The Impact of Finfluencers on Retail Investment

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Discussant: Man Zhang NUS IREUS • Trading platform with social features in four Nordic countries

• Users can choose to make their trading decisions public, allowing them to follow others or be followed

• Main Findings:

- Who have more followers?
 - * \uparrow Past performance and number of trades
 - * \uparrow Male (inferred from username)
 - * \uparrow Common country and language (inferred from username)
 - * \uparrow Long-term rational investors (inferred from bio description)
- Platform employee influencers' incentive:
 - $\ast~$ Trade more products issued by the platform



• Causal impact of influencers on their followers

- Holding/trading portfolio overlap: 3.5% vs.1.6% for pseudo-pairs
- IV: Influencers who are employees of the platform (=7) and were assigned to users at the time of account creation.
- Estimated impact:
 - * Holdings: \uparrow 3.8% ; Sales: \uparrow 4.6%
- Heterogeneity effects
 - Influencers: \uparrow more followers, \uparrow more central in the network, \uparrow active in group discussion
 - − Followers: \uparrow follow fewer influencers, \uparrow female, \uparrow middle-aged
 - *Products:* \uparrow ETFs/index; \downarrow risky stocks

Finfluencers

- Finance content creators who share financial knowledge/advice on social media
- Source of income: click/view rates, ads, and rebates
- Incentive: increase the number of followers and the engagement











• This paper: online trading buddy peer effect

Motivation

- Kakhbod et al. (2023) finds that unskilled finfluencers attract more followers
 - Potential *conflict of interest* between maximizing follower counts and making optimal investment advice
 - *Retail investors* prone to cognitive limitations and behavioral biases, making them particularly susceptible to influence
- This paper: popular finfluencers are associated with strong performance & long-term rational behavior
 - Motivation for testing causal impact
 - Re-framing from a different angle—e.g. as an exploration of peer influence within online trading communities as oppose to existing literature that focuses on offline, real-life social networks.

Empiric - sample and measures

- Selection of users with public profile
 - # of users: 33K, number of followers: 11K
 - Total # of users on the platform: 80K in 18 mths; 300K with the brokerage firm
 - Can users follow others while keeping their own profile private?
 - What is the percentage of users who switch between private to public and vice versa?
 - Gender and age (available for 10% of sample) infer from profile photo?
- Assumption of equal-weighted portfolio
 - Is a stock assumed to be no longer in the portfolio once it is observed to be sold?
 - $-\,$ Kakhbod et al. (2023): naive abnormal alpha
- Finfluencer-follower relationship measured at the time of data scraping
 - Tests conducted around the time of data scraping?



- Pseudo Influencer-follower pair
 - all possible combinations vs combination under common characteristics (e.g. country, age etc.) serve as counterfactual for portfolio similarity?
- Calendar month as time unit
 - timing of influence on followers aligns with calendar month boundaries?
 - Time lag/price difference test design relies on this assumption



• Random / Conditional Random Assignment of Peers

- Shue (2013), Stolper and Walter (2019)
- $-\,$ M&A driven change of peers: Dimmock et al. (2018)
- Teaching schedule: Maturana and Nickerson (2019)
- **Testable Assumption :** For each characteristic, the observed peer similarity lies within the expected distribution under the assumption of random assignment.
- IV : Brokerage firm employee influencers
 - Institution background : facilitates communication random?
 - Users are free to follow/unfollow; unfollow cost is minimal
 - $\ast~$ Influencer-follower relationship is a static snapshot
 - $\ast~$ Endogenous choice of whom to follow

Empiric - Alternative Design

- Exploit random shocks to the behavior of the influencer in an endogenously formed peer group
 - Bailey et al. (2018), Agarwal et al. (2020), Kalda (2020)
- Exogenous factor that affects influencer's trading decision
 - Huang et al. (2021)



- Treatment : non-mutual followers
 - follow only one influencer
 - no other directed path from influencer to followers in the network
- Control : non-followers
 - similar as the followers (i.e. gender, age, country, trading freq.)
 - no directed path between influencer and non-followers in the network



- Influencer Behavior in Discussion Groups
 - Do influencers who provide more detailed information and clearer explanations for their trading decisions exert a stronger influence?
 - Does the use of persuasive or confident language enhance their impact?
- Follower Characteristics
 - Are followers with stronger behavioral biases or more irrational trading patterns more likely to be influenced?
- Social Transmission Bias (Hirshleifer (2020))
 - In a network where A follows B and B follows C, how does C's trading behavior propagate through to A?
- Comparing Online vs. Real-Life Peer Influence
 - Drawing on insights from prior literature may help contextualize the magnitude of peer effects estimated in this study.



- This paper assembles and analyzes a novel dataset from a trading platform with integrated social features.
- It documents evidence of *homophily* in the formation of peer groups among retail investors online.
- The analysis suggests that followers tend to imitate the trading strategies of influential users.
- The paper contributes to the growing but still underexplored literature on peer effects that emerge outside of traditional, real-world social interactions—offering valuable insights into this distinct, digitally mediated economic mechanism.
- I enjoyed reading the paper and appreciate the authors' effort. Wishing you all the best!



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