Game On: Social Networks and Markets

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Extended slide deck - ASSA deck will be abbreviated Latest version of the paper available here: www.lhpedersen.com



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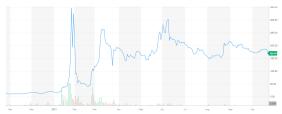
Game on!

Social networks have influenced equity trading since

- its beginning in the 17th century
- trading clubs connected to Amsterdam Stock Exchange (De la Vega (1688))
- coffee houses where London Stock Exchange operated (Standage (2006))

Now social media make

- social networks larger and more observable to researchers
- example: GameStop



► This paper

- ▶ Model: people trade based on what they learn from social network
- Application: GameStop and beyond

Main results

Closed-form

- beliefs:
 - network spillover effects
 - convergence to mix of rational and fanatic views
 - thought leaders and influencers matter

prices:

- social network effects
- bubbles
- excess volatility
- price momentum and fundamental momentum (e.g., PEAD)
- long-run reversal

portfolios:

- differ across investors
- bursts of high volume

Helps explain

- GameStop
- the anatomy of historical bubbles (Kindleberger (2000), Shleifer (2000))
- financial markets more broadly (momentum, reversal, etc.)

Related literature

Theory

- DeGroot (1974) model and persuasion bias, DeMarzo et al. (2003)
 → Introduce rational agents+asset markets into DeGroot model
- ▶ Networks, surveys by Jackson (2010) and Golub and Sadler (2016)
- Cascades of defaults, survey by Jackson and Pernoud (2020)
- Information percolation (Duffie et al. (2009)) with social transmission bias (Hirshleifer (2020)) → Add network effects
- Behavioral finance, survey by Barberis and Thaler (2003)
 → New theory of momentum, reversal, and excess volatility, and network price dynamics (distinguishing feature cf. other theories)

Empirical finance literature: social networks affect

- housing market expectations and prices, based on Facebook data (Bailey et al. (2018))
- ▶ local bias and firm values (Kuchler et al. (2020))
- equity market participation of retail investors (Hong et al. (2004), Brown et al. (2008), Kaustia and Knüpfer (2012))
- ▶ portfolios of money managers (Hong et al. (2005))
 → Model these phenomena + new predictions: influencers, thought leaders, network as driver of anomalies and volume

Outline of talk

- ► Model
- ► Solution and results
- Case study of GameStop

Model: assets and investors

- ▶ Stock trades at discrete times, t = 0, 1, 2, ...
 - Supply of shares s
 - ▶ Payoff: $v + u_{\tau} \in \mathbb{R}$ at revelation time $\tau \sim \text{geometric}(\pi)$
 - u_t observable random walk with $Var(\Delta u_t) = \sigma_u^2$
 - v unobserved; each time t, v {is revealed with probability π remains unknown with prob. 1π
 - Price:

$$price(t) = p(t)1_{(t < \tau)} + [v + u(t)]1_{(t \ge \tau)}$$

- N investors
 - ► Each investor *i* receives a signal at time 0: $x_i(0) = v_i$, where
 - $v = \sum_{i=1}^{N} \kappa_i v_i$
 - ▶ known weights sum to one, $\sum_{i=1}^{N} \kappa_i = 1$
 - ► Four types:
 - 1. Naive (boundedly rational, persuasion bias)
 - 2. Fanatic
 - 3. Rational short-term investors
 - 4. Long-term investors

Model: learning in a social network

Naive learning in a social network:

$$x_i(t) = A_i x(t-1)$$

where weights sum to one, $\sum_{i} A_{ij} = 1$

► Example

$$\begin{pmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ x_5(t) \end{pmatrix} = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ * & * & * & * & * \end{pmatrix} \begin{pmatrix} x_1(t-1) \\ x_2(t-1) \\ x_3(t-1) \\ x_4(t-1) \\ x_5(t-1) \end{pmatrix}$$

Model: learning in a social network

► Naive learning in a social network:

$$x_i(t) = A_i x(t-1)$$

where weights sum to one, $\sum_{i} A_{ij} = 1$

Example

$$\begin{pmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_f \\ x_5(t) \end{pmatrix} = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ * & * & * & * & * \end{pmatrix} \begin{pmatrix} x_1(t-1) \\ x_2(t-1) \\ x_3(t-1) \\ x_f \\ x_5(t-1) \end{pmatrix}$$

► Fanatic: $A_{ii} = 1$, $A_{ij} = 0$ for $j \neq i$

Model: rational learning in a social network

▶ Time 1:

$$x_i(1) = x_r = E(v|x_1(0), ..., x_N(0)) = (\kappa_1, ..., \kappa_N)x(0)$$

Example:

$$\begin{pmatrix} x_1(1) \\ x_2(1) \\ x_3(1) \\ x_f \\ x_5(1) \end{pmatrix} = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ 20\% & 20\% & 20\% & 20\% & 20\% \end{pmatrix} \begin{pmatrix} x_1(0) \\ x_2(0) \\ x_3(0) \\ x_4(0) \\ x_5(0) \end{pmatrix}$$

▶ Time t > 2:

$$x_i(t) = x_r = e_i' x(t-1)$$

Example:

$$\begin{pmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_f \\ x_r \end{pmatrix} = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(t-1) \\ x_2(t-1) \\ x_3(t-1) \\ x_f \\ x_r \end{pmatrix}$$

Model: trading and equilibrium

Equilibrium price: supply equals demand

$$s = \sum_{i=1}^{N} d_i(t)$$

▶ Demand from naive, fanatic, or rational long-term investor:

$$\max_{d_i} d_i E_t \left[x_i(t) + u(\tau) - p(t) \right] - \frac{1}{2w_i} \text{Var}_t \left[d_i (x_i(t) + u(\tau) - p(t)) \right]$$

where $w_i = wealth_i/\gamma_i$ is the absolute risk tolerance.

Solution using that $Var_t(u_\tau) = \sigma_u^2 E(\tau - t) = \sigma_u^2 / \pi$

$$d_i(t) = \frac{\pi w_i}{\sigma_u^2} \left(\underbrace{x_i(t) + u(t)}_{\text{fundamental value}} - p(t) \right)$$

▶ Demand from rational short-term investor

$$d_i(t) = \frac{w_i}{\sigma_u^2} \underbrace{((1-\pi)E_t(p(t+1)) + \pi(x_r + u(t))}_{\text{expected price at time } t+1} - p(t))$$

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Evolution of beliefs (warm-up: special cases)

► Everyone is naive and connected (DeGroot, DeMarzo et al.)

$$x(1) = Ax(0)$$
 $x(2) = Ax(1) = A^{2}x(0)$ $x(3) = Ax(2) = A^{3}x(0)$

$$x(t) = A^{t}x(0) \rightarrow \begin{pmatrix} z_{1} & z_{2} & \dots & z_{N} \\ \vdots & \vdots & & \vdots \\ z_{1} & z_{2} & \dots & z_{N} \\ z_{1} & z_{2} & \dots & z_{N} \end{pmatrix} x(0) = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} z'x(0)$$

where eigenvector z'A = z' is related to Google's page rank

▶ Rationality in the echo champer: the stubbornness of truth

$$x(t) = A^{t-1}x(1) \rightarrow 1_N e'_N x(1) = 1_N x_r$$

Cf. Golub and Jackson (2010): all opinions in a large society converge to the truth ⇔ influence of the most influential agent vanishes

▶ One fanatic in the echo chamber

$$x(t) = A^{t}x(0) \rightarrow 1_{N}e'_{N}x(0) = 1_{N}x_{N}(0)$$

▶ Time 2

$$\begin{pmatrix} x_1(2) \\ x_2(2) \\ x_3(2) \\ x_f \\ x_r \end{pmatrix} = \begin{matrix} A \ x(1) = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(1) \\ x_2(1) \\ x_3(1) \\ x_f \\ x_r \end{pmatrix}$$

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► Time 3

$$\begin{pmatrix} x_1(3) \\ x_2(3) \\ x_3(3) \\ x_f \\ x_r \end{pmatrix} = A^2 x(1) = \begin{pmatrix} 49\% & 0 & 0 & 34\% & 17\% \\ 44\% & 16\% & 0 & 22\% & 18\% \\ 44\% & 0 & 16\% & 22\% & 18\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(1) \\ x_2(1) \\ x_3(1) \\ x_f \\ x_r \end{pmatrix}$$

▶ Time 11

$$\begin{pmatrix} x_1(11) \\ x_2(11) \\ x_3(11) \\ x_f \\ x_r \end{pmatrix} = A^{10}x(1) = \begin{pmatrix} 2.8\% & 0 & 0 & 64.8\% & 32.4\% \\ 3.8\% & .01\% & 0 & 58.6\% & 37.6\% \\ 3.8\% & 0 & .01\% & 58.6\% & 37.6\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(1) \\ x_2(1) \\ x_3(1) \\ x_f \\ x_r \end{pmatrix}$$

▶ Time 101

$$\begin{pmatrix} x_1(101) \\ x_2(101) \\ x_3(101) \\ x_f \\ x_r \end{pmatrix} = A^{100}x(1) = \begin{pmatrix} 0\% & 0\% & 0 & 66.7\% & 33.3\% \\ 0\% & 0\% & 0 & 61.1\% & 38.9\% \\ 0\% & 0 & 0\% & 61.1\% & 38.9\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_1(1) \\ x_2(1) \\ x_3(1) \\ x_f \\ x_r \end{pmatrix}$$

- ▶ **Hardheaded investors** *h*: collection of rational and fanatics
- ► Transition matrix:

$$A = \begin{bmatrix} A_{nn} & A_{nh} \\ 0 & I \end{bmatrix}$$

- ► **Assumption 1 (hardheaded-connected agents)** Any *i* influenced by a hardheaded *j*, either
 - directly, i.e., $A_{ii} > 0$, or
 - ► indirectly, i.e., $A_{ik_1} > 0$, $A_{k_1k_2} > 0$, ..., $A_{k_2j} > 0$

Proposition (Network belief spillover and convergence)

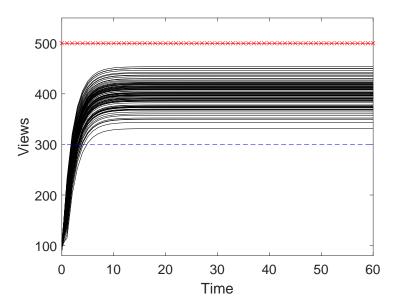
Naive agent views for t = 2,3,...

$$x_n(t) = A_{nn}^{t-1} x_n(1) + \sum_{k=0}^{t-2} A_{nn}^k A_{nh} x_h$$

In the limits as $t \to \infty$ *, convex combination of fanatic and rational views*

$$x_n(t) \to (I - A_{nn})^{-1} A_{nh} x_h$$

Numerical example: beliefs



► Fanatic has 57.8% thought leadership: $\bar{x}(t) \rightarrow 57.8\%x_f + 42.2\%x_r$

- ► Fanatic has 57.8% thought leadership: $\bar{x}(t) \rightarrow 57.8\%x_f + 42.2\%x_r$
- What determines thought leadership?
 - ► How much people listen
 - ► Their influencer values

$$\mathbf{57.8\%} = \frac{66.7\% + 61.1\% + 61.1\% + 1 + 0}{5}$$

$$57.8\% = \begin{pmatrix} 1.56 & 0.33 & 0.33 \end{pmatrix} \begin{pmatrix} 20\% \\ 10\% \\ 10\% \end{pmatrix} + \frac{1}{5} \quad A = \begin{pmatrix} 70\% & 0 & 0 & 20\% & 10\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$1.56 \quad 0.33 \quad 0.33$$

- ► Fanatic has 57.8% thought leadership: $\bar{x}(t) \rightarrow 57.8\%x_f + 42.2\%x_r$
- What determines thought leadership?
 - How much people listen
 - Their influencer values

$$57.8\% = \frac{66.7\% + 61.1\% + 61.1\% + 1 + 0}{5}$$

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Meaning of influencer values: 1% increase in following leads to

 $\bar{x}_n \rightarrow 59.3\% x_f + 40.7\% x_r$ an increase of 1.56% in thought leadership

$$59.3\% = \begin{pmatrix} 1.56 & 0.33 & 0.33 \end{pmatrix} \begin{pmatrix} 21\% \\ 10\% \\ 10\% \end{pmatrix} + \frac{1}{5} \quad A = \begin{pmatrix} 70\% & 0 & 0 & 21\% & 9\% \\ 40\% & 40\% & 0 & 10\% & 10\% \\ 40\% & 0 & 40\% & 10\% & 10\% \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Average opinion: $\bar{x}(t) = \sum_{i=1}^{N} \frac{w_i}{w_i} x_i(t) = \frac{1}{w_i} w' x(t)$

Definition. The vector of all agents' thought leaderships is

$$\theta' = \frac{1}{w} w' \lim_{t \to \infty} A^t$$

such that , $\sum_{j=1}^{N} \theta_j = 1$, and

$$\bar{x}(t) \rightarrow \theta' x(1) = \sum_{j=1}^{N} \theta_j x_j(1)$$

Definition. The vector μ of naive agents' influencer values is

$$\mu' = \frac{1}{w} w_n' \underbrace{(I - A_{nn})^{-1}}_{=\sum_{k=0}^{\infty} A_{nn}^k \text{ (echo matrix)}}$$

Influencers and thought leaders, continued

Proposition (Influencers and thought leaders)

A. The thought leadership of any naive agent is zero, $\theta_i = 0$, and the vector of thought leaderships of hardheaded agents, θ_h , depends on how much attention they get from naive agents, A_{nh} , and their influencer values, μ :

$$\theta_h' = \mu' A_{nh} + \frac{w_h'}{w}.$$

B. If naive agent i increases his following A_{ij} of hardheaded agent j by ε at the expense of a lower following of other hardheaded agents, then

$$\frac{\partial \theta_j}{\partial \varepsilon} = \mu_i$$

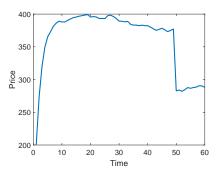
Equilibrium price

Equalizing supply and demand, $s = \sum_{i=1}^{N} d_i(t)$, yields

$$p(t) = (1-c) \left[\frac{w_n}{w} \bar{x}_n(t) + \frac{w_f}{w} \bar{x}_f + \frac{w_l + w_s}{w} x_r + u(t) - \frac{s\sigma_u^2}{\pi w} \right] + cE_t(p(t+1))$$

where $c = \frac{1}{1 + \frac{w_c}{w_s} \frac{\pi}{1 - \pi}} < 1$. **Solution**: iterate forward to infinity

► Numerical example:



Social network effect on price

Proposition (Network effects on price)

Equilibrium price

$$p(t) = p_r(t) + p_n(t)$$

Rational part:

$$p_r(t) = x_r + u(t) - \frac{s\sigma_u^2}{\pi w}.$$

Network part:

$$p_n(t) = \frac{w_n \cdot (1 - c)}{w} \sum_{k=0}^{\infty} c^k (\bar{x}_n(t + k) - x_r) + \frac{w_f}{w} \cdot (\bar{x}_f - x_r)$$

As $t \to \infty$, network part converges to

$$p_n^{\infty} = \sum_{j=N_n+1}^{N_n+N_f} \theta_j(x_j - x_r)$$

Price dependence on thought leaders and influencers

Proposition (Thought leader effect on price)

Fanatic moves the price based on valuation, x_j , and thought leadership θ_j :

$$\frac{\partial p_n^{\infty}}{\partial x_i} = \theta_j$$

Proposition (Influencer effect on price)

Naive agent i moves price based on influencer value μ_i when increasing following of fanatic agent j by ϵ at the expense of rational agent:

$$\frac{\partial p_n^{\infty}}{\partial \varepsilon} = \mu_i \left(x_j - x_r \right)$$

Value and momentum

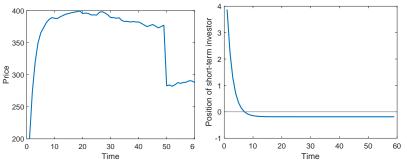
► Returns:

$$E_t(r(t+1)) = (1-\pi)E_t(\Delta p(t+1)) + \pi(x_r + u(t) - p(t))$$

$$= (1-\pi) \underbrace{\Delta p_n(t+1)}_{\text{network momentum}} + \pi \underbrace{b(t)}_{\text{value}}$$

network mom \cong price mom, $\Delta p_n(t+1) \cong \Delta p_n(t) = \Delta p(t) - \Delta u(t)$

Numerical example



Short-term trading behavior: momentum and reversal

Proposition (Value and momentum effects)

Under certain conditions, there exists a number a>0 such that the value-momentum strategy, $b(t)+a\Delta p(t)$, has a positive expected return, $E\left[(b(t)+a\Delta p(t))r_{t+1}\right]>0$, for all t.

Proposition (Value and momentum trading)

Short-term investors

- ▶ initially buy the rising undervalued asset (value and momentum)
- ► continue to hold when the asset becomes over-valued (momentum)
- ▶ and finally shorts when the over-valuation is large enough (value)

if the asset is a bubble (vice versa if the asset is undervalued) and if A_{nn} satisfies certain conditions

Spike in volume and excess price variation

Proposition (Spike in volume and excess volatility)

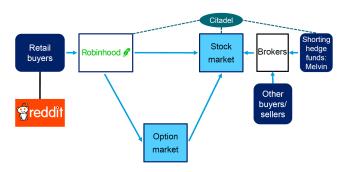
With naive and fanatic agents,

- ▶ the trading volume is greater, but dies down over time
- the valuation ratio (price minus fundamental u(t)) varies more

Outline of talk

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- ► Case study of GameStop

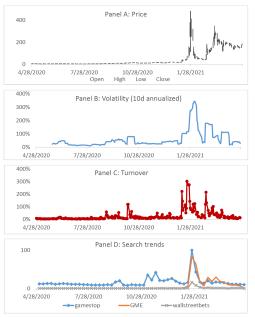
Overview of the GameStop event



Further details, YouTube talk at Markus' Academy, Princeton University:

https://bcf.princeton.edu/events/lasse-pedersen-on-gamestop-and-predatory-trading/

GameStop: price, volatility, volume, public interest



Links between model and GameStop

- 1. Investment idea spreads via social networks (Proposition 1)
- 2. Fanatic ideas gain prominence over time (Propositions 2)
 - ► E.g. Keith Gill, aka DeepF**ingValue, Roaring Kitty
 - ▶ Diamond hands meme: $A_{ff} = 1$

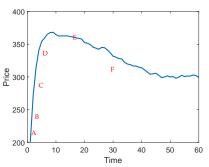


- 3. Social network effects on price (Proposition 4)
- 4. Fanatic view creates a bubble (Proposition 5)
 - Extreme view: Rocket meme and YOLO trade



- 5. Price increases when influencer follows fanatics (Proposition 6)
 - ► Tweet by Elon Musk: "Gamestonk!!" with link to WallStreetBets
 - ► Influencer: $A_{i,Elon Musk} > 0$ for many i
 - ► Following fanatic: $A_{\text{Elon Musk,WallStreetBets}} > 0$
- 6. Sophisticated momentum and value investors (Proposition 7-8)
- 7. Spike in trading volume and volatility that die down faster than the bubble (Proposition 9)

Conclusion: social network effects everywhere



	Model elements	Bubble anatomy†	GameStop	Asset pricing
A	Investors receive news, fanatics fo- cus on one element	Initial displacement	Retail investors focus on plan to pivot online	Announcement effects, e.g.post- earnings drift
В	Short-term investors bet on network spillovers	Speculation	Some institutional investors are long	Momentum and fundamental momentum
C	Opinions spread through the network	Mania and emulation	More and more people hear about GameStop	Local bias and network spillover effects
D	Influencers follow a fanatic	Authoritative blessing	Elon Musk tweets a link to Wall- StreetBets	Excess volatility
E	Rational traders bet on reversal	Insiders sell out	Institutional investors sell	Value investing
F	Fundamentals are revealed or fa- natics gradually learn	Crash: revelation or revulsion	Drops in January, March earnings announcement	Long-run reversal and value effect

 \dagger Stylized evolution of historical bubbles of Kindleberger (2000) and Shleifer (2000)

References cited in slides

Brief list – numerous additional references cited in the actual paper

Bailey, M., R. Cao, T. Kuchler, and J. Stroebel (2018). The economic effects of social networks: Evidence from the housing market. Journal of Political Economy 126(6), 2224–2276.

Barberis, N. and R. Thaler (2003). A survey of behavioral finance. Handbook of the Economics of Finance 1, 1053–1128.

Brown, J. R., Z. Ivković, P. A. Smith, and S. Weisbenner (2008). Neighbors matter: Causal community effects and stock market participation. The Journal of Finance 63(3), 1509–1531.

De la Vega, J. (1688). Confusion de Confusiones: Portions Descriptive of the Amsterdam Stock Exchange. Number 13. Colchis Books.

DeGroot, M. H. (1974). Reaching a consensus. Journal of the American Statistical Association 69(345), 118–121.

DeMarzo, P. M., D. Vayanos, and J. Zwiebel (2003). Persuasion bias, social influence, and unidimensional opinions. The Quarterly Journal of Economics 118(3), 909–968.

Duffie, D., S. Malamud, and G. Manso (2009). Information percolation with equilibrium search dynamics. Econometrica 77(5), 1513–1574.

Golub, B. and M. O. Jackson (2010). Naive learning in social networks and the wisdom of crowds. American Economic Journal: Microeconomics 2(1), 112–49.

Golub, B. and E. Sadler (2016). Learning in social networks. The Oxford Handbook of the Economics of Networks.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. The Journal of Finance 75(4), 1779-1831.

Hong, H., J. D. Kubik, and J. C. Stein (2004). Social interaction and stock-market participation. The journal of finance 59(1), 137-163.

Hong, H., J. D. Kubik, and J. C. Stein (2005). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. The Journal of Finance 60(6), 2801–2824.

Jackson, M. O. (2010). Social and economic networks. Princeton university press.

Jackson, M. O. and A. Pernoud (2020). Systemic risk in financial networks: A survey. Available at SSRN.

Kaustia, M. and S. Knüpfer (2012). Peer performance and stock market entry. Journal of Financial Economics 104(2), 321-338.

Kindleberger, C. P. (2000). Manias, panics and crashes: a history of financial crises. Palgrave Macmillan.

Kuchler, T., Y. Li, L. Peng, J. Stroebel, and D. Zhou (2020). Social proximity to capital: Implications for investors and firms. Technical report, National Bureau of Economic Research.

Shleifer, A. (2000). Inefficient markets: An introduction to behavioural finance. OUP Oxford.

Standage, T. (2006). A History of the World in 6 Glasses. Bloomsbury Publishing USA.