Loan Guarantees in a Crisis: An Antidote to a Credit Crunch

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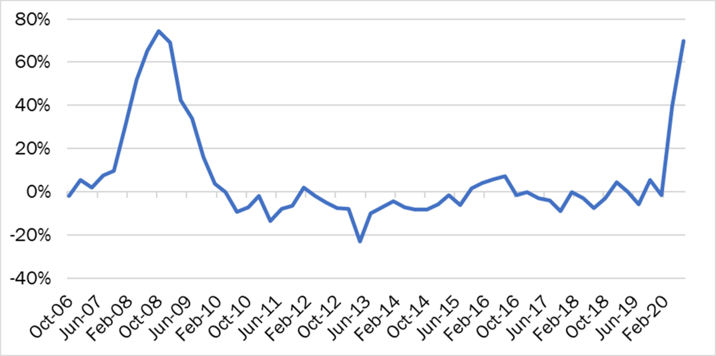
Motivation

- Credit contractions amplify recessions
  - Limited tools to counteract them
  - Credit guarantees one of them
- Credit guarantees previously used as solutions to:
  - Credit rationing in normal times
  - Banking crises
- Do government guarantees preserve lending in an exogenous economic crisis?
  - COVID-19 shock as a case in point
  - Strong bank balance sheets, but defensive responses
  - Policy intervention: Paycheck Protection Program
    - Large loan guarantee program
    - Channel funds to small businesses toward preserving employment

Banks tightened lending standards most steeply since GFC

Net Percentage of Banks Tightening Standards for Commercial and Industrial Loans to Small Firms



Source: FRED, Senior Loan Officer Opinion Survey.

The Paycheck Protection Program

- Introduced under the CARES Act in March 2020
- Unprecedented guarantee program, total funding $\sim$ \$1 trillion
- Forgivable, fully-guaranteed loans to non-financial small firms
- Forgiveness criterion: funds predominantly used for payroll
- Banks are main conduits for channeling funds
  - Process applications
  - Disburse loans using own capital
- Outsized participation by small banks

PPP Timeline Bank participation

Research Questions and Empirical Approach

Research Questions:

- Did the PPP forestall a credit crunch or crowd out private credit?
  - Effects on bank profits and risk-taking
  - Determinants of bank participation and intensity

Problems:

- Simultaneity: Banks participate if more likely to profit from PPP
- Counterfactuals required to evaluate lending if not for PPP

Empirical Approach:

- Joint Bayesian model of participation, intensity, and outcomes
  - Generate covariances and counterfactuals

Results Preview

The PPP averted a credit crunch, provided backstop outside program

- Loan category supported by PPP:
  - Business lending grew by 90%,
  - Would have contracted otherwise
- Loan categories not supported by PPP:
  - No measurable effects on loan growth,
  - But, forestalled lending decline

Funding capacity and risk aversion, not program profitability, determined participation

- Participating banks were:
  - Larger, more profitable
  - Less capitalized, more exposed to business loans
- Margins declined for participants relative to 2019

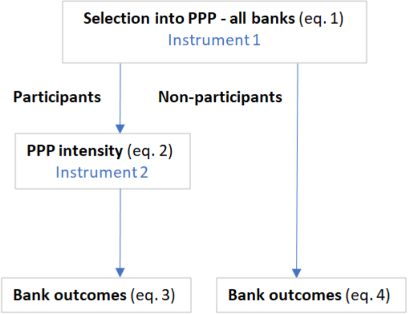
PPP Program: Bank decisions

- *Key Bank Decisions: Whether and how much to participate*
- Revenue: interest and fees
  - Interest rate of 1%, fees accrued over loan term or on forgiveness
    - Banks required cheap funding sources
- Costs: opportunity cost of capital
  - Weighed on leverage ratios, but exempt from risk-based ratios
    - Required capital buffer space vs expand risk-free lending
- Operational constraints: Technology to process online applications

SBA E-tran applications

Bayesian Joint Model

Model of PPP participation, intensity, and bank outcomes



Outcomes: ΔNIM, C&I Growth, Non-PPP C&I Growth, CRE Growth

Components of the model

Instrument 1: Technological Access

Relevance:

- Banks with access to technology are more likely to participate
- Statistically important effects on participation

Dependent variable:	PPP participation
Tech exp. to assets	-0.17
	[-0.26, -0.07]

Exclusion:

- Loan size, and thereby, intensity invariant to technological access
- "...banks with greater technology investment made a larger share of loans of all sizes.." (FDIC Quarterly, Sep 2021)

Tech. Access: Measurement

Instrument 2: COVID-affected employment share

Relevance:

- Demand for PPP loans rises with COVID-affected employment share. (Balyuk et al., 2021; Bartik et al., 2020)

Dependent variable: PPP intensity	
COVID-affected employment share	0.08
	[0.06, 0.1]

Exclusion:

- The share of COVID-affected industries does not reflect strategic supply decisions
- Approval rates not biased against COVID-affected sectors (Bartik et al., 2020) Approval Rates by Sector COVID-affected employment share: Measurement

PPP Expanded Lending, but Compressed Margins

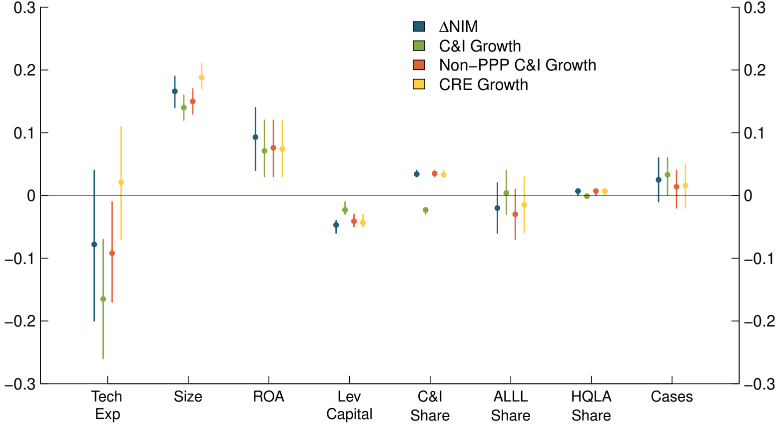
	Δ NIM (bps.)	C&I Growth (%)	Non-PPP C&I Growth (%)	CRE Growth (%)
Average bank effect	-36.3	89.5	-0.5	1.9
95% prob. interval	[-51.3, -23.0]	[78.7, 101.0]	[-12.4, 4.9]	[-4.6,8.6]

The average small bank held 8.5% of loans as PPP.

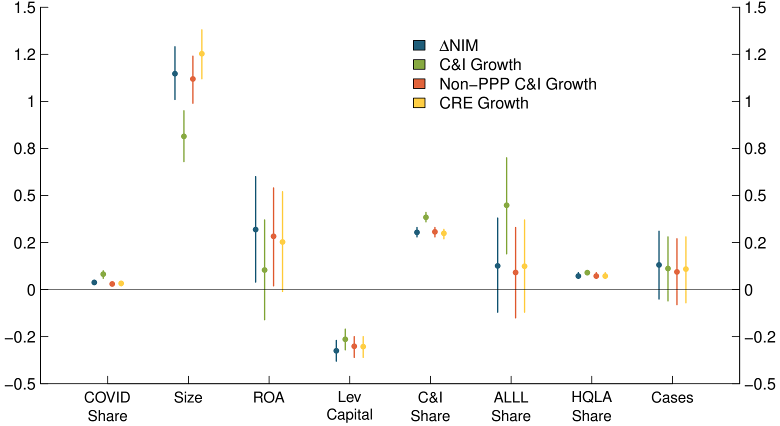
- Incremental participation compressed interest margins
- The PPP supported loan growth within the program
- But did not boost lending outside the program

Robustness Covariances

Participation Driven by Funding Capacity, Capital Preservation

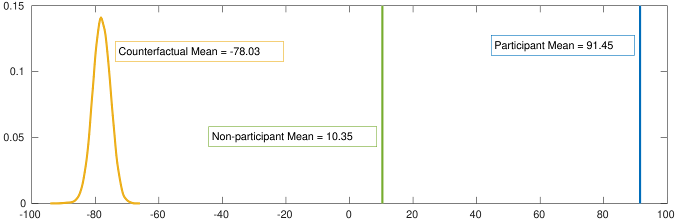


Intensity Driven by Funding Capacity, Capital Preservation, and Liquidity



The PPP Offset A Potential Decline in Bank Lending

Counterfactual and Observed C&I Growth



GFC-era growth rates in small bank loans

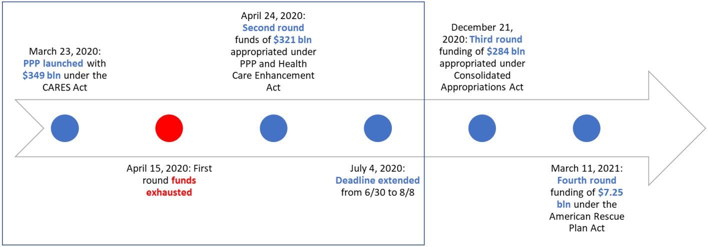
Key Takeaways and Conclusion

- The PPP averted a credit crunch
  - Effective fiscal policy measure for future crises
  - Net benefits depend on state of banking industry, economic shock
- Participation driven by risk aversion, rather than profit motive
  - Likely protected existing loans
  - Revenue source during economic uncertainty
  - Full guarantee an important parameter of the program
- Loan guarantee programs avert a credit crunch during an exogenous economic crisis

APPENDIX

The Paycheck Protection Program

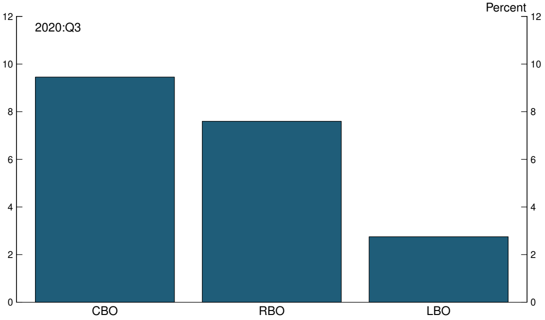
PPP Implementation Timeline



PPP Features

Outsized Participation by Community Banks

PPP Loans to Total Loans



Source: Call Reports.

PPP Features

Components of the Bayesian Joint Model

$$\begin{aligned}
\text{Selection into PPP - all banks: } y_{i1}^{*} &= \mathbf{x_i'}\beta_{\mathbf{1}} + z_{i1}'\gamma_1 + \epsilon_{i1}, && (1)\\
\text{PPP intensity - participants: } y_{i2} &= \mathbf{x_i'}\beta_{\mathbf{2}} + z_{i2}\gamma_2 + \epsilon_{i2}, && (2)\\
\text{Bank outcomes - participants: } y_{i3} &= \mathbf{x_i'}\beta_{\mathbf{3}} + y_{i2}\delta + \epsilon_{i3}, && (3)\\
\text{Bank outcomes - non-participants: } y_{i4} &= \mathbf{x_i'}\beta_{\mathbf{4}} + \epsilon_{i4}. && (4)
\end{aligned}$$

$$\boldsymbol{\epsilon}_{i,p} \sim \mathcal{N}(0, \boldsymbol{\Omega}_p), \boldsymbol{\epsilon}_{i,np} \sim \mathcal{N}(0, \boldsymbol{\Omega}_{np}).$$

$$\Omega_p = \begin{pmatrix} 1 & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{pmatrix}, \quad \Omega_{np} = \begin{pmatrix} 1 & \Omega_{14} \\ \Omega_{41} & \Omega_{44} \end{pmatrix}.$$

Bayesian Joint Model

Augmented Posterior

$$f(\theta, \Omega_p, \Omega_{np}, y_1^*|y) \propto f(y, y_1^*|\mathbf{x_i}, \theta, \Omega_p, \Omega_{np}) f(\theta) f(\Omega_p) f(\Omega_{np})$$

where,

$$f(\theta) = f_{\mathcal{N}}(\theta|\Theta_0, T_0), \theta = [\gamma_1, \gamma_2, \delta, \boldsymbol{\beta}], \text{and } \boldsymbol{\beta} = \{\beta_1, \beta_2, \beta_3, \beta_4\},$$

and

$$f(\Omega_p) = f_{\mathcal{IW}}(\Omega_p|\nu_p, Q_p), f(\Omega_{np}) = f_{\mathcal{IW}}(\Omega_{np}|\nu_{np}, Q_{np}),$$

which are independent of priors assigned to the coefficients.

Estimation: Strategy for multiple selection mechanisms in Li, 2011 and Vossmeyer, 2016.

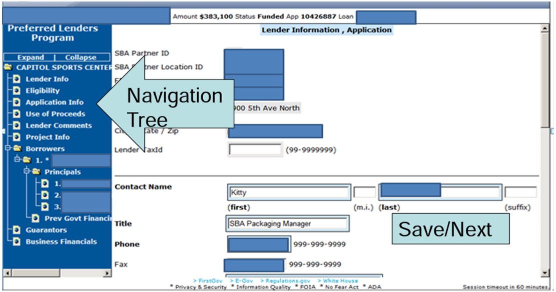
Gibbs Sampler Details

The likelihood and priors we have specified generate conditional conjugacy. We use a Gibbs sampler to estimate the model.

- Sample Ω from $\Omega|\theta, y, y_1^*$ in one block by partioning into sub-matrices, where $\theta = [\beta, \gamma_1, \gamma_2, \delta]'$
- Sample θ from the distribution $\theta|\Omega, y, y_1^*$
- Sample y_{i1}^* from $y_{i1}^*|\theta, y, \Omega$ for $i = 1, 2, \ldots, n$

Bayesian Model

SBA Application Portal



www.sba.gov/for-lenders

Implications for Lenders

Excluded Variables: Technical Access

$$z_{i1} = \frac{\text{Data processing and telecom expenses}}{\text{Total assets}}$$

- Included in equation for participation in the PPP
- Excluded from remaining equations

Tech. Access: Exclusion and Relevance

Excluded Variables: COVID-affected employment share

$$z_{i2} = \frac{\sum_{j=1}^{J} Emp_j d_{i,j}}{\sum_{j=1}^{J} d_{i,j}},$$

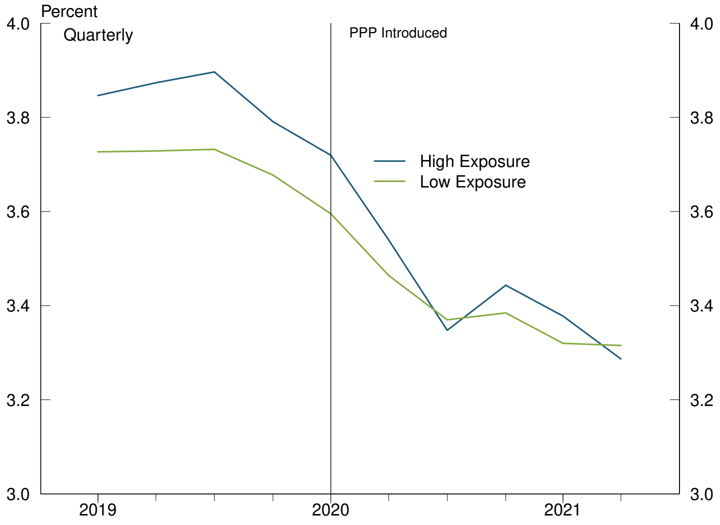
Emp_j = COVID-affected employment share in county j,

$d_{i,j}$ = 2019 deposits of bank i in county j.

- Included in equation for PPP intensity
- Excluded from remaining equations

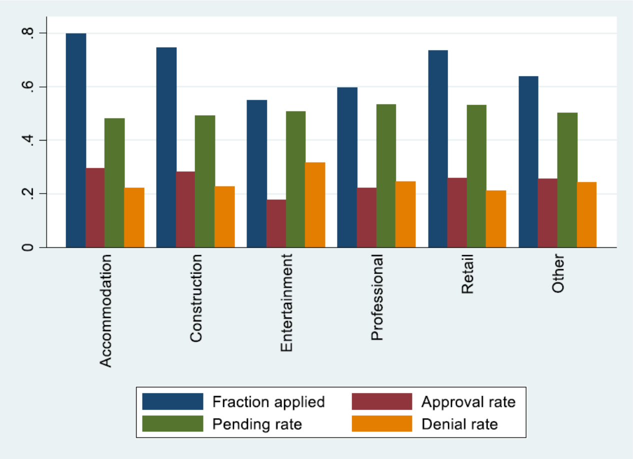
COVID-affected employment share: Exclusion and Relevance

Net Interest Margins By PPP Participation Intensity



NIM Counterfactual

Approval Rates by Sector



Source: Bartik et al., 2020. COVID-affected employment share: Exclusion and Relevance

Summary Statistics

Table: *Summary Stats By PPP Lending Intensity*

	High PPP		Low PPP		Non-Participants	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Pre-pandemic Averages						
Tech Exp. to Assets	0.20	(0.13)	0.18	(0.14)	0.21	(0.19)
COVID-affected emp. share	19.69	(6.99)	17.05	(8.38)	18.33	(10.12)
C&I to Assets	10.85	(6.93)	7.57	(5.33)	8.27	(9.81)
C&I Commitments to Assets	15.42	(9.78)	9.84	(6.69)	10.09	(11.00)
Unused C&I Commitments to Assets	4.57	(3.87)	2.26	(2.32)	1.83	(2.96)
Small C&I to Assets	6.22	(4.00)	5.31	(3.81)	6.42	(8.42)
Core Deposits to Assets	71.62	(10.29)	68.09	(10.45)	67.50	(13.25)
Liquid Assets to Total Assets	20.63	(11.90)	19.09	(11.38)	25.17	(15.21)
ALLL to Total Loans	1.32	(0.64)	1.34	(0.59)	1.50	(1.21)
Total Assets ($ Millions)	0.68	(1.02)	0.42	(0.87)	0.23	(0.63)
$ln($*Total Assets*$)$	12.78	(1.10)	12.20	(1.09)	11.59	(1.05)
Leverage Ratio	10.90	(2.20)	11.85	(3.21)	12.77	(4.44)
Tier 1 Ratio	15.60	(5.80)	17.57	(7.05)	21.49	(10.36)
$ROA^{2019\ Avg}$	1.19	(0.61)	1.19	(0.57)	0.96	(0.70)
Post-Pandemic Outcomes						
PPP Share	13.15	(6.98)	3.91	(1.83)	0.00	(0.00)
NIM	3.46	(0.59)	3.49	(0.62)	3.38	(0.78)
ΔNIM	-50.06	(49.65)	-39.57	(38.07)	-48.65	(47.38)
CI Gwth	129.97	(118.09)	51.47	(62.72)	10.14	(36.46)
CI Gwth Less PPP	-3.70	(22.15)	-2.64	(25.11)	10.14	(36.46)
Total Banks	1,824		1,689		378	

Quarterly Results

Table: *Quarterly Treatment Effects by Outcome*

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
Q2 2020	-6.91	10.72	0.36	0.20
	[-9.15, -4.92]	[8.65, 12.92]	[-0.89, 1.71]	[-0.71, 1.09]
Q3 2020	-0.19	9.53	-0.33	0.41
	[-2.54, 2.39]	[7.18, 12.04]	[-2.33, 1.54]	[-0.76, 1.61]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000. Main Results

Robustness: Alternative Instruments

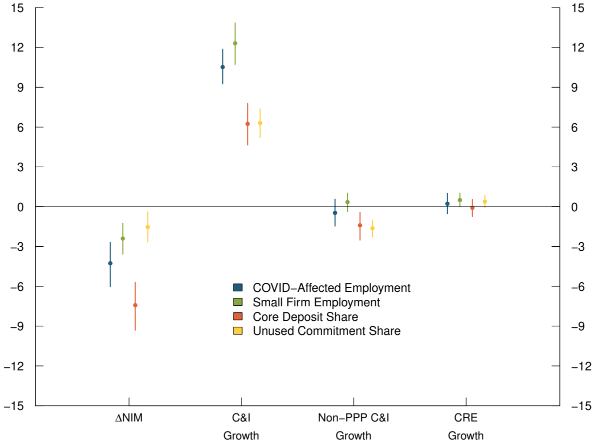
Table: *Alternative Instrument Effects*

	COVID-affected Employment	Small firm Employment	Core Deposit Ratio	Unused C&I Cmmt Ratio
	(1)	(2)	(3)	(4)
Mean	0.093	-0.135	0.106	0.263
	[0.07, 0.11]	[-0.16, -0.11]	[0.09, 0.13]	[0.24, 0.29]

Note: Table shows standardized coefficients for each exogenous variable on PPP intensity. Coefficients are estimated using the Bayesian joint model shown in equations 2 - 4. 95% credibility intervals are shown in brackets. Main Results

Robustness of Treatment Effects: Alternative Instruments

Treatment effects by instrument



Source: Call Reports.

Main Results

Robustness: Effects of Drawdowns in 2020 Q1

Table: *C&I Loan Draw Effects*

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
Baseline + CI gwth top qrtile	-3.92	12.13	0.20	0.29
	[-5.45, -2.37]	[10.67, 13.61]	[-0.78, 1.17]	[-0.46, 0.99]

Note: The reported values are posterior means of the parameters, and 95% credibility intervals in brackets. The results are based on 55,000 MCMC draws with a burn-in of 5000. Main Results

Robustness: Comparison with Classical Methods

Table: *OLS and Two-stage Least Squares Estimation*

	ΔNIM(bps)	C&I Gwth(%)	Non-PPP C&I Gwth(%)	CRE Gwth(%)
	(1)	(2)	(3)	(4)
Baseline	-4.27	10.52	-0.46	0.23
	[-6.03, -2.7]	[9.26, 11.87]	[-1.46, 0.57]	[-0.54, 1.01]
OLS	-1.22***	11.26***	-0.10*	0.18***
	(-5.00)	(47.74)	(-2.10)	(4.41)
IV	-3.25***	15.07***	0.77*	0.26
	(-4.61)	(15.15)	(2.15)	(0.87)

Notes: Table shows estimates of PPP intensity on bank profitability and balance sheet outcomes from the Bayesian joint model ("Baseline") as well as a standard OLS and a two-stage least squares model. The two-stage least squares model uses the share of COVID-affected employment in a bank's local market as the instrument. For the baseline model, 95% credibility intervals are shown in brackets. T-statistics are shown in parenthesis for the OLS and two-stage least squares estimates.

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$ Main Results

Participation, intensity, and outcomes positively correlated

Table: *Covariance estimates from the Bayesian joint model*

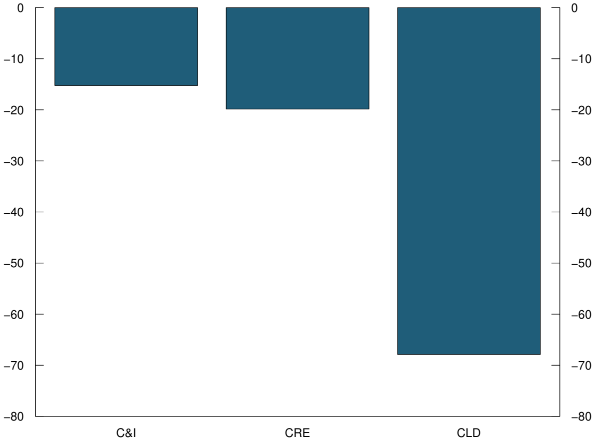
	ΔNIM	C&I Gwth	Non-PPP C&I Gwth	CRE Gwth
COV(participation, intensity)	+	+	+	+
COV(participation, bank outcome)	+	+	+	−
COV(intensity, bank outcome)	+	+	+	−
COV(non-participation, bank outcome)	−	−	−	−

Notes: Blue and red symbols denote statistically important positive and negative covariances respectively. Grey symbols represent covariance estimates that were not statistically important.

Participation Intensity Determinants

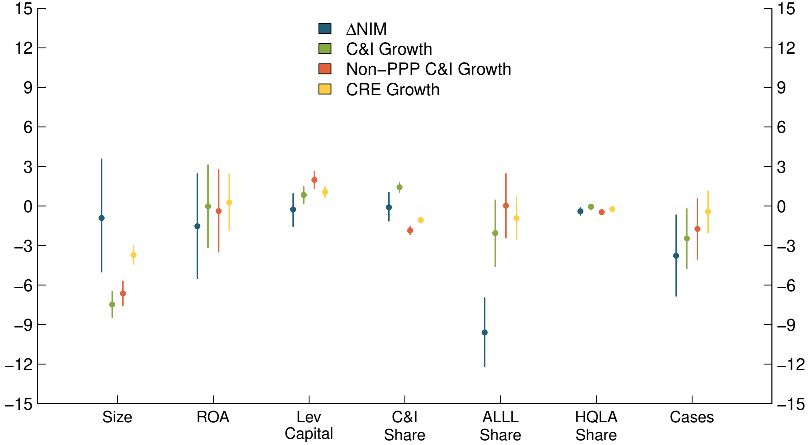
Is the Counterfactual Estimate Reasonable?

GFC-era Community Bank Growth Rates



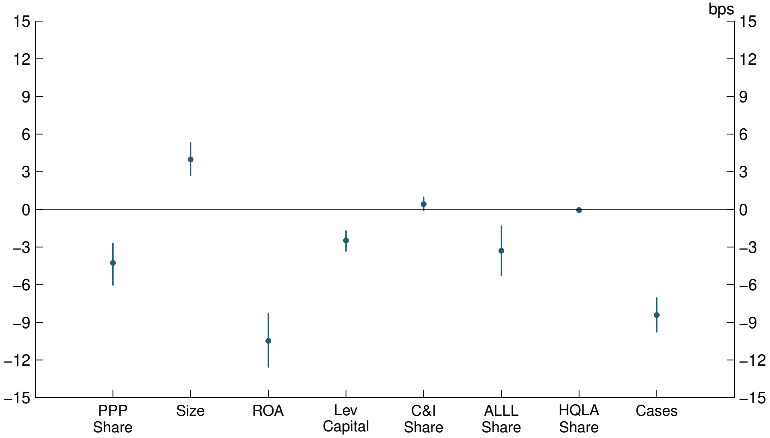
Counterfactual C&I growth

Outcomes for non-participants



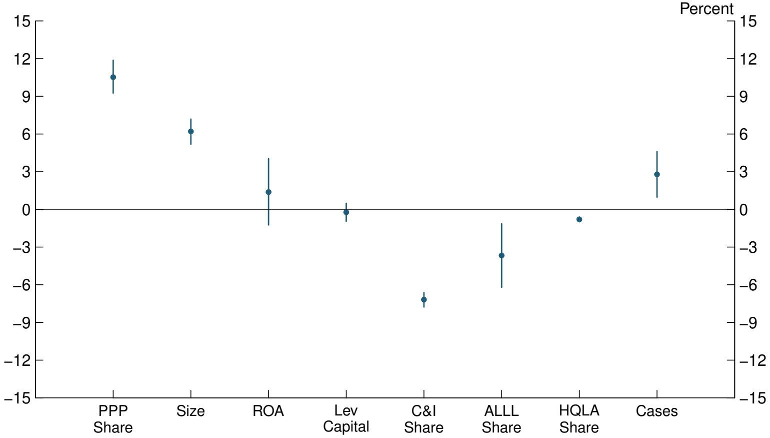
PPP intensity compressed bank margins

Dependent variable $= \Delta NIM$



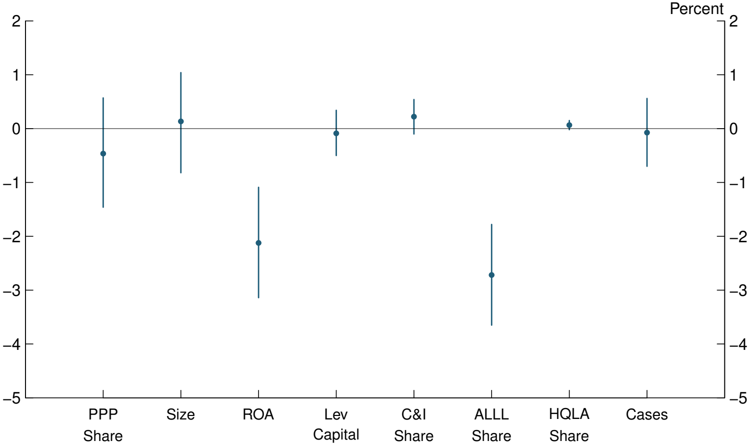
C&I loans grew with PPP intensity

Dependent variable = C&I growth



The PPP did not induce lending outside the program

Dependent variable = Non-PPP C&I growth



Risk-taking via CRE loans did not rise with PPP intensity

Dependent variable = CRE growth