SOCIAL MEDIA AS A BANK RUN CATALYST

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MOTIVATION

A bank run can be a **self-fulfilling prophecy**:

- "good" equilibrium: depositors have a low belief in running ➔ $P[run]$ is low.
- "bad" equilibirum: depositors have a high belief in running ➔ $P[run]$ is high.

Why/when do depositors end up in the "bad" equilibrium?

- `sunspots', communication via word of mouth, social propagation mechanisms (Angeletos and Werning 2006, Iyer and Puri 2012, Ziebarth 2017)

Our question: Does exposure to social media – as a communication technology – raise the risk of bank runs?

OUR SETTING
THE WAKE OF SILICON VALLEY BANK'S FAILURE

SVB failed: March 10th, 2023

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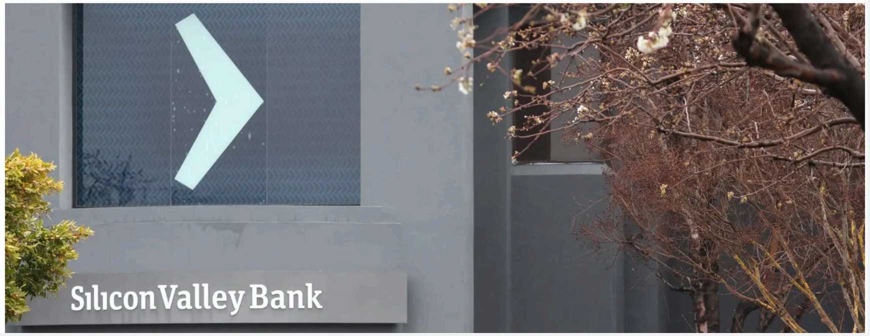
SVB is the first social media bank run in history. The crisis will change the banking industry forever.

Kali Hays Mar 13, 2023, 9:01 PM MDT



The first "social media, internet bank run in U.S. history"

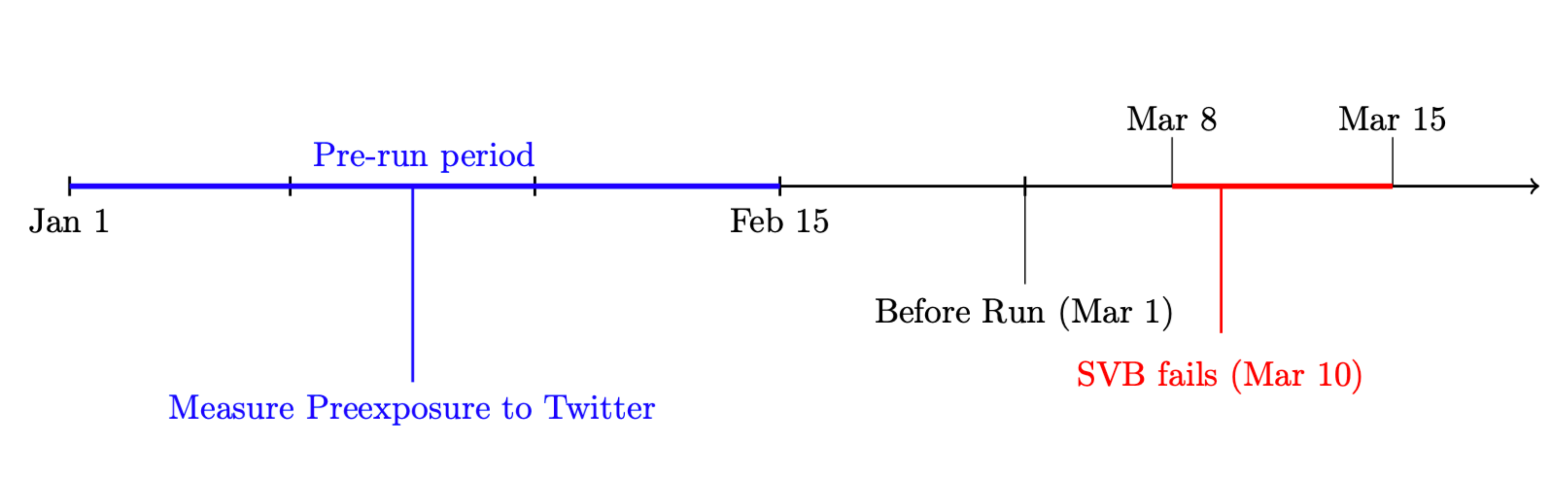
– Senator, Mark Warner

"If a bank has an overwhelming run that's spurred by social media ... so that it is seeing deposits flee at that pace, the bank can be put in danger of failing,"

– Janet Yellen, Treasury Secretary

Our Interest: Did social media exposure matter for *other* banks?

OUR EMPIRICAL STRATEGY:
TWITTER DATA AND RUN-PERIOD RETURNS



Outcome is **bank stock returns**

- High frequency deposit outflows are unavailable (e.g., hourly).
- We also look at Q1:2023 deposit outflows.

A menagerie of complementary tests:

- **CX**. Relate ***Twitter preexposure*** *(Jan 1 – Feb 15)* to ***bank stock losses*** *(Mar 1 to Mar 15)*.
- **Also, at high frequency:** Hourly within the run & at the tweet level.

OUR FINDINGS

High preexposure to Twitter predicts bank stock losses in the run period.

- **6.6 percentage points more stock losses** during the run for top tercile Twitter preexposure.
- By comparison, a sd increase in % uninsured deposits is associated with **4.1 ppt loss**.

Social media amplifies classical bank run risk factors

- Twitter preexposure interacts significantly with ***% uninsured deposits and mark to market losses.***
- Also true at higher frequency.

Twitter pre-exposure also relates to outflows of uninsured deposits in Q1:2023.

MECHANISMS

In-Run Twitter conversation was full of run and contagion keywords.

- Including these in-run tweet activity measures crowds out the preexposure effect.

Tweets started with investors.

- **SIVB** is Silicon Valley Bank's ticker, but **SVB** is how general users refer to the bank.
- Retweets of notable pre-run tweets did not pick up before the run.

'Tech' Twitter users – *likely depositors in SVB* – played outsized role.

- Startup tweets increase during the run, not just for SVB.
- Startup user tweets have more high frequency market impact.

CONTRIBUTION

Bank runs in the age of social media and digital banking

- Classical bank runs are about communication and contagion.
- We contribute to an understanding of this period of banking distress (Jiang et al 2023; Dreschler et al 2023; Koont et al 2023).

Contagion via social media, not just social networks

- Social networks and contagion are thought to be critical for banking distress (Iyer and Puri 2012).
- Social media is not just a social network, but a platform that coordinates ideas.
- Social media's widespread reach & two-way communication are distinctive.

DATA AND CONTEXT

DATA

- **Tweet Data** drawn from the **Twitter API**:
  - 5.4 million cashtagged tweets ($SIVB, $FRC…)
  - Publicly traded banks (SIC 602, 603, 609) from 1/1/2020– 3/14/2023
  - Tweets on general conversations: "Silicon Valley Bank" or "SVB" and "First Republic Bank"
  - User details on 544,888 Twitter users who contributed these tweets

- **Minute-level stock data** from FirstRate.

- **Banking Data**. FDIC and FFIEC.
  - Compute **% Asset Decline** (mark to market) from 2022:Q1 to 2023:Q1 following Jiang et al (2023).
  - Compute **% Uninsured Deposits**, drawing from the FDIC call reports data.

CONTENT OF TWEETS AND PRE-RUN EXPOSURE

We build textual dictionaries based on "run" and "contagion" ideas & apply it to the run period.

The top-5 banks by "run" exposure well identify banks with notable run discussions.

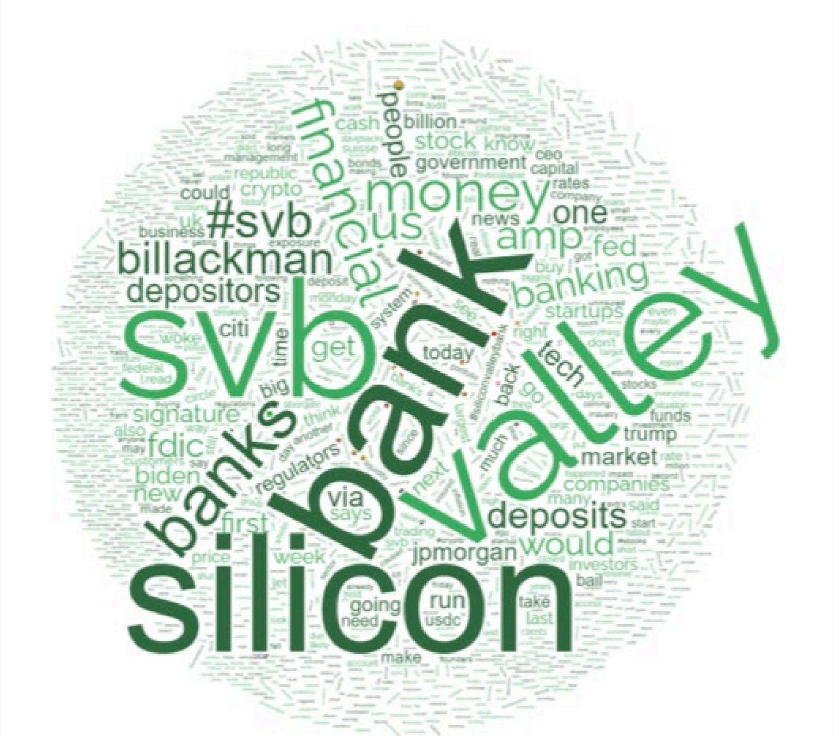
	Run	Contagion	Tweets Pre-Run
SIVB	6,528	9,662	1,163
FRC	1,249	1,368	1,257
SI	343	342	20,774
SBNY	260	106	2,403
JPM	206	245	30,063
90th Percentile	3	2	784

All these banks are high on Tweets pre-run. *Motivates our exposure strategy*.

CONTEXTUAL EVIDENCE
PRE-RUN VERSUS RUN LANGUAGE

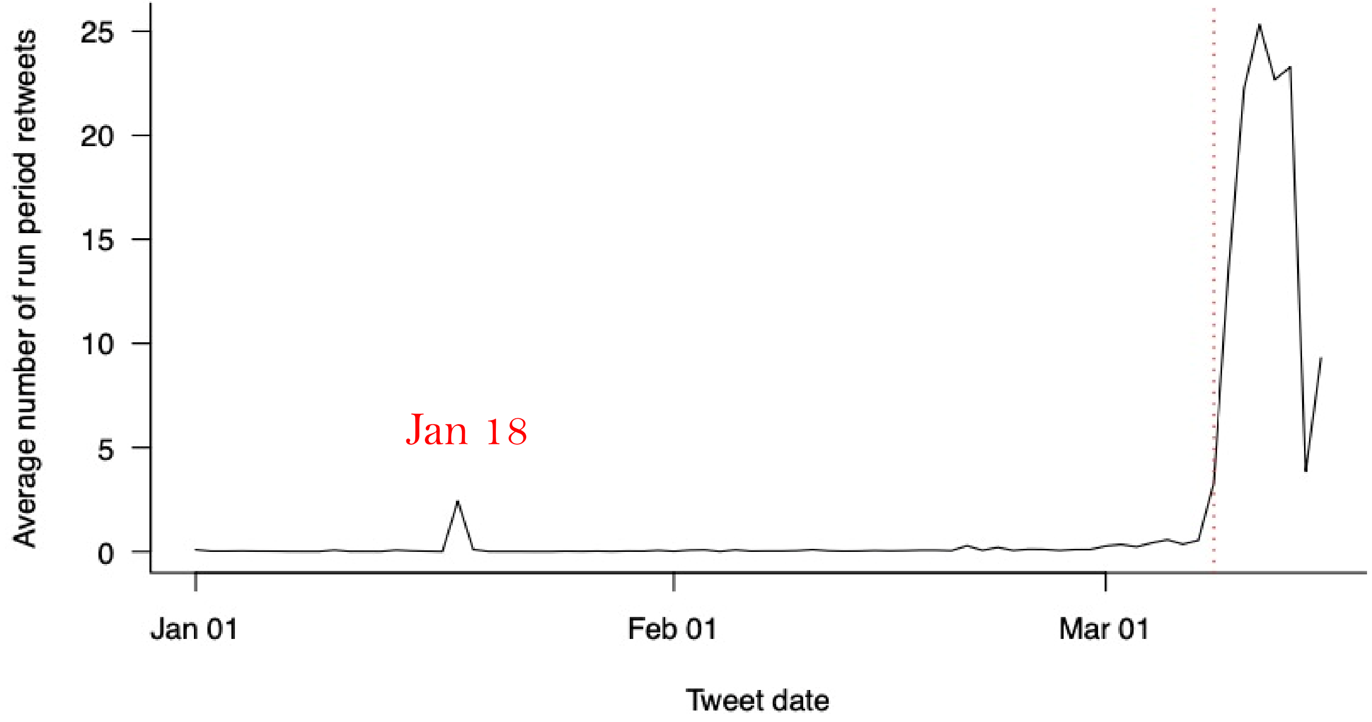
Pre-Run (Jan 1-Feb 15)

Run Period (Mar 8-13)



PRE-RUN TWEETS WERE RARELY RETWEETED DURING THE RUN

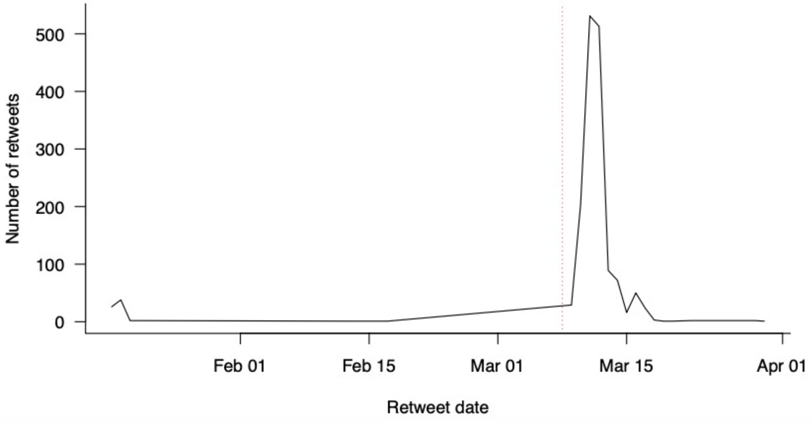
(b) Average Number of Run Period Retweets by Original Tweet Date



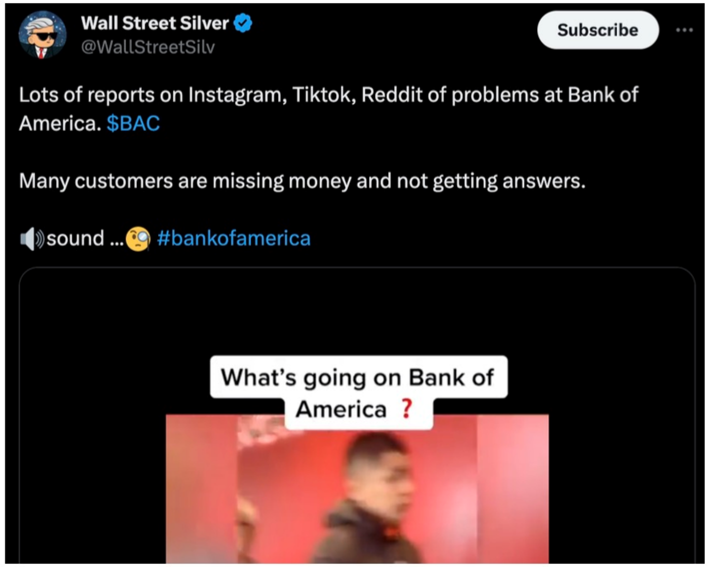
HIGHLY RETWEETED PRE-RUN TWEETS WERE REDISCOVERED DURING THE RUN

(a) Raging Capital Ventures Tweet on Jan 18, 2023

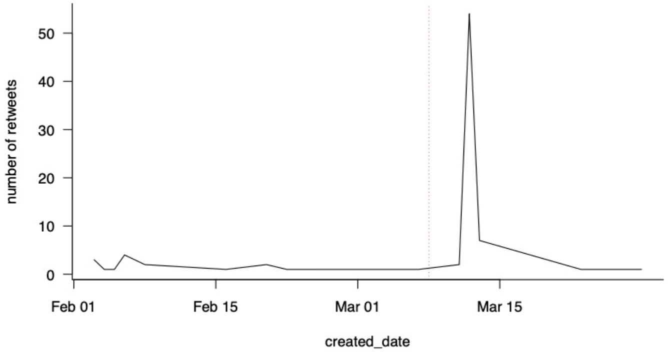
(b) Dynamics of Retweets of Raging Capital Ventures Tweet



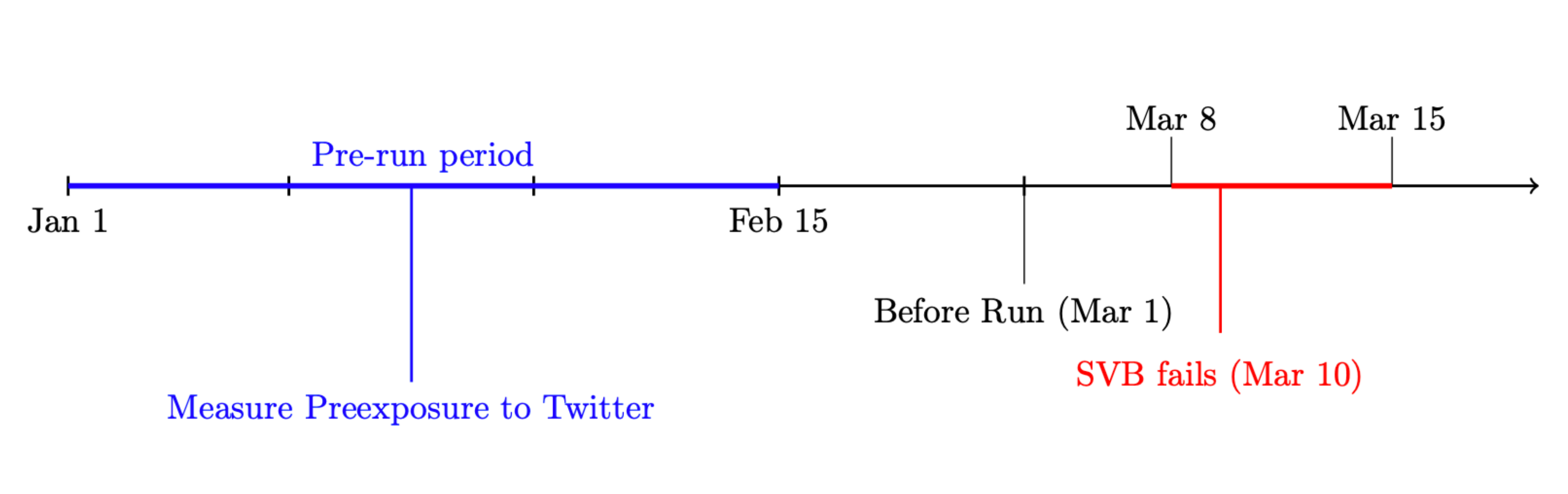
(a) WallStreetSilv Tweet about Bank of America on Jan 18, 2023



(b) Dynamics of Retweets of Bank of America Tweet



CROSS-SECTIONAL RESULTS



CX REGRESSION EVIDENCE

- Col (1): Consistent with classical factors, % Uninsured predicts **4.1pp** bank stock losses during run.
- Col (2): Top tercile Twitter activity in pre-run period ➔ **6.66pp** more bank stock losses.

	Dependent variable:				
	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	$\boxed{4.117^{***}}$		1.223		1.288
	$\boxed{(1.025)}$		(0.895)		(0.893)
% Loss (z)	0.804			−0.069	−0.487
	(0.873)			(0.362)	(0.733)
% Uninsured (z):% Loss (z)	0.943				−0.980
	(0.735)				(0.782)
Mid SocialExp (T2)		0.579	0.074	0.575	0.276
		(0.798)	(0.870)	(0.834)	(0.861)
... × % Uninsured (z)			1.527		1.588
			(1.143)		(1.150)
... × % Loss (z)				0.461	1.425
				(0.689)	(0.966)
... × % Uninsured (z):% Loss (z)					0.990
					(1.005)
High SocialExp (T3)		$\boxed{6.660^{***}}$	5.209***	6.464***	6.302***
		$\boxed{(1.490)}$	(1.306)	(1.542)	(1.497)
... × % Uninsured (z)			3.278*		4.157**
			(1.831)		(2.016)
... × % Loss (z)				−0.866	2.170
				(1.201)	(1.990)
... × % Uninsured (z):% Loss (z)					3.014**
					(1.277)
Constant	16.368***	13.453***	13.893***	13.477***	13.735***
	(0.618)	(0.538)	(0.686)	(0.587)	(0.665)
Observations	280	280	280	280	280
R^2	0.158	0.093	0.219	0.097	0.258

CX REGRESSION EVIDENCE

- Col (1): Consistent with classical factors, % Uninsured predicts **4.1pp** bank stock losses during run.
- Col (2): Top tercile Twitter activity in pre-run period ➔ **6.66pp** more bank stock losses.
- Col (3)-(5): Interaction between preexposure to Twitter and balance sheet health ➔ more stock losses.
  - Main effects on balance sheet variables are small and insignificant.
- Separately, **Twitter pre-exposure predicts more outflows of uninsured deposits** in Q1:2023.

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CX EVIDENCE ON Q1:2023 OUTFLOWS

- Twitter pre-exposure predicts more **outflows** of deposits in Q1:2023.
- Mostly driven by uninsured deposits.
- Evidence on outflows is more tentative because this is outflows for the full quarter, not just run period.

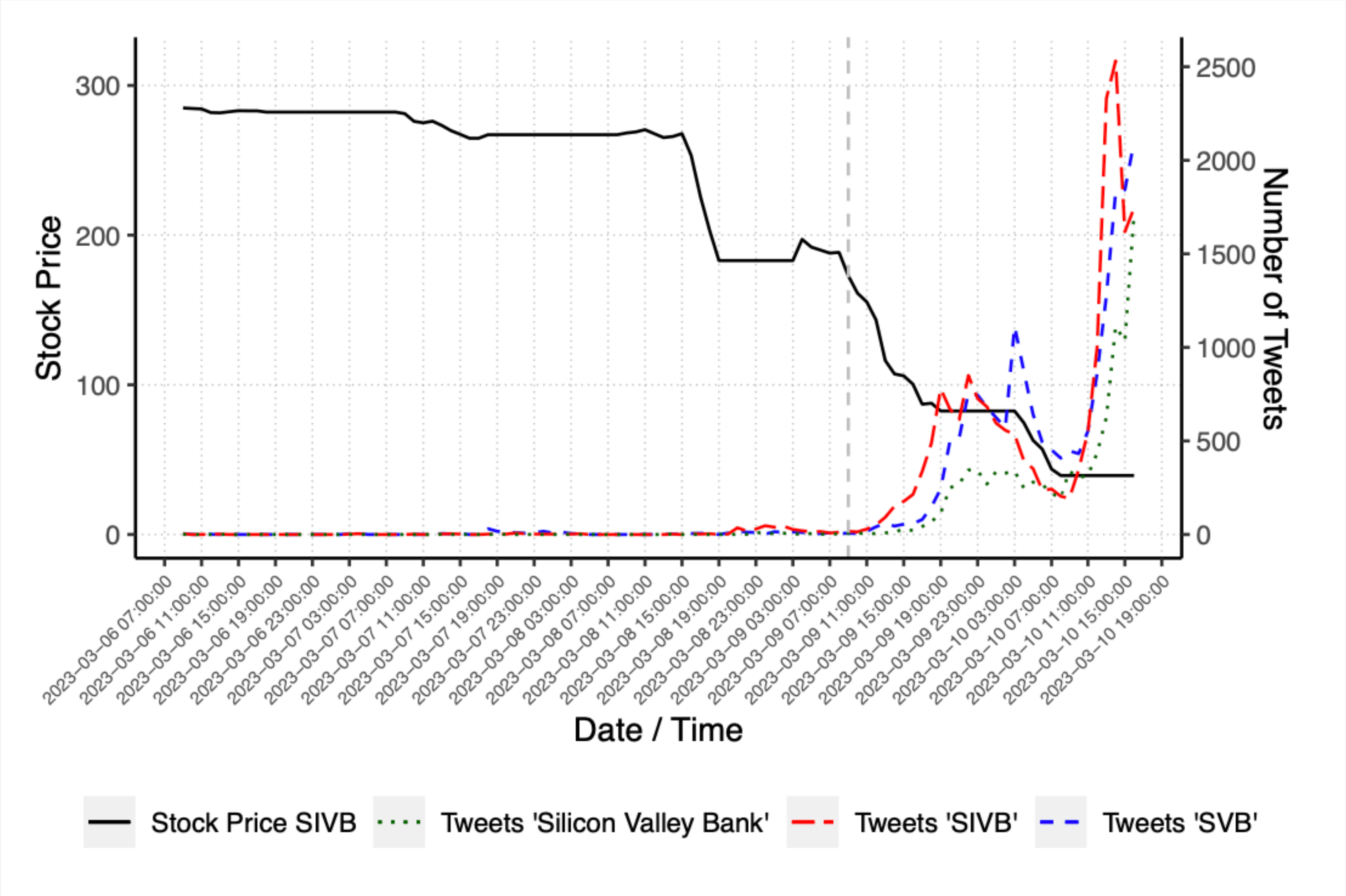
	Deposit Outflows (%)			
	Uninsured		Total	
	(1)	(2)	(3)	(4)
% Uninsured (z)	4.381***	1.109	2.282***	-0.662
	(1.315)	(1.529)	(0.787)	(1.268)
% Loss MTM (z)	1.216	-1.826	0.529	-0.632
	(1.014)	(1.111)	(0.750)	(0.921)
% Uninsured (z) × % Loss MTM (z)	-0.118	-2.725*	0.245	-0.847
	(0.821)	(1.540)	(0.747)	(1.192)
1(Social Exp. Tercile = 3) (T3)		1.181		0.882
		(2.405)		(1.780)
T3 × % Uninsured (z)		3.789		4.165**
		(2.372)		(2.051)
T3 × % Loss MTM (z)		4.721**		1.751
		(2.019)		(1.731)
T3 × % Uninsured (z) × % Loss MTM (z)		3.370*		1.625
		(1.867)		(1.708)
Constant	5.512***	6.160***	-0.929	-0.720
	(0.965)	(1.074)	(0.689)	(0.821)
Observations	258	258	233	233
R^2	0.067	0.104	0.039	0.072

HIGHER FREQUENCY

DESCRIPTIVE EVIDENCE OF CONVERSATION SPILLOVER (FOR SVB)

<u>SIVB vs SVB</u>

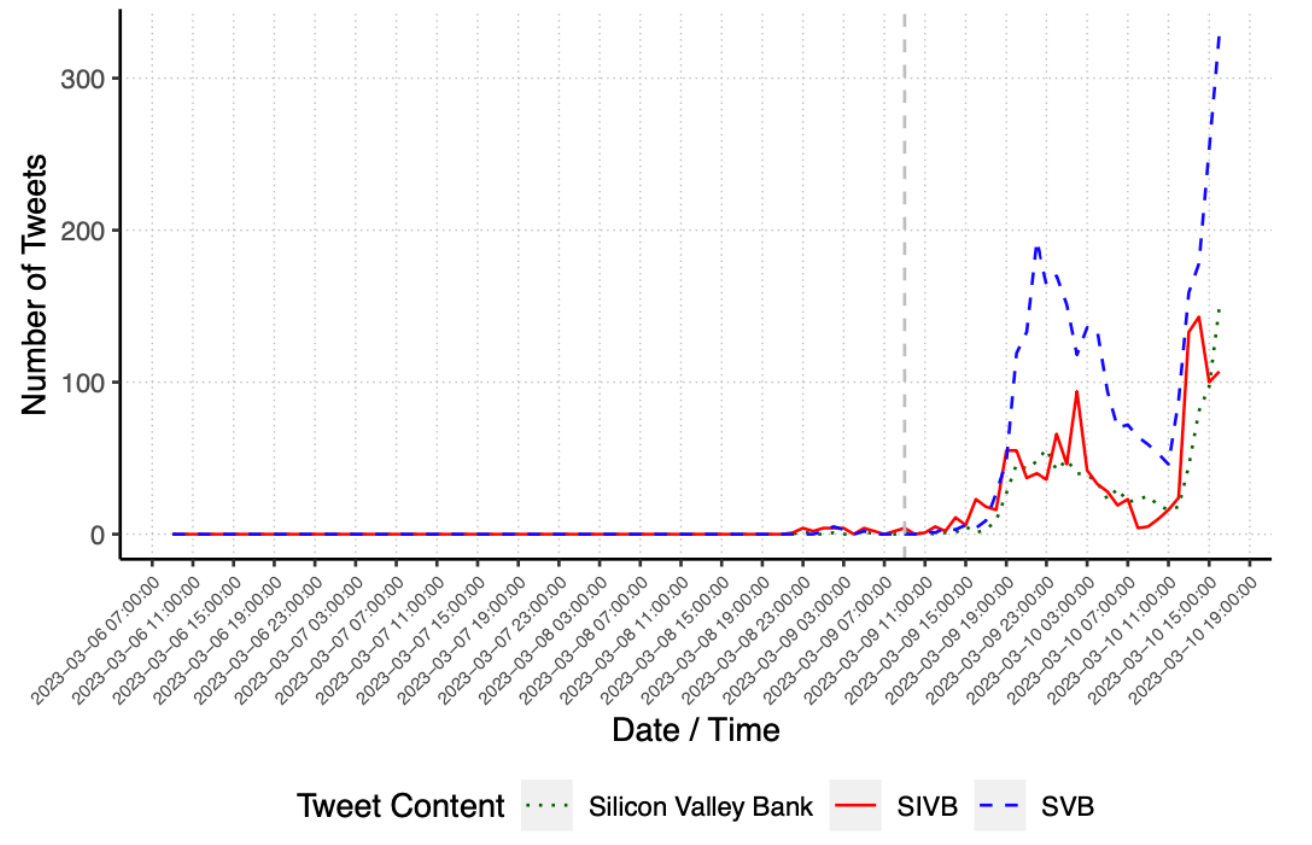
Investor tweets ($SIVB) spike in volume first, followed by more keywords from more general conversations (SVB, Silicon Valley Bank)



STARTUP COMMUNITY TWEETS COME LATER AND ARE MOSTLY "GENERAL DISCUSSION"

<u>Consistent with "tech" users being depositors.</u>

Twitter Startup Community users post mostly general discussion tweets, which start distinctly after the initial wave of tweets.

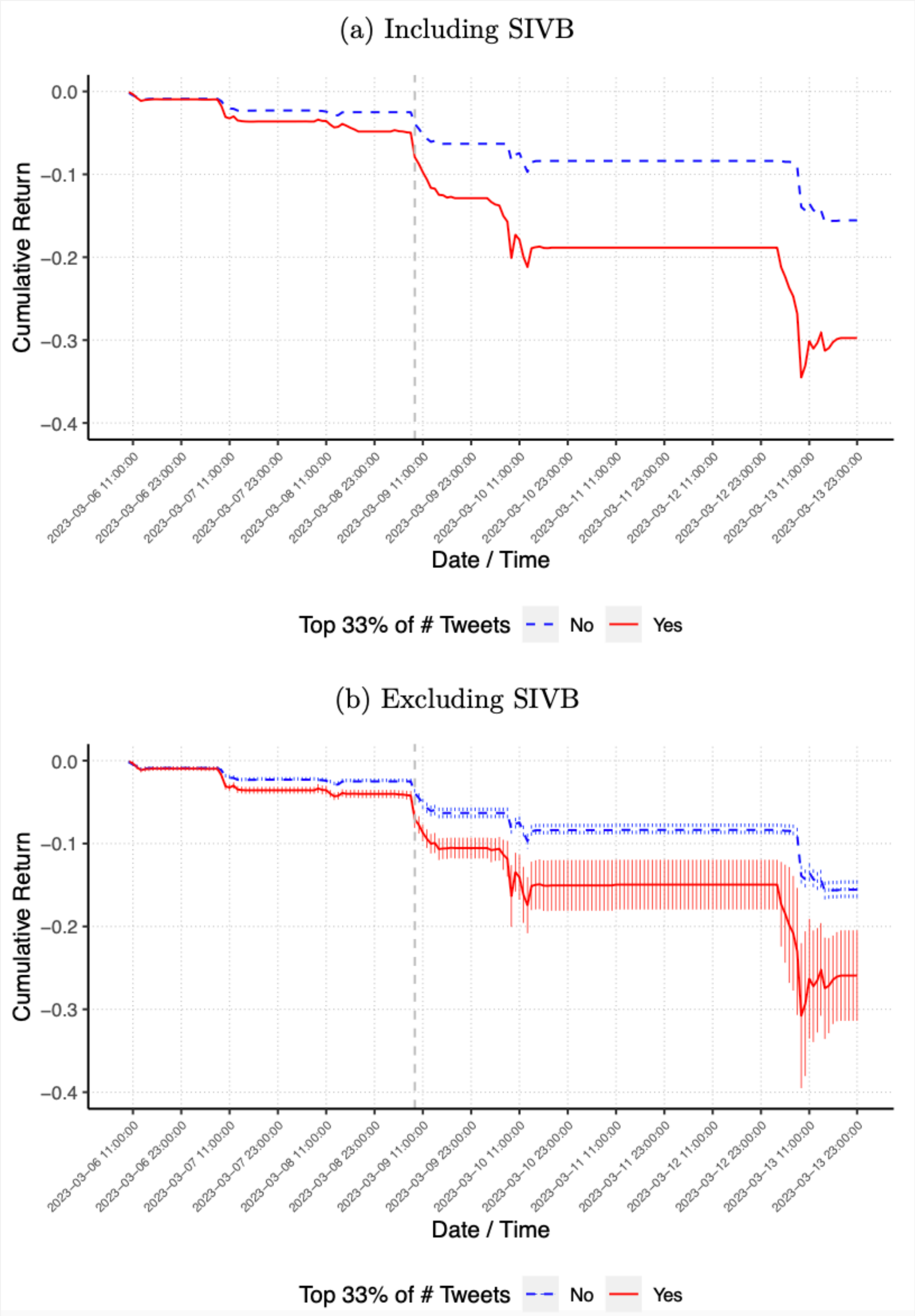


HOURLY FREQUENCY

More tweet volume predicts worse bank stock performance at the hourly frequency in the run period.

For "Run Exposed" Banks,
Top Tercile of Tweets vs Bottom Two Terciles

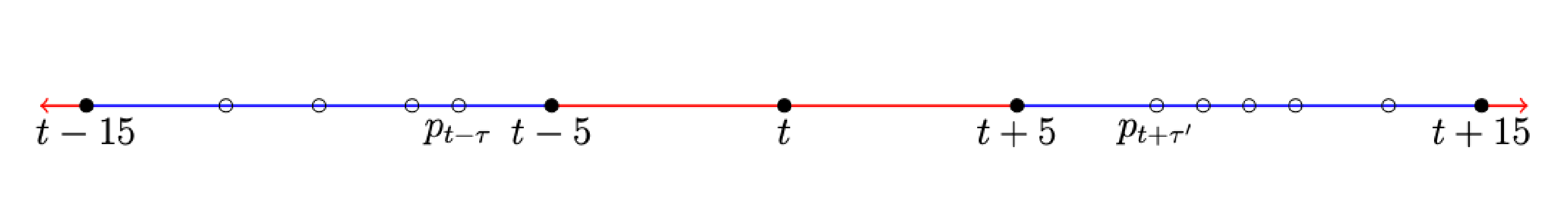
Holds with or without SIVB in the sample.



TWEET-LEVEL TESTS

<u>Following Bianchi et al (2023)</u>

We next examine the immediate impact of tweets in and out of the run, examining price change from [-15min,-5min] to [5min,15min]



Outcome is Δp = difference in logged prices ~ 10minutes

$$\Delta p_{it} = p_{i,t+\tau} - p_{i,t-\tau}$$

TWEET-LEVEL TESTS

Even at this timescale, negative sentiment tweets have:

- More 10-min impact during the run – see constant term.
- Outsized *negative sentiment impact* for tweets that mention *contagion* or are by *tech community*.
- Asymmetry: negative sentiment has impact, but not positive sentiment.

	(1)	(2)	(3)	(4)
	$\Delta p_{i,t}$	$\Delta p_{i,t}$	$\Delta p_{i,t}$	$\Delta p_{i,t}$
VADER Pos(z)	-0.06	-0.02	-1.59	-1.46
	(0.16)	(0.16)	(1.43)	(1.44)
VADER Neg(z)	-1.60^{***}	-1.56^{***}	-2.72	-2.62
	(0.27)	(0.28)	(2.20)	(2.38)
Startup Flag		3.49^{***}	4.92	
		(1.29)	(10.86)	
VADER Pos(z) $\times$ Startup Flag		-1.49^{*}	9.85	
		(0.82)	(8.89)	
VADER Neg(z) $\times$ Startup Flag		-2.13^{**}	-21.82^{***}	
		(0.93)	(7.29)	
Contagion Tweet				41.71
				(36.77)
VADER Pos(z) $\times$ Contagion Tweet				21.68
				(23.73)
VADER Neg(z) $\times$ Contagion Tweet				-28.18^{**}
				(14.32)
Constant	-0.78	-0.85	-26.17^{***}	-26.06^{***}
	(0.78)	(0.76)	(4.79)	(4.88)
Observations	1521078	1521078	43597	43597
R^2 (%)	1.01	1.02	2.47	2.47
Bank FE	✓	✓	✓	✓
Sample	All	All	$\geq$ Mar09	$\geq$ Mar09

CONCLUSION

What do we learn from studying the first social media induced bank run?

- Twitter communication and coordination have an **imprint beyond SVB**.
  - Existing run risks are greater in the presence of social media.
  - Social media is distinctive in its *virality*: broad audience reach can come from anywhere.

- Preexposure to Twitter conversation matters, tweets by startup community members (who are depositors) have more impact, so do contagion conversations.