The Impact of Finfluencers on Retail Investment

Isaiah Hull[1] Yingjie Qi[2]

[1]Rethinc.Labs UNC, DeepLearning.AI, CogniFrame, Inc.

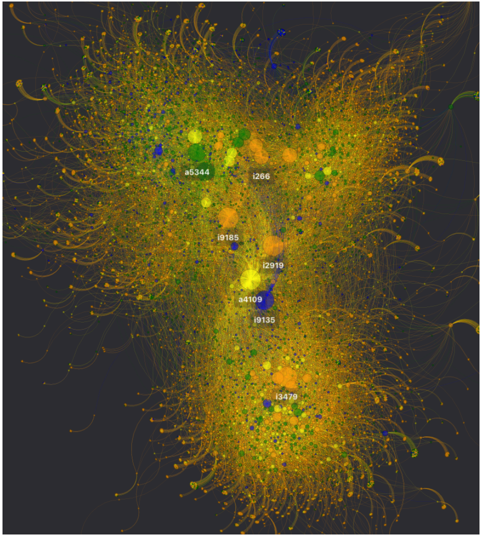
[2]Copenhagen Business School

The rise of finfluencers

- The growth of investor-focused social media (Tiktok #FinTok, Stocktwits, Instagram, YouTube, Reddit, Twitter, etc.)
- Contributed to the rise of financial influencers (finfluencers) on social media
- 47% of Gen-Z investors in the US cite social media influencers as a major factor in their investment decisions (FINRA)
- Rejuvenated interests in understanding social transmission of ideas
- Important to understand influencers on social media
  - Policy: better market participation or exploitation of uninformed traders?
  - Market efficiency: more herding and noise in the market?

This paper

- **Research question:**
  - What are finfluencers' impact on their followers' investment decisions?
    - What contributes to popularity?
    - What types of influencers are more impactful?
    - What types of followers are more susceptible to impact?
    - Which types of trades are more impactful?
- **What is new?**
  - Data on network and transactions
  - Identification strategy



What we find

- **Popularity**: Popular influencers have high Sharpe ratios, are male, trade frequently, use long-term rational strategies, and share a common language or country with their followers.
- **Influencer Impact**: Followers mimic influencers in holdings (109%) and trading decisions (18-192% in purchases and sales).
- **Heterogeneity**:
  - **Influencers**: more followed, central, active in discussions
  - **Followers**: following fewer, female
  - **Security Type**: ETFs > risky trades

Related literature

- **The behavior of individual investors** Barber-Odean 2001, 2002, 2013; Barber-Lee-Liu-Odean 2009; Barberis-Huang 2001; Barberis-Xiong 2009; Barberis-Shleifer-Vishny 1998; Barberis-Huang-Thaler 2006; Daniel-Hirshleifer 2015; Frydman-Barberis-Camerer-Bossaerts-Rangel 2014; Guiso-Sapienza-Zingales 2008; Hirshleifer 2001, 2015, 2020; Odean 1998

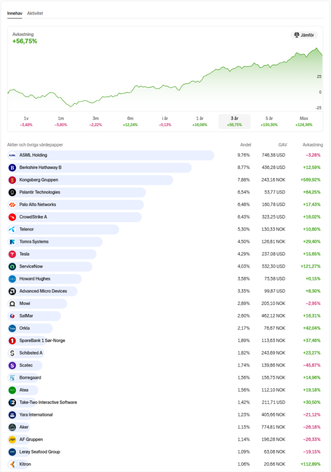
- **Transmission of ideas through social networks** Bikhchandani-Hirshleifer-Welch 1998; Bikhchandani-Tamuz-Welch 2021; Cookson-Niessner 2020; Barber-Huang-Odean-Schwarz 2022; Han-Hirshleifer-Walden 2022; Hong-Kubik-Stein 2004; Manski 2000; Ozsoylev-Han-Walden-Yavuz-Bildik 2014; Pedersen 2021; Sui-Wang (WP)

- **Social media analysts and finfluencers** Guan (WP); Kakhood-Kazempour-Livdan-Schurhoff (WP); Benetton-Mullins-Niessner-Toczynski (WP); Dim (2025)
    - **main contribution of this paper:** actual transaction data + causality

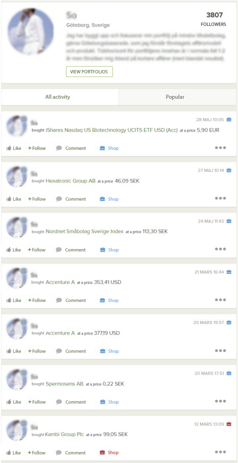
Data and the platform

Social trading platform in Northern Europe

(a) Portfolio



(b) Trading history

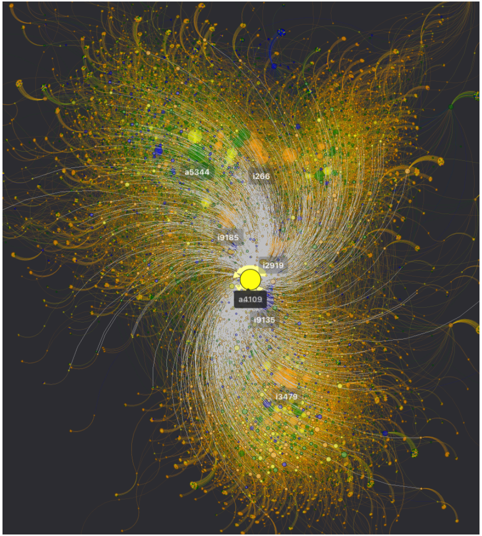


Network and trading data

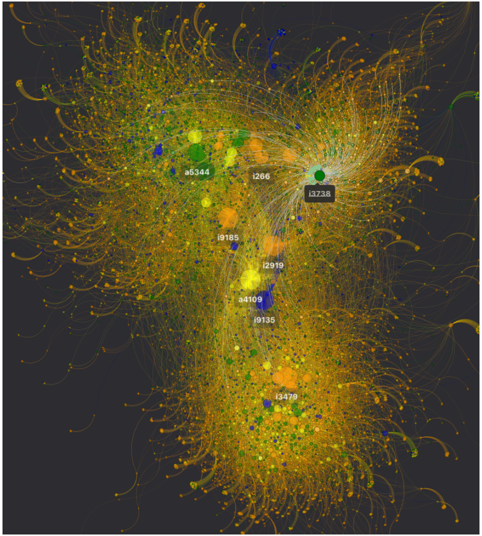
- Investors from Denmark, Finland, Norway and Sweden register with E-identify
- We collected all data available to followers
  - 160,158 distinct and directed user-follower pairs formed by 33,662 users
  - individual trading activities (action, security, and price)
    - 5,666,676 trades; 51,487 securities (domestic and international);
    - March 27, 2014 - March 3, 2023; 2,459 trading days; 121 trading months
  - investor characteristics more detail
    - past performance (rating and return), # of followers
    - for a subsample of investors: trading style, gender, age

Finfluencer follower examples

(a) A large influencer



(b) A small influencer



Summary statistics

Variable	Obs	Mean	Std. Dev.	P1	P50	P99
Panel b: Influencer level						
# of trades (all)	100	211.55	153.084	2.5	168	620.5
# of purchases (all)	100	77.76	64.238	.5	67	234
# of sales (all)	100	133.79	108.325	1.5	118	559.5
Max number of followers	100	27436.84	64956.61	853	1876	266553
Max rating	100	.94	1.023	0	1	3
Years on the platform	100	4.18	2.83	0	4	9
Male	21	.857	.359	0	1	1
Panel f: All users level						
# of trades (all)	33662	168.355	144.117	1	125	420
# of purchases (all)	33662	54.408	61.786	0	29	212
# of sales (all)	33662	113.906	97.155	0	88	368
Max number of following	12843	35.083	63.488	1	14	338
Years on the platform	32269	3.882	2.372	0	4	8
Male	5293	.788	.409	0	1	1
Birth year	104	1983.135	12.156	1956	1984	2001

What is associated with influencer popularity?

What is associated with influencer popularity?

- Cross-influencer regression reveals that *number of followers* is associated with
  - **Higher ratings (Sharpe ratio):** compared to unrated influencers, those with ratings of 1, 2, and 3 have follower counts that are 10% (14), 15.2% (22), and 26.2% (38) higher on average, respectively.
  - **More trades:** one additional trade $\uparrow$ 55 followers
  - **Male:** $\uparrow$ 4198 followers
- Follower-influencer pair-wise regression reveals that a follower is *more likely to follow* an influencer
  - if both live in the **same country**
  - if **language is common**
  - if influencer is **long-term rational > fanatic > short-term rational**

Identifying influencer impact

Portfolio overlap

$$\text{PortOverlap}_{f,i,t} = \frac{\sum_{k \in \mathcal{H}_t} \min\left\{ I_{f,k,t}, I_{i,k,t} \right\}}{\sum_{k \in \mathcal{H}_t} I_{f,k,t}}, \tag{1}$$

- specification following Pool-Stoffman-Yonker (2005)
- f = follower; i = influencer; k = security; t = time;
- $\mathcal{H}_t$ = all the securities f holds at t
- *Example:* at time t,
  - PortOverlap = 0 if f holds securities A, B, C and i holds D, E, F
  - PortOverlap = 0.5 if f holds securities A, B and i holds A, E, F
  - PortOverlap = 1 if f holds securities A, B, C and i holds A, B, C, D, E, F

Trade overlap

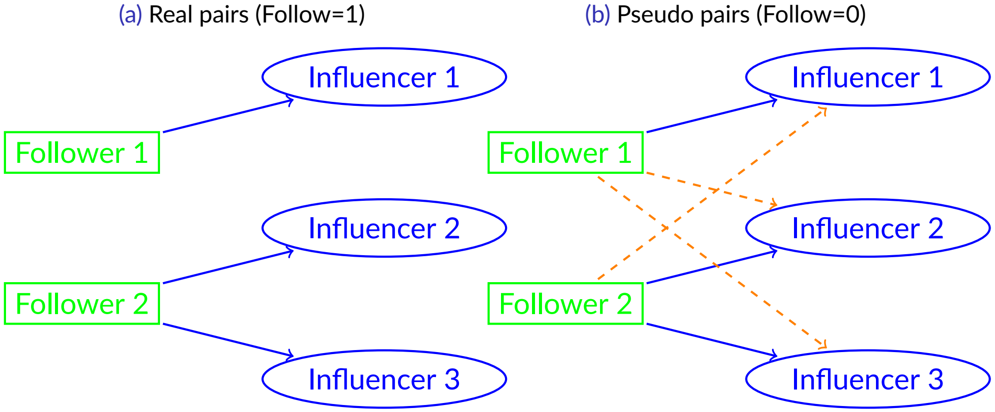
$$
\begin{aligned}
\text{BuyOverlap}_{f,i,t} &= \frac{\sum_{k\in\mathcal{T}_t} \min\left\{ I^{+}_{f,k,t}, I^{+}_{i,k,t} \right\}}{\sum_{k\in\mathcal{T}_t} I^{+}_{f,k,t}} \\
\text{SaleOverlap}_{f,i,t} &= \frac{\sum_{k\in\mathcal{T}_t} \min\left\{ I^{-}_{f,k,t}, I^{-}_{i,k,t} \right\}}{\sum_{k\in\mathcal{T}_t} I^{-}_{f,k,t}}
\end{aligned} \tag{2}
$$

- f = follower; i = influencer; k = security; t = time;
- $\mathcal{T}_t$ = all the securities f trades at t

Is overlap higher for follower-influencer pairs than random ones?

- We test whether the overlap ratios for real (Follow=1) and pseudo (Follow=0) follower-influencer pairs are different

-



Endogeneity issue

- OLS is biased

$$y_{f,i,t} = \alpha_{f,t} + \beta \text{Follow}_{f,i} + \Gamma \text{Controls}_{f,t} + \Gamma' \text{Controls}_{i,t} + \epsilon_{f,i,t}, \tag{3}$$

- Threats to internal validity
  - Omitted variable bias
    - expertise; preference; information exposure
  - Reverse causality bias
    - influencers trade popular securities to gain popularity

Identification Strategy—Instrumental Variable

- Upon joining the trading forum, investors automatically follow a few platform employees (they answer questions about the platform etc.)
  - Z_i uncorrelated with unobserved variables such as preference/information exposure
  - Z_i affects the endogenous independent variable *Follow*
  - Z_i has no direct effect on Y_i
- IV TSLS
  - First stage slide
  -

$$y_{f,i,t} = \alpha_{f,t} + \beta \widehat{\text{Follow}}_{f,i} + \Gamma \text{Controls}_{f,t} + \Gamma' \text{Controls}_{i,t} + \epsilon_{f,i,t}, \tag{4}$$

Pair-wise regression results on portfolio overlap

	OLS	Second stage	OLS	Second stage
	PortOverlapRatio			
	(1)	(2)	(3)	(4)
Follow	0.020^{***}	0.036^{***}	0.020^{***}	0.038^{***}
	(0.000)	(0.002)	(0.000)	(0.002)
Influencer # of unique securities	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
# of unique securities	-0.000^{***}	-0.000^{***}		
	(0.000)	(0.000)		
Investor FE	Yes	Yes	No	No
Investor x Time FE	No	No	Yes	Yes
Adj. R2	0.039	0.019	0.046	0.020
No of obs	30,356,165	30,356,165	30,356,165	30,356,165

- $\mu_{PortOverlapRatio} = 0.035 \Rightarrow$ influencer $\uparrow$ portfolio overlap by 109%.

Pair-wise regression results on buying overlap

	OLS	Second stage	OLS	Second stage
	BuyOverlapRatio			
	(1)	(2)	(3)	(4)
Follow	0.011***	0.004***	0.011***	0.003***
	(0.000)	(0.001)	(0.000)	(0.001)
Influencer # of unique securities	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
# of unique securities	-0.000***	-0.000***		
	(0.000)	(0.000)		
Investor FE	Yes	Yes	No	No
Investor x Time FE	No	No	Yes	Yes
Adj. R2	0.012	0.004	0.024	0.004
No of obs	4,001,975	4,001,975	4,001,953	4,001,953

- $\mu_{BuyOverlapRatio} = 0.017 \Rightarrow$ influencer $\uparrow$ buying overlap by 18%.

Pair-wise regression results on sale overlap

	OLS	Second stage	OLS	Second stage
	SaleOverlapRatio			
	(1)	(2)	(3)	(4)
Follow	0.013^{***}	0.053^{***}	0.012^{***}	0.046^{***}
	(0.000)	(0.002)	(0.000)	(0.002)
Influencer # of unique securities	0.003^{***}	0.003^{***}	0.003^{***}	0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
# of unique securities	0.000^{***}	0.000^{***}		
	(0.000)	(0.000)		
Investor FE	Yes	Yes	No	No
Investor x Time FE	No	No	Yes	Yes
Adj. R2	0.033	0.008	0.042	0.011
No of obs	11,680,342	11,680,342	11,680,342	11,680,342

- $\mu_{SaleOverlapRatio} = 0.024 \Rightarrow$ influencer $\uparrow$ sale overlap by 192%.

Further findings

- **Heterogeneity:** The impact is more pronounced for
  - Popular influencers ⏩ slide
  - Central influencers ⏩ slide
  - Active influencers ⏩ slide
  - Followers who follow fewer people ⏩ slide
  - Female followers ⏩ slide
  - No significant difference between the young and old ⏩ slide
- **Followers are selective regarding what trades to mimic**
  - Passive investments are more passed-through than risky ones (crypto-related securities) ⏩ slide
- **Influencers monetize from their impact?**
  - Platform-affiliated influencers more likely to trade their own products ⏩ slide
  - Platform-affiliated influencers trade more yet do not lead to higher rating ⏩ slide

Robustness

- **Who mimics whom?**
  - Followers trade <= 1 day after influencer trade ⏩ slide
- **Is the static network a problem?**
  - We re-scrapped the website in 2025 and found 70 percent of the relations remain ⏩ slide
- **Individuals may self-select into treatment**
  - We focus on investors' behavior during their first month of trading on the platform and find qualitatively similar results
    - Effects on holdings and sales $\downarrow$ and purchases $\uparrow$

Conclusion

- We study whether and how much finfluencers generate impact on their followers' trading decisions
- We find better past performance, more trades, common country of residence, common language, appearing to be a male, and long-term rational trading styles positively correlate with influencer popularity
- IV regressions quantify influencers' sizable impact
- Significant heterogeneity across influencer and follower types
- These findings shed novel light on the rise and impact of finfluencers
    - Finfluencers can drive market behavior
    - Followers seem to be selective in what to follow
    - Concerns over conflicts of interest

Investor Type: Example

<u>Bio</u>: *"I am committed to a mix of index investing and selective stock picking, with a horizon stretching beyond a decade. My portfolio is built around firms known for their robust performance and consistent dividend payouts. And I reinvest those dividends back into more shares. Occasionally, a few emerging tech startups find their way into my collection. The strategy is all about incremental increases in my investment contributions and adhering to my long-term plan."*

<u>Class Scores</u>: *[fanatic: 0.003517, long-term rational: 0.872214, naive: 0.006504, short-term rational: 0.117765]*

Investor Type: Example

<u>Bio</u>: *"I move fast. Overly concentrated in Danish tech firms. I buy when stocks are rising and sell when they fall. I try not to focus on losses, but instead think about the future."*

<u>Class Scores</u>: *[fanatic: 0.264301, long-term rational: 0.024658, naive: 0.12586, short-term rational: 0.585181]*

First stage

	Follow (1)
Instrument	0.150***
	(0.002)
Investor FE	Yes
F	4180
Adj. R2	0.060
No of obs	978,728

Heterogeneity at the influencer level

	Portfolio Overlap Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	-3.084**	-3.084**	-0.036***	-0.036***	-0.999***	-0.999***
	(1.235)	(1.235)	(0.009)	(0.009)	(0.231)	(0.231)
Follow x HighPopularity	3.164**	3.164**				
	(1.237)	(1.237)				
HighPopularity	-0.056***	-0.056***				
	(0.019)	(0.019)				
Follow x Central			1.033***	1.033***		
			(0.232)	(0.232)		
Central			-0.009***	-0.009***		
			(0.003)	(0.003)		
Follow x ManyGroups					0.283***	0.283***
					(0.014)	(0.014)
ManyGroups					-0.051***	-0.051***
					(0.002)	(0.002)
Time FE	Yes	No	Yes	No	Yes	No
Investor x Time FE	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	30,356,165	30,356,165	30,356,165	30,356,165	30,356,165	30,356,165

Heterogeneity at the follower level

	Portfolio Overlap Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	0.020***	0.020***	0.051***	0.047***	0.019	0.014
	(0.002)	(0.002)	(0.008)	(0.007)	(0.037)	(0.036)
Follow x HighAttention	0.027***	0.026***				
	(0.003)	(0.003)				
HighAttention	-0.001***					
	(0.000)					
Follow x Male			-0.021**	-0.015*		
			(0.009)	(0.009)		
Male			-0.002**			
			(0.001)			
Follow x Young					0.031	0.038
					(0.042)	(0.041)
Young					-0.005	
					(0.004)	
Time FE	Yes	No	Yes	No	Yes	No
Investor x Time FE	No	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	30,356,165	30,356,165	4,068,163	4,068,163	236,922	236,922

Impact by securities type

	ETF ratio in b.p.		Risky ratio in b.p.	
	(1)	(2)	(3)	(4)
Follow	5.492***	4.712***	-0.016***	-0.015***
	(0.144)	(0.125)	(0.002)	(0.002)
Investor FE	Yes	No	Yes	No
Investor x Time FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
No of obs	30,356,165	30,356,165	30,356,165	30,356,165

Influencer incentives

	Own product	Number of trade per month	Max rating
	(1)	(2)	(3)
Platform related=1	0.148***	2.924***	0.339
	(0.029)	(0.618)	(0.209)
Fixed effects	Year-month	Year-month	Trading years
Cluster	Stock	Year-month	Robust
Adj. R2	0.031	0.020	0.007
No of obs	5,665,765	679,400	22,868

Trading time

	Purchases		Sales	
	Time lag (day)			
	(1)	(2)	(3)	(4)
Follow	0.823***	1.183***	0.276*	0.764***
	(0.100)	(0.122)	(0.146)	(0.183)
Security FE	Yes	Yes	Yes	Yes
Investor FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Investor x Time FE	No	Yes	No	Yes
Adj. R2	0.213	0.402	0.165	0.426
No of obs	369,184	369,184	49,514	49,514

Execution price

	Purchases		Sales	
	Price difference (unit)			
	(1)	(2)	(3)	(4)
Follow	1.934***	1.290***	-4.323***	-4.555***
	(0.363)	(0.333)	(0.988)	(1.226)
Security x Currency FE	Yes	Yes	Yes	Yes
Investor FE	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Investor x Time FE	No	Yes	No	Yes
Adj. R2	0.084	0.262	0.046	0.290
No of obs	366,630	366,630	49,005	49,005

Investor characteristics

- Collect profile text to extract NLP features to label investors
  1. fanatic ⏩ example
  2. naive ⏩ example
  3. long-term rational ⏩ example
  4. short-term rational ⏩ example

- Assigned gender and age to a subsample of investors using their username
  - We manually went through 32,269 user names
    - `Matilda1996`: female born in 1996
    - `MattiKorhonen198105`: male with unknown birth year
    - `JensFredrikssen`: male with unknown birth year

  - Manual classification robust to using a fine-tuned `CANINE` model—a 121M parameter LLM pretrained to process text at character-level in multiple languages.

Survivorship by cohort

Cohort	Mean	P50	Number of pairs
0	0.69	1.00	2,059
1	0.66	1.00	17,226
2	0.74	1.00	26,258
3	0.73	1.00	20,254
4	0.72	1.00	14,161
5	0.68	1.00	11,555
6	0.68	1.00	11,854
7	0.67	1.00	9,343
8	0.61	1.00	7,553
Total	0.70	1.00	120,263