vacancy

Main data sources

Vacancy data

- Largest job postings website in the UK
- ∼5.9 million vacancies in 2019, with ∼370 thousand manually entered firm names
- Active period, firm, and region of vacancy

Balance-sheet data

- Annual balance sheet information for all registered UK companies
- Bias due to reporting requirements by firm size
- We use 2019 pre-pandemic balance sheets

Main data sources

Vacancy data

- Largest job postings website in the UK
- ∼5.9 million vacancies in 2019, with ∼370 thousand manually entered firm names
- Active period, firm, and region of vacancy

Balance-sheet data

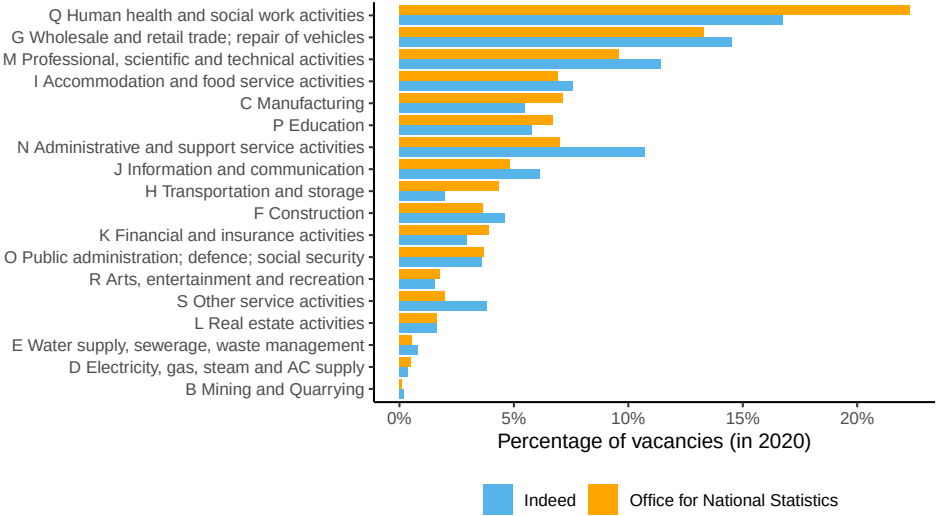
- Annual balance sheet information for all registered UK companies
- Bias due to reporting requirements by firm size
- We use 2019 pre-pandemic balance sheets

Matching

- Calculate similarity between Indeed and FAME names
- Match accuracy of 90% → recover 75.5% of vacancies and 73.1% of Indeed firms

Matching Approach

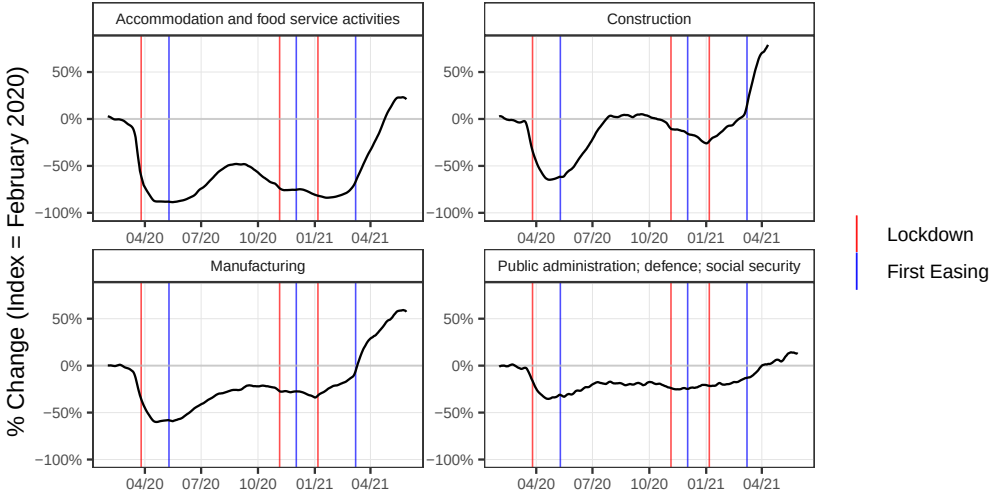
Matching details | Time series data | More validation



Empirical Strategy

- Trace out balance sheet propagation to vacancies:
  1. "Pandemic shock": firm-level regresssions (non-causal)
  2. Difference-in-differences designs (causal)
- Main outcome: log(1+vacancies) *online* at date t by firm-region
- Balanced panels of firms with at least one vacancy online in sample period
- Consider role of assets, cash, leverage, credit score

Pandemic Shock: Descriptives



Pandemic shock: Regression approach

- Pre- vs. post-WHO pandemic declaration on March 11, 2020
- Sample period March 1 2019, to May 10, 2020.

$$\ln(1 + v_{ijt}) = \alpha_{ij}^{U} \cdot D_{ij} + \alpha_{l(ij),t}^{T} \cdot D_{l(ij),m(t)} + \boldsymbol{\beta} \cdot \delta_t^{\text{WHO}} \cdot X_{ijt},$$

with v_{ijt} firm i's vacancy stock in NUTS2 j in week-year t; D_{ij} firm-NUTS2 FEs; $D_{l(ij),m(t)}$ flexible $l(i,j)$ (NUTS2 or SIC) by $m(t)$ (week-year or month-of-the-year) FEs; δ_t^{WHO} March 11 dummy; X_{ijt} firm-level controls.

Pandemic Shock

Takeaways:

- 30% decline in vacancies
- Strong interactions with balance sheets. More vacancy cuts for firms that ...
  - are larger
  - are more leveraged
  - are cash-strapped
  - have a lower credit score

Pandemic Shock

Takeaways:

- 30% decline in vacancies
- Strong interactions with balance sheets. More vacancy cuts for firms that ...
  - are larger
  - are more leveraged
  - are cash-strapped
  - have a lower credit score

→ Mix of supply and demand shocks → non-causal estimates

Policy interventions: Methodology

- Difference-in-differences (DiD) designs exploiting natural variation → causal estimates
- Deploy TWFE estimator and doubly-robust estimator that accommodates staggered treatment and non-parallel trends (Callaway et al., 2021)
- Consider role of assets, cash, leverage, credit score

Continuous DiD Doubly-robust estimator

Tier Restrictions

Policy:

- Local restrictions on movement and commerce
  - Period between Sep 20–Nov 22, 2020
  - Natural variation in *lockdown* due to staggered increase in restriction intensity (Sep 20 to Nov 22, 2020)

Tier 1	Meet six (indoors + outdoors) 10pm pub/restaurant curfew
Tier 2	No mixing indoors 10pm pub/restaurant curfew
Tier 3	Restaurants not serving food closed Guidance against leaving area
Tier 4	Stay-at-home order, meet one (outside) Retail and other venues close

Empirical strategy:

- Discretized treatment: being in Tier 2 or higher
- Controls: COVID cases & deaths in the area + firms' balance sheets

Tier Restrictions

Policy:

- Local restrictions on movement and commerce
  - Period between Sep 20–Nov 22, 2020
  - Natural variation in *lockdown* due to staggered increase in restriction intensity (Sep 20 to Nov 22, 2020)

Tier 1	Meet six (indoors + outdoors) 10pm pub/restaurant curfew
Tier 2	No mixing indoors 10pm pub/restaurant curfew
Tier 3	Restaurants not serving food closed Guidance against leaving area
Tier 4	Stay-at-home order, meet one (outside) Retail and other venues close

Empirical strategy:

- Discretized treatment: being in Tier 2 or higher
- Controls: COVID cases & deaths in the area + firms' balance sheets

$$\ln(1 + v_{ijt}) = \alpha_{ij} + \gamma_{k(ij),t} + \delta \cdot \text{Tier}_{jt} + \beta' \cdot X_{ijt} + \epsilon_{ijt}$$

.

Tier Restrictions

DV: Log(1+Vacancies):	
Doubly-robust estimator	
Post (Tier $\geq$ 2)	-0.1081***
	(0.0391)
Week $\times$ control:	
COVID-19	X
Pop. Density	X
Log(1+assets)	X
Leverage / assets	X
Cash / assets	X
Credit score	X

Clustered NUTS-2) standard-errors

Tier Restrictions

DV: Log(1+Vacancies):	
Doubly-robust estimator	
Post (Tier $\geq$ 2)	-0.1081***
	(0.0391)
Week $\times$ control:	
COVID-19	X
Pop. Density	X
Log(1+assets)	X
Leverage / assets	X
Cash / assets	X
Credit score	X

Clustered NUTS-2) standard-errors

Takeaways:

- $\sim$ 8-10% drop in vacancies based on doubly-robust estimates
- Little heterogeneity across firms
- Other support measures might have helped firms to withstand shock

Eat Out to Help Out Scheme (August 2020)

Policy:

- UK Treasury programme to support hospitality sector
- Subsidized 50% of meal or non-alcoholic drink (£10 cap) per customer
- Total subsidy of £849 million

Empirical strategy:

- Exploit granular variation in uptake of EOHO scheme across England (Fetzer, 2021)
- Treatment: Participating restaurants / meals claimed in area
- Firms with one trading address → local demand shock on local vacancies

$$\ln(1 + v_{jt}) = \alpha_j + \gamma_{l(j),t} + \delta \cdot \text{Post}_t \cdot \text{EOHO}_j + \beta' \cdot X_{jt} + \epsilon_{jt}$$

where EOHO_j captures EOHO exposure (# of restaurants / # of meals) in MSOA j.

Eat Out to Help Out Scheme

Effect on vacancy postings (log)		
EOHO exposure (in levels)		
Covered meals	0.0316***	
	(0.0066)	
Restaurants		0.0337***
		(0.0086)
EOHO exposure per capita (in log)		
Log(Covered meals p.c.)	0.0404***	
	(0.0056)	
Log(Restaurants p.c.)		0.0501***
		(0.0062)
Observations	88,283	88,283

Clustered (LAD) standard-errors in parentheses

Robustness No hospitality Event studies

Eat Out to Help Out Scheme

DV: Log(1+Vacancy Stock), interaction: dummies		
Treat	0.0504***	0.0532**
	(0.0151)	(0.0225)
Treat × Leverage/assets	-0.0388**	-0.0388**
Treat × Log(1+assets)		0.0091
		(0.0200)
Treat × Cash/assets		-0.0256
		(0.0180)
Treat × Credit score		0.0106
		(0.0102)
Mean(exp(DV)-1)	6.3127	6.3456
Observations	66,599	66,144
Additional controls	4,119	4,158
Clusters	316	316

Clustered (LAD) standard-errors in parentheses

Takeaways:

- Substantial increase in vacancies due to scheme (25-35K)
- Spillover effect: Vacancy boost even after excluding hospitality sector
- Weaker effect for leveraged firms
  - Connects to literature: higher employment cuts for leveraged firms in response to negative shocks (Giroud and Mueller, 2017)

Bounce Back Loan Scheme

Policy:

- 100% government-backed loans at no interest for 12 months, 2.5% after
- Cap of min{25% of turnover, £50,000}
- 42,772 firms that got BBLS loan could be matched to our FAME-Indeed firms

Empirical strategy:

- First three weeks of programme (May 2020): media reports that banks overwhelmed with applications:
  - Outages of application pages
  - Understaffing
- Treat date of loan disbursement as pseudo-randomly assigned

$$\ln(1 + v_{ijt}) = \alpha_i + \gamma_{l(i),)t} + \delta \cdot \text{Post}_{i,j,t} \cdot \text{Loan / Turnover}_i + \beta' \cdot X_{i,j,t} + \epsilon_{j,t},$$

Bounce Back Loan Scheme

Effect on vacancy postings (log)		:
Loan/turnover	0.0008	-0.0052*
	(0.0006)	(0.0029)
... × Credit score		0.0089***
		(0.0028)
... × Log(1+assets)		0.0007
		(0.0028)
... × Cash / assets		-0.0016
		(0.0025)
... × Leverage/assets		0.0018
		(0.0024)
Observations	1,390,413	686,103
Additional controls	5,810	5,963

Clustered (Firm in NUTS2 & Day) standard-errors

Takeaways:

- No significant overall effect of BBLS
- High credit score firms increase vacancies after receiving loan
- Further evidence that financial constraints limit firms' employment decisions also in response to positive shocks
- But would firms not anticipate loan?
  - Credit constraints may mean they are not able to
  - If they do, both control and treatment group would (all received loans within 3 weeks): "cash-in-hand" effect

Conclusion and policy implications

Substantial decline in vacancies at onset of pandemic (30%). Worse for leveraged, cash-strapped, large firms with low credit score

Policy	Direct effect on vacancies	Balance sheet effects
Tier restrictions	Strong decline	-
Eat Out to Help Out	Strong increase	High leverage $\downarrow$
Bounce Back Loan Scheme	-	Low credit score $\downarrow$

Policy implications

Improved understanding of how shocks propagate to labour demand through balance sheets + role of policy

- Asymmetries in response to initial negative shock, but not later on (policy support?)
- Asymmetries in response to positive shock! Job creation mostly driven by firms in better financial health

References I

Aristizábal-Ramırez, Marıa and Christian Posso (2021) "Dynamics of Corporate Credit Markets, Employment and Wages: Evidence from Colombia."

Benmelech, Efraim, Nittai Bergman, and Amit Seru (2021) "Financing labor," *Review of Finance*, 25 (5), 1365–1393.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna (2021) "Difference-in-Differences with a Continuous Treatment," *arXiv preprint arXiv:2107.02637*.

Callaway, Brantly and Pedro HC Sant'Anna (2020) "Difference-in-differences with multiple time periods," *Journal of Econometrics*.

Chodorow-Reich, Gabriel (2014) "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 129 (1), 1–59.

Fetzer, Thiemo (2021) "Subsidising the spread of COVID-19: Evidence from the UK'S Eat-Out-to-Help-Out Scheme*," *The Economic Journal*, 10.1093/ej/ueab074, ueab074.

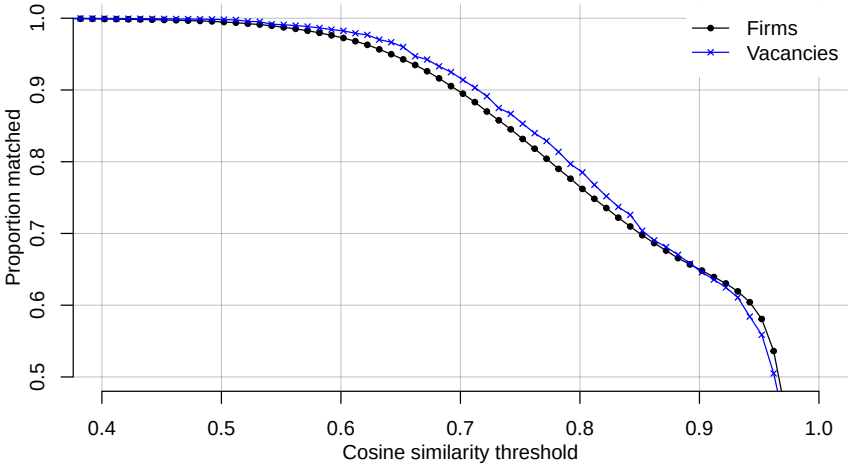
Giroud, Xavier and Holger M Mueller (2017) "Firm leverage, consumer demand, and employment losses during the great recession," *The Quarterly Journal of Economics*, 132 (1), 271–316.

Giroud, Xavier, Holger M Mueller, Alex Stomper, and Arne Westerkamp (2012) "Snow and leverage," *The Review of Financial Studies*, 25 (3), 680–710.

Sharpe, Steven A (1994) "Financial market imperfections, firm leverage, and the cyclicality of employment," *The American Economic Review*, 84 (4), 1060–1074.

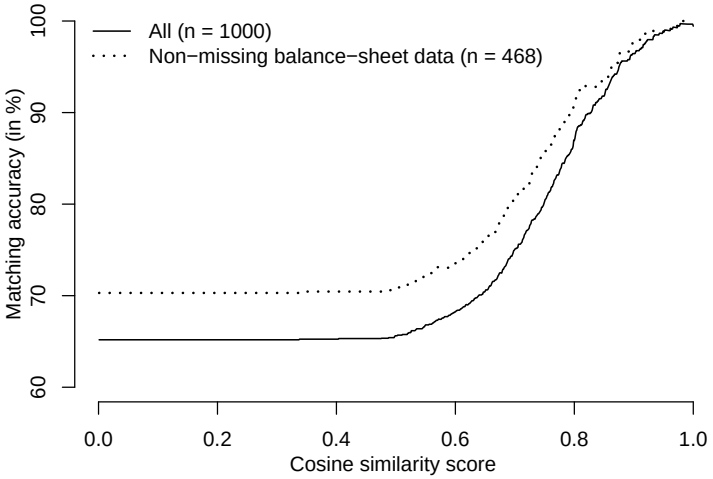
Appendix

Proportion Matched by Cutoff



Back

Matching Accuracy by Cutoff



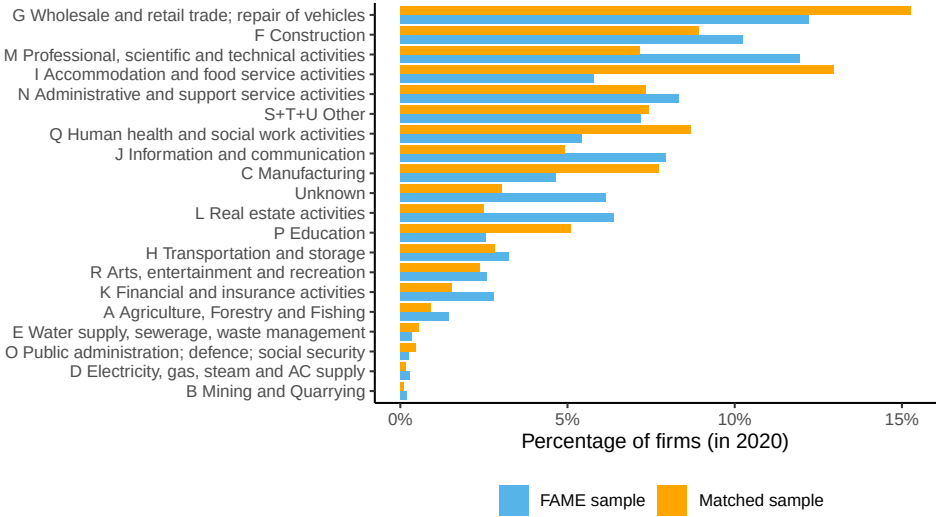
Addressing Match Biases

1. Chain stores matched to headquarters (e.g. "[Supermarket chain name] Lombard Street" to "[Supermarket chain name]")
   $\Rightarrow$ manually inspected all FAME firms with more than 10 Indeed firms matched to them
   - 'Sinkhole' firms (e.g. "barber shop"): drop
   - Actual chain stores: relax similarity cutoff
2. Recruitment firms sometimes post vacancies under their name
   $\Rightarrow$ drop all related SICs
   $\Rightarrow$ drop firms with employment- or recruitment-related names
3. Conglomerates
   $\Rightarrow$ drop firms with consolidated balance sheets
   $\Rightarrow$ dummy for part of corporate group $\Rightarrow$ study issue in data: no cases of FAME firms with 10+ matches due to conglomerates

Addressing Match Biases

1. Chain stores matched to headquarters (e.g. "[Supermarket chain name] Lombard Street" to "[Supermarket chain name]")
   $\Rightarrow$ manually inspected all FAME firms with more than 10 Indeed firms matched to them
   - 'Sinkhole' firms (e.g. "barber shop"): drop
   - Actual chain stores: relax similarity cutoff
2. Recruitment firms sometimes post vacancies under their name
   $\Rightarrow$ drop all related SICs
   $\Rightarrow$ drop firms with employment- or recruitment-related names
3. Conglomerates
   $\Rightarrow$ drop firms with consolidated balance sheets
   $\Rightarrow$ dummy for part of corporate group $\Rightarrow$ study issue in data: no cases of FAME firms with 10+ matches due to conglomerates

Comparison to Full FAME Sample: Industries

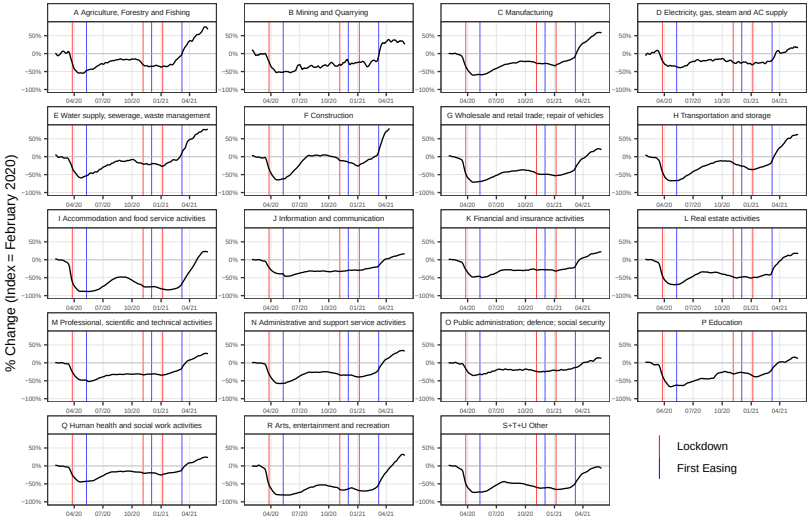


Back

Comparison to Full FAME Sample: Variables

	FAME (N=4938785)			**Matched** (N=266994)		
Variable	Mean	Median	Pct. NA	Mean	Median	Pct. NA
Total Assets th GBP 2019	10048.11	40.00	0.47	12666.42	261.00	0.45
No of companies in corporate group	10.81	0.00	0.00	16.12	0.00	0.01
Current Liabilities th GBP 2019	-4344.70	-25.00	0.52	-6347.17	-127.00	0.46
Bank & Deposits th GBP 2019	665.86	16.00	0.74	1376.69	74.00	0.62
No of subsidiaries	0.08	0.00	0.00	0.16	0.00	0.01
Number of employees 2019	14.61	2.00	0.70	51.40	10.00	0.57
Credit score	39.55	37.00	0.46	51.34	45.00	0.44
Age 2020	7.98	5.00	0.19	11.96	8.00	0.34
Listed	0.00	0.00	0.00	0.00	0.00	0.01

Industry Time Series



Back

Doubly-Robust Estimator

General form (Callaway and Sant'Anna, 2020):

$$ATT_{dr}^{ny}(g,t;\delta) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_{g,t+\delta}(X)(1-D_{t+\delta})(1-G_g)}{1-p_{g,t+\delta}(X)}}{\mathbb{E}\left[\frac{p_{g,t+\delta}(X)(1-D_{t+\delta})(1-G_g)}{1-p_{g,t+\delta}(X)}\right]}\right)\left(Y_t - Y_{g-\delta-1} - m_{g,t,\delta}^{ny}(X)\right)\right]$$

,

with ny not-yet-treated units; g "treatment" cohort; t time relative to treatment; δ treatment anticipation (assume none); G 1 if a unit first treated in period g; $p_{g,t+\delta}$ propensity score, conditional on pre-treatment covariates X; $D_{t+\delta}$ 1 if a unit treated in period $t+\delta$; Y_t is the outcome variable (log of vacancy stocks) in period t; and $m_{g,t,\delta}^{ny}(X) = \mathbb{E}[Y_t - Y_{g-\delta-1} \mid X, D_{t+\delta} = 0, G_g = 0]$.

Back

Continuous DiD

- Most of our designs have continuous (EOHO, BBLS) or multivalued (tiers) treatments
- May be biased if treated units self-select into doses (Callaway et al., 2021)
  - EOHO: voluntary sign-up, but similar estimates using discretized measure
  - BBLS: choose amount to borrow up to a cap
  - Tiers: set by government
- In absence of self-selection, TWFE DiD can be interpreted as weighted average of causal responses on treated at dose d (ACRT(d—d)) or of average treatment effect on treated at dose d $\rightarrow$ focus on these
- For staggered design, bias even in absence of self-selection if treatment effect heterogeneity across cohorts
  - Tiers: doubly-robust estimates with discretized measure
  - BBLS: scrutinize treatment effect dynamics

Back

Pandemic Shock

Effect on vacancy postings (log)		:
Post WHO	-0.2980***	
	(0.0020)	
... × Log(1+assets)		-0.0908***
		(0.0040)
... × Leverage/assets		-0.0143**
		(0.0060)
... × Cash/assets		0.0036**
		(0.0015)
... × Credit score		0.0239***
		(0.0030)
...		
Observations	6,533,793	2,525,040
Adjusted R^2	0.59030	0.57947

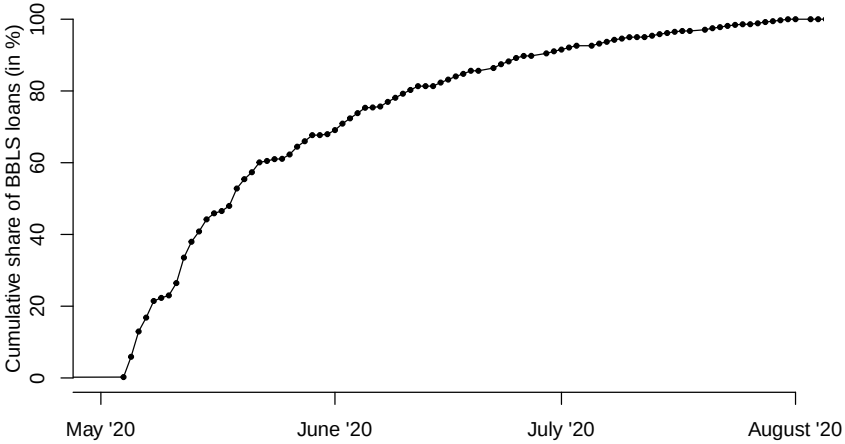
Clustered (Firm-NUTS2) standard-errors

Tier restrictions

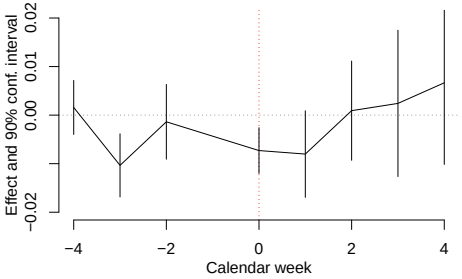
DV: Log(1+Vacancies):	(1)	(2)	(3)	(4)	(5)	(6)
Doubly-robust estimator						
Post (Tier $\geq$ 2)	-0.0251*	-0.0363*	-0.075***	-0.0761***	-0.1054***	-0.1081***
	(0.0151)	(0.0325)	(0.025)	(0.0225)	(0.0343)	(0.0391)
Observations	784,564	784,564	471,889	456,819	356,829	349,921
Additional controls	802	812	822	832	842	852
Sector by Week FE:	SIC-2	SIC-2	SIC-2	SIC-2	SIC-2	SIC-2
Week $\times$ control:						
COVID-19	X	X	X	X	X	X
Pop. Density		X	X	X	X	X
Log(1+assets)			X	X	X	X
Leverage / assets				X	X	X
Cash / assets					X	X
Credit score						X

Clustered (NUTS-2) standard-errors

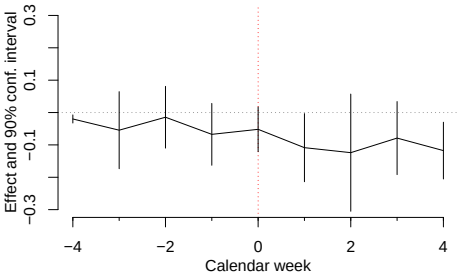
BBLS Uptake


Cumulative share of BBLS loans (in %)
0
20
40
60
80
100
May '20
June '20
July '20
August '20

Tier System: Event Studies



TWFE



Doubly-robust

Back

EOHO: Robustness

Back

DV: Log(1+Vacancy Stock):	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: EOHO exposure: meals								
Post × EOHO covered meals	0.0316***	0.0327***	0.0327***	0.0177***	0.0174***	0.0178***	0.0178***	0.0130*
	(0.0066)	(0.0071)	(0.0070)	(0.0064)	(0.0065)	(0.0065)	(0.0066)	(0.0067)
Mean(exp(DV)-1)	4.8426	4.8426	4.8426	6.3127	6.3127	6.3127	6.3456	6.3456
Observations	88,283	88,283	88,283	66,599	66,599	66,599	66,144	66,144
Additional controls	4,119	4,131	4,143	4,142	4,154	4,166	4,178	4,190
Panel B: EOHO exposure: restaurants								
Post × EOHO restaurants	0.0337***	0.0337***	0.0337***	0.0196***	0.0193***	0.0198***	0.0197***	0.0151**
	(0.0086)	(0.0095)	(0.0094)	(0.0072)	(0.0073)	(0.0073)	(0.0074)	(0.0075)
Mean(exp(DV)-1)	4.8426	4.8426	4.8426	6.3127	6.3127	6.3127	6.3456	6.3456
Observations	88,283	88,283	88,283	66,599	66,599	66,599	66,144	66,144
Additional controls	4,119	4,131	4,143	4,142	4,154	4,166	4,178	4,190
Panel C: EOHO exposure: doubly-robust								
Post × EOHO restaurants	0.054***	0.0527***	0.053***	0.0556*	0.0553*	0.0624**	0.06*	0.0473
	(0.0138)	(0.0146)	(0.0147)	(0.0307)	(0.0325)	(0.0295)	(0.0336)	(0.033)
Mean(exp(DV)-1)	4.8426	4.8426	4.8426	6.3127	6.3127	6.3127	6.3456	6.3456
P-val par. trends	0.0000	0.0000	0.0000	0.0642	0.0639	0.0881	0.1241	0.1427
Area by Week FE:	LAD	LAD	LAD	LAD	LAD	LAD	LAD	LAD
Week *times* additional control:								
Population density		X	X	X	X	X	X	X
Spring 2020 COVID-19 exposure			X	X	X	X	X	X
Log(1+assets)				X	X	X	X	X
Leverage / assets					X	X	X	X
Cash / assets						X	X	X
Credit score							X	X
Student exposure								X
Tenure types								

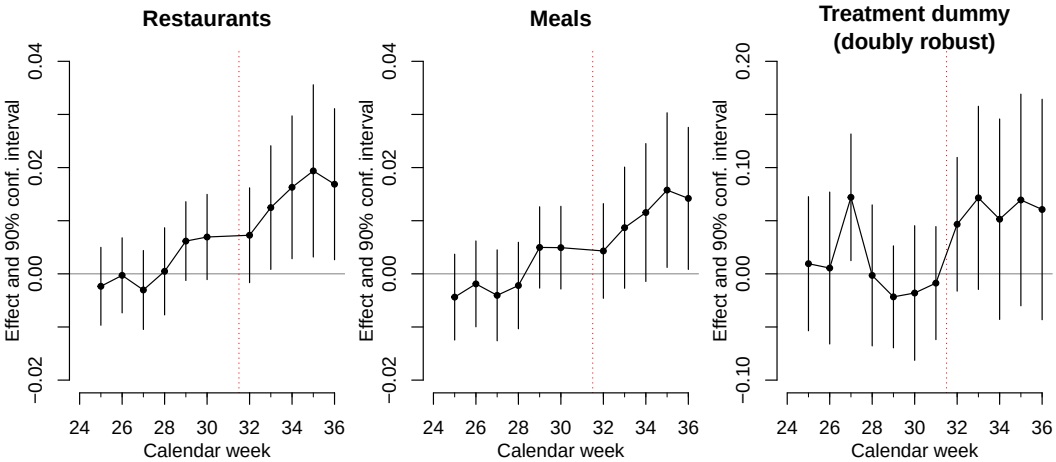
EOHO: No Hospitality

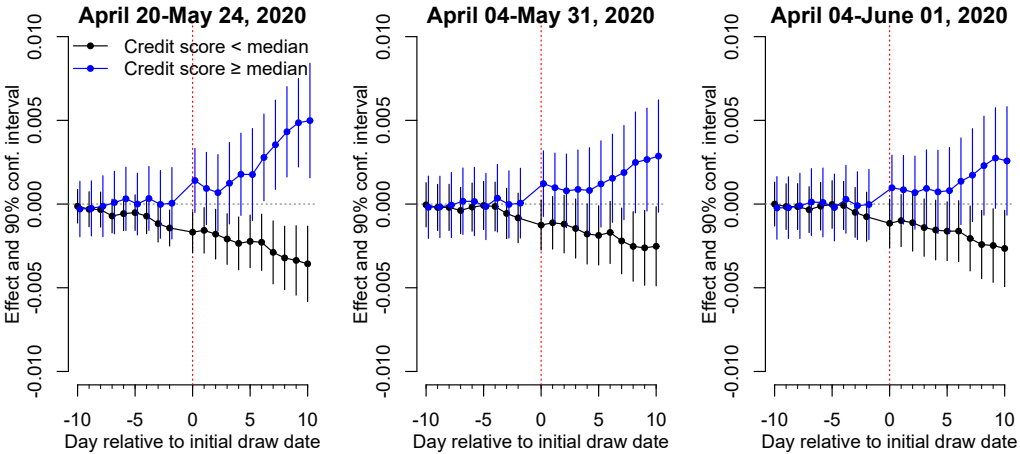
Back

DV: Log(1+Vacancy Stock):	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: EOHO exposure in levels						
Post × EOHO covered meals	0.0232***	0.0240***	0.0247***			
	(0.0055)	(0.0058)	(0.0060)			
Post × EOHO restaurants				0.0262***	0.0264***	0.0272***
				(0.0071)	(0.0074)	(0.0081)
Observations	88,283	88,283	88,283	88,283	88,283	88,283
Mean(exp(DV)-1)	4.5809	4.5809	4.5809	4.5809	4.5809	4.5809
MSOA	6,791	6,791	6,791	6,791	6,791	6,791
Additional controls	388	1,207	4,119	388	1,207	4,119
Clusters	317	317	317	317	317	317
Panel B: EOHO exposure in log						
Post × Log(1+EOHO covered meals)	0.0322***	0.0323***	0.0327***			
	(0.0049)	(0.0052)	(0.0053)			
Post × Log(1+EOHO restaurants)				0.0434***	0.0443***	0.0453***
				(0.0054)	(0.0057)	(0.0060)
Mean(exp(DV)-1)	4.5809	4.5809	4.5809	4.5809	4.5809	4.5809
Observations	88,283	88,283	88,283	88,283	88,283	88,283
MSOA	6,791	6,791	6,791	6,791	6,791	6,791
Additional controls	388	1,207	4,119	388	1,207	4,119
Clusters	317	317	317	317	317	317
Area by Week FE	NUTS2	NUTS3	LAD	NUTS2	NUTS3	LAD

Clustered (LAD) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

EOHO: Event Studies Back



BBLS: Event Studies

Back