Social media and finance

FIRN Masterclass – Day 4

J. Anthony Cookson
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My plan

1. Social media landscape (today)
   Definitions, growth over time, data sources
   Some key examples

2. **Social media as a lens**
   Examples and approach, opportunities with new formats and features

3. Social transmission bias and social media signals
   Examples and approach.

4. **Effects of social media**
   Subtopic: production, consumption, and distribution of information
   Opportunities and challenges

Social media and real effects

After GameStop, there has been significant interest in

We've seen a couple of different manifestations of real impacts

- Social transmission bias (day 3)
- Stock market participation (day 1, Müller et al 2025 WP).
  - South-by-Southwest instrument: Karsten's other research gains a lot of traction with this.

Dessaint et al (2024JF) – does big data (social media) reshape financial forecasting?

Social media as alternative data

Does social media's introduction reshape the content of analyst forecasts?

Key insight and RQ: *social media is informative of short horizons*.

Introduction could make analyst information more informative of short horizons.

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The Journal of THE AMERICAN FINANCE ASSOCIATION

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Does Alternative Data Improve Financial Forecasting? The Horizon Effect

OLIVIER DESSAINT, THIERRY FOUCAULT, and LAURENT FRESARD*

ABSTRACT

Existing research suggests that alternative data are mainly informative about short-term future outcomes. We show theoretically that the availability of short-term-oriented data can induce forecasters to optimally shift their attention from the long term to the short term because it reduces the cost of obtaining short-term information. Consequently, the informativeness of their long-term forecasts decreases, even though the informativeness of their short-term forecasts increases. We test and confirm this prediction by considering how the informativeness of equity analysts' forecasts at various horizons varies over the long run and with their exposure to social media data.

Social media as alternative data

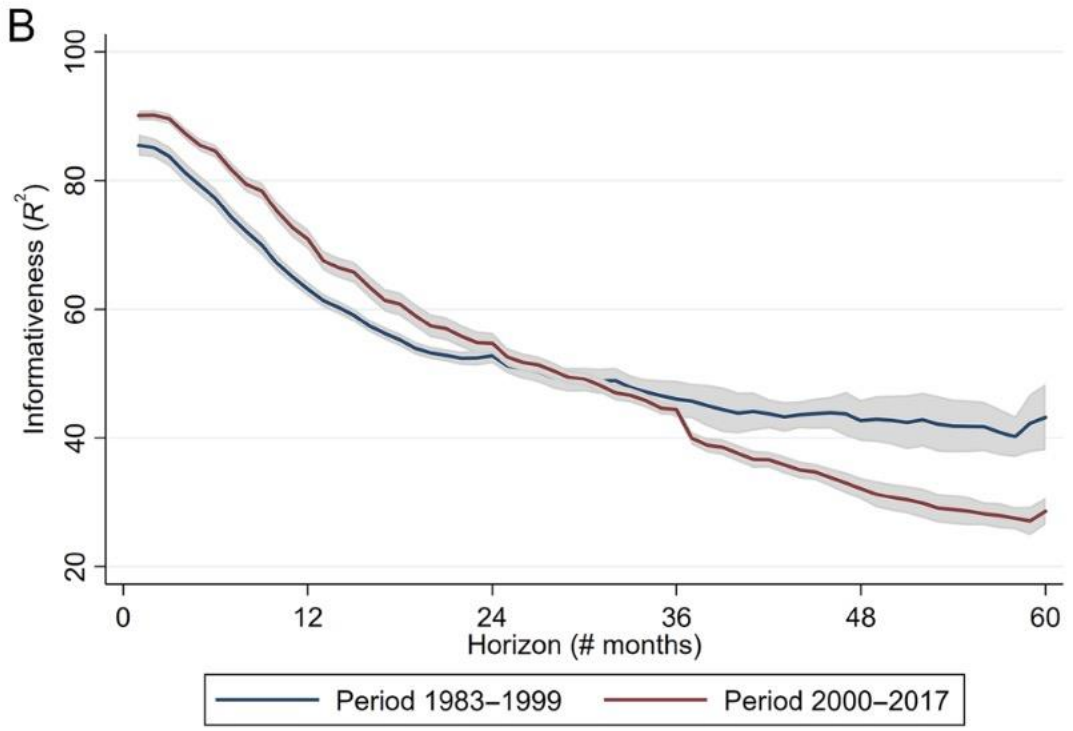
Implementation:

- At each forecast horizon, measure the **R-squared** for the fraction of earnings variation that is explained by analyst forecasts.
  - Cross-firm regression of earnings on forecasts within a given time period.

- Relate to changes over time and around introductions of alternative data
  - Paper's message is broader than social media, but key tests use social media.

Changes to informativeness by horizon over time

Short horizon forecasts become more informative in recent period



What about social media?

Explosive growth and unrelated to endogenous supply of data vendors

They use variation in adoption across firms. **Some firms are discussed a lot on the platform early on**, while others take longer for a discussion to emerge.

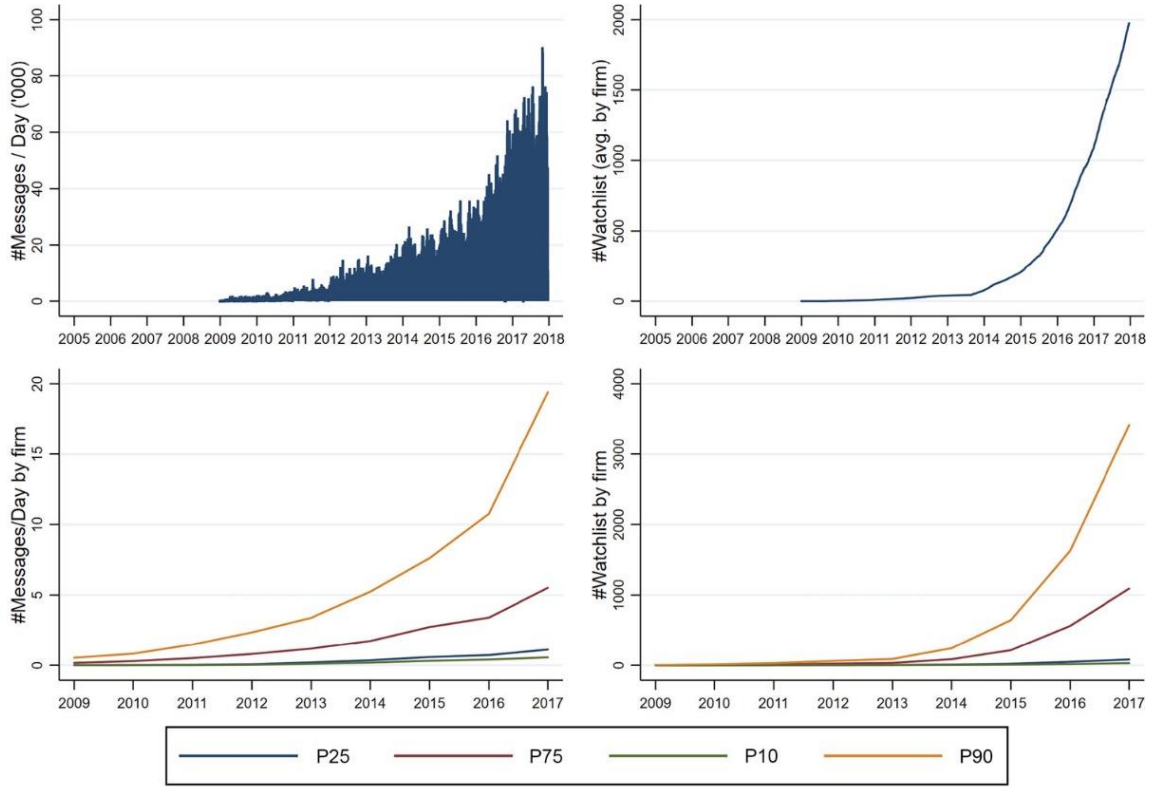


Figure 6. StockTwits' expansion. This figure shows descriptive statistics on the evolution of StockTwits between 2005 and 2017. The upper-left panel presents the total number of messages per day. The upper-right panel presents the number of users who have a given firm in their watch-

What about social media?

Shapes the short run

Predictions, particularly for short horizons, are related to sentiment on StockTwits

Also in the paper: Analyst exposure to social media activity ➔ *increases the Rsquared for short horizons but decreases it for long horizons.*

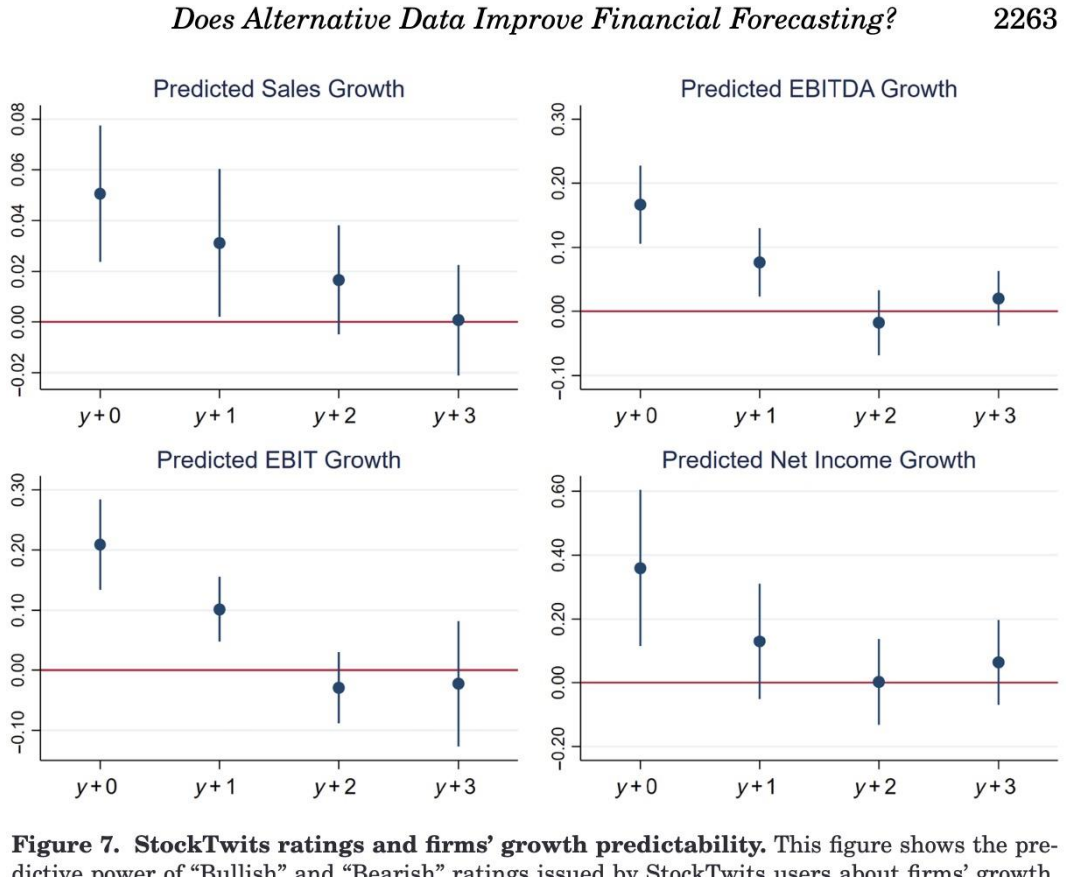


Figure 7. StockTwits ratings and firms' growth predictability. This figure shows the predictive power of "Bullish" and "Bearish" ratings issued by StockTwits users about firms' growth

Real effects of social media

Social media has become an important part of the information environment.

Where is the literature on real effects?

- Information quality as in Dessaint et al (2023JF).
- Fake news as in Kogan, Moskowitz and Niessner (2023RF)
- Deterioration of information quality after GME (Bradley et al 2024 RFS)
- Asset pricing effects as in Pedersen (2022JFE)
- *Information feedback, disclosure quality, interactions between investors and firms*.

Social media and informational efficiency

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Can Social Media Inform Corporate Decisions? Evidence from Merger Withdrawals

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Forthcoming at
Journal of Finance

Motivation

1. Social media and related technologies have transformed how investors interact with markets as a source of information.
   - Social platforms to share investment ideas, apps to trade from anywhere.
   - Sophisticated investors, too, rely on social media signals

2. Yet, social media has been at the center of recent trading controversies (Pedersen, 2021), and can reflect / exacerbate biases (Barber et al, 2021; Cookson et al, 2022), and propagate fake news (Kogan et al, 2022).

Tension: Social media can reflect information or be a source of noise.

Unclear whether it adds information to pay attention to it (interesting if it does).

MOTIVATION

Much has been made of social media as an information signal for ***investors***.

In 2013, Intel's head of IR talking about StockTwits said:

> *"We also […] listen and get a read on what is resonating with this audience. We can also see when we are trending through alerts and see the topics driving that interest. Over time, we'll build a feedback process to our teams so they can see this as well."*

Our Question

We ask whether social media can also provide a useful signal for ***firms***.

- Natural question given longstanding interest in firms' reliance on external signals – e.g., feedback from stock prices and news.

Is social media a sideshow?

Empirical Challenges & Strategy

Three empirical challenges

- Firm-day social media data is difficult to obtain systematically.

We measure social media sentiment using StockTwits at the firm-day level.

- Social media information arrives at high frequency, while corporate investment decisions are slower wave.

We study the decision to withdraw (or proceed with) an announced merger.

- Firm decisions generate social media reactions, raising reverse causality concern.

If a merger is withdrawn, firm manager plausibly changed mind.

Our findings

A negative social media reaction to merger announcement predicts merger withdrawals.

- A 1SD decrease in social media sentiment increases withdrawal prob by 0.64 ppt (16.6% of average likelihood of withdrawals). Similar to coef on traditional news sentiment and CARs
- Insensitive to controls, including controlling for market reactions & news sentiment.

Our findings

A negative social media reaction to merger announcement predicts merger withdrawals.

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- Insensitive to controls, including controlling for market reactions & news sentiment.

Compelling heterogeneity. Social media effect is larger when…

- Firms are more active on social media via a corporate Twitter account.
- Information is fundamental and tweets are more detailed.
- Information is external to manager. Analyst calls use more negative and constraining terms
  - Not presentation portion, but Q&A (suggests external info source)

- **Not governance as in Ang et al (2021), unrelated to manager networks.**

Contribution

Informativeness of data in asset markets and beyond.

- More information isn't always good (Dugast and Foucault 2018).
- Controversy about data in general, but social media in particular (Pedersen 2021; Cookson et al, 2022).
- Contribution: social media can be a useful signal, as informative as other widely studied sources.

Link between asset market & corporate decisions

- Classic to think about this (Morck et al 1990). Also, large literature (Edmans, Goldstein, etc.).

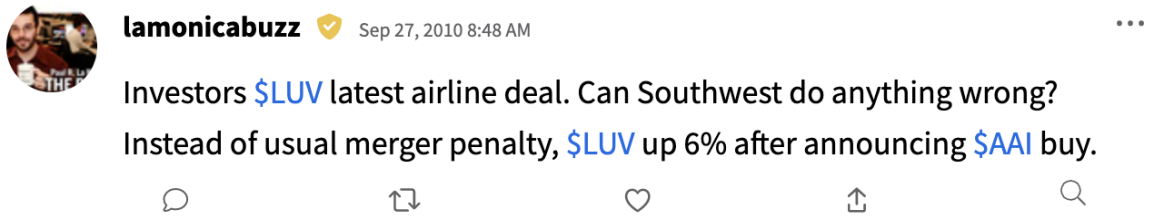
Measurement

Measuring Firm-specific Sentiment with StockTwits

We use the sentiment of *firm-specific tweets* from 2010-2021.

- Though tweets are sentiment stamped (discrete), we use the StockTwits provided sentiment measure (continuous).

"Sent = -0.879"



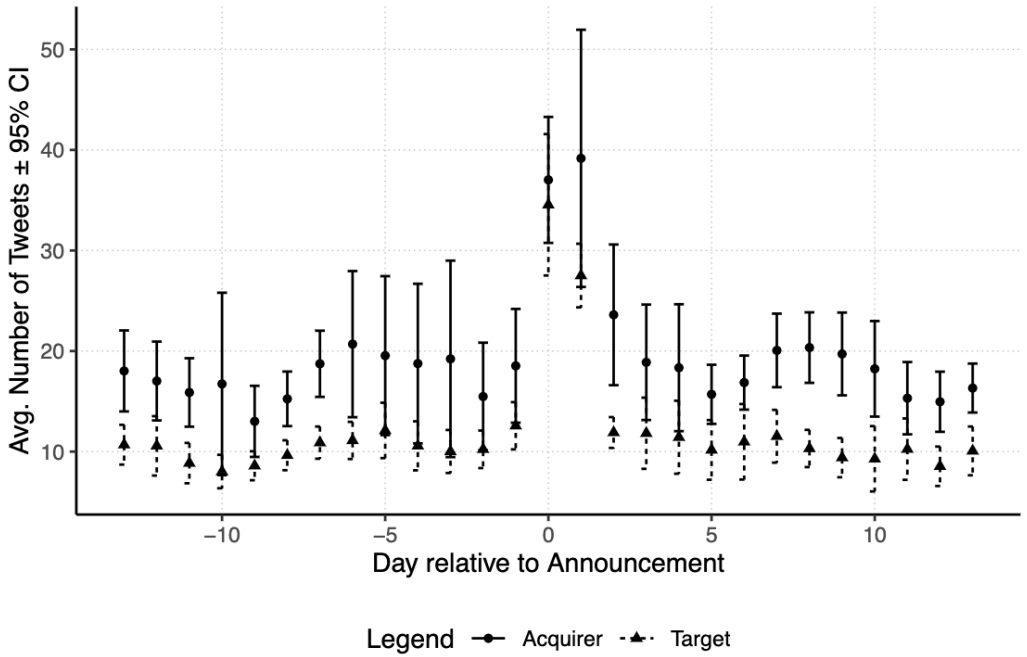
"Sent = 0.781"

- **Black box**, but useful in this context.
  - If attuned to social media info, firm managers *likely* rely on a similar signal.
  - **Robust** to sentiment measure based on Twitter data from SMA. And, also doing our own Entropy and Bayes classification + sentiment stamped tweets.

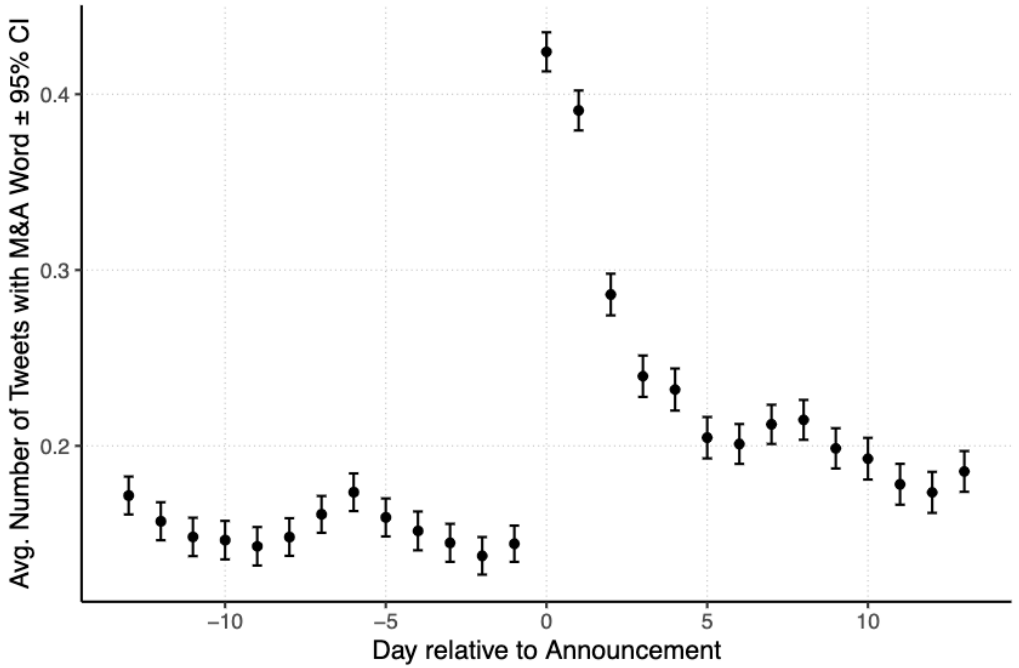
Does Social media notice M&As?

More Tweets

Figure 1: Number of Tweets around Merger Announcements



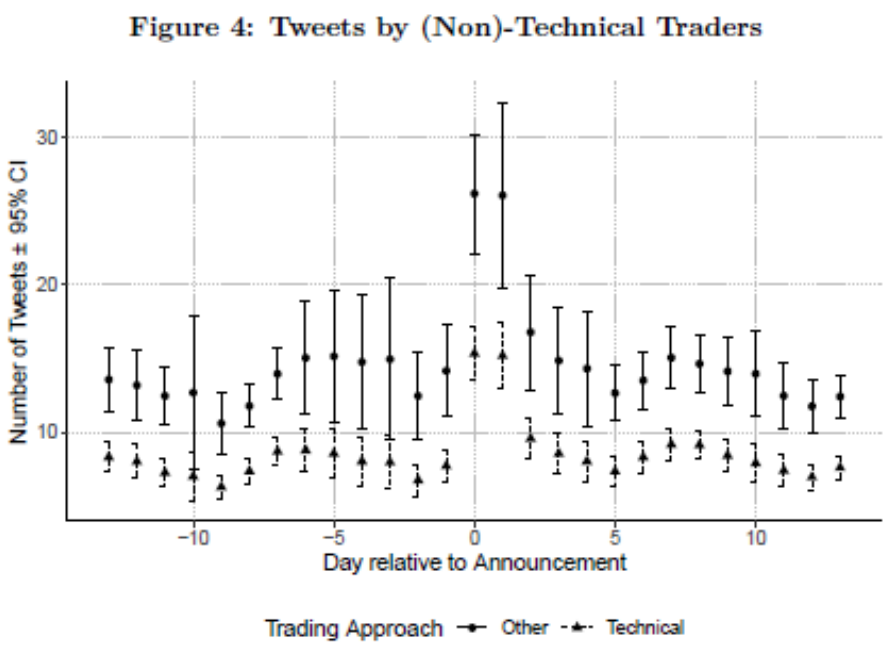
More Tweets about M&A



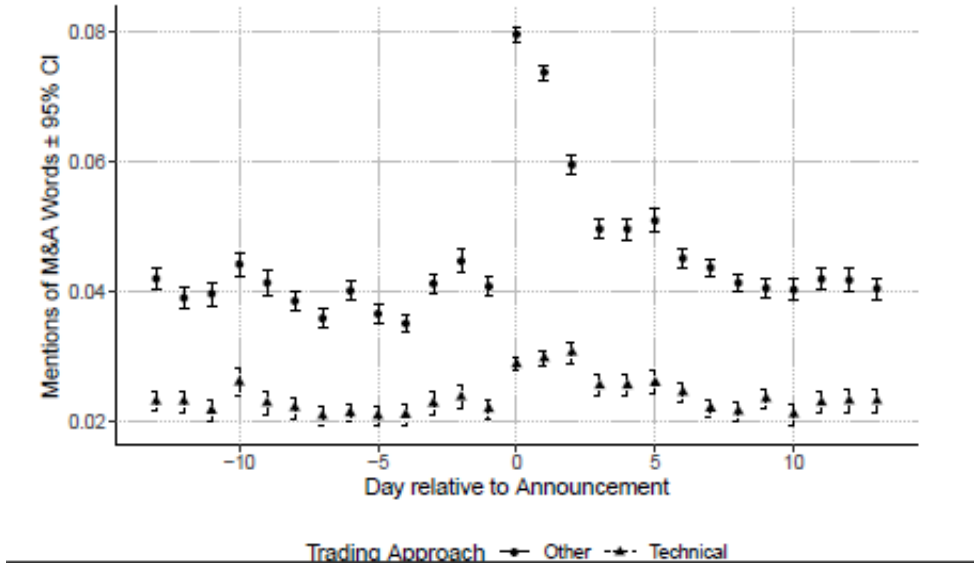
(a) Tweets about Acquirer

Do **all** investors notice M&As?

More Tweets by non-technical investors



More Tweets *about M&A* by non-technical investors



Days -13 to -7

Days 0 to 4

Distinctive Words pre versus Post Merger Announcement

Examples from the Adobe-Figma Merger Announcement (9/15)

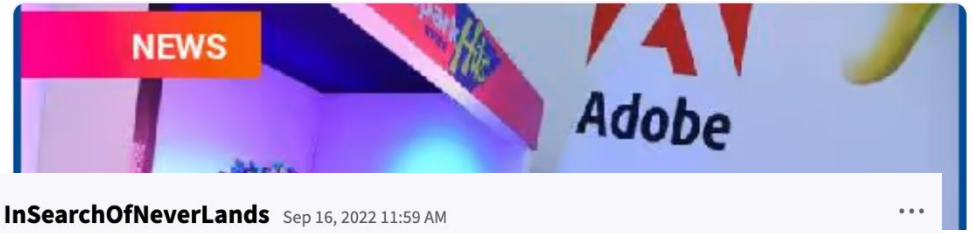
InvestorsAnteDOTcom Sep 16, 2022 11:59 AM

$ADBE will now transform their technology (into cloud & collab) with the code from FIGMA (no need to hire additional engineers to R&D for years)... and then jack up the prices (seems like the expectation is for prices to go up nearly 30%)....

Market share owned by Adobe after acquisition - roughly 90% (TAM I'd estimated to be over 16 billion)

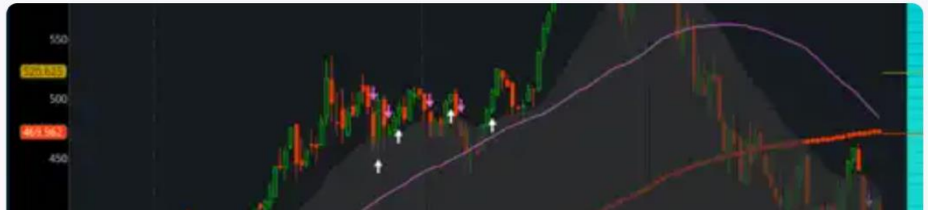
STCKPRO Sep 16, 2022 11:41 AM

$ADBE NEW ARTICLE : Adobe stock heads for worst week in 20 years as 'stratospheric' price for Figma causes doubts stck.pro/news/ADBE



InSearchOfNeverLands Sep 16, 2022 11:59 AM

$ADBE : Dind't check but i hope pay to FIGMA was by equity : BRUTAL to say the least , look at the VOLUME of dumping !



Examples from the Adobe-Figma Merger Announcement (9/15)

Dr_Claw Sep 16, 2022 10:09 AM

$ADBE total joke. Glad they paid good money for Figma, which is an actual market leader in the design space. Bearish

1

GinkoTrading Sep 16, 2022 12:58 PM

$ADBE like todays candle so much! Bullish

PunkinPower Sep 16, 2022 1:40 PM

$ADBE buy buy buy Bullish

caesars23 Sep 16, 2022 10:05 AM

$ADBE stupid sellers Bullish

2

InvestorsAnteDOTcom Sep 16, 2022 11:59 AM

$ADBE will now transform their technology (into cloud & collab) with the code from FIGMA (no need to hire additional engineers to R&D for years)... and then jack up the prices (seems like the expectation is for prices to go up nearly 30%)....

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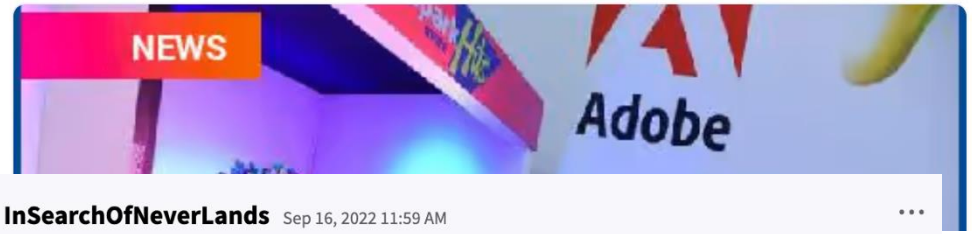

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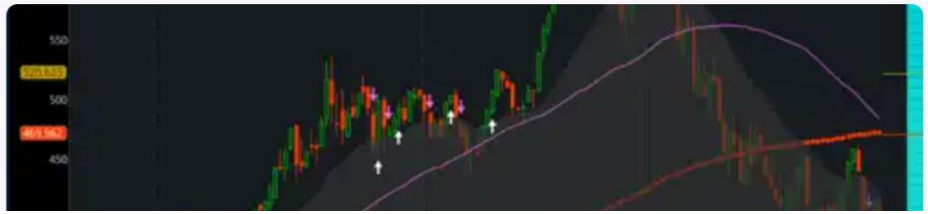

Measuring *Abnormal* Sentiment

Sample scope: all tweets that mention *at most* two tickers.

Then, for a merger announcement at date $t = 0$, compute abnormal sentiment in window after announcement (vs. a week prior, skipping a week).

$$\text{AbnSent}_i = \left(\frac{1}{|J_{i,[0,3]}|} \sum_{j \in J_{i,[0,3]}} Sentiment_{i,j(t)} \right) - \left(\frac{1}{|J_{i,[-13,-7]}|} \sum_{j \in J_{i,[-13,-7]}} Sentiment_{i,j(t)} \right)$$

Default is a 4-day period [0,3], but alternative windows deliver a similar index.

Sentiment & Merger withdrawals

Empirical Specification

Our tests focus on M&A **deal-level data** using the linear probability model:

$$Deal\ Withdrawn_i = \beta_1 \times AbnSent_i + \beta_2 \times CAR_i + \Gamma \cdot \mathbf{X_i} + \alpha_\mathbf{t} + \gamma_\mathbf{j} + \epsilon_\mathbf{i}$$

- *Deal Withdrawn* is an indicator {0,100} for whether deal i was withdrawn.
- *AbnSent* is our abnormal social media sentiment measure.
- *CAR* is the cumulative abnormal return – [-1,10] window using FF3, following Luo (2005).
  - Also control for [-5,-1] CAR.
- *Fixed effects α_t is year-quarter, γ_j is industry (GIC2).*
- *Other controls (**X**) are taken from the (vast) M&A literature.*

Main Result

One sd decrease in AbnSent predicts a **0.64 ppt increase** in merger withdrawal.

	𝟙(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.6434***	-0.7712***	-0.7153***	-0.7165***	-0.7294***	-0.7110***
	(0.2185)	(0.2167)	(0.2165)	(0.2066)	(0.2067)	(0.2099)
CAR Acq. (z) [-1;10]			-0.8760***	-0.9090***	-0.9259***	-0.8353***
			(0.2620)	(0.2562)	(0.2563)	(0.2689)
CAR Acq. (z) [-5;-1]			0.6584**	0.4687*	0.4713*	0.4688*
			(0.2601)	(0.2614)	(0.2663)	(0.2630)
News Sentiment Acq. (z)					-1.024***	-1.019***
					(0.2633)	(0.2578)
Analyst Rec. Changes (z)						-0.9653***
						(0.3246)
N Analyst Rec.						0.0986
						(0.1898)
N News Articles					0.0092	0.0094
					(0.0102)	(0.0101)
Log Deal Value ($B)		8.275***	8.262***	7.795***	8.009***	8.115***
		(0.7574)	(0.7667)	(0.8927)	(0.9041)	(0.9721)
% Shares Held Prior		0.0350	0.0324	0.0434*	0.0380	0.0385
		(0.0228)	(0.0236)	(0.0228)	(0.0232)	(0.0232)
Acq. White Knight (0/1)				0.5101	0.2363	-0.2203
				(16.27)	(16.21)	(16.29)
Competing Bidder (0/1)				43.02***	42.89***	42.77***
				(5.341)	(5.340)	(5.296)
Rumored Deal (0/1)				-1.196	-1.174	-1.196
				(1.144)	(1.151)	(1.136)
Hostile Deal (0/1)				76.96***	76.16***	76.16***
				(6.683)	(6.530)	(6.448)
Termination Fee Target ($M)				-0.0167***	-0.0171***	-0.0165***
				(0.0045)	(0.0045)	(0.0044)
N Tweets					-0.0002***	-0.0002***
					(0.00004)	(0.00004)
Mean(LHS)	3.885	3.763	3.776	3.776	3.776	3.776
Observations	6,306	5,979	5,932	5,932	5,932	5,932
R^2	0.0011	0.0710	0.0738	0.2107	0.2137	0.2161
Firm Controls		✓	✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

Main Result

One sd decrease in AbnSent predicts a **0.64 ppt increase** in merger withdrawal.

- Magnitude is robust to including acquirer firm controls.

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% Shares Held Prior		0.0350	0.0324	0.0434*	0.0380	0.0385
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Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

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Main Result

One sd decrease in AbnSent predicts a **0.64 ppt increase** in merger withdrawal.

- Magnitude is robust to including acquirer firm controls.
  And to controlling for market signals.
- Magnitude is similar to market reaction (*both standardized, so comparable*).

	𝟙(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.6434***	-0.7712***	-0.7153***	-0.7165***	-0.7294***	-0.7110***
	(0.2185)	(0.2167)	(0.2165)	(0.2066)	(0.2067)	(0.2099)
CAR Acq. (z) [-1;10]			-0.8760***	-0.9090***	-0.9259***	-0.8353***
			(0.2620)	(0.2562)	(0.2563)	(0.2689)
CAR Acq. (z) [-5;-1]			0.6584**	0.4687*	0.4713*	0.4688*
			(0.2601)	(0.2614)	(0.2663)	(0.2630)
News Sentiment Acq. (z)					-1.024***	-1.019***
					(0.2633)	(0.2578)
Analyst Rec. Changes (z)						-0.9653***
						(0.3246)
N Analyst Rec.						0.0986
						(0.1898)
N News Articles					0.0092	0.0094
					(0.0102)	(0.0101)
Log Deal Value ($B)		8.275***	8.262***	7.795***	8.009***	8.115***
		(0.7574)	(0.7667)	(0.8927)	(0.9041)	(0.9721)
% Shares Held Prior		0.0350	0.0324	0.0434*	0.0380	0.0385
		(0.0228)	(0.0236)	(0.0228)	(0.0232)	(0.0232)
Acq. White Knight (0/1)				0.5101	0.2363	-0.2203
				(16.27)	(16.21)	(16.29)
Competing Bidder (0/1)				43.02***	42.89***	42.77***
				(5.341)	(5.340)	(5.296)
Rumored Deal (0/1)				-1.196	-1.174	-1.196
				(1.144)	(1.151)	(1.136)
Hostile Deal (0/1)				76.96***	76.16***	76.16***
				(6.683)	(6.530)	(6.448)
Termination Fee Target ($M)				-0.0167***	-0.0171***	-0.0165***
				(0.0045)	(0.0045)	(0.0044)
N Tweets					-0.0002***	-0.0002***
					(0.00004)	(0.00004)
Mean(LHS)	3.885	3.763	3.776	3.776	3.776	3.776
Observations	6,306	5,979	5,932	5,932	5,932	5,932
R^2	0.0011	0.0710	0.0738	0.2107	0.2137	0.2161
Firm Controls		✓	✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

Main Result

One sd decrease in AbnSent predicts a **0.64 ppt increase** in merger withdrawal.

- Magnitude is robust to including acquirer firm controls.
  And to controlling for market signals.
- Magnitude is similar to market reaction (*both standardized, so comparable*).
- Also robust to deal-level controls.
  which soak up R^2

	𝟙(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.6434***	-0.7712***	-0.7153***	-0.7165***	-0.7294***	-0.7110***
	(0.2185)	(0.2167)	(0.2165)	(0.2066)	(0.2067)	(0.2099)
CAR Acq. (z) [-1;10]			-0.8760***	-0.9090***	-0.9259***	-0.8353***
			(0.2620)	(0.2562)	(0.2563)	(0.2689)
CAR Acq. (z) [-5;-1]			0.6584**	0.4687*	0.4713*	0.4688*
			(0.2601)	(0.2614)	(0.2663)	(0.2630)
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R^2	0.0011	0.0710	0.0738	0.2107	0.2137	0.2161
Firm Controls		✓	✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

Main Result

One sd decrease in AbnSent predicts a **0.64 ppt increase** in merger withdrawal.

- Magnitude is robust to including acquirer firm controls.
  And to controlling for market signals.
- Magnitude is similar to market reaction (*both standardized, so comparable*).
- Also robust to deal-level controls.
  which soak up R^2
- Impervious to controlling for news sentiment, analyst rec changes (also, manager networks)
  Liu and McConnell (2013), Becher et al (2015)

	𝟙(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.6434***	-0.7712***	-0.7153***	-0.7165***	-0.7294***	-0.7110***
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			(0.2620)	(0.2562)	(0.2563)	(0.2689)
CAR Acq. (z) [-5;-1]			0.6584**	0.4687*	0.4713*	0.4688*
			(0.2601)	(0.2614)	(0.2663)	(0.2630)
News Sentiment Acq. (z)					-1.024***	-1.019***
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				(6.683)	(6.530)	(6.448)
Termination Fee Target ($M)				-0.0167***	-0.0171***	-0.0165***
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N Tweets					-0.0002***	-0.0002***
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Mean(LHS)	3.885	3.763	3.776	3.776	3.776	3.776
Observations	6,306	5,979	5,932	5,932	5,932	5,932
R^2	0.0011	0.0710	0.0738	0.2107	0.2137	0.2161
Firm Controls		✓	✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

Robustness I

Result is robust to…

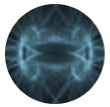
- Alternative sentiment measures.
- Public target subsample (larger magnitude).
- Target abnormal sentiment.
- Target spread.
- Dropping small deals.
- Including acquirer FE.

- Using **Twitter** Sentiment from SMA (not pictured)

Specification	1(Deal Withdrawn)							
	MaxEnt	Bayes	Public Targets				Drop Small	Acq. FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Sentiment (z) (MaxE)	-0.5835***							
	(0.1971)							
Abn. Sentiment (z) (Bayes)		-0.4268**						
		(0.2053)						
Abn. Sentiment (z) (StTw)			-2.133**	-2.962**	-2.804*	-2.607*	-1.170***	-0.8011**
			(0.9750)	(1.438)	(1.447)	(1.492)	(0.2785)	(0.3337)
Abn. Sent. Target (z) (StTw)				0.1704	0.0286	0.0228		
				(1.119)	(1.160)	(1.167)		
CAR Acq. (z) [-1;10]	-0.9461***	-0.9609***	-1.443	-2.042*	-1.949	-1.129	-1.315***	-1.278***
	(0.2501)	(0.2560)	(1.178)	(1.213)	(1.189)	(1.240)	(0.2813)	(0.3612)
CAR Acq. (z) [-5;-1]	0.5323**	0.5319**	1.064	0.7762	1.176	0.9680	0.6810**	0.7815**
	(0.2598)	(0.2593)	(1.154)	(1.280)	(1.328)	(1.421)	(0.3218)	(0.3277)
CAR Target (z) [-1;10]			-1.230		-1.571	-1.921		
			(1.148)		(1.245)	(1.440)		
CAR Target (z) [-5;-1]			-0.7008		-0.5146	-0.7775		
			(1.146)		(1.183)	(1.121)		
News Sentiment Acq. (z)	-1.007***	-1.004***	-3.932**	-4.022***	-4.036***	-2.440*	-1.612***	-1.049***
	(0.2566)	(0.2579)	(1.500)	(1.433)	(1.461)	(1.381)	(0.3662)	(0.3757)
N Tweets	-0.0002***	-0.0002***	-0.0006	-0.0008*	-0.0007	-0.0013***	-0.0002***	0.0002
	(0.00004)	(0.00004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.00004)	(0.0006)
N News Articles	0.0087	0.0089	0.0551	0.0272	0.0353	0.0112	0.0102	0.0129
	(0.0102)	(0.0103)	(0.0636)	(0.0585)	(0.0566)	(0.0461)	(0.0103)	(0.0120)
Target Spread						20.23*		
						(11.54)		
Mean(LHS)	3.791	3.791	4.139	11.57	11.63	10.91	3.914	3.825
Observations	5,988	5,988	880	683	679	605	4,445	5,896
R^2	0.2117	0.2113	0.3372	0.3523	0.3567	0.3639	0.2344	0.5536
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Firm FE								✓

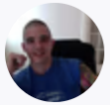
Robustness II

Result is smaller on “non feedback” subsamples: regulator-withdrawn and target-withdrawn.



cerebraltrades Mar 20, 2011 3:41 PM

@marketfolly I think the $T and TMob merger could be blocked due to anti monopoly issues but maybe it goes through with concessions.



JoshPritchard Mar 20, 2011 4:10 PM

DOJ should finally end $GOOG + ITA scrutiny and focus on real acquisitions with real antitrust issues, like $T and $TMOBILE ... 8 months??

(b) Deal rejection reasons

Deal Rejected by:	𝟙(Deal Withdrawn)	
	Regulator	Target
	(1)	(2)
Abn. Sentiment (z) (StTw)	-0.2020**	-0.1504
	(0.0883)	(0.1219)
CAR Acq. (z) [-1;10]	-0.0226	-0.2921***
	(0.0725)	(0.0974)
CAR Acq. (z) [-5;-1]	0.2586**	0.0806
	(0.1139)	(0.1168)
News Sentiment Acq. (z)	-0.2009*	-0.8442***
	(0.1141)	(0.2059)
N Tweets	-3.81×10^{-5}**	-7.73×10^{-5}***
	(1.48×10^{-5})	(1.88×10^{-5})
N News Articles	0.0041	0.0038
	(0.0080)	(0.0060)
N Deals Withdr.	30	74
Observations	5,734	5,776
R^2	0.0564	0.2790
Deal Controls	✓	✓
Firm Controls	✓	✓
Year-by-Quarter FE	✓	✓
Acq. Industry (GIC2) FE	✓	✓

Reaction to Withdrawn Deals

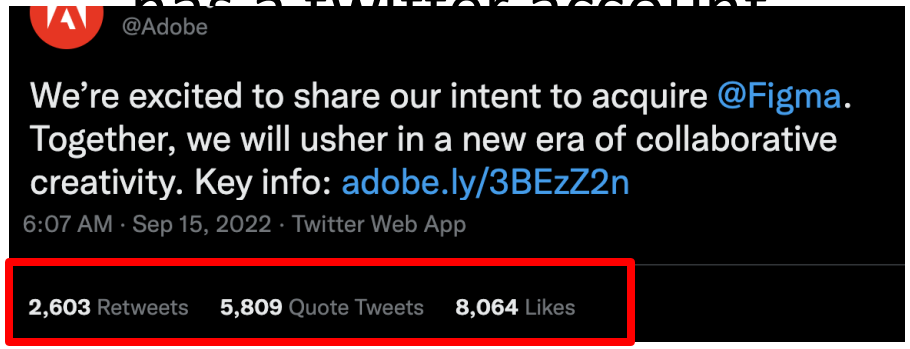
Market "celebrates" withdrawal of negative sentiment mergers.

	BHAR Acq. [+11; Deal Conclusion]			
	Delay>25 days		Delay>75 days	
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw) × 1(Deal Withdr.)	-0.1009**	-0.1087**	-0.1427***	-0.1528***
	(0.0390)	(0.0423)	(0.0309)	(0.0357)
Abn. Sentiment (z) (StTw)	-0.0078	-0.0074	-0.0154*	-0.0150
	(0.0050)	(0.0050)	(0.0090)	(0.0090)
1(Deal Withdr.) × CAR Acq. (z) [-1;10]		0.1505		0.1710
		(0.1018)		(0.1347)
1(Deal Withdr.) × CAR Acq. (z) [-5;-1]		0.0212		0.0319
		(0.0449)		(0.0558)
1(Deal Withdr.)	-0.0608	-0.0242	-0.0715	-0.0328
	(0.0622)	(0.0785)	(0.0820)	(0.1018)
CAR Acq. (z) [-1;10]	0.0389***	0.0324***	0.0624***	0.0519***
	(0.0114)	(0.0100)	(0.0204)	(0.0181)
CAR Acq. (z) [-5;-1]	0.0116	0.0096	0.0211	0.0175
	(0.0118)	(0.0116)	(0.0218)	(0.0218)
News Sentiment Acq. (z)	0.0115**	0.0118**	0.0233**	0.0226**
	(0.0051)	(0.0051)	(0.0096)	(0.0093)
Mean(LHS)	3.857	3.857	3.890	3.890
Observations	3,343	3,343	1,784	1,784
R^2	0.0444	0.0523	0.0781	0.0864
(Soc) Media Controls	✓	✓	✓	✓
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Heterogeneity and Mechanisms

Are Firms listening?

Prediction is stronger for announced deals in which the acquirer firm has a twitter account



	1(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw) × 1(Acq. Twitter)	-0.4711	-0.4472				
	(0.4025)	(0.4206)				
Abn. Sentiment (z) (StTw) × 1(Acq. HighFollow)			-0.9646**	-0.9559**		
			(0.4352)	(0.4608)		
Abn. Sentiment (z) (StTw) × 1(Acq. Verified)					-1.301**	-0.9259*
					(0.5019)	(0.5262)
Abn. Sentiment (z) (StTw)	-0.4356*	-0.4998	-0.3400*	-0.3764	-0.4000**	-0.5430
	(0.2495)	(0.3752)	(0.2002)	(0.3025)	(0.1981)	(0.3277)
1(Acq. Twitter)	0.4215	-0.8588				
	(0.5940)	(1.766)				
1(Acq. HighFollow)			0.4742	-1.722		
			(0.6047)	(3.602)		
1(Acq. Verified)					0.7672	-3.835
					(0.6698)	(3.799)
Mean(LHS)	3.776	3.776	3.776	3.776	3.776	3.776
Observations	5,932	5,932	5,932	5,932	5,932	5,932
R^2	0.2139	0.5538	0.2144	0.5541	0.2148	0.5542
Deal Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
(Social) Media Controls	✓	✓	✓	✓	✓	✓
CAR Controls	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓
Acq. Firm FE		✓		✓		✓

Information in the Signal (I)

Prediction is strongest when the **tweets are longer** & coming from **non-technical investors**

GinkoTrading Sep 16, 2022 12:58 PM

$ADBE like todays candle so much! Bullish

InvestorsAnteDOTcom Sep 16, 2022 11:59 AM

$ADBE will now transform their technology (into cloud & collab) with the code from FIGMA (no need to hire additional engineers to R&D for years)... and then jack up the prices (seems like the expectation is for prices to go up nearly 30%)....

Market share owned by Adobe after acquisition - roughly 90% (TAM I'd estimated to be over 16 billion)

	𝟙(Deal Withdrawn)			
	Technical Traders		Tweet Length	
	(1)	(2)	(3)	(4)
Abn. Sent (z) Technical=N	-1.105***	-1.080***		
	(0.2905)	(0.2884)		
Abn. Sent (z) Technical=Y	-0.3497	-0.2744		
	(0.3095)	(0.3010)		
Abn. Sent (z) Long=Y			-1.214***	-1.222***
			(0.3033)	(0.2983)
Abn. Sent (z) Long=N			-0.0525	0.0140
			(0.2664)	(0.2616)
CAR Acq. (z) [-1;10]		-1.023***		-0.8895***
		(0.3024)		(0.2837)
CAR Acq. (z) [-5;-1]		0.3161		0.4885
		(0.2983)		(0.2914)
News Sentiment Acq. (z)		-1.191***		-1.202***
		(0.3365)		(0.3239)
Mean(LHS)	4.239	4.247	3.909	3.920
Observations	3,680	3,650	4,042	4,005
R^2	0.2331	0.2430	0.2272	0.2361
(Soc) Media Controls		✓		✓
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Information in the Signal (II)

We did a topic analysis (biterm model, BTM) to separate the signal into subtopics.

- Effect driven by discussions of "company/business," "deal terms," and "disclosure."
- No effect for meme tweets, technical tweets, and trading tweets.

(b) Abnormal Sentiment by tweet topic

	𝟙(Deal Withdrawn)				
	(1)	(2)	(3)	(4)	(5)
Abn. Sent (z) Company/Business	-1.202***				
	(0.3160)				
Abn. Sent (z) Deal-Terms		-1.139***			
		(0.2983)			
Abn. Sent (z) Disclosure			-0.8675**		
			(0.3987)		
Abn. Sent (z) Meme				-0.2804	
				(0.6155)	
Abn. Sent (z) Technical					-0.4872
					(0.3391)
Abn. Sent (z) Trading	0.1189	0.1649	0.5371	-1.082	-0.3840
	(0.2733)	(0.2771)	(0.3953)	(0.7547)	(0.3508)
CAR Acq. (z) [-1;10]	-1.091***	-0.8503***	-0.9082***	-1.159***	-0.9557***
	(0.2858)	(0.2869)	(0.3209)	(0.3449)	(0.2714)
CAR Acq. (z) [-5;-1]	0.5760*	0.4322	0.4014	-0.0846	0.7333**
	(0.3007)	(0.3320)	(0.4072)	(0.4911)	(0.3166)
News Sentiment Acq. (z)	-0.9505**	-1.366***	-1.158***	-0.4856	-1.419***
	(0.3645)	(0.3482)	(0.4149)	(0.6599)	(0.3654)
Mean(LHS)	4.339	4.202	4.030	4.103	4.333
Observations	3,941	4,117	3,151	1,121	3,600
R^2	0.2450	0.2531	0.2480	0.2345	0.2546
(Soc) Media Controls	✓	✓	✓	✓	✓
Deal Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓

Conclusion

Social media is not a sideshow for corporate decisions.

- In predicting the decision to withdraw a merger, abnormal sentiment after merger announcement is *as important as market and traditional news signals*.
  - Stronger prediction for firms with corporate Twitter accounts.
  - Strongest when managers have the most to learn from external information (analyst calls and complex, tough-to-value deals).

Results imply that managers can learn from social media, and suggest that they do learn from social signals in M&A.

Social media can also have real effects via coordination and contagion

GameStop, for example, illustrated what can happen when retail traders coordinate.

Public forums provide an avenue to coordinate on positive (or negative) news.

This was true for GameStop, but also a phenomenon present in the Silicon Valley Bank (SVB) run.

The Sky's the Limit: Asset price spirals when margin traders are all in *

67 Pages • Posted: 18 Feb 2021 • Last revised: 31 Aug 2021

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Date Written: August 30, 2021

Abstract

We analyze a setting in which some investors are all in and buy as much of a risky asset as their margin allows. A higher price of the asset increases all-in investors' wealth, and they borrow against this wealth to buy more shares. If all-in investors have enough wealth and access to enough leverage, then prices can spiral upward indefinitely. This is true even if there exist deep pocketed investors with no explicit limits to arbitrage. Our theory applies to markets as diverse as housing, meme stocks, and cryptocurrencies.

Keywords: All in, Price spiral, GameStop, meme stock, House price, Cryptocurrency JEL Codes: G12, G30

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.

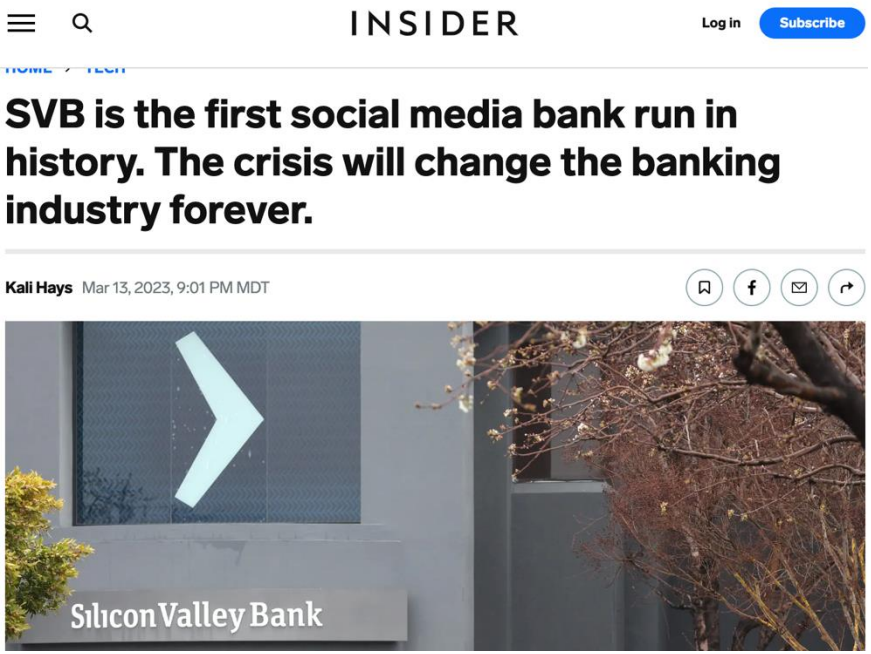
Why/when do depositors end up in the "bad" equilibrium?

- `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



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

- Senator, Mark Warner

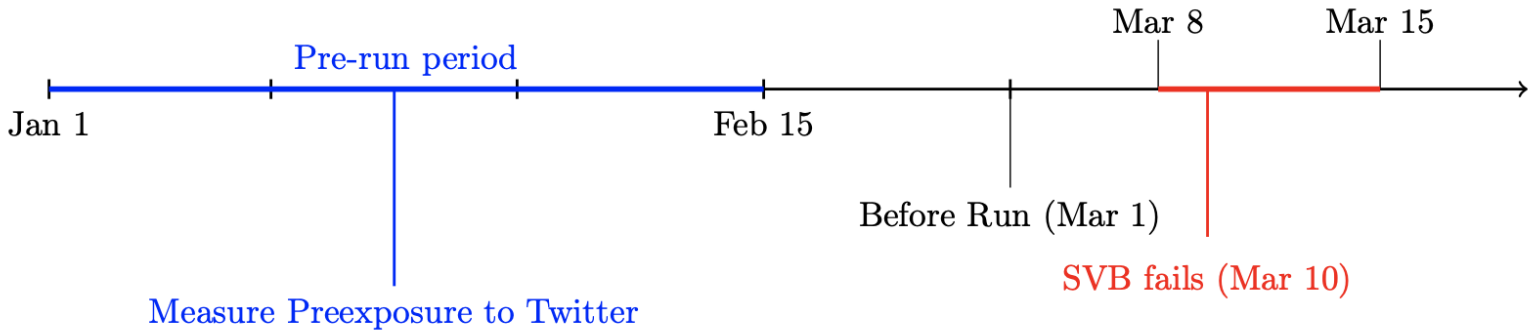
"If a bank has an overwhelming run that's spurred by social media ... so that it is seeing deposits flee at that pace, the bank can be put in danger of failing,"

- 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 and deposit outflows 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.***

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.
- High frequency effects on returns are not just driven by SIVB.
- 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.

Contextual Evidence

Contextual evidence:

Banks with high pre-run tweet volume also have high volume of run-period "run" and "contagion" tweets.

Run and contagion mentions are rare pre-run, but not after March 8.

Retweets analysis:

Even ex-post prescient tweets about SVB (i.e., *Raging Capital Ventures)* were not retweeted much before the run began.

Vast majority of retweets of pre-run tweets were after the run began.

High-retweet tweets reflect both information sharing (RCV) and spread of fear (BoA).

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*.

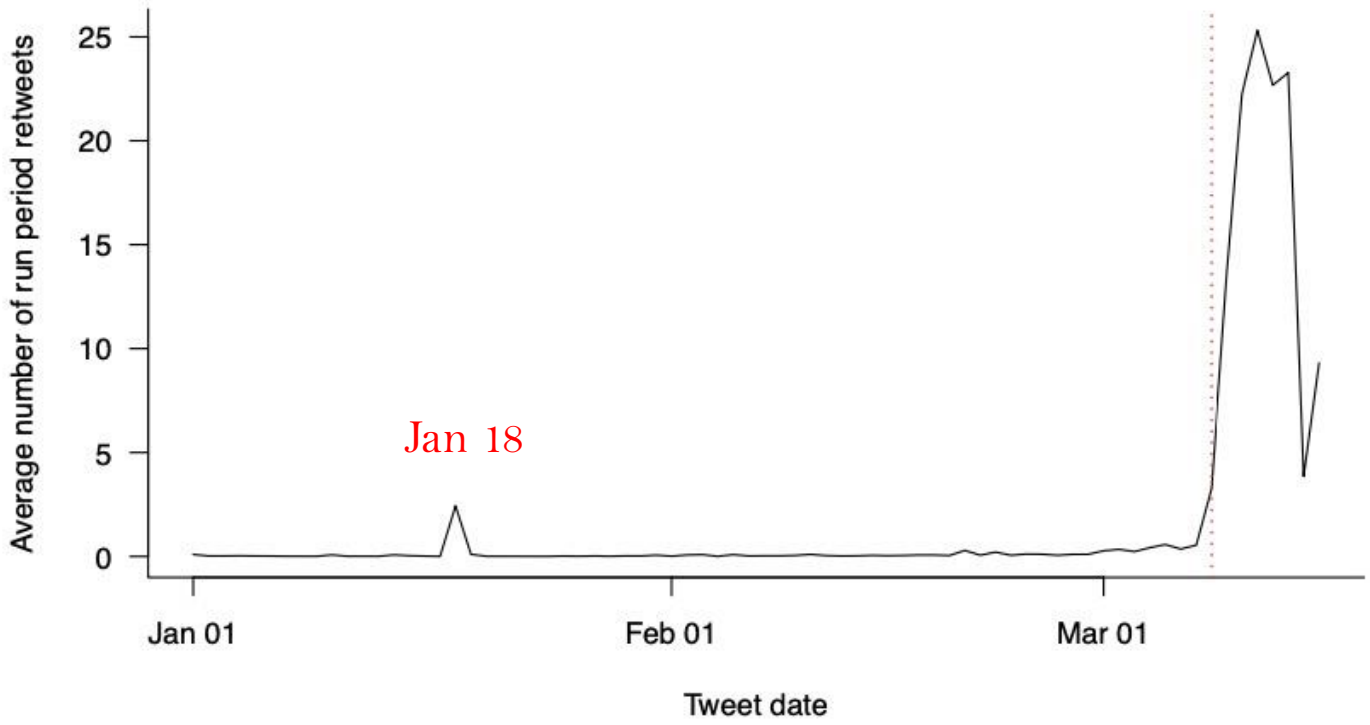
Pre-run versus Run Language

Pre-Run (Jan 1-Feb 15)

Run Period (Mar 8-13)

Pre-run Tweets were rarely Retweeted During the run

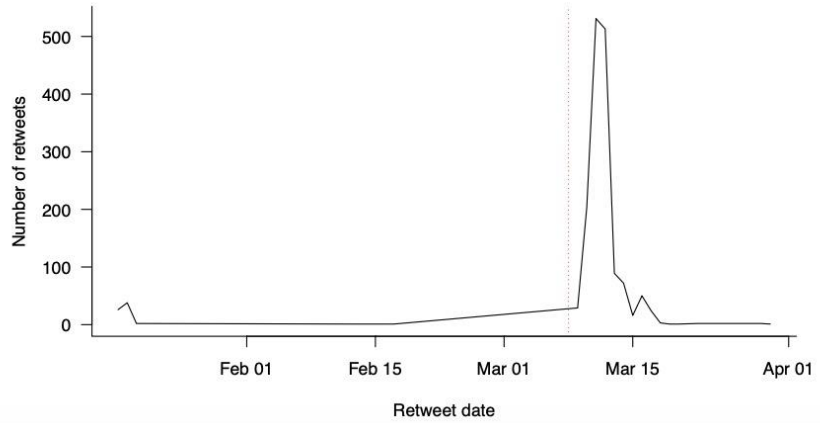
(b) Average Number of Run Period Retweets by Original Tweet Date



highly retweeted pre-run Tweets were Rediscovered during the run

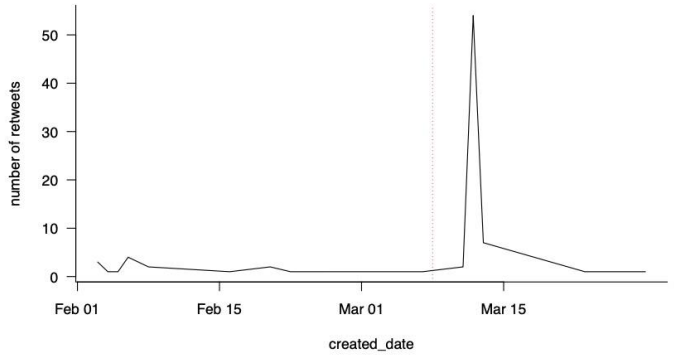
(a) Raging Capital Ventures Tweet on Jan 18, 2023

(b) Dynamics of Retweets of Raging Capital Ventures Tweet

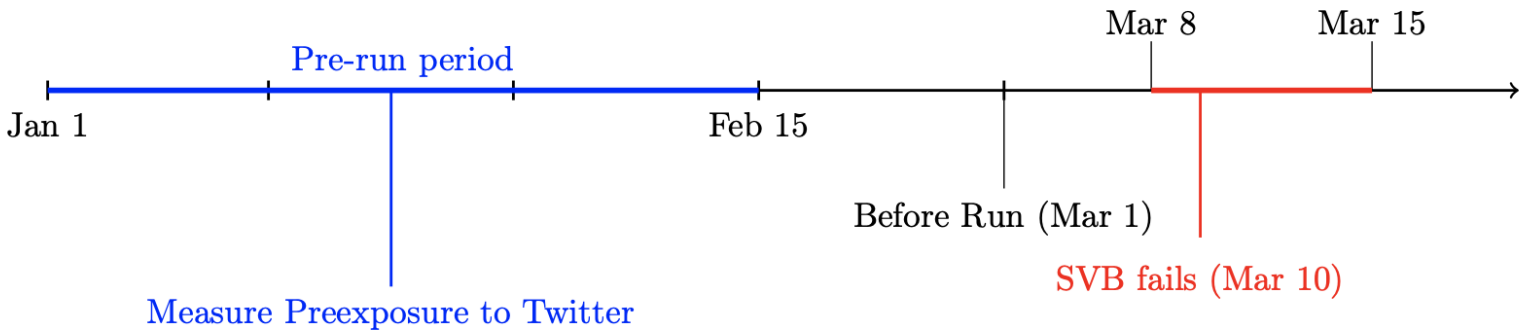


(a) WallStreetSilv Tweet about Bank of America on Jan 18, 2023

(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)	4.117***		1.223		1.288
	(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)		6.660***	5.209***	6.464***	6.302***
		(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.

	Dependent variable:				
	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		1.223		1.288
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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.

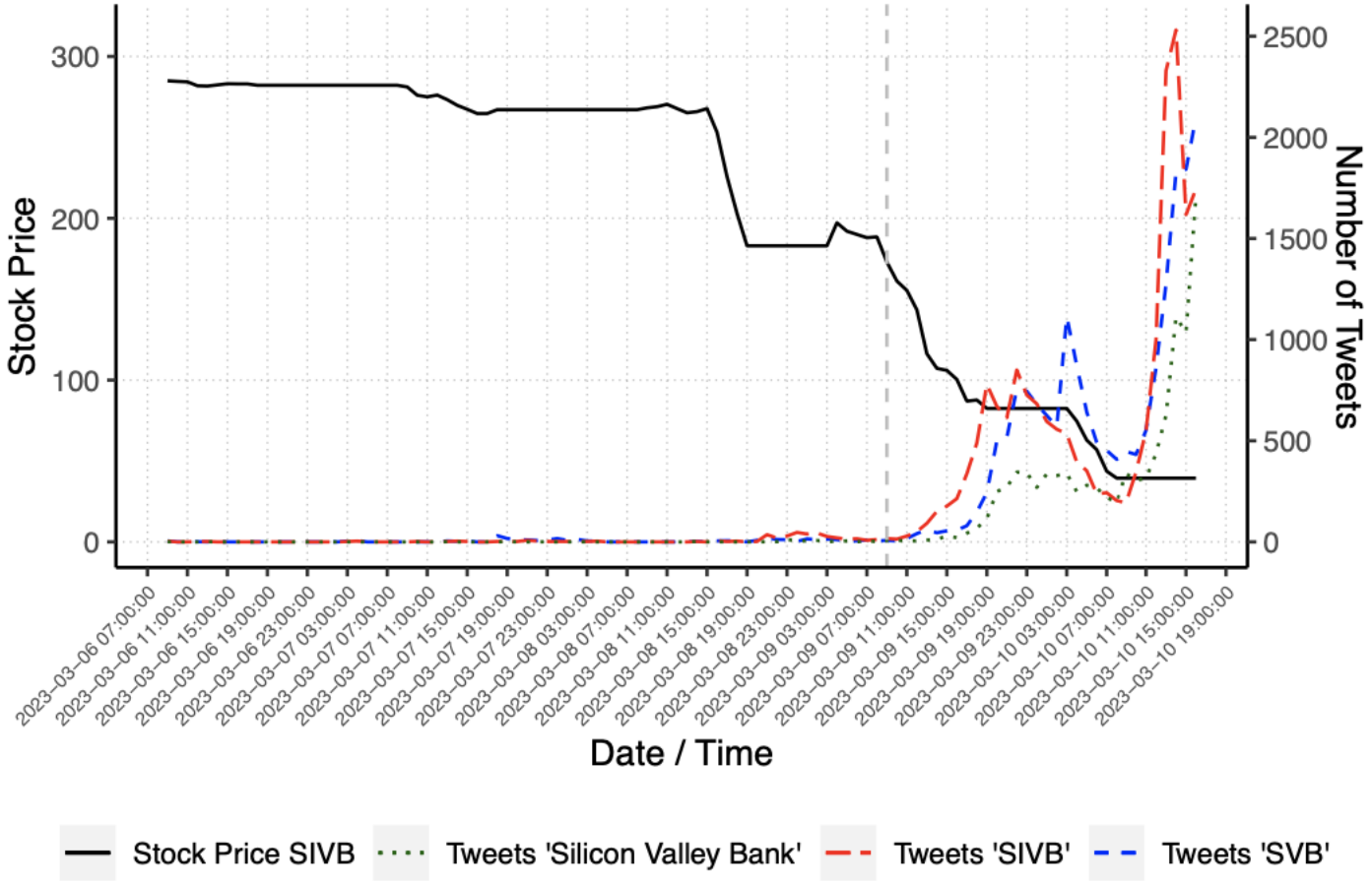
	Deposit Outflows (%)			
	Uninsured		Total	
	(1)	(2)	(3)	(4)
% Uninsured (z)	4.381***	1.109	2.282***	-0.662
	(1.315)	(1.529)	(0.787)	(1.268)
% Loss MTM (z)	1.216	-1.826	0.529	-0.632
	(1.014)	(1.111)	(0.750)	(0.921)
% Uninsured (z) × % Loss MTM (z)	-0.118	-2.725*	0.245	-0.847
	(0.821)	(1.540)	(0.747)	(1.192)
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)

SIVB vs SVB

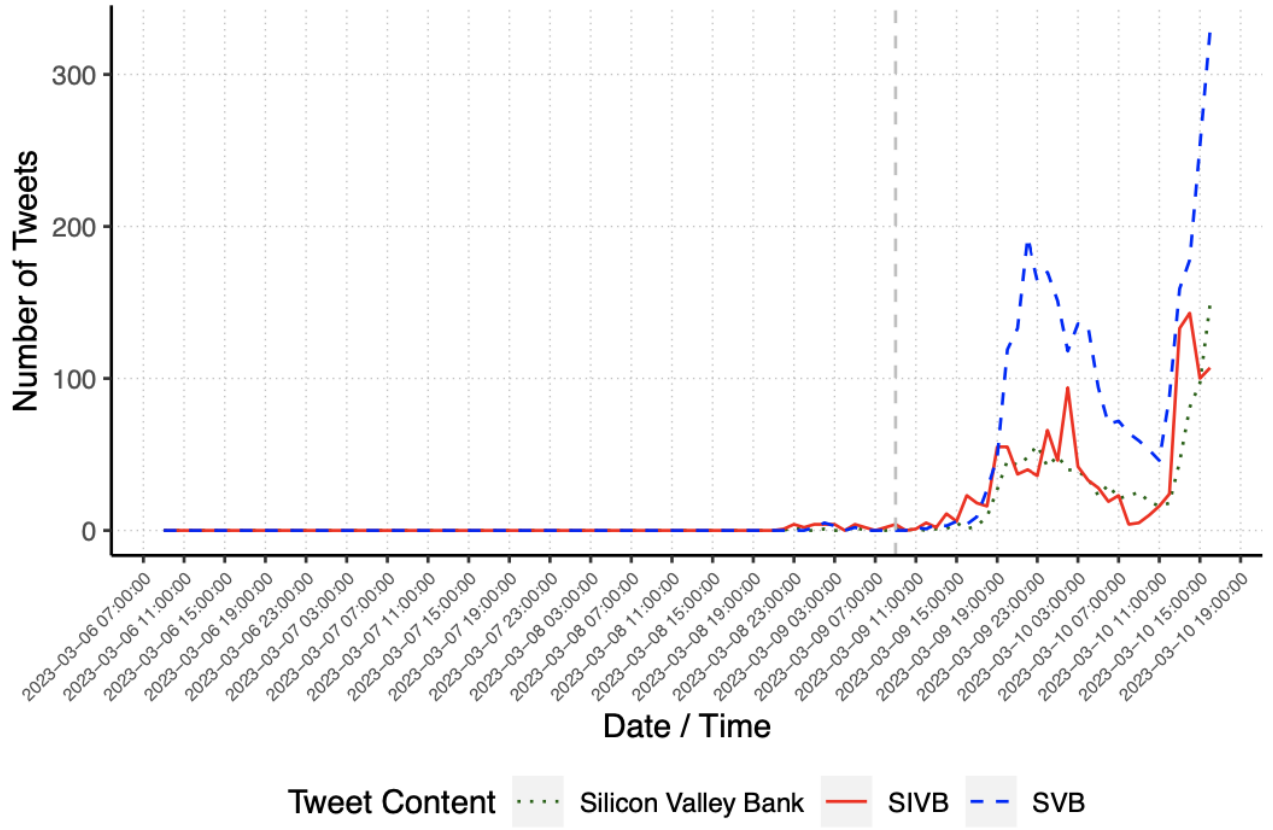
Investor tweets ($SIVB) spike in volume first, followed by more keywords from more general conversations (SVB, Silicon Valley Bank)



Startup community Tweets come Later and are mostly “general Discussion”

Consistent with “tech” users being depositors.

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



Hourly bank Stock Returns
Explained by 4-hour lagged Tweet Activity

In-Run Tweet Activity Depresses Bank Stock Prices

This is especially so for troubled banks:
"Run Exposure" = % Uninsured x % MTM Loss

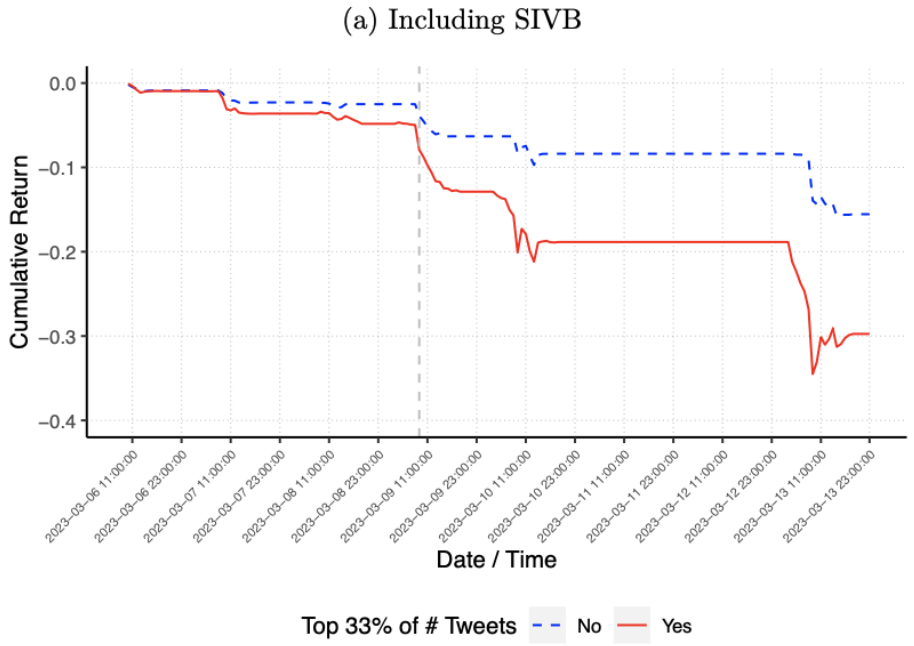
	Hourly Stock Return (%)		
	(1)	(2)	(3)
(Intercept)	-0.1437***		
	(0.0087)		
1(≥ Mar 09)	-0.4462***	-0.4712***	
	(0.0226)	(0.0281)	
Run Exposure (z)	-0.0002		
	(0.0131)		
# Tweets (4h) (z) (t-1)	-0.0435	0.1233	-0.3499
	(0.1189)	(0.2322)	(0.2643)
1(≥ Mar 09) × Run Exposure (z)	-0.0960***	-0.1374***	-0.1321***
	(0.0321)	(0.0378)	(0.0346)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	-0.3022	-0.4407	-0.1424
	(0.3453)	(0.3139)	(0.3604)
Run Exposure (z) × # Tweets (4h) (z) (t-1)	0.2839	1.175***	1.103***
	(0.1951)	(0.3947)	(0.3650)
1(≥ Mar 09) × Run Exposure (z) × # Tweets (4h) (z) (t-1)	-0.1908	-1.058***	-0.9453***
	(0.2093)	(0.3443)	(0.3264)
Observations	12,915	12,915	12,915
R^2	0.0138	0.0263	0.2630
Within R^2		0.0135	0.0085
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

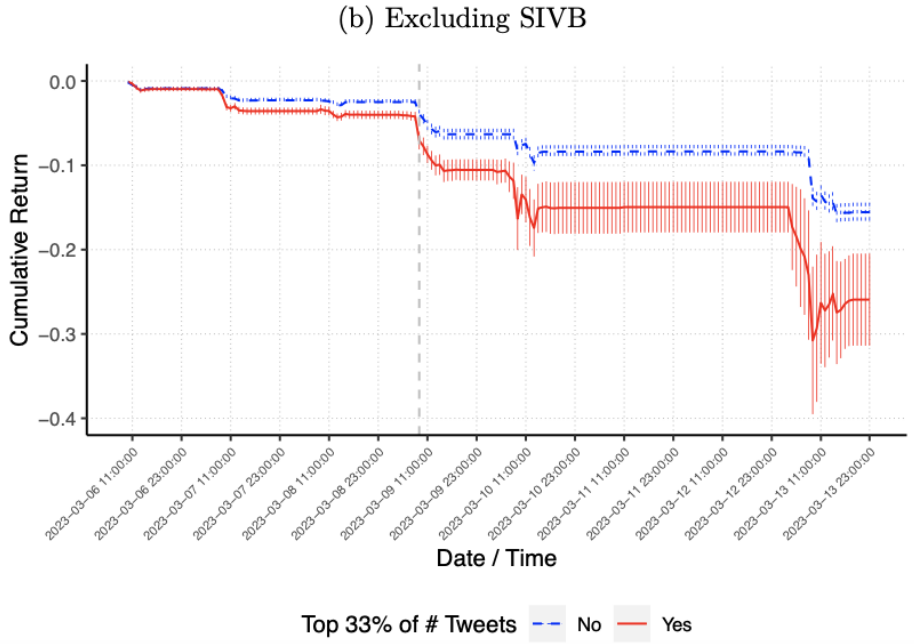
Hourly Frequency

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

Top Tercile of Tweets vs Bottom Two Terciles

Holds with or without SIVB in the sample.

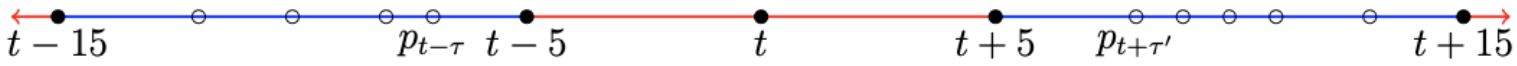




Tweet-Level Tests

Following Bianchi et al (2023)

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) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$
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) × 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)
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	≥ Mar09	≥ 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.

Looking Forward

The intersection of social media and finance is a promising area.

Where to look for interesting new topics:

- **Shifts and changes to technology**: ChatGPT, new platforms, new formats etc.
- **Connections to the broader economy**: these are becoming more important and are (so far) understudied.
- **Do not neglect social media *as a lens***: Social media is an abundant data source on characteristics we could not measure otherwise.