Finfluencers

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Rise of the Finfluencer 1

Finfluencers Meet Gen Z Audiences Where They Are

1 Finfluencers have an addressable audience	**75%** Started investing before the age of 21
2 Finfluencers establish credibility through relatability	**71%** Appreciate financial information coming from someone like themselves
3 Finfluencers are easy to access via social networks	**46%** turn to social networks for information on investments

- Finfluencers = individuals providing "free" investment advice on social media
- investwithqueenie: 160,000 Instagram, 65,000 YouTube, 225,000 TikTok

Rise of the Finfluencer 2

In recent years, consumers have become less trusting of traditional sources…

Instead, Consumers Trust Individuals They Know On A Personal Level

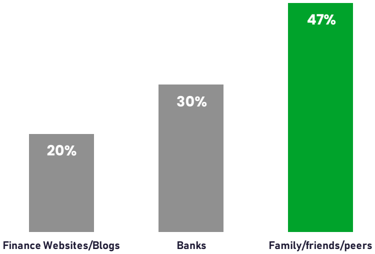
#15

of the 16 industry sectors identified by Edelman,

financial services ranked 15th in trustworthiness

Peers play a key role in financial advice

% of Americans who trust the following when looking for financial advice



- Finfluencers are friends/peers in the digital age
- Finfluencers can propagate and amplify poor investment advice, especially if less skilled finfluencers are more active and their tweets attract more followers

Rise of the Finfluencer 3

- Self-directed retail investing is on the rise
- Little known about quality, activity & followers of finfluencers
- Our study uses data on 29,000 finfluencers from one social media platform

We assess quality of investment advice provided by different types of finfluencers, categorized as skilled, unskilled, antiskilled, and explore activity & followers

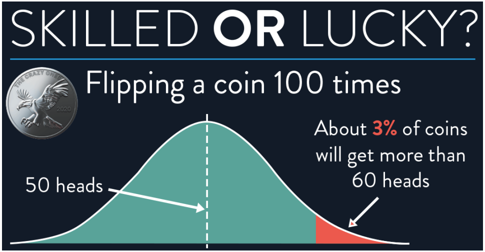
Main results: Based on Stocktwits data

1. Is the majority of finfluencers skilled? No, only 29% provide valuable investment advice leading to 2.6% average monthly abnormal return
2. Is the majority of finfluencers unskilled? No, only 16% finfluencers unskilled
3. Who are remaining 55% of finfluencers? Antiskilled, defined as those with negative alpha, and their advice yields -2.3% monthly abnormal return
4. Un/antiskilled have more activity & more followers than skilled finfluencers
5. Un/antiskilled more engaging but posting excessively optimistic tweets
   - Antiskilled ride return & social sentiment momentum & chase returns
   - Skilled are return-, social sentiment-, and news-contrarian
   - Following advice by un/antiskilled finfluencers creates overly optimistic beliefs
6. Findings support model where social media prioritizes engagement over skill, spreading false advice and distorting belief aggregation.
   - Quality-based visibility boosts (best for skilled), penalizing low-quality content (best against antiskilled), transparency & verification

Big data

- Combine several data sources over a sample period Jul2013 to Jan2017
  - Tweet-level data (time, content, ticker, user name) from Stocktwits
  - News data from Bloomberg to control for public news arrival
  - Stock returns from CRSP
  - Short interest from Markit
  - Retail orders from TAQ
- NLP-based sentiment analysis
  - Out of 72 million tweets, 11%/77%/12% are positive/neutral/negative
  - Out of 36 million news stories, 12%/59%/29% are positive/neutral/negative

Machine-learning model to extract finfluencer skill



- Extract naïve skill $\tilde{\alpha}_i$ from average signed abnormal return

$$\text{Naïve skill } \tilde{\alpha}_i = \text{True skill } \alpha_i + \text{Luck } \epsilon_i$$

- Extract probability of being un/anti/skilled for each finfluencer
  1. Skilled finfluencers, whose true alpha is positive: $\alpha_i > 0$
  2. Unskilled finfluencers, whose true alpha is zero: $\alpha_i = 0$
  3. Antiskilled finfluencers, whose true alpha is negative: $\alpha_i < 0$

Mixture model of finfluencer skill

- True skill α distributed according to finite mixture distribution

$$f(\alpha) = \mathbb{1}\{\alpha > 0\} \sum_{k=1}^{K^+} \pi_k^+ g(\alpha; \mu_k^+) + \pi^0 \mathbb{1}\{\alpha = 0\} - \mathbb{1}\{\alpha < 0\} \sum_{k=1}^{K^-} \pi_k^- g(\alpha; \mu_k^-)$$

  - Shares π_k^+, π^0, π_k^-; Distributions $g(\alpha; \mu)$ if $\mu > 0$ ($-g(\alpha; \mu)$ if $\mu < 0$)
  - Use exponential and Normal for $g(\alpha; \mu)$
  - Use K^+ (K^-) $=$ 1,2,3 types of users with positive (negative) skills
- Estimated alphas $\tilde{\alpha}_i$ are convolution of f & mean-zero Normal distribution

$$\mathcal{G}(\tilde{\alpha}_i; \tilde{\sigma}_i, \Theta) = (f * \phi_{\tilde{\sigma}_i})(\tilde{\alpha}_i)$$

  where $\tilde{\sigma}_i$ is standard error of user i's abnormal return
- Estimate $\Theta = (\mu_1^+, ..., \mu_{K^+}^+, \mu_1^-, ..., \mu_{K^-}^-, \pi_1^+, ..., \pi_{K^+}^+, \pi_1^-, ..., \pi_{K^-}^-)$ by ML

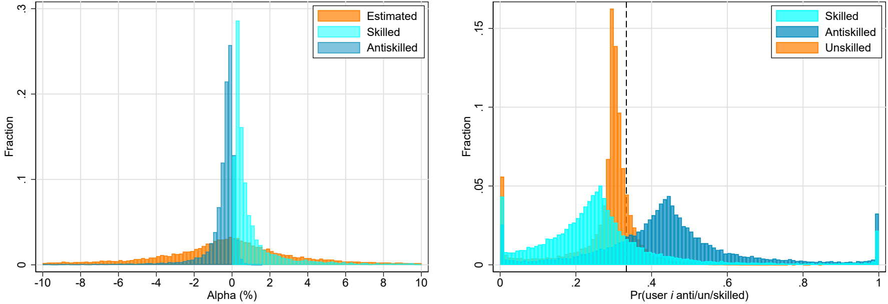
$$\mathcal{L}(\tilde{\alpha}_1, ..., \tilde{\alpha}_I; \tilde{\sigma}_1, ..., \tilde{\sigma}_I, \Theta) = \prod_{i=1}^{I} \mathcal{G}(\tilde{\alpha}_i; \tilde{\sigma}_i, \Theta)$$

Mixture model: Finfluencer types

	μ_k (%)		π_k (%)
Skilled type 2	8.14		5.1
	(0.49)		(0.6)
Skilled type 1	1.49		23.5
	(0.10)		(1.0)
Unskilled	0.00		16.6
			(2.7)
Antiskilled type 1	-1.19		45.5
	(0.08)		(1.8)
Antiskilled type 2	-9.15		9.3
	(0.33)		(0.5)
N		29,475	
Log Likelihood		-88,878	
AIC		177,771	
BIC		177,838	

- Antiskilled: 55%
- Skilled: 29%
- Unskilled: 16%

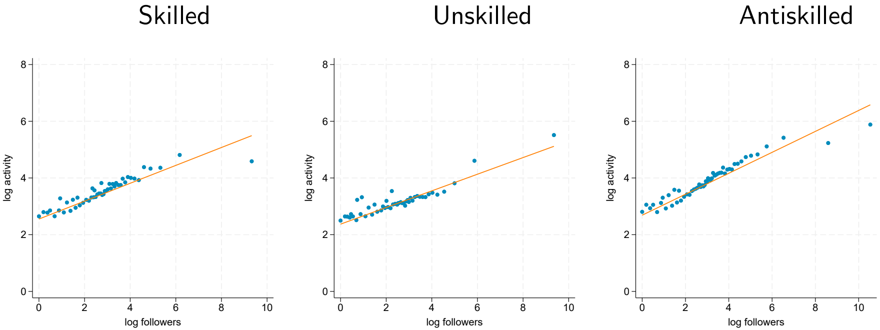
Distribution of finfluencers' skill



- Most skilled finfluencers have true alpha less than 2%, peak at 0.2%
- Most antiskilled finfluencers have true alpha above -2%, peak at -0.3%
- Large dispersion in probability of being skilled or antiskilled
- <3%/5% of finfluencers are unambiguously skilled/antiskilled

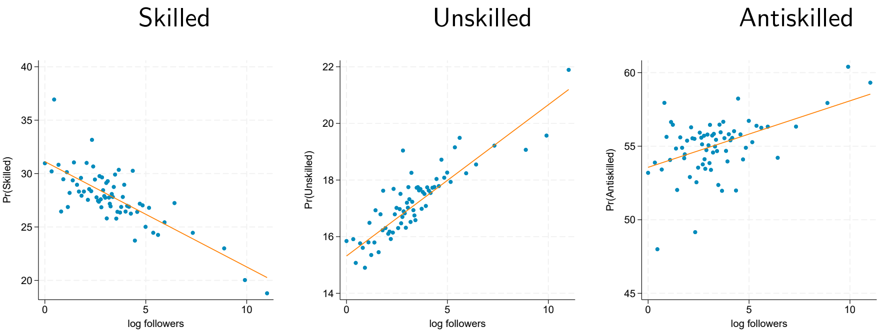
Is the market for finfluencers "efficient"?

User engagement is important



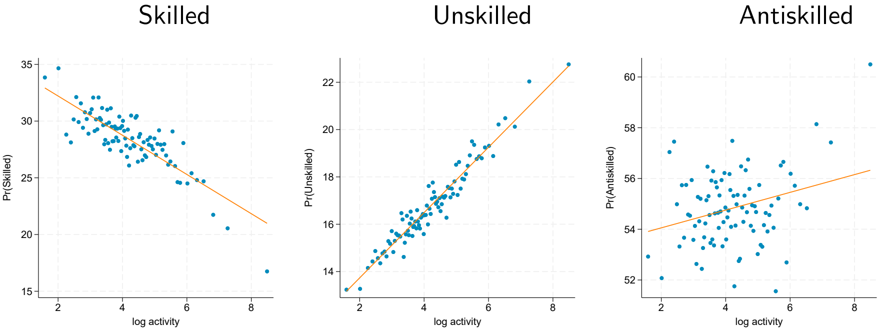
- No. followers are measured after the sample period ends (out-of-sample)
- Positive relation between followers & activity
- Also holds in cross-sectional regressions

Do more skilled users have a larger follower base? NO



- Positive relation between followers & probabilities of being un/antiskilled
- Also holds in cross-sectional regressions

How do un/antiskilled create engagement? 1. Activity



- Tweeting activity positively related to finfluencers' probability of un/antiskill
- Investors prefer message over the outcome

2. Finfluencers' tweeting strategies

	Pr(user i skilled)	Pr(user i unskilled)	Pr(user i antiskilled)
$TweetingActivity_i$	-3.34***	2.45***	0.88***
	(0.29)	(0.13)	(0.32)
$FractionPositive_i$	-0.06***	-0.02***	0.08***
	(0.01)	(0.00)	(0.01)
$ReturnChasing_i$	-0.03***	0.00	0.03***
	(0.01)	(0.00)	(0.01)
$ContrarianTweet_i$	0.02*	0.01*	-0.02**
	(0.01)	(0.00)	(0.01)
$PositiveHerding_i$	-0.03	0.02**	0.01
	(0.02)	(0.01)	(0.02)
$NegativeHerding_i$	0.03	-0.02**	-0.02
	(0.02)	(0.01)	(0.02)
SSI_i *(Positive Tweets)*	-0.01	-0.36***	0.38***
	(0.08)	(0.03)	(0.08)
SSI_i *(Negative Tweets)*	0.25***	-0.20***	-0.05
	(0.08)	(0.02)	(0.08)
Constant	36.10***	17.06***	46.84***
	(0.80)	(0.27)	(0.83)
N	19,593	19,593	19,593

- Antiskilled: more positive & herding on positive sentiment & chase returns
- Skilled: return-, social sentiment-, and news-contrarian
- Investors prefer positive messages

Beliefs biases & Failure in the wisdom of the crowd

Concerns about finfluencers

- Finfluencers are not registered as investment advisers or brokers
- SEC advises investors to be cautious when considering investment advice
- Un/antiskilled finfluencers may induce systematic belief biases

Aggregate finfluencer-induced beliefs

- $\textit{Visibility}_i$ for user $i \Rightarrow \textit{SocSent}_{i,j,t}$ aggregated across all tweets
- For each stock j on day t:

$$\textit{VisibleSent}_{j,t} = \sum_{\text{all } i} \frac{\textit{Visibility}_i}{\sum_{\text{all } i} \textit{Visibility}_i \times \textit{Active}_{i,j,t}} \times \textit{SocSent}_{i,j,t}$$

$$\textit{Un/Anti/SkilledSent}_{j,t} = \frac{\sum_{\text{all } i} \Pr(\text{user } i \text{ un/anti/skilled}) \times \textit{SocSent}_{i,j,t}}{\sum_{\text{all } i} \Pr(\text{user } i \text{ un/anti/skilled}) \times \textit{Active}_{i,j,t}}$$

- Average daily abnormal social sentiment

$$\textit{VisibleAbnSent}_t = \frac{1}{J} \sum_{\text{all } j} (\textit{VisibleSent}_{j,t} - \textit{SkilledSent}_{j,t})$$

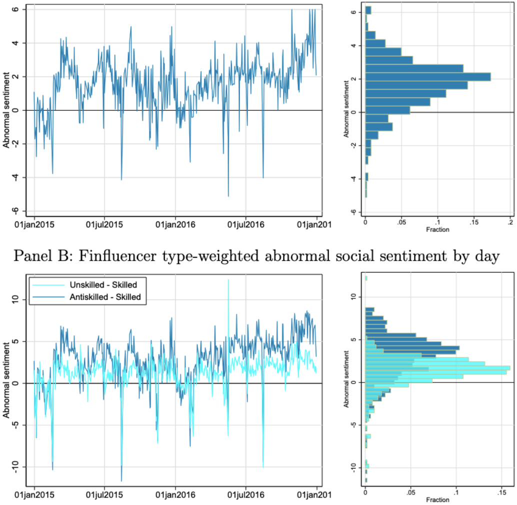
$$\textit{Un/AntiskilledAbnSent}_t = \frac{1}{J} \sum_{\text{all } j} (\textit{Un/AntiskilledSent}_{j,t} - \textit{SkilledSent}_{j,t})$$

	N	Mean	S.D.	Min	p10	p50	p90	Max
$\textit{VisibleAbnSent}_t$ (%)	692	1.42	1.72	-5.12	-0.60	1.41	3.33	16.17
$\textit{UnskilledAbnSent}_t$ (%)	692	0.99	2.41	-10.05	-1.78	1.21	3.08	14.32
$\textit{AntiskilledAbnSent}_t$ (%)	692	2.47	2.99	-11.70	-1.21	2.67	5.87	13.96

Belief biases by un/antiskilled and visible finfluencers

Panel A: Visibility-minus-skill weighted abnormal social sentiment by day

Panel B: Finfluencer type-weighted abnormal social sentiment by day



- Users following antiskilled and visible finfluencers are overly optimistic

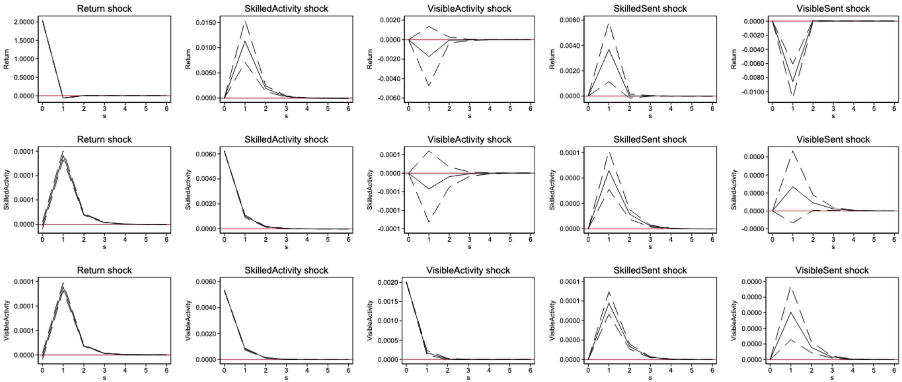
Panel VAR (PVAR)

- $Activity_{i,j,t}$ is sum of $SocSent^{+}_{i,j,t}$, $SocSent^{-}_{i,j,t}$, and $SocSent^{0}_{i,j,t}$
- Compute stock-day level activity for each stock j and day t as

$$\begin{aligned} VisibleActivity_{j,t} &= \sum_{\text{all } i} \frac{Visibility_i}{\sum_{\text{all } i} Visibility_i \times Active_{i,j,t}} \times Activity_{i,j,t} \\ Un/Anti/SkilledActivity_{j,t} &= \frac{\sum_{\text{all } i} \Pr(\text{user } i \text{ un/anti/skilled}) \times Activity_{i,j,t}}{\sum_{\text{all } i} \Pr(\text{user } i \text{ un/anti/skilled}) \times Active_{i,j,t}} \end{aligned}$$

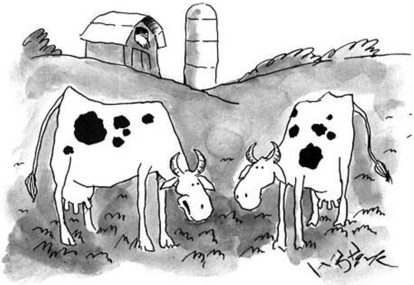
- Panel VAR specification $Y_{j,t} = \alpha_j + \sum_{l=1}^{L} A_l Y_{j,t-l} + \epsilon_{j,t}$ with 5 endogenous variables
  $Y_{j,t} = (Ret_{j,t}, SkilledActivity_{j,t}, VisibleActivity_{j,t}, Antiskilled\_PosSent_{j,t},$
  $SkilledSent_{j,t}, VisibleSent_{j,t})$
- System GMM with lags as instruments (Arellano & Bover, 1995)
- Stock-level fixed effects by Helmert transformation

PVAR evidence



- Skilled (visible) activity & sentiment predict returns in right (wrong) direction
- Pooled sentiment predicts positive next-day returns (Cookson et al., 2022)
- Higher skilled & visible activity & positive sentiment follow positive returns

Conclusions



"In the final analysis, it's all cud."

- Finfluencers gain in reach, trust & importance
- Finfluencers complement, not substitute to traditional financial advice
- Finfluencers propagate & amplify poor investment advice since less skilled finfluencers are more engaging & their tweets attract more followers