Social Media as a Bank Run Catalyst

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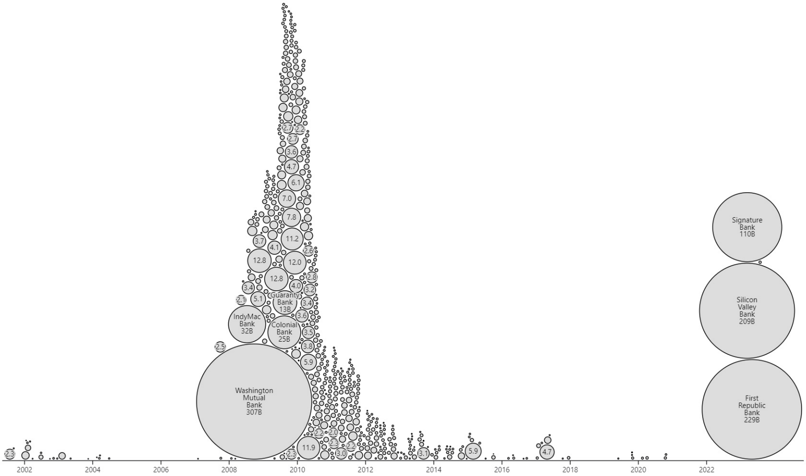
Bank Failures, Size and Date

- The 2023 US bank failures were not insignificant



Source: https://observablehq.com/@mbostock/bank-failures

Bank Failures, Size and Date

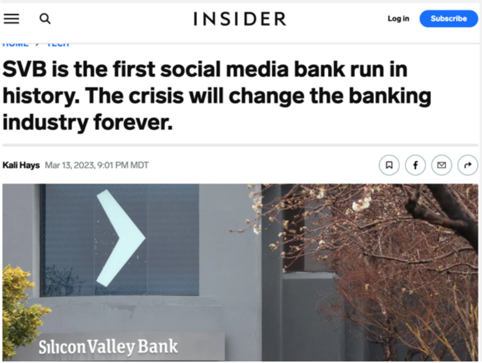
- Deposit outflows at unprecedented speed

Selected Deposit Runs from 1984 to 2023

Bank	Date run started	Deposit insurance coverage (%)	Total outflow (%)	Duration of outflow
Continental Illinois	May 7, 1984	15	30	10 days (7 bus. days)
Washington Mutual	Sep. 8, 2008	74	10.1	16 days (12 bus. days)
Wachovia	Sep. 15, 2008	61	4.4	19 days (15 bus. days)
Silvergate	2022 Q4	11	52	Possibly 7 days or less
Silicon Valley Bank	Mar. 9, 2023	6	25 + 62*	1 day + expected next day
Signature Bank	Mar. 10, 2023	10	20 + 9*	1 day + expected next day
First Republic	Mar. 10, 2023	32	57	About 7-14 days (5-10 bus. days)

Source: https://research.stlouisfed.org/publications/economic-synopses/2023/05/26/understanding-the-speed-and-size-of-bank-runs-in-historical-comparison

Silicon Valley Bank: The first social media bank run?



The first "social media, internet bank run in U.S. history" ***U.S. 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, U.S. Secretary of the Treasury***

Motivation

- In models of bank runs, a bank run is a self-fulfilling prophecy driven by beliefs about other depositors' actions (Diamond Dybvig, 1983; Goldstein and Pauzner, 2005).
- Social media can serve as a public signal on which depositors coordinate (Morris and Shin, 2000; Angeletos and Werning, 2006; Iyer and Puri 2012; Ziebarth 2017).
- Social media can also serve as an information channel to communicate banks' fundamental insolvency (Calomiris and Mason, 1997)

Our question:

Does exposure to social media amplify the risk of bank runs?

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The Social Media Channel in 2023

Pre-existing bank run risks

- Held-to-maturity assets had lost significant value (Granja, 2023).
- Insufficient hedging of interest rate risk (Jiang, Matvos, Piskorski, and Seru, 2023a)
- Large fraction of uninsured deposits (Jiang, Matvos, Piskorski, and Seru, 2023b).

Role of social media

- Like traditional media: Produces and spreads information
- Two-way communication: It reveals other users' beliefs, intentions
- Takes place in real time, any time of the day, any day of the week, everywhere in the world

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The Social Media Channel in 2023

Christina Qi
@christinaqi

I'm not a financial advisor but... if anyone has company money in SVB, withdraw while you can. The website went down for many folks, withdrawals are becoming more and more difficult. If you need to run payroll and keep operations going, get another bank account now.

10:36 PM · Mar 9, 2023 · **39.1K** Views

What we do

We collect comprehensive Twitter data

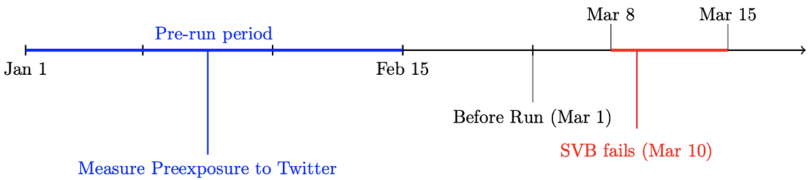
- All Tweets with *Cashtags* of bank stocks (e.g. $SIVB, $FRC) back to January 1 2020.
- Augment with tweets that mention notable banks (e.g. Silicon Valley Bank, First Republic Bank) and user data

We relate Twitter activity to bank stock returns

- Available at high frequency
- Stock returns objective quantitative measure of bank distress (Baron, Verner, Xiong 2021)
- Stock prices as a coordinating mechanism (Angeletos and Werning 2006).

For validation, we also look at quarterly deposit flows

Timeline and Strategy



Three complementary tests:

- **CX.** Relate Twitter pre-exposure (Jan 1 - Feb 15) to bank stock losses (Mar 1 to Mar 15).
- **Hourly**. Relate hourly bank stock returns from Mar 8 onward to 4-hour lagged tweet volume.
- **High-Frequency**. Relate negative tweet sentiment to 10-minute returns in and out of the run.

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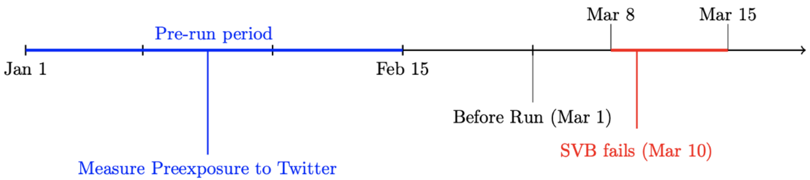

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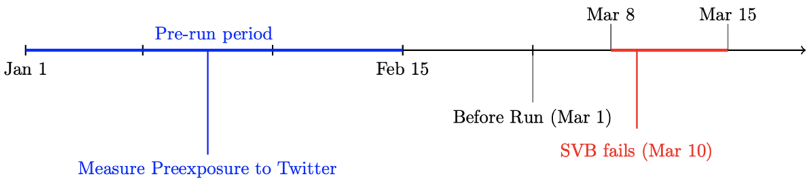

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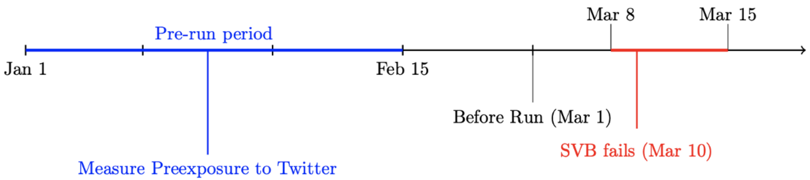

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Our Findings

Higher preexposure to Twitter predicts larger bank stock losses in the run period

- 6.6 percentage points larger stock losses during the run for banks in top tercile of Twitter preexposure.

Evidence consistent with social media amplifying bank run risks:

- Twitter pre-exposure interacts significantly with risks (% uninsured deposits and mark to market losses)

Twitter conversations about a bank followed by stock price changes:

- Tweet intensity over past 4 hours depresses bank stock prices at hourly freq.
- Negative sentiment has an immediate effect (within 10 minutes).

Important role of startup or "tech" Twitter users:

- Startup user tweets have more market impact.

Contribution

Banking crisis of 2023

- We contribute to an understanding of this period of banking distress (Jiang et al 2023a, 2023b; 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 ties trascend all barriers.

Communication technologies and contagion

- Radio, television, print media are one-way communication devices (Ziebarth 2017).
- Two-way communication is distinct in its ability to facilitate contagion and coordination.

Social economics

- Social economics is affecting politics, investing, housing choices. Now: banking stability?

Measurement

Data

- From the Twitter API, we collect
  - 5.4 million tweets with "cashtags" (e.g., $SIVB) of publicly traded banks from 1/1/2020–3/14/2023.
  - Our query begins with all tickers in SIC codes 602, 603 and 609.
  - From Jan 1, 2023 onward, collect tweets on general conversations containing "Silicon Valley Bank" or "SVB" and "First Republic Bank".
  - We also collect author data for 544,888 Twitter users who contributed these tweets, including user description.
- FirstRate gives intraday stock trade data (granular at the minute level)
- FDIC data drawn from FFIEC to collect information on balance sheet health.
  - 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.
  - Deposit outflows from 2022:Q4 to 2023:Q1

Twitter Language Content

- **Contextual dictionaries** using *bag-of-words* approach: banks with high 'run' and 'contagion' tweets in **run-period** $\leftrightarrow$ many **pre-run tweets** . Dictionaries
- 'Run' and 'contagion' words are very rare pre-run, but dominate the Twitter conversation after March 08. Pre- vs post-run words
- Retweets of pre-run bank-related tweets occur almost exclusively after run-start, even when they contain information about SVB balance sheet risks. Analysis of Retweets
- Anecdotal evidence of misinformation about Bank of America, which did not experience a run in March 2023. Example of Misinformation

Takeaway: Supports the interpretation that **tweets in pre-run period** reflect general social media exposure, rather than **run-related information**.

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Cross-sectional Results

CX Regression Evidence

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	$\boxed{4.117^{***}}$		1.223		1.288
	(1.025)		(0.895)		(0.893)
% Loss MTM (z)	0.804			−0.069	−0.487
	(0.873)			(0.362)	(0.733)
% Uninsured (z) × % Loss MTM (z)	0.943				−0.980
	(0.735)				(0.782)
1(Social Exp. Tercile = 2) (T2)		0.579	0.074	0.575	0.276
		(0.798)	(0.870)	(0.834)	(0.861)
T2 × % Uninsured (z)			1.527		1.588
			(1.143)		(1.150)
T2 × % Loss (z)				0.461	1.425
				(0.689)	(0.966)
T2 × % Uninsured (z) × % Loss MTM (z)					0.990
					(1.005)
1(Social Exp. Tercile = 3) (T3)		6.660***	5.209***	6.464***	6.302***
		(1.490)	(1.306)	(1.542)	(1.497)
T3 × % Uninsured (z)			3.278*		4.157**
			(1.831)		(2.016)
T3 × % Loss MTM (z)				−0.866	2.170
				(1.201)	(1.990)
T3 × % Uninsured (z) × % Loss MTM (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

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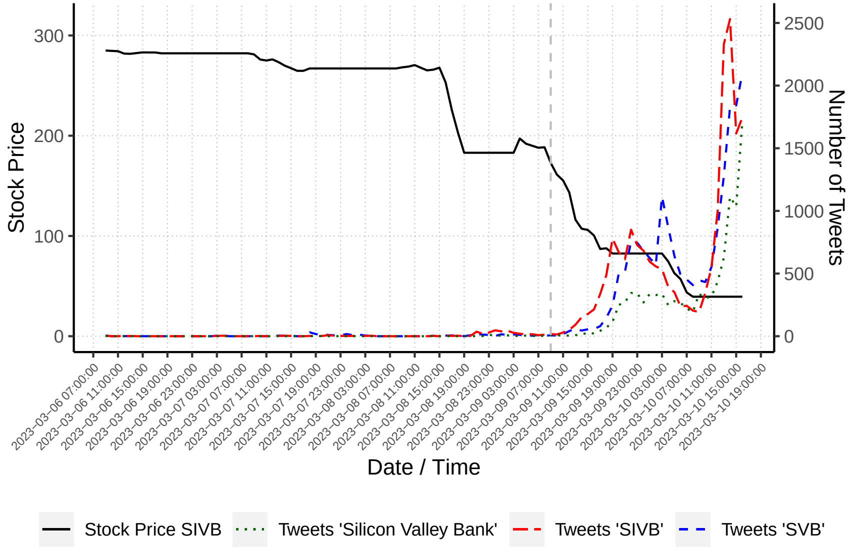
Robustness and Additional Analysis

- Alternative estimation periods for Twitter preexposure.
- Exclude largest banks (i.e., $\geq$ 500 \$B in deposits).
- Analysis of deposit outflows from 2022:Q4 to 2023:Q1:
  Deposit Outflow Analysis
- Use ‘startup’ tweets during run-period instead of preexposure.
  Start-up tweets
- Inclusions of ‘run’, ‘contagion’, and ‘startup’ tweets during run-period. Run-period vs pre-run tweets

Hourly Frequency

Evidence of Conversation Spillover (for SVB)



Hourly Stock Returns and 4-hour Lagged Tweets

Period: March 6 - March 14

Balance Sheet Risk = Loss MTM $\times$ % Uninsured

	Hourly Stock Return (%)		
	(1)	(2)	(3)
$1(\geq$ Mar 09)	-0.4462***	-0.4712***	
	(0.0226)	(0.0281)	
Balance Sheet Risk (z)	-0.0002		
	(0.0131)		
# Tweets (4h) (z) (t-1)	-0.0435	0.1233	-0.3499
	(0.1189)	(0.2322)	(0.2643)
$1(\geq$ Mar 09) $\times$ Balance Sheet Risk (z)	-0.0960***	-0.1374***	-0.1321***
	(0.0321)	(0.0378)	(0.0346)
$1(\geq$ Mar 09) $\times$ # Tweets (4h) (z) (t-1)	-0.3022	-0.4407	-0.1424
	(0.3453)	(0.3139)	(0.3604)
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	(0.1951)	(0.3947)	(0.3650)
$1(\geq$ Mar 09) $\times$ Balance Sheet Risk (z) $\times$ # Tweets (4h) (z) (t-1)	-0.1908	-1.058***	-0.9453***
	(0.2093)	(0.3443)	(0.3264)
Constant	-0.1437***		
	(0.0087)		
Observations	12,915	12,915	12,915
R^2	0.0138	0.0263	0.2630
Within R^2		0.0135	0.0085
Bank FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Bank	Bank	Bank

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Balance Sheet Risk (z) $\times$ # Tweets (4h) (z) (t-1)	0.2839	1.175***	1.103***
	(0.1951)	(0.3947)	(0.3650)
1($\geq$ Mar 09) $\times$ Balance Sheet Risk (z) $\times$ # Tweets (4h) (z) (t-1)	-0.1908	-1.058***	-0.9453***
	(0.2093)	(0.3443)	(0.3264)
Constant	-0.1437***		
	(0.0087)		
Observations	12,915	12,915	12,915
R^2	0.0138	0.0263	0.2630
Within R^2		0.0135	0.0085
Bank FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Bank	Bank	Bank

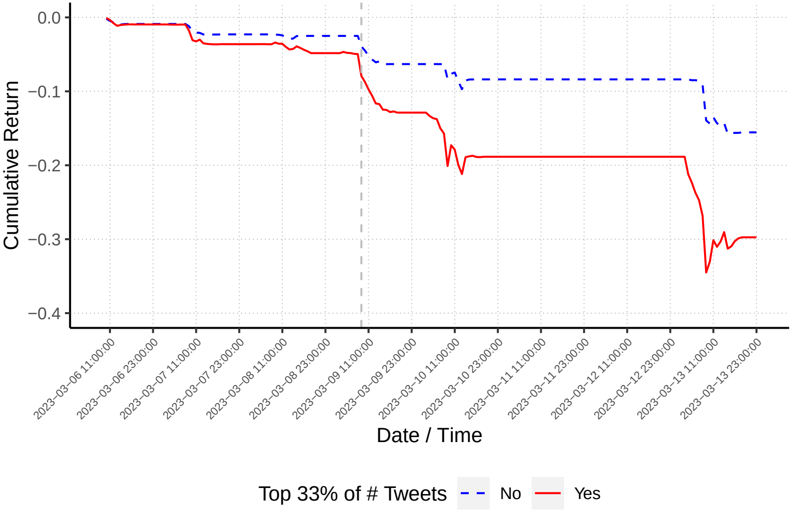
Hourly Bank Stock returns explained by 4-hour lagged tweet activity

Similar conclusions when we:

- Exclude SIVB; exclude largest banks
- Control for lagged returns
- Study shorter time-window (March 8 - March 9)

Graphical evidence on hourly frequency

Including SVB



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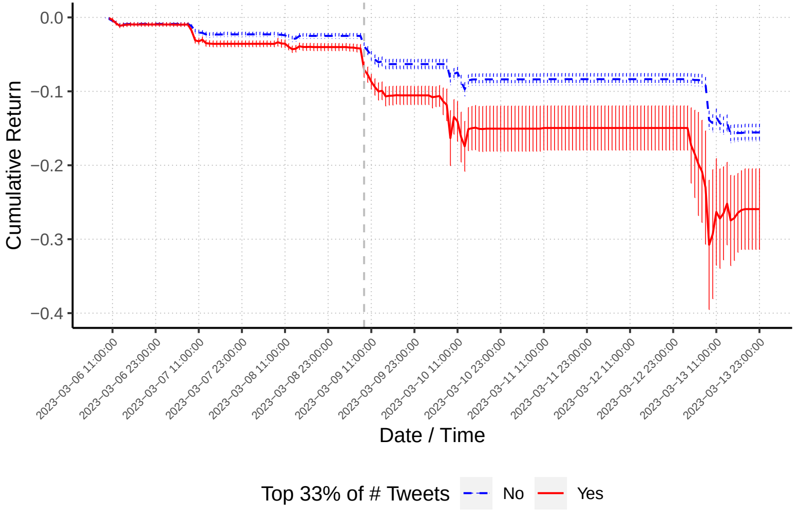
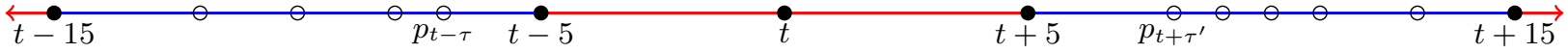


High Frequency

High Frequency Tests

- We borrow the identification strategy of Bianchi, Gomez-Cram, Kind and Kung (2023) and Bianchi, Gomez-Cram and Kung (2022)
- Identification assumption: nothing else happens within a very short time window around a tweet



- Define log returns: $\Delta p_{i,t} = p_{i,t+\tau'} - p_{i,t-\tau}$

$$\Delta p_{i,t} = a + b \times \text{VADER Pos (z)}_{it} + c \times \text{VADER Neg (z)}_{it} + \gamma_i + \epsilon_{i,t}$$

High Frequency Tests

	(1) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$	(5) $\Delta p_{i,t}$	(6) $\Delta p_{i,t}$
VADER Pos(z)	-0.06	-0.02	-1.59	-1.46	-1.54	-0.79
	(0.16)	(0.16)	(1.43)	(1.44)	(1.57)	(0.92)
VADER Neg(z)	-1.60***	-1.56***	-2.72	-2.62	-3.21	-4.61***
	(0.27)	(0.28)	(2.20)	(2.38)	(1.97)	(1.41)
Startup Flag		3.49***	4.92			
		(1.29)	(10.86)			
VADER Pos(z) × Startup Flag		-1.49*	9.85			
		(0.82)	(8.89)			
VADER Neg(z) × Startup Flag		-2.13**	-21.82***			
		(0.93)	(7.29)			
Contagion Tweet				41.71		
				(36.77)		
VADER Pos(z) × Contagion Tweet				21.68		
				(23.73)		
VADER Neg(z) × Contagion Tweet				-28.18**		
				(14.32)		
Run Tweet					-2.68	
					(8.12)	
VADER Pos(z) × Run Tweet					5.32	
					(7.63)	
VADER Neg(z) × Run Tweet					-0.52	
					(9.69)	
High Balance Sheet Risk						
VADER Pos(z) × High Balance Sheet Risk						-0.79
						(2.41)
VADER Neg(z) × High Balance Sheet Risk						1.93
						(3.23)
Constant	-0.78	-0.85	-26.17***	-26.06***	-25.90***	-26.19***
	(0.78)	(0.76)	(4.79)	(4.88)	(4.83)	(4.63)
Observations	1521078	1521078	43597	43597	43597	43597
R^2 (%)	1.01	1.02	2.47	2.47	2.46	2.45
Bank FE	✓	✓	✓	✓	✓	✓
Sample Period	All	All	≥Mar09	≥Mar09	≥Mar09	≥Mar09

High Frequency Tests

	(1) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$	(5) $\Delta p_{i,t}$	(6) $\Delta p_{i,t}$
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Conclusions

What have we learned?

- Preexposure to Twitter conversation matters
- Twitter communications seem to interact with bank risks to make banks more vulnerable, beyond SVB.
- Tweets by startup community members (= depositors) have more impact
- ...as well as contagion and run conversations.
- Consistent with social media being a new channel for communication and coordination among bank depositors.

Implications:

→ Should banks/supervisors monitor social media?

→ Can social media risk be mitigated? How? Communication?

→ Measurement of social media risk and integration with other measures of systemic risk?

→ Liquidity regulation?

→ Pricing of deposit insurance?

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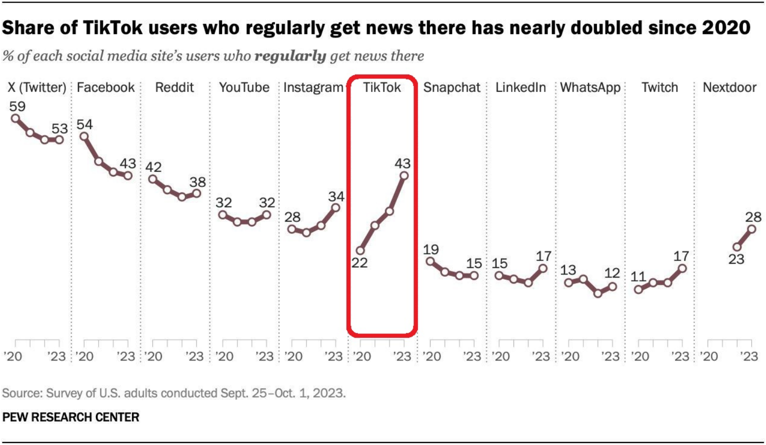
Social Media as a Source of News



Appendix Slides

Bag-of-words approach:

1. Started with a few seed words.
2. Flagged the tweets containing these words.
3. Added words that were in the top 40 most salient words (& not in the other dictionaries).

Dictionaries

Top-5 banks by 'run' dictionary

	Run	Contagion	Tweets Pre-Run	Crypto Pre-Run
SIVB	6,528	9,662	1,163	20
FRC	1,249	1,368	1,257	343
SI	343	342	20,774	356
SBNY	260	106	2,403	106
JPM	206	245	30,063	275
90th Percentile	3	2	784	3

- All these banks are high on Tweets pre-run (and Crypto mentions pre-run).
- Motivates our preexposure strategy.

Main Slide

Twitter Language Content

Contextual Dictionaries

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Main Slide

Contextual Dictionaries

to Flag Different kinds of Tweets

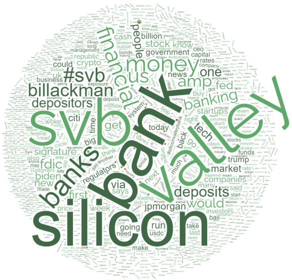
Balance Sheet	*Run Behavior*	*Contagion*	*Crypto*	*Startup Community*
duration	*run*	*systemic*	*crypto*	VC
cover & cash	*withdraw*	*spillover*	USDC	entrepreneur
mortgage backed securities	deposit money	fed	Circle	start up
mismatch	access accounts	regulator	Bitcoin	startup
long maturity	pull & out	#contagion	stablecoin	founder
maturity mismatch	*get & out*	backstop	tech	_venture
marked to market		whole system	FTX	venture capital
mark to market		spreading	peg	
portfolio management		sparks	BlockFi	
liquidity		broader effects	Ripple	
insured deposits		financial system	depeg	
MBS		meltdown	#crypto	
hold to maturity		*contagion*	#blockchain	
HTM			BTC	
portfolio of loans			*silverlake*	
liquidity management				
uninsured deposits				
balance sheet				

Dictionaries

Pre-run versus run-language

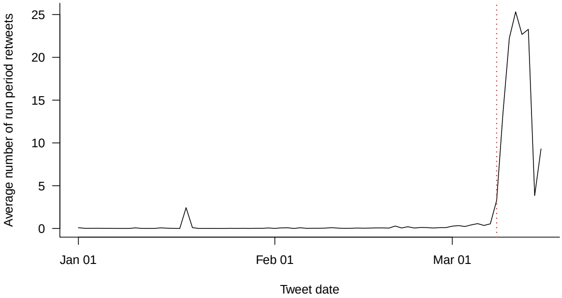
Pre-Run (Jan 1-Feb 15)

Run Period (Mar 8-13)



Main Slide

Average number of run-period retweets by original tweet date



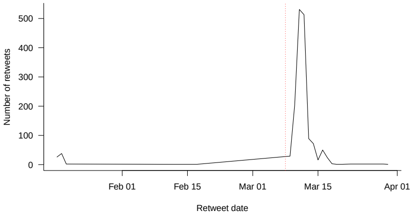
Main Slide

Retweets of pre-run tweets

Information Sharing and Social Contagion

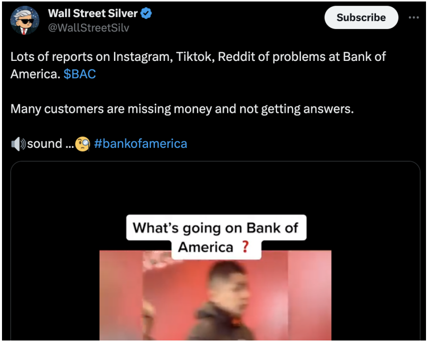
Raging Capital Ventures Tweet (Jan 18)

Retweets



Main Slide

'WallStreetSilv' Tweet about BAC (Jan 18)



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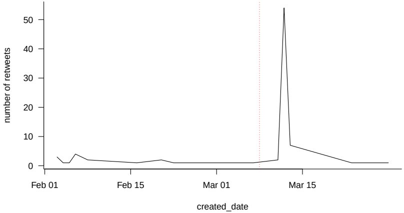

Main Slide

Deposit Flows from 2022:Q4 to 2023:Q1

	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 = 2) (T2)		-3.056*		-1.828
		(1.807)		(1.193)
T2 × % Uninsured (z)		5.085		3.031*
		(3.236)		(1.573)
T2 × % Loss MTM (z)		1.812		0.960
		(2.020)		(1.319)
T2 × % Uninsured (z) × % Loss MTM (z)		1.110		1.374
		(2.328)		(1.509)
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

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Main Slide

Start-up Tweets instead of Twitter Pre-exposure

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		0.691		0.654
	(1.025)		(0.555)		(0.615)
% Loss MTM (z)	0.804			−0.051	0.753
	(0.873)			(0.303)	(0.518)
% Uninsured (z) × % Loss MTM (z)	0.943				0.666
	(0.735)				(0.411)
1(Startup Tweets Tercile = 2) (T2)		0.801	0.602	0.689	0.556
		(0.747)	(0.745)	(0.744)	(0.773)
T2 × % Uninsured (z)			1.853**		2.026**
			(0.869)		(1.012)
T2 × % Loss MTM (z)				−1.047**	−0.993
				(0.528)	(0.795)
T2 × % Uninsured (z) × % Loss MTM (z)					−0.060
					(0.779)
1(Startup Tweets Tercile = 3) (T3)		8.200***	6.322***	8.112***	6.706***
		(1.561)	(1.269)	(1.569)	(1.341)
T3 × % Uninsured (z)			3.633**		4.544**
			(1.668)		(1.831)
T3 × % Loss MTM (z)				−0.949	−0.989
				(1.391)	(1.422)
T3 × % Uninsured (z) × % Loss MTM (z)					2.083
					(1.412)
Constant	16.368***	13.116***	13.346***	13.124***	13.464***
	(0.618)	(0.470)	(0.526)	(0.479)	(0.526)
Observations	280	280	280	280	280
R^2	0.158	0.139	0.244	0.145	0.280

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Run-period Tweets vs. Twitter Preexposure

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
1(Social Exp. Tercile = 2) (T2)	0.579	0.562	0.456	-0.298	0.133
	(0.798)	(1.280)	(1.271)	(1.459)	(1.275)
1(Social Exp. Tercile = 3) (T3)	6.660***	2.589*	1.950	2.533	0.210
	(1.490)	(1.368)	(1.396)	(1.741)	(1.543)
1("Contagion" Tweets in Run $<$ Median)		10.814***			5.050
		(2.914)			(3.117)
1("Contagion" Tweets in Run $\geq$ Median)		17.712***			9.301***
		(1.983)			(2.651)
1("Run" Tweets in Run $<$ Median)			3.282		1.128
			(2.212)		(2.288)
1("Run" Tweets in Run $\geq$ Median)			19.177***		11.282***
			(1.992)		(2.762)
1(Startup Tweets Tercile = 2) (T2)				0.589	0.507
				(1.407)	(1.229)
1(Startup Tweets Tercile = 3) (T3)				6.536***	2.705*
				(1.624)	(1.514)
Constant	13.453***	13.204***	13.453***	12.927***	13.034***
	(0.538)	(0.992)	(0.983)	(1.180)	(1.030)
Observations	280	280	280	280	280
R^2	0.093	0.310	0.322	0.151	0.363

Main Slide

Run-period Tweets vs. Twitter Preexposure

	% of Stock Value Lost During Run				
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		(2.914)			(3.117)
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