Blind Date: Network Initiation and Status Competitions in an Influencer Economy

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Abstract

Status competitions are acknowledged as consequential in markets and organizations, with at least two formal mechanisms of control: category control and formal commensurations and rankings, respectively. While such competitions are explicit in influencer economies, their dynamics and control mechanisms remain empirically underinvestigated. Using a dataset with over 51,000 ties from a financial influencer economy, we explore how participants compete for status by sending and accepting link requests. Participants are more likely to initiate ties following a change in trading performance, but less likely to accept ties from higher-performing individuals. In terms of ulterior performance, traders who accept a tie benefit more than those who initiate it. The outcomes of this initiation dynamics are multiple networks in which traders maintain ties with those performing worse than them. Traders performing less well repeatedly seek new ties and are more likely to receive link requests from others. Based on this, we argue that status competitions lead to multiple networks (instead of a unique one), within which an influencer would dominate, performance-wise, a group of followers. Theoretically, we draw attention to initiation processes as an informal mechanism of competition control. Empirically, we highlight the role of status competitions in social media-supported economies.

Key words: network initiation, influencer economy, status competition, trading, investor performance

1. Introduction

Status competitions are omnipresent in markets and organizations, and are consequential on multiple levels, including firm or individual revenue, compensation structures for participants, as well as participants' engagement (e.g., Sonnenshein, Nault, and Obodaru, 2017; Jain and Qian, 2021). Winners of such competitions can play a key role in information dissemination and trigger further competitions for attention (Gelper, van der Lans and Van Bruggen, 2021). Status competitions can have a formal organization or an informal one and are often anchored in (in)formal social networks (Jacobs and Watts, 2021). Two major mechanisms of status competitions are hierarchical organization and control of market categories and formal rankings and commensurations, respectively (e.g., Podolny, 1993, 2005; Mennicken and Espeland, 2019).

Since markets can have a network structure (White, 2001), market-related status competitions can unfold within networks of participants. A case in point are influencer economies: markets organized around social media-supported networks that seek to monetize attention, based on such competitions (Hu, Milner and Wu, 2016; Seong and Godart, 2018; Roccapriore and Pollock, 2023). Over the past fourteen years or so, influencer economies have propagated across different domains, from fashion to finance, and influencer positions are seen as playing a key role in the organization and management of such economies (Mallipeddi et al., 2022). A relevant question for understanding the organization of influencer economies is, how are status competitions initiated and run within such networks?

Current literature (e.g., Pagan et al., 2021; Hund, 2023; Lorenz, 2023) depicts these competitions as being won bassed on skills, learning processes, and better information—in short, they emphasize a meritocratic model. The role played by network initiation and its consequences have been much less examined. This is puzzling, as influencer economies are widely regarded as (non-)consensual networks; hence, we would expect network initiation processes to play a role in status competitions.

In the following, we investigate this question for the case of an influencer economy from finance, also known as social trading platforms (STPs). STPs integrate financial trading with social media and offer participants, among others, the possibility of forming consensual, trading-centered social networks, communicating with each other, and seeing each other's true financial performance in real time. Generally, influencer economies in finance are seen as facilitating the distribution of information and learning, but also as potentially inducing herding behavior (Bikhchandani, Hirshleifer, and Welch, 1992; Hong, Kubik, and Stein, 2005; Ozsoylev and Walden, 2011; Gemayel and Preda, 2018). Evidence from field experiments (e.g., Escobar and Pedraza, 2023) as well as from the analysis of trading datasets (e.g., Tong and Preda, 2023) shows that influencers play a significant role with regard to trading decisions, financial performance, and survival in the market. By contrast, competitions for influencer positions, although highly relevant, has been much less investigated.

In the following, we investigate this question based on the analysis of a dataset from an STP. Our dataset comprises 3,522 active traders, with 51,866 link requests and 662,613 daily logs over a period of 18 months. Before a link request is sent and accepted, parties can see only a general online profiles of other traders, including a screen name, possibly a profile photo, a generic "statement of faith" in trading, and comments on a platform-wide discussion forum. After a link request has been accepted, however, parties can see each other's truthful financial performance and trades. Recipients of requests can cancel links after having accepted them. The mechanism of revealing the parties' real and unmodifiable financial information only after a request has been accepted makes the STP setup salient with regard to status competitions. Traders who send and receive link requests have to go on "blind dates," in the sense of not being able to see truthful financial information (the reason for networking) before the “date” is accepted. Parties can cancel accepted links without explanation. This setup allows us to investigate the conditions under which networks are initiated and how this relates (or not) to status competitions.

In addressing these issues, we employ the Temporal Exponential Random Graph Model, or TERGM (Leifeld, Cranmer, and Desmarais, 2018). Its primary strength lies in reflecting how prior network configurations influence current network characteristics, a dynamic ill-suited for traditional regression.

We find that traders are more likely to send and receive requests after a (positive or negative) change in their financial performance. Recipients are more likely to accept requests when these come from individuals performing worse than them, and less likely to cancel a link with someone who performs worse than them. Post acceptance, recipients tend to reduce trading frequency and the range of traded assets in order to show better performance. Senders, however, improve their performance much less post acceptance. These changes fade away over time, indicating that the impact of a recently accepted request is stronger than that of older links. Network members with a lower trading performance in their current networks keep seeking new connections, but they are also sought after by other traders, who send them link requests. Based on these findings, we argue that a meritocratic explanatory model doesn’t properly account for winning influencer status. What emerges out of initiations is an “influencer” position connected to “followers” who do less well. Networks are selective, in that they tend to exclude traders who would threaten the status of the “influencer”. Influencers’ skill improvement and learning (as proxied by better financial performance) are not so significant before network initiation and are more likely to take place after the influencer status has been obtained. Influencers benefit financially more than other members of the network. We make a double contribution: conceptually, by highlighting the role of network initiation as an informal mechanism for organizing status competitions, distinct from category controls and formal rankings; empirically, by shedding light on the organizational dynamics and effects of influencer economies.

The remainder of this paper is organized as follows: first, we present an overview of the modus operandi of STPs. After this, we review several strands of literature with regard to status competitions, learning, and information: the literature on status competitions in organizations, on social media-supported networks, the sociology of finance literature, and the financial economics literature. In a third step, we present the data and methods. The fourth step presents and discusses the results, together with robustness tests. The fifth step consists in a discussion of status competitions in influencer economies. The conclusion is the sixth and final step of this paper.

2. STPs

Influencer economies built on social media-supported networks are classified into consensual and non-consensual. In consensual networks, a link request has to be sent and accepted for the tie to form. In non-consensual ones, clicking “follow” creates a tie (Gaudeul and Giannetti, 2013; Pagan et al., 2021). STPs are consensual networks that integrate social media with financial trading. The most popular STPs have over twenty million registered users. Users connect their brokerage accounts to their STP accounts, synchronizing trading history to the STP. They can choose to display real names or screen names, gender and age, a profile photo, as well as sketchy, trading-centered bios and “statements of faith” about their trading goals and strategies. However, STP users do not provide any other personal information in their profiles. They can also choose to participate in a platform-wide discussion forum dedicated to finance and trading.

Users who trade most profitably (also called “trade leaders”) are ranked according to platform-wide metrics of trading success, such as returns over a defined period of time.

Ranking and metrics of trade leaders are visible to all users. A user can choose to employ a copy algorithm that will automatically replicate the transactions of a selected trade leader in the user's brokerage account (the trade leader will usually get around 20% of the profits made by users who sign up for the copy algorithm). While users can see the metrics and ranking of trade leaders, they cannot see the trading histories of any participants (be they trade leaders or not) and cannot see the ranking and metrics of those who are not trade leaders.

Users can send and receive link requests: once a request has been accepted, trading "friends" can see each other's trading histories and can chat in real time. Subsequent orders and performance will also be visible in real time among trading "friends." As trading accounts from (different) brokerage houses are synchronized to the platform, users cannot manipulate their trading histories (e.g., by deleting losses and keeping only winnings). Sending or accepting a friend request means thus requesting, offering, and giving access to accurate trading records, as well as to future trades that will be truthful. Once two traders are linked, they can also send private messages to each other, which are invisible to others. Thus, we can assume that in sending/accepting friend requests traders send/accept signals of trust as a gateway to personal, truthful trading and financial information. We can also assume that by comparing trading performance, they enter into competitions concerning their status as traders. A user can also deny or ignore a link request or can cancel an accepted request. That is, a signal of trust can be rejected or ignored, denying thus access to truthful information. An accepted signal can also be reversed (by delinking): that could mean, among others, that the comparison is seen as irrelevant or useless (see Fig. 1).

[Fig. 1]

Thus, we have: (a) an official commensuration and ranking that produce a hierarchy of relatively few trade leaders and (b) a much larger population of traders who can choose to simply copy the top ranked traders, to network with its members, or to compete among themselves (or combinations thereof). Both formal rankings and categorical hierarchies are thus present on STPs.

As users explicitly focus on financial trading and no personal information is available (beyond optional, summary trading-centered statements), we assume that their motivation in sending, accepting, or ignoring link requests is exclusively related to trading: in other words, the initiation of networks is instrumental and finance-centric (and not motivated by, for instance, the desire to find other users with similar non-financial hobbies). We also assume that network initiation (by sending/accepting link requests) is driven by the desire to access truthful financial and trading information, both past and future, on a reciprocity basis. Reciprocal access to this information is the payoff of accepting a link request and a major factor in status competitions. This provides us with the entry point for examining the latter in relationship to network initiation.

3. Literature review

3.1 Status competitions, information, and social networks

Scholars of status competitions have argued that markets should be conceived as hierarchies of status categories (Podolny, 1993, 2005; White 2001), with participants forming ties and collaborating with other competitors primarily within their own category, but shunning categories downstream, as downstream ties could damage their status and impact their revenues. Two mechanisms for organizing status competitions are category controls and formal commensurations and rankings, respectively. Category controls imply establishing categorical hierarchies of market participants, controlling access to upstream categories, and avoiding ties or associations with downstream categories (Podolny, 1993; Hong, Kubik, and Stein, 2005; Bothner, Kim, and Lee, 2015; Bajo et al., 2016; Han and Pollock, 2021). Formal commensurations and rankings imply the use of common metrics and criteria for evaluating and ordering competitors (e.g., Mennicken and Espeland, 2019).

Status is seen as distinct from reputation, in that it "captures differences in social rank that generate privilege or discrimination," while reputation "captures differences in perceived to actual quality or merit that generate earned performance based rewards" (Pollock et al., 2015: 483). Influencer economies are known to use traffic metrics (e.g., number of views, or likes) in order to rank participants. These rankings are fed back to participants, creating thus official positions (Wasserman and Faust, 1994: 174) at the top of a platform hierarchy, positions that are associated with financial compensation. In the case examined here, reputation would be given by being formally ranked as one of the top traders; direct rewards can be derived from this position, since other traders can choose to copy the top ones in exchange for a part of the profits.

This, however, does not automatically make everyone else into a follower. Participants can initiate and organize informal competitions by sending link requests based on the information available to them. If social rank is important, we should expect them to initiate informal competitions, as reputation based on financial performance would be available to only a few participants. As status and reputation are seen as distinct, one could still engage in status competitions, even if reputation were to be reduced to a handful of positions at the top of official rankings. In a network-based influencer economy where participants compete on a single dimension (e.g., financial performance), a status competition would be a competition for rank within a given network of followers, along the relevant dimension. This would require that a network is initiated by sending/receiving/accepting link requests, in such a way that rank is achieved within the network. If this is so, then network initiation is a mechanism for organizing status competitions.

We could ask, why do participants initiate networks and not disclose their accounts platform-wide? As the information contained in the account is truthful and exact, it enables a trader to claim status, but it will also expose them to commensuration of the own performance against network peers (Burt, 2005: 181). In principle, traders could give everyone on the platform access to their trading history. If they were to do that, they would run the risk of other traders not reciprocating. In the end, if they were to give access to trading history platform-wide, they would not be able to commensurate their performance against others. Traders could also enter one-on-one tournaments, but this would be lengthy and would not allow dynamic comparisons, as trading performances are bound to change over time. Therefore, a better strategy for status competitions is to initiate networks by accepting link requests and disclosing only within a network that can potentially grow as their status is acknowledged by others.

Network initiation in organizations has been examined from the perspectives of creativity fostering, participants' performance and identity, and visual cues, among others (Wang et al., 2010; Bai and Tian, 2023; Carnabuci and Quintane 2023; Ingram 2023). Depending on their structural position (Burt, 1995), participants can derive significant organizational advantages from networks, including financial benefits different from performance-related rewards (Li and Schürhof, 2018). This resonates with studies showing that, by forming networks, investors and fund managers reduce information acquisition costs, tend to gain informational advantages, and circulate investment ideas (Shiller and Pound, 1989; Bikhchandani and Sharma, 2000; Cohen, Frazzini and Malloy, 2008; Ozsoylev and Walden, 2011; Zhou and Delios, 2012; Pedersen, 2022). Weak ties facilitate rather than hinders the circulation of information (Granovetter, 1973). Hence, participants in an influencer economy would have informational incentives to initiate networks—as outlined in the previous section, the payoff of sending/accepting link requests is getting access to truthful information about other members' trading accounts. Such an informational incentive, however, would not preclude but rather encourage status competitions, as each participant could gain social rank in their network. Hence, while information searches can be regarded as a motivational factor in network initiation, they are distinct from initiation effects.

Having distinguished between reputation—associated with formal rankings—and status competitions, we would expect that participants seek ties with other traders, not with those officially ranked as best. The previously discussed logic of categorical hierarchies and control would imply that participants shun ties with those having a worse performance and would seek ties with those having a similar or better performance (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992; Cont and Bouchaud, 2000; Hong, Kubik, and Stein, 2005; Fudenberg and Levine, 2009; Crawford, 2013; Wang and Wang, 2018; Gong and Diao, 2023). As they can see trading performance only after having accepted a tie, we would expect that traders take public communication (i.e., in the discussion forum) as a signal of performance, but cancel ties deemed to do status damage (Burt, 1995).

3.2 Status competitions and commensuration in networks

Connecting to other traders entails disclosure of trading accounts (as the basis of commensuration) which in turn will expose traders to uncertainties: if one's network peers have a relatively better trading performance, the trader in question will have a lower status. Hence, a trader aiming at a higher status would enter ties in such a way that disclosing and comparing trading accounts allows them to claim and maintain a relatively higher status.

Sociologists of economic organizations have argued that firms can gain more if they enter a new market second, not first (Podolny, 2005: 253-4). Extending this argument, traders who aim at a higher status will more likely receive rather than send links (Wasserman and Faust, 1994: 202). They will accept and keep ties selectively, in a way that ensures their trading status vis-à-vis network peers.

Participants are likely seek comparisons with others in order to evaluate changes in their status as proxied by trading performance. Relative to those who send, traders receiving link requests will be less likely to do so after a (positive or negative) change in performance. In other words: someone wanting to commensurate the own performance will seek do to so by sending a request after a change in performance, when they need to re-evaluate their position relative to other traders. Someone aiming at a higher status will be more likely to wait to receive requests from others. They too would be more likely to receive requests after a change in performance, but less so relative to senders. At the same time, someone aiming at higher status will tend to keep links with traders doing less well, so that their status is maintained in the network. This would contradict meritocratic explanatory models of the influencer economy, according to which skill, talent, and hard work lead to influencers gaining a network of followers.

Studies of both individual and institutional commensurations in contexts ranging from university rankings to sports competitions and digital platforms emphasize durable stratification as a consequence of commensuration (e.g., Mennicken and Espeland, 2019; Pagan et al., 2021). Once participants compare performances against each other, status hierarchies emerge. Participants interested in consolidating a higher position in the hierarchy will compare selectively in order to maintain their position. One way of comparing selectively is for traders to keep links primarily with traders that are doing worse than themselves. In other words, a superior (by comparison) status is ensured not exclusively by merit (i.e., skill-based trading performance), but by disclosing this performance primarily (if not exclusively) to others who are doing worse. As traders are more likely to compare their performance against those who are doing worse than them, this would fragment the circulation of information into to specific status brackets: a trader with a specific performance will be more likely to accept and keep links from traders doing worse than her/him. This mechanism will limit both learning and performance of network members.

Based on the above, we hypothesize that: (1) traders will likely engage in informal status competitions by initiating networks with other traders; (2) in order to achieve this, they will be more likely to send/accept trade requests after a (positive or negative) change in trading performance; (3) traders will be more likely to accept and keep links with other traders that are doing worse than them. Thus, they will build and lock in audiences to whom their status (and improvements thereof) is displayed. As a consequence of (1)-(3), an influencer economy becomes an emergent property of network initiation.

4. Data and methods

4.1 Data description

4.1.1 Dataset

The dataset comes from a retail STP. All participants trade foreign exchange. The dataset records detailed daily account performance, connections with directions of requests, posts, comments and likes in the discussion forum, and profile information. The STP also offers a copy trade algorithm, allowing users to automatically replicate trade leaders' transactions. The platform officially ranks 172 traders as the best, based on past trading performance. Nonetheless, only 7 leaders have accrued 13 followers. This indicates that participants are not really interested in following trade leaders, from which they cannot gain reputation. To mitigate the copy algorithm's influence, all follower trading records have been excluded, though leader records remain. We identify 3,522 active accounts with 51,866 friend link requests and 662,613 daily logs from January 2009 to June 2010.

The dataset is relevant for several reasons. First, when probing the catalysts of network initiation, early-phase influencver economies are pivotal. The STP in question underwent private testing during 2007 and 2008, only becoming public in January 2009, which is also the beginning of our dataset. Second, other recent studies covering the same period of time, but face to face instead of online networks, make comparisons possible

(Escobar and Pedraza, 2023). Third, all ties and communication on the STP are human-initiated (as opposed to driven by bots). We know thus that link requests are genuine. Fourth, post the 2008 crisis, traders persisted, indicating that those documented in the dataset weathered external disturbances. We also control for the market factors in our models (details in the following). Fifth, the dataset covers the emergence period of the influencer economy, as detailed in recent accounts (Lorenz, 2023). Finally, studies such as Heimer's (2016) highlight the representativeness of such datasets across different asset classes.

4.1.2 Trading profiles

Table 1 presents statistics of trading activities daily, such as closed trades, close volume, win trades and win rates. Notably, the average win rate stands at 0.60, with its median being 0.67. These figures, however, do not imply that most investors profit from forex trading. This is because these numbers are influenced by traders with extensive trading histories in the dataset. Additionally, the disposition effect (Weber and Camerer, 1998), suggesting traders are more likely to close profitable trades and hold onto losing assets, can also inflate these numbers. Only 26.15% of accounts reported profits, with the remainder experiencing losses during the observation period.

[Table 1]

Traders have the option to trade a total of 92 forex pairs (e.g., "EUR/USD", "GBP/USD", and "EUR/CAD"). The five most traded forex pairs are "EUR/USD" (33.45%), "GBP/USD" (18.41%), "GBP/JPY" (7.26%), "EUR/JPY" (7.12%), and "USD/JPY" (6.18%). Typically, traders hold onto their foreign exchanges briefly, with the average duration being around 28 hours. Over 75% of transactions are closed within a day. Traders come from 126 countries, the top ten being the United States (26.89%), UK (7.36%), Malaysia (6.21%), Indonesia (6.11%), Nigeria (5.43%), Singapore (3.51%), Australia (3.51%), Canada (3.36%), Israel (3.00%), and India (2.45%). The youngest declared age is 18, and the oldest is 99, considering January 1st, 2010, as the baseline.

4.1.3 Investor networks

Traders can send friend link requests to any user. The recipient can accept (marked as accepted), ignore (marked as pending), or decline (marked as declined). Established ties can also be canceled. After being linked, parties can send private messages. There are 4,178 messages that have been sent between friend pairs during our observing period.

[Table 2]

Table 2 summarizes monthly friend link requests. The STP was publicly launched in January 2009 and the first friend link request was made in February 2009. Thus, the social networks span across 71 weeks (17 months, or 6 quarters). A total of 51,866 friend link requests were made, with a 44.74% average acceptance rate. 94.01% of all investors (3,522) are interconnected. The acceptance rate indicates that traders are selective in accepting links that would reveal their trading information. However, almost all traders manage to establish a network. We assume that some traders then will keep sending requests until some get accepted. Appendix 1 visually represents these monthly established ties and Appendix 2 shows the related statistics of the monthly networks. The fact that there are only 4,178 messages exchanged among those who establish 51,866 ties indicates that traders are not as much interested in private communications as they are in getting access to each other's trading histories.

4.2 Methodology

4.2.1 The TERGM model

While the classical framework of statistical inference and the Bayesian framework fundamentally rely on the independence assumption (Cranmer, Desmarais and Morgan, 2020), this isn't the case for networks. In network data, points are either embedded within the structure or the relationships emerge dependently (Cranmer and Desmarais, 2016). Specifically, the likelihood of a tie forming between two nodes is influenced by the remainder of the network structure (Cranmer and Desmarais, 2011). This makes the classical framework of statistical inference methods problematic, leading to inefficient estimates or entirely incorrect inferences (Ernst and Albers, 2017). The exponential random graph model (ERGM) is designed to specify network dependence forms without making exact assumptions. Specifically, N indicates some representation within a social network, and $\mathcal{N}$ is the set of all possible networks accordingly. Hence, the probability distribution function (PDF) for a ERGM can be written as:

$$\mathcal{P}(N) = \frac{1}{Z(\boldsymbol{\theta})} \exp\{\boldsymbol{\theta}' \mathbf{u}(N)\} \tag{1}$$

Where: $\boldsymbol{\theta} \in \mathbb{R}^k$, u: $\mathcal{N} \to \mathbb{R}^k$, and $Z(\boldsymbol{\theta})$ is a normalization constant. The $\mathbf{u}$ fuction represents a vector of clique potentials. The representation includes multiple relation types, including actor and relation attributes. The most common one is the single-relation social networks (like ours), where A_{ij}^t is the strength of the directed relation between the i^{th} actor and j^{th} actor.

In dynamic settings, where network structure evolves over time, a Markov assumption is made. A^t(the weight matrix representation of a single-relation social network at time t) is independent of A^1, …, A^{t-2}given A^{t-1}. Hence:

$$\mathcal{P}(A^2, A^3, \dots, A^t | A^1) = \mathcal{P}(A^t | A^{t-1}) \mathcal{P}(A^{t-1} | A^{t-2}) \cdots \mathcal{P}(A^2 | A^1) \tag{2}$$

And then, a specified function $\boldsymbol{\Psi}$: $\mathbb{R}_{\boldsymbol{n \times n}} \times \mathbb{R}_{\boldsymbol{n \times n}} \to \mathbb{R}^k$ can be applied as a temporal potential over cliques across two time-adjancent networks. The conditional PDF should be:

$$\mathcal{P}(A^t | A^{t-1}, \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta}, A^{t-1})} \exp\{\boldsymbol{\theta}' \boldsymbol{\Psi}(A^t, A^{t-1})\} \tag{3}$$

Which refers the TERGM, an ERGM extension that accommodates inter-temporal dependence in longitudinally observed networks (Leifeld, Cranmer, and Desmarais, 2018).

For more please see Hanneke, Fu and Xing (2010) and Cranmer, Desmarais and Morgan (2020). The application details for our research are provided in Appendix 3 and the results are shown by Table 3 and 4.

4.2.2 Regression

In Section 5.5, we examine the impact of the network formed at time “t” on investors' performance and behaviors at time “t+1” from three perspectives: performance, trading frequency, and asset selection. For performance, we use the average return during each time interval (week, month, or quarter). For trading frequency, we use the average daily closed trades. As to the asset selection, investors can trade as many forex pairs as they want. Based on the Herfindahl-Hirschman Index (HHI), we measure asset concentration in a way similar to measuring market concentration. We calculate the concentration of asset selection by the sum of the squared proportions of each forex pairs over all the pairs traded by a trader. We use 1 minus the square root of the sum and then times 100 to standardize the value. Hence, we calculate the parameter for asset selection as:

$$A_s = \left(1 - \sqrt[2]{\sum_{1}^{n} \left(\frac{K_i}{\sum_1^n k_i}\right)^2}\right) * 100 \tag{4}$$

Where: K_i is the number of closed trades on forex pair “i” during each time interval, and “n” refers to the number of forex pairs traded by the investor. The value of A_s ranges from 0 to 100. If investors trade on only one forex pair, it takes the value of 0. However, the more pairs investors trade on, the higher values of A_s will be.

(1) Performance

$$R_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t \tag{5}$$

Where:

a) R_{t+1} is the average return at time “t+1”.

b) B_{t-1}, Better return, is the dummy variable indicating whether investors outperform their previous term. Correspondingly, W_{t-1}, Worse return, is the dummy variable indicating whether investors underperform their previous term.

c) Ls_t stands for the online friend link sent at time "t". It can be substituted by La_t (link accepted at time "t").

d) X_t represents the control variables: pending (friend link sent, but ignored by receivers), declined (friend link sent, but rejected by receivers), canceled (prior established friend links that have been cancelled), accepted rate (total friend link accepted divided by total friend link sent), balance (average amount of money in investors accounts), net deposit (the money of top-up and withdrawal), age, and market factors (details in Section 6).

(2) Trading Frequency

$$F_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t \tag{6}$$

where F_{t+1} is the average daily closed trades at time "t+1".

(3) Asset Selection

$$As_{t+1} = \alpha + \beta_1 \cdot B_{t-1} + \beta_2 \cdot Ls_t + \beta_3 \cdot (B_{t-1} \times Ls_t) + \beta_4 \cdot X_t + \varepsilon_t \tag{7}$$

where As_{t+1} is the asset selection indicator at time "t+1".

In the regression equations (5), (6), and (7), we investigate the influence of Ls_t and La_t, as well as B_{t-1} and W_{t-1}. This gives rise to four variable combinations[3]: better performance & link sent (B_{t-1}×Ls_t), worse performance & link sent (W_{t-1}×Ls_t), better performance & link accepted (B_{t-1}×La_t), worse performance & link accepted (W_{t-1}×La_t).

[3] Not all the investors send and receive link request during each time interval (week/month/quarter), these interaction terms (B_{t-1}×Ls_t, W_{t-1}×Ls_t, B_{t-1}×La_t, W_{t-1}×La_t) help to focus on the subgroups who are involved in the network initiation process rather than the entire sample.

These combinations address our core concerns related to performance, trading frequency, and asset selection[4].

5. Network initiation

In this section, we examine the external and internal factors influencing the initiation of social networks. We also investigate: whose friend link requests will be accepted and maintained; the relationship between requests and the ranking of investors in their current networks; the impact of established networks on investor performance and behaviors.

5.1 Link requests following better or worse returns

We find that investors are more likely to send and receive link requests after a (positive or negative) change in their trading performance (Table 3). Panel A depicts the influence of financial performance on sending link requests, while Panel B focuses on receiving link requests. We conduct seven sub-tests within each panel for Tables 3, exploring various combinations of Better return, Worse return, Return, Max daily return, Min daily return, Max transaction return, and Min transaction return. The coefficients represent the variables' effect on the log-odds of sending or receiving a friend link request. Asterisks denote the significance of coefficients, indicating if they fall within the 90%, 95%, or 99% confidence intervals excluding zero.

[Table 3]

After a change in financial performance relative to the previous month, the probability of sending or receiving friend links increases. All these coefficients are statistically significant across all the seven sub tests.[5] If we take the estimates from Panel A sub test (7) as

[4] In Appendix 4, we also control for extra factors, such as in degree and out degree centrality of investors in networks, marked as C_in and C_out as well as Lr_t (link received at time "t"). We also change the time interval from month to week and quarter in Appendix 5.

[5] The coefficients are quite similar in sub tests (3) to (7), but higher than the coefficients in sub tests (1) and (2). This was caused by the relationship between Better and Worse return per se, which is proven to be robust in the robustness checks.

an example, investors have a probability of $\frac{e^{1.064}}{1+e^{1.064}} = 74.35\%$ to send out a link request after a better return and a probability of $\frac{e^{1.130}}{1+e^{1.130}} = 75.58\%$ to send out a link request after a worse return. The probabilities to receive a link request after performing better or worse are 65.34% and 63.06%, respectively (from Panel B sub test (7)). That is, after a change in performance, traders seek to commensurate against peers and evaluate their new status. Therefore, they send out link requests. While recipients too are more likely to get a request after a change in performance, their likelihoods are markedly lower compared with those of senders.

In panels A and B, we control for additional attributes. Posting in the forum (Discussion) makes it more likely to receive a request. A reply to or liking an already existing post have a negative effect on the likelihood of receiving a request. Posting in the forum is thus seen as a quality signal, while likes and replies are seen as the reverse. This indicates that not all communication forms (discussion, reply and likes) are taken as signals of value: if they were, traders who post likes or replies would seek links to others who do the same. Forum communication appears rather as a means of preliminary sifting two categories: traders who want to evaluate their status after a change in performance (senders) and traders who want to maintain their status (recipients), with the latter deciding on the disclosure of trading histories or not. Seen in a different perspective, not posting replies or likes is a consequential means of attracting attention and of positioning oneself in a more advantageous position. Drawing on the insights from Cao *et al.* (2020), we hypothesize that the presence of a profile photo may influence the propensity to send/receive requests. To this end, we introduce the variable "*Avatar*[6]" to denote whether an investor has uploaded a profile photo. While having the latter does not significantly affect the likelihood of sending requests, it does

[6] Investors can choose one of the avatars provided by the STP as their profile photo, or they can upload their own photos. The “Avatar” factor only counts for these who uploaded their own photos since only 68 out of 3,522 investors chose the STP avatars. There are 794 investors with profile photos and 2,728 without. We also conduct subgroup tests based on the “avatar” factor. Our results are robust for both groups.

increase the probability of receiving them. Based on past successful trading, the STP officially ranks 172 "leaders". Traders can use a copy algorithm to replicate the trades of any of these “leaders”. We find significant negative estimates of the “*Leader*” factor for receiving link requests.

Investors trading the same primary forex pairs or from the same country are more likely to establish ties. Age similarity, however, reduces the likelihood of ties. The positive coefficients for Mutual suggest a propensity for reciprocation within an already formed network: a trader who has already links with some network members will be more likely to be accepted by other network members as well. Negative coefficients for Edges indicate a network stabilization trend, consistent with the declining acceptance rate in Table 2. Taken together, they mean that formed networks of traders tend to stabilize over time and to not accept new entrants. As the number of requests grows, participants become more selective: they cancel few links overall, but declined and pending requests go up. As access to trading information is the main reward of accepting link requests, this means that over time traders tend to limit the network size within which they disclose trading information.

We validate our results using a goodness-of-fit approach[7] (Leifeld, Cranmer, & Desmarais, 2018) (Appendix 4). Also, after controlling for centrality (Appendix 5) and challenging the identification settings[8] (Appendix 6), our results are still robust.

[7] For each time step, we simulate 50 networks based on the estimated model parameters in Table 3 subtest (7) and compare them to observed networks. As indicated by Appendix 4, our models show excellent alignment with edge-wise shared partner, geodesic distances, and degree distributions. Thus, we can confidently assert the validity of our estimates.

[8] In Table 3, Better and Worse returns are defined by performance relative to the previous month. We now test their definitions more stringently. We label a return as Better only when it exceeds its predecessor by 5%, 10%, or 20%, and vice versa for a Worse return. The results are displayed in Panels A2, A3, A4, and Panels B2, B3, B4 of Appendix 6. Even with these stricter definitions, coefficients remain consistent and significant. Additionally, we adjust the time intervals. While the initial interval was monthly, we now also provide estimates on weekly and quarterly basis (Panels A5, A6, and Panels B5, B6). Panels A1 and B1 present the original monthly coefficients for comparison. Changing the time interval does not alter the significant positive coefficients for Superior and Inferior returns. Our findings, therefore, hold under sensitivity analysis.

5.2 Network topology

We follow the framework established by Cranmer, Desmarais, and Morgan (2020), and consider the network topology, presented in Table 4 (with the same other controls from Table 3). When looking at this topology, it appears to be different for links sent and link received and namely the factors, especially Ctriple (indicating network closure) is higher for link received compared with link sent. It means that network closure decreases the likelihood of sending links requests and it decreases the likelihood of receiving links requests even more. In other words, networks are closed, participants start forming new ones (which will be further discussed in Section 5.3 and 5.4). The transitive ties, on the other hand, which indicates transitivity across adjacent networks. The positive coefficients mean exactly that once the network is closed, participants branch out, seek to establish new networks.

[Table 4]

5.3 Whose link requests will be accepted and maintained?

Given that performance records (returns, leverage, trading frequency, etc.) are not accessible to others until a link request is accepted, both senders and recipients have to make their choice based on information such as existence of a profile photo, screen name, and participation in online discussion forums. We check if request recipients have higher returns, leverage, trading frequency, and balance compared with the senders. We then examine if the acceptance and continuation of ties are influenced by these factors. From Table 5, the significant coefficients for sR_Performance (recipients perform better than senders) in Panel A1 are much higher than those of Sr_Performance in Panel B1. Also, we can find positive significant coefficients of sR_Leverage, sR_Trading frequency and sR_Balance in Panel A1 as well as negative significant coefficients of Sr_Leverage, Sr_Trading frequency and Sr_Balance in Panel B1. If we accept that investors trade with higher leverage, frequency and balance are expected to be more informed and sophisticated, it reveals that traders are more likely to accept link requests from individuals who perform worse than them and information sharing and learning may not play a key role in the network initiation process. The status seeking effect is more pronounced. When checking the link canceled, the coefficients of sR_Performance in Panel A2 are negative while coefficients of Sr_Performance are positive in Panel B2. This evidence reveals that traders are less likely to cancel ties with the ones who perform worse than them but are more willing to do so with their better performing peers. It appears that traders aim primarily at keeping their position in a status hierarchy where their trading "friends" tend to do less well.

[Table 5]

5.4 Link Requests and Ranking in the Networks

Once a link request is accepted, traders can compare each other's trading performance[11]. What happens though with those traders who have a lower performance in their network? Do they accept their lower status, or do compete for a higher one, in a new network? If network initiation is driven primarily by status seeking, traders with a lower performance should keep trying to improve their status in a new network, where they can hope to have a higher position. For this, they will keep sending out links requests, in the hope of initiating new networks where their status will be higher. We have argued that existing networks tend to stabilize and not accept new entrants. Traders with a higher status in existing networks will be less likely to join new ones, as they have little incentive for jeopardizing their position. After a while, sending out repeated links requests comes to signal a lower trading performance. Traders who seek others doing less well than them will tend to send out links requests to those who keep sending links requests. Thus, as new networks are initiated, lower ranked traders will tend to become popular as recipients of requests too (see Table 6). The

[11] We also test the ranking of trading frequency and asset selection on link requests, and we find the same results with performance ranking.

ranking[12] of traders is defined from high to low, with a smaller number denoting a higher return, and hence a higher status in the network. The networks include all the linked friends during a given time interval (week, month, and quarter). Across all three panels, the significant and positive coefficients of the rankings on *link sent* mean that traders with a low status in their current networks keep seeking new connections more actively than traders with a higher ranking. However, they are also popular with other traders, as evidenced by the significant and positive coefficients for *link received*. In other words: lower ranked traders seek to improve their status position by initiating or joining new networks where they might be compare more favorably to others. For this, they keep sending link requests outside their existing networks, but also receiving requests. (Others lower ranked traders will seek others doing less well than them.) Thus, while networks are not static, newly formed ones will have a limited impact on changing the status of traders, rather reinforcing the status of influencers instead of reducing stratification.

[Table 6]

5.5 Investor performance in networks

If traders accept and maintain links with "friends" primarily to gain and maintain relatively higher status, we should expect this to have more of an effect on their trading performance compared with the performance of "friends" who sent a request. In other words: traders who accept and keep link requests will strive more to improve their performance in order to show within their network that they are indeed better. Traders who send requests will be less likely to improve their performance, as they occupy an inferior position in the group.

We ascertain whether sending/accepting a link request has an impact on subsequent financial performance. Since not all the investors send and receive link request during each

[12] As a default, we calculate the average ranking for investors when their performances are identical. In addition, we obtain the same results when ranking investors with the highest or lowest among others who achieve the same results in their networks.

time interval (week/month/quarter), we construct the interaction terms (B_{t-1}×Ls_t, W_{t-1}×Ls_t, B_{t-1}×La_t, W_{t-1}×La_t) as our main independent variables to test the impact of previous performance and social network conducts on the future performance of investors. Our primary model encompasses several factors, including the number of receiving, pending, declined, and canceled friend link requests; leverage[13], balance and net deposit; communication, mobility, and investors' age. To address concerns regarding potential FX market conditions influencing investor performance and behaviors, we also incorporate market factors, namely carry (Carry), momentum (Mom), value (Value), and volatility (Vol), which are regarded as representative of various trading strategies adopted by currency traders (Pojarliev & Levich, 2008). In line with previous studies (e.g., Abbey & Doukas, 2015), the proxies for these four factors are sourced from Deutsche Bank's DBIQ database[14].

Table 7[15] indicates that traders who improved their performance at time "t-1" (compared with t-2) and sent a friend link requests at "t" (B_{t-1}×Ls_t) improve performance at "t+1" by 0.4%. However, if the link request is accepted at "t" after a better performance at "t-1" (B_{t-1}×La_t), traders who accept improve returns by 1.7% at "t+1", which is significantly more than traders who send. Across scenarios, (B_{t-1}×Ls_t, W_{t-1}×Ls_t, B_{t-1}×La_t, W_{t-1}×La_t), sending/accepting link requests after both superior or inferior performances leads to reduced trading frequencies (more so for accepting). Compared to sending, accepting link requests reduces asset concentration more. Overall, the results indicate that an accepted friend link wields a greater impact than merely sending a request. The acceptor grants a "favor" to the sender by accepting reciprocal access to trading records. Acceptors (with improved

[13] Similar to performance, trading frequency and asset selection, we also test the impact of sending and accepting link requests on leverage, but we have not found any significant evidence.
[14] The Deutsche Bank (DB) Currency Carry USD Index serves as the proxy for carry trading strategy, the DB FX Momentum (USD) acts as the proxy for trend-following trading strategy, the DB FX Purchasing Power Parity (PPP) (USD), and the 60-day volatility, computed based on the Deutsche Bank (DB) G10 Currency Harvest Index (USD), serves as the proxy for market volatility.
[15] Since there are 211 (6%) investors are not linked at all in our sample, we also have done the same regression with only linked investors (3,311). The sub-group test does not change our results.

performance, shown by B_{t-1}) will strive to keep the position by improving their performance and showing their friends that they are better in terms of financial performance. As discussed in Section 5.3 and 5.4, friends who implicitly challenge this status are more likely to be unfollowed. Acceptors will tend to keep friends who perform financially less well than themselves. While efforts to show improved performance fade after a while, they are likely to be renewed with the acceptance of a new link request. Similar to previous sections, we control for extra factors (such as centrality) and adjust the time interval from monthly to weekly and quarterly, respectively. The results are shown in Appendix 7 and 8. Our findings hold with even stronger significance by weekly and quarterly intervals.

[Table 7]

6. Status competitions and network initiation

Status competitions in influencer economies has received little empirical attention, although it is of prime significance. In many instances, initiation processes can determine the emergent properties of a network and the behavior of participants—and influencer economies are network-based ones. Seen in the context of finance, such economies have considerably gained in significance over the past decade, as social media networks are increasingly harnessed by institutional investors in their investment decisions, not least with the help of tools such as AI and machine learning. It becomes even more relevant to understand how network initiation shapes the behavior of participants.

Current explanations emphasize merit—i.e., skill, talent, hard work—in attaining influencer status. Displays of skill and talent attract followers. Our findings show that status competitions unfold by: building a network of followers in such a way that the top status cannot be challenged; consolidation of this status by precluding subsequent challenges. Following the distinction between status and reputation, established in the literature, we find that investors tend to forego copying the few trade leaders who have reputation[16] (based on the official rankings of the platform) and compete for status by initiating networks. For this, they need access to truthful trading histories, so that they can commensurate their past performance against other traders. Disclosing own trading history platform-wide would be counter-productive, as other traders will benefit from this action without reciprocating. Hence, they initiate networks (ensuring thus reciprocity of disclosure). They have the option of sending a link request or waiting to receive such a request and then decide whether to accept, ignore, or reject it. This second move option (wait to receive requests) already gives an advantage to recipients.

Friend link requests sent by traders with returns higher than the recipients are less likely to be accepted (as shown by Panel A1 and B1, Table 5) and are significantly canceled (as indicated in Panel A2, Table 5). More sophisticated investors who trade with higher leverage, frequency and balance are less favorable (again, shown by Panel A1 and B1, Table 5) Investors ranked lower in their already existing networks become more sought after (Table 6). During our observation period, there were a total of 51,866 friend link requests, contrasted with a mere 4,178 private messages exchanged among investors. On average, each investor boasts approximately 15 online friends yet sends fewer than one message to peers over an 18-month span. Panel A in Table 7 shows that followers do not benefit much in terms of trading performance from influencers, especially if they had a worse performance before sending link requests.

Our analysis shows that senders are more likely to look for recipients who post in forum discussions (especially after an improved performance), but who do not reply to or like

[16] By average, the accept rate of a link request for all investors is 44.74% (shown by Table 2), however, the accept rate for the link requests sent by “leaders” is 35.71% and the accept rate for the link requests received by “leaders” is 60.89%. Given the fact that these “leaders” have a nice historical trading performance, we can claim that they seek to establish status outside the official platform ranking as well even though they are not preferred by other investors.

other posts. Replies and likes are not taken by senders as status signals, although they practice them themselves. If recipients regard replies and likes in the same way as senders, this puts the latter from the start in an inferior position vis-à-vis recipients, who will be more likely to accept and maintain links with traders doing less well than them but will also strive to improve their performance short term, so that they maintain their superior position.

This leads to the emergence of an influencer economy with little incentives to circulate information platform wide. In this economy, a recipient of requests has a group of followers likely to do less well and less likely to benefit from the trader at the top (see also Li, Li, Li, and Li 2020). However, this economy is a dynamic one. Those occupying lower positions in existing networks continue competing for status by seeking new connection,s in the hope of obtaining a higher status in a new network. As sending out new link requests repeatedly has become a signal of lower performance, those who do are also sought after: they are more likely to receive new link requests. Thus, new network formation does little to change the dynamic of status competitions. The picture we get is that of many such groups (as illustrated by Appendix 1, especially from Jan. 2010 onwards) within which hierarchies are maintained. This is in line with the overall financial performance of the STP, which shows that a majority of traders does not improve their financial performance over time, while a minority does.

7. Conclusion

In markets and organizations status competitions are consequential with regard to participants' performance and engagement, among others. As the profile of influencer economies has grown over the past decade, understanding the organization of such competitions within the networks that constitute these economies can shed light on their dynamics. Recent studies of such economies have emphasized the hierarchical character of networks in which an "influencer" at the top connects to a group of followers (Rieder et al., 2023: 14). The influencer position has been discussed in relationship to agency and creativity (e.g., Pagan et al, 2021; Hund, 2023), or to fanatic beliefs (e.g., Pedersen, 2022), but less so as an effect of network initiation dynamic. Departing from current explanatory models, we highlight how the initial steps of network formation are intrinsic to status competitions. On a conceptual level, we draw attention to initiation dynamics as an informal mechanism of competition control, adding thus to the literature on category controls and commensuration as formal control mechanisms. On an empirical level, we use network initiation on STPs as a quasi-natural experiment in order to investigate the dynamic of influencer status: participants are only interested in financial information and seek reciprocal access to trading account information as the major, if not the only payoff of establishing networks. In an economy based on consensual networks, investors have to do “blind dates”, where they will have access to others’ truthful trading information only after a successful “date” (link request accepted). Hence, it becomes possible to investigate the extent to which participants compete for status by initiating and accepting “dates”, and what happens thereafter.

We argue that influencer status is attained by locking in an audience and precluding potential challengers from joining it. Subsequent skill improvements are unequal: audiences profit significantly less, performance-wise, from network formation, relative to influencers. After having accepted link requests, influencers reduce frequency and concentrate their asset selection to show better performance. While striving to improve performance relative to others in the network, they aim at maintaining their status by accepting links from others who perform less well or rank low. Those who are low status in current networks seek new connections more actively. What counts in influencer economies are comparisons over time with peers that are in a similar situation—i.e., experience changes in their performance. These economies seem to comprise two kinds of participants: those who seek to compare themselves to peers after a change in their situation or performance (request senders) and those who seek to come on top in informal comparisons (request acceptors). Over time, informal networks evolve; high-status participants tend to grant access to account information within their networks, but also to exclude other traders from joining, while low-status ones keep seeking new networks. This network dynamics suggests that information dissemination and learning are limited by these emerging network properties.

Due to lack of space, we can only point here to further questions that should be investigated: for instance, what are the relationships among “influencers” and how do they change over time? Do already established influencers perform better than newly emerging ones, in terms of financial performance, as well as of followers? Do “influencer” networks also collapse, and if yes, what are the drivers of such processes? One limitation of our study is that the population of STP traders is overwhelmingly male. Network initiation dynamics may well have a gender component that could make this process and its consequences look different on an STP with overwhelmingly female traders, or in other types of influencer economies. We therefore acknowledge that different status competitions may have different initiation dynamics. This, among others, is why we call herewith for a more sustained, data grounded program of research into influencer economies and network initiation processes.

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Tables and Figures

Fig. 1. Four possible outcomes of sending and receiving link requests

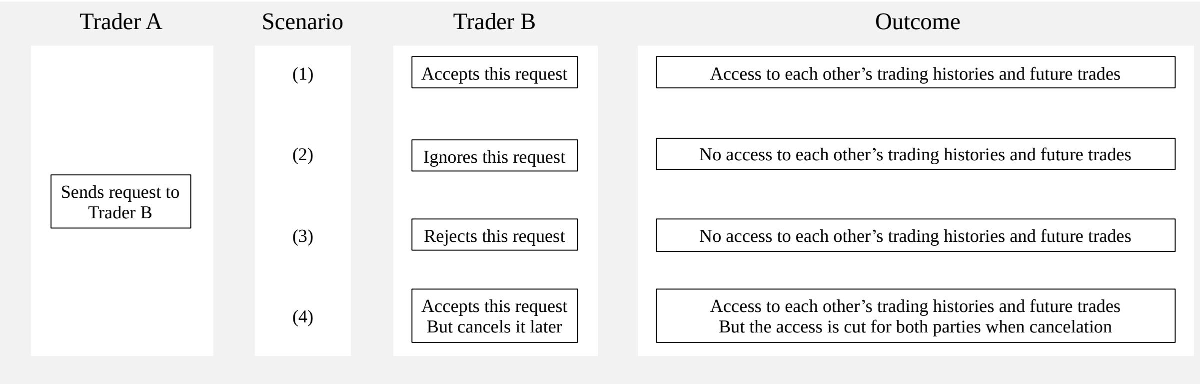


Table 1. Descriptive Statistics (Daily)

	Closed Trades	Close Volume	Win Trades	Win Rate	Results ($)	Balance ($)	Net Deposit	Age (01/01/2010)
Mean	7.69	207,785	4.76	0.60	398	8,276	151	35
Median	4.00	20,000	2.00	0.67	1.46	860	-0.19	33
Mode	1.00	10,000	1.00	1.00	0.00	0.00	-0.12	21
S.E.	0.09	5,103	0.07	0.00	293	278	67.38	0.22
S.D.	32.11	1,789,995	23.81	0.367	102,834	97,617	9,614	12.56
Count	123,019	123,019	123,019	123,019	123,019	123,019	20,361	3,303

Table 2. Summary of Friend Link Request by Month

Month	Friend link Request	Accepted	Accepted Rate	Pending	Declined	Canceled	Investors (cumulative)	Percent (cumulative)
Feb-09	18	14	77.78%	3	0	1	11	0.31%
Mar-09	195	132	67.69%	24	24	15	37	1.05%
Apr-09	392	269	68.62%	111	5	7	82	2.33%
May-09	674	449	66.62%	210	14	1	120	3.41%
Jun-09	352	226	64.20%	120	5	1	163	4.63%
Jul-09	450	277	61.56%	161	9	3	246	6.98%
Aug-09	1,049	630	60.06%	394	16	9	333	9.45%
Sep-09	1,714	992	57.88%	656	65	1	452	12.83%
Oct-09	4,219	2,474	58.64%	1,584	115	46	786	22.32%
Nov-09	4,672	2,301	49.25%	2,131	228	12	1,013	28.76%
Dec-09	3,125	1,603	51.30%	1,416	98	8	1,237	35.12%
Jan-10	3,308	1,929	58.31%	1,267	93	19	1,511	42.90%
Feb-10	4,520	2,273	50.29%	2,080	127	40	1,859	52.78%
Mar-10	6,347	2,561	40.35%	3,554	207	25	2,264	64.28%
Apr-10	10,032	3,544	35.33%	6,110	372	6	2,671	75.84%
May-10	6,013	2,137	35.54%	3,616	246	14	3,073	87.25%
Jun-10	4,786	1,393	29.11%	3,272	112	9	3,311	94.01%
Total	51,866	23,204	44.74%	26,709	1,736	217	3,311	94.01%

Table 3. Link Requests by Month

We employ the TERGM to investigate whether the desire to compare triggers investors to form social networks initially. The primary variables encompass various combinations of returns, while the control variables account for node attributes, edge covariates, and fundamental network characteristics. Our primary focus is on the 'Better Return' and 'Worse Return' compared to previous periods; both are treated as dummy variables. Panel A and Panel B respectively present the influence of these factors on link request sent and received. *, **, *** means coefficients are in 90%, 95%, 99% confidence interval without zero inside respectively. (Bootstrapping sample size: 1000)

Panel A: Link Sent			(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary Variables		Better return	0.725***		1.062***	1.062***	1.059***	1.067***	1.064***
		Worse return		0.800***	1.133***	1.133***	1.130***	1.133***	1.130***
		Return				0.000	-0.002	0.000	-0.002
		Max daily return					0.021		0.022
		Min daily return					0.003		0.003
		Max transaction return						0.000	0.000
		Min transaction return						0.000	0.000
Control Factors	Node Attributes	Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Trading frequency	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Discussion	0.249***	0.255***	0.224***	0.224***	0.225***	0.228***	0.230***
		Reply	1.123***	1.124***	1.101***	1.101***	1.100***	1.096***	1.095***
		Likes	0.931***	0.917***	0.875***	0.875***	0.873***	0.877***	0.876***
		Avatar	0.003	0.008	-0.008	-0.008	-0.007	-0.007	-0.006
		Leader	0.104	0.129	-0.007	-0.007	-0.005	-0.005	-0.003
		Mobility	0.825***	0.840***	0.641***	0.641***	0.641***	0.640***	0.641***
	Edge Covariates	Same main pair	0.049***	0.050***	0.045***	0.045***	0.045***	0.046***	0.046***
		Country	0.340***	0.340***	0.355***	0.355***	0.355***	0.353***	0.353***
		Age (3)	-0.109***	-0.108***	-0.113***	-0.113***	-0.113***	-0.112***	-0.112***
	Network Basics	Edges	-9.385***	-9.410***	-9.450***	-9.450***	-9.450***	-9.449***	-9.450***
		Mutual	8.844***	8.863***	8.755***	8.755***	8.756***	8.756***	8.756***

Panel B: Link Received			(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary Variables		Better return	0.463***		0.634***	0.634***	0.634***	0.634***	0.634***
		Worse return		0.312***	0.532***	0.532***	0.533***	0.534***	0.535***
		Return				0.000	0.001	0.000	0.001
		Max daily return					-0.005		-0.005
		Min daily return					-0.001		-0.001
		Max transaction return						0.000	0.000
		Min transaction return						0.000	0.000
Control Factors	Node Attributes	Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Trading frequency	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Discussion	0.344***	0.366***	0.343***	0.343***	0.342***	0.340***	0.340***
		Reply	-0.171***	-0.172***	-0.195***	-0.195***	-0.195***	-0.192***	-0.192***
		Likes	-0.197***	-0.206***	-0.225***	-0.225***	-0.225***	-0.227***	-0.226***
		Avatar	0.216***	0.219***	0.215***	0.215***	0.215***	0.214***	0.214***
		Leader	-0.314***	-0.290***	-0.389***	-0.389***	-0.389***	-0.390***	-0.390***
		Mobility	-0.947***	-0.935***	-0.977***	-0.977***	-0.977***	-0.977***	-0.977***
	Edge Covariates	Same main pair	0.042***	0.043***	0.040***	0.040***	0.040***	0.039**	0.039**
		Country	0.341***	0.340***	0.345***	0.345***	0.345***	0.347***	0.347***
		Age (3)	-0.107***	-0.106***	-0.108***	-0.108***	-0.108***	-0.108***	-0.108***
	Network Basics	Edges	-7.040***	-7.026***	-7.106***	-7.106***	-7.106***	-7.106***	-7.106***
		Mutual	8.841***	8.859***	8.756***	8.756***	8.756***	8.757***	8.757***

Table 4. Link Requests with Topology by Month

Drawing from our baseline model presented in Table 3, we account for network topology with TERGM. Panel A and Panel B respectively present the results on link request sent and received with exactly the same controls from Table 3. *, **, *** means coefficients are in 90%, 95%, 99% confidence interval without zero inside respectively. (Bootstrapping sample size: 1000)

Panel A: Control with Topology (Sent)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary variables	Better return	0.418***		0.705***	0.705***	0.701***	0.711***	0.707***
	Worse return		0.493***	0.772***	0.772***	0.767***	0.774***	0.769***
Topology	Ttriple	0.227***	0.227***	0.223***	0.223***	0.223***	0.223***	0.223***
	Ctriple	-0.589***	-0.589***	-0.577***	-0.577***	-0.577***	-0.576***	-0.577***
	Transitiveties	1.054***	1.052***	0.999***	0.999***	0.999***	1.000***	0.999***
Control Factors		Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Control with Topology (Received)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary variables	Better return	0.322***		0.458***	0.458***	0.458***	0.458***	0.458***
	Worse return		0.219***	0.393***	0.393***	0.393***	0.394***	0.394***
Topology	Ttriple	0.241***	0.241***	0.242***	0.242***	0.242***	0.242***	0.242***
	Ctriple	-0.612***	-0.613***	-0.614***	-0.614***	-0.614***	-0.614***	-0.614***
	Transitiveties	1.119***	1.127***	1.094***	1.094***	1.094***	1.094***	1.094***
Control Factors		Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Whose Link Requests Will Be Accepted and Maintained

In the light of status competition, we define dependent variables to denote whether recipients have a higher return, leverage, trading frequency and balance compared to senders (marked as sR_Performance, sR_Leverage, sR_Trading frequency, and sR_Balance). Subsequently, we investigate whether these factors influence the acceptance and continuation of online friendships, as demonstrated by models (1) to (4). The variables to denote whether senders have a higher return, leverage, trading frequency and balance compared to recipients are marked as Sr_Performance, Sr_Leverage, Sr_Trading frequency, and Sr_Balance respectively. The control variables are deposit, communication, mobility, same main pair, country, age. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A1: Link Accepted				Panel A2: Link Canceled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sR_Performance	0.024***	0.022***	0.023***	0.021***	-0.002**	-0.002**	-0.002**	-0.002**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
sR_Leverage	0.078***			0.053***	-0.001			0.000
	(0.007)			(0.008)	(0.001)			(0.001)
sR_Trading frequency		0.075***		0.035***		-0.001		-0.001
		(0.008)		(0.008)		(0.001)		(0.001)
sR_Balance			0.046***	0.032***			-0.001	0.000
			(0.007)	(0.007)			(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,728	51,728	51,728	51,728	51,728	51,728	51,728	51,728
R^2	0.614	0.614	0.612	0.615	0.077	0.077	0.077	0.077

	Panel B1: Link Accepted				Panel B2: Link Canceled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sr_Performance	0.012**	0.013**	0.012**	0.016***	0.002**	0.001**	0.002**	0.001**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)
Sr_Leverage	-0.034***			-0.021***	0.000			0.000
	(0.006)			(0.007)	(0.001)			(0.001)
Sr_Trading frequency		-0.033***		-0.011		0.000		0.000
		(0.006)		(0.007)		(0.001)		(0.001)
Sr_Balance			-0.040***	-0.033***			0.000	0.000
			(0.007)	(0.007)			(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time and Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,728	51,728	51,728	51,728	51,728	51,728	51,728	51,728
R^2	0.611	0.611	0.611	0.612	0.077	0.077	0.077	0.077

Table 6. Link Requests and Ranking in the Networks

We test whether the rankings of investors' performance (compared with their linked online peers) in their contemporary networks will affect their link requests send out and received in. The ranking is defined as the orders from high to low, which means a small number ranking is better, e.g., a smaller ranking of performance means a higher return. We show the results for different time intervals, week, month and quarter, by Panel A, Panel B and Panel C respectively. The significant and positive coefficients of the rankings on link sent across Panel A, B and C mean a low status of investors in their current networks will lead them seek new connections more actively. However, they are also more welcomed by others, evident by the significant and positive coefficients for link received. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Week		Panel B: Month		Panel C: Quarter	
	Link sent	Link received	Link sent	Link received	Link sent	Link received
Ranking	0.007** (0.003)	0.013*** (0.003)	0.029*** (0.011)	0.056*** (0.013)	0.145*** (0.036)	0.180*** (0.046)
Link sent		0.084*** (0.014)		0.143*** (0.023)		0.128*** (0.033)
Link received	0.115*** (0.012)		0.135*** (0.018)		0.086*** (0.023)	
Pending	1.329*** (0.072)	-0.099*** (0.018)	1.324*** (0.064)	-0.175*** (0.029)	1.350*** (0.056)	-0.162*** (0.044)
Declined	1.124 (0.871)	-0.127* (0.071)	1.488* (0.898)	-0.190 (0.121)	1.231 (0.868)	-0.143 (0.175)
Canceled	2.180*** (0.201)	0.145 (0.117)	3.160*** (0.442)	-0.106 (0.167)	3.308*** (0.574)	0.143 (0.257)
Leverage	Yes	Yes	Yes	Yes	Yes	Yes
Balance	Yes	Yes	Yes	Yes	Yes	Yes
Net deposit	Yes	Yes	Yes	Yes	Yes	Yes
Communication	Yes	Yes	Yes	Yes	Yes	Yes
Mobility	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
Time FE.	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes
N	220,358	220,358	56,287	56,287	19,866	19,866
R^2	0.975	0.130	0.979	0.271	0.984	0.420

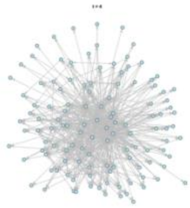
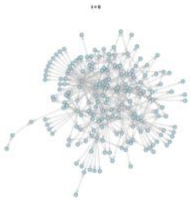
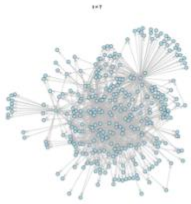
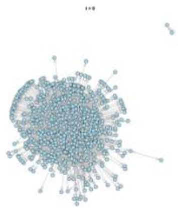
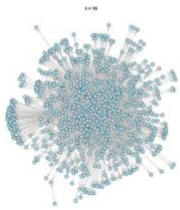
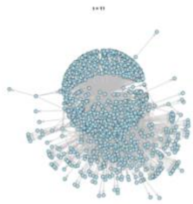
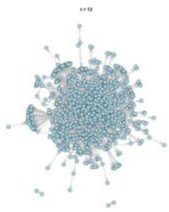
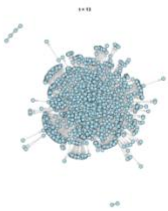
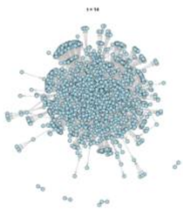
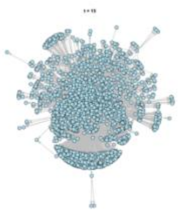
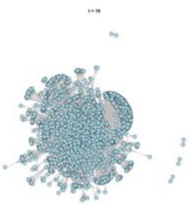
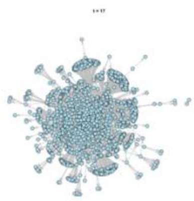
Table 7. The Impact of Established Social Networks on Investor Performance and Behaviors by Month

This table presents results examining the extent to which investor performance and behaviors at time "t+1" are influenced by friend link requests at time "t". In the preceding section, we established that friend link requests at time "t" correlate with the Better and Worse returns at time "t-1" (B_{t-1} and W_{t-1}). Consequently, we evaluate the effects of both Ls_t (link sent) and La_t (link accepted), as well as B_{t-1} and W_{t-1}. This gives rise to four variable combinations: $B_{t-1}\times Ls_t$, $W_{t-1}\times Ls_t$, $B_{t-1}\times La_t$, and $W_{t-1}\times La_t$. Beyond the fundamental control variables, we also integrate market factors. These encompass the carry factor, momentum factor, value factor, and volatility factor, which are considered emblematic of various trading strategies employed by currency traders, as suggested by Pojarliev and Levich (2008). Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Performance (t+1)				Panel B: Trading frequency (t+1)				Panel C: Asset selection (t+1)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$B_{t-1}\times Ls_t$	0.004*				-0.013***				-0.036*			
	(0.002)				(0.004)				(0.019)			
$W_{t-1}\times Ls_t$		-0.001				-0.004				-0.013		
		(0.001)				(0.003)				(0.013)		
$B_{t-1}\times La_t$			0.017*				-0.052***				-0.189***	
			(0.009)				(0.013)				(0.064)	
$W_{t-1}\times La_t$				-0.004				-0.025**				-0.056
				(0.004)				(0.013)				(0.043)
B_{t-1}	-1.778***		-1.786***		3.375***		3.396***		9.022***		9.123***	
	(0.494)		(0.498)		(0.145)		(0.146)		(0.282)		(0.284)	
W_{t-1}		0.795***		0.797***		1.993***		2.011***		14.511***		14.542***
		(0.196)		(0.198)		(0.255)		(0.257)		(0.316)		(0.319)
Ls_t	0.001	-0.007*			-0.019	-0.029**			0.386***	0.301***		
	(0.002)	(0.004)			(0.014)	(0.014)			(0.063)	(0.052)		
La_t			-0.004	-0.005			-0.003	-0.020			0.452***	0.321***
			(0.005)	(0.003)			(0.015)	(0.013)			(0.071)	(0.060)
Received	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pending	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Declined	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Canceled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Communication	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mobility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874
R^2	0.046	0.045	0.046	0.045	0.150	0.137	0.150	0.137	0.369	0.409	0.370	0.409

Appendix 1. Friend Link Established in Each Month

This figure illustrates the online connections formed monthly. The first friend link request dates back to February 2009. Over the period, a total of 51,866 friend link requests were initiated, yielding an acceptance rate of 44.74%. Remarkably, a vast majority of investors, 94.01% or 3,522 individuals, are interconnected.

Jan-09	Feb-09	Mar-09
No friend link requests were made this month.		
Apr-09	**May-09**	**Jun-09**
		
Jul-09	**Aug-09**	**Sep-09**
		
Oct-09	**Nov-09**	**Dec-09**
		
Jan-10	**Feb-10**	**Mar-10**
		
Apr-10	**May-10**	**Jun-10**
		

Appendix 2. The Statistics of Networks in Each Month

We show the statistics of the networks established by each month only and do not include the investors who are linked before. For example, an investor linked during February 2009 will not be counted into the networks in March 2009.

Month	Number of networks	Average size	Min size	Max size	S.D. of size
Feb-09	6	3.33	2	5	1.03
Mar-09	22	7.00	2	18	4.72
Apr-09	39	7.90	2	35	8.28
May-09	52	9.63	2	78	14.05
Jun-09	40	6.65	2	27	6.43
Jul-09	52	6.33	2	40	7.37
Aug-09	82	8.68	2	93	13.44
Sep-09	104	10.54	2	101	15.75
Oct-09	238	11.39	2	296	25.59
Nov-09	216	11.65	2	122	18.98
Dec-09	184	9.71	2	352	26.66
Jan-10	271	8.12	2	72	11.00
Feb-10	269	9.45	2	186	19.69
Mar-10	318	9.05	2	290	20.88
Apr-10	358	10.90	2	492	36.50
May-10	300	8.12	2	214	18.81
Jun-10	197	8.07	2	159	17.31

Appendix 3. The TERGM model

1. Exogenous and Endogenous Dependencies

TERGM can detect both exogenous and endogenous dependencies (Cranmer, Desmarais, and Morgan, 2020). Exogenous factors are external influences on network dynamics, like node attributes and edge covariates. These are often tested in regression models. For instance, investor-applied leverage and returns are node attributes. Conversely, if investors originate from the same country or share an age range, these are treated as edge covariates. Endogenous factors pertain to tie dependencies within the same time frame due to the inherent network structure. Examples encompass reciprocity and other network structural properties. The later-applied model incorporates both dependencies for a thorough network dynamics capture (for more, refer to Leifeld, Cranmer, and Desmarais, 2018).

2. TERGM Models

We run separate models in order to distinguish the factors that influence sending and receiving friend links. The R package we utilized is the '**btergm** package', as outlined by Leifeld, Cranmer, and Desmarais (2018), which uses the bootstrapped pseudolikelihood inference methods (Desmarais and Cranmer, 2012) and generates the confidence interval for estimates.

Model 1:

Model.sending <- **btergm** (mc_list ~ *edges* + *mutual*+ *ttriple* + *ctriple* + *transitiveties* + *nodeocov*("idegsqrt") + *nodeocov*("odegsqrt") + *nodeocov*("M_1") + …+ *nodeocov*("M_n") + *edgecov*("N_1") + … + *edgecov*("N_n"), R = 1000)

Model 2:

Model.receiving <- **btergm** (mc_list ~ *edges* + *mutual*+ *ttriple* + *ctriple* + *transitiveties* + *nodeicov*("idegsqrt") + *nodeicov*("odegsqrt") + *nodeicov*("M_1") + …+ *nodeicov*("M_n") + *edgecov*("N_1") + … + *edgecov*("N_n"), R = 1000)

Models 1 and 2 are designed to capture the factors that influence sending and receiving friend link requests respectively. Below are explanations for the components and functions:

1) There are some build-in functions in the **btergm** package, including *"edges"*, *"mutual"*, *"ttriple"*, *"ctriple"*, *"transitiveties"*, *"nodeicov"*, *"nodeocov"* and *"edgecov"*.

   a) The *"edges"* function captures the overall tendency for edges to form in the network. It accounts for the number of edges in the network at each time point.

   b) The *"mutual"* term captures the tendency for edges to be reciprocated. If there is an edge from node A to node B, there is a higher likelihood of an edge from node B to node A.

   c) The *"ttriple"* term represents the tendency for two nodes with a common neighbour to form a triangle.

   d) The *"ctriple"* term represents the tendency for two nodes with a common neighbour to form a triangle even if they are not directly connected. It captures closure in the network.

   e) The *"transitiveties"* term captures the overall tendency for transitive triads to form in the network.

   f) *"nodeicov"* and *"nodeocov"* detect node attributes for sending and receiving friend links.

   g) *"edgecov"* tests the shared characteristics of edge covariates.

2) Variables enclosed in parentheses, including "idegsqrt", "odegsqrt", "$M_1, \ldots, M_n$", "$N_1, \ldots, N_n$".

   a) "idegsqrt" and "odegsqrt" means the in degree and out degree centrality of nodes.

   b) "$M_1, \ldots, M_n$" are concerned variables and control variables, including Better return than previous term, Worse return than previous term, Return, Max daily return, Min daily return, Max transaction return, Min transaction return, Leverage, Trading frequency, Balance, Net deposit, Communication (whether investors engaged in communication in the STP community), and Mobility (whether investors travelled to different continents[18]). As introduced before, all these variables are at time “t-1” whereas the corresponding networks in the models are at time “t”.

c) “N_1, …, N_n” are the dummy variables of edge covariates, Same main pair, Country and Age (3). If investors trade the same main pair (by volume), originate from the same country, or have an age difference of less than three years, these variables are assigned a value of one; otherwise, they are assigned a value of zero.

3) The “mc_list” is the list of data for our longitudinally observed networks, which are consecutive 3522 × 3522 binary matrices in which a 1 indicates a directional connection between investors.

4) “R = 1000” means we take 1,000 replications for all the models in our paper.

3. Goodness-of-fit of TERGM Models

We validate results through goodness-of-fit, which. in the context of TERGM pertains to the degree to which the model accurately represents the observed data (Leifeld, Cranmer and Desmarais, 2018). Evaluating this fit is pivotal in assessing the model's reliability and precision. A prevalent method involves simulating networks using the estimated model parameters and contrasting these simulated networks with the observed one. If the statistics of the observed network lie within the bounds of the simulated networks, it indicates a satisfactory fit. Discrepancies between observed and simulated distributions pinpoint areas where the model might not encapsulate the observed structural patterns entirely.

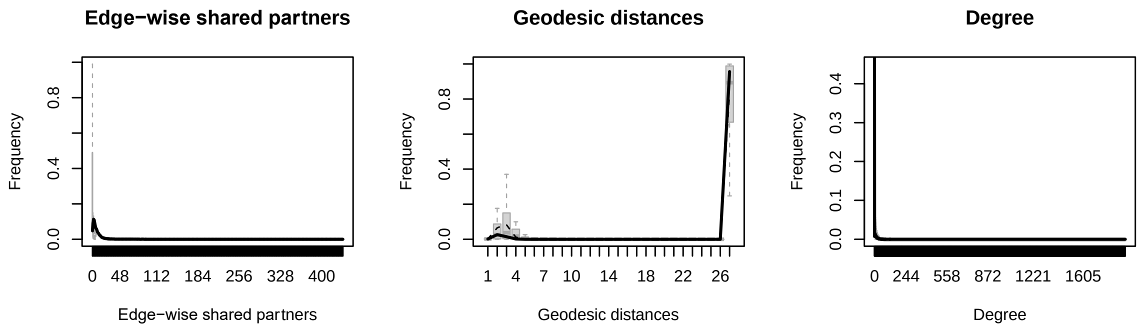
We check the goodness-of-fit from three perspectives, edge-wise shared partner, geodesic distance, and degree distributions. Edge-wise shared partner refers to the number of common neighbors shared by pairs of nodes connected by an edge in the network. Comparing the edge-wise shared partner distribution between the observed network and networks simulated from the TERGM model helps evaluate whether the model captures the tendency for nodes with shared neighbors to form networks. Geodesic distance is the shortest path length between two nodes in a network. A good fit indicates that the model reproduces the observed patterns of how connected or disconnected nodes are in terms of shortest paths. The degree of a node represents the number of edges connected to it. The degree distribution is the distribution of node degrees across the network. It assesses whether the model captures the observed heterogeneity in the number of networks nodes have. A good fit indicates that the model reproduces the observed variability in node degrees.

[18] We can only track the IP address of investors at the continent level.

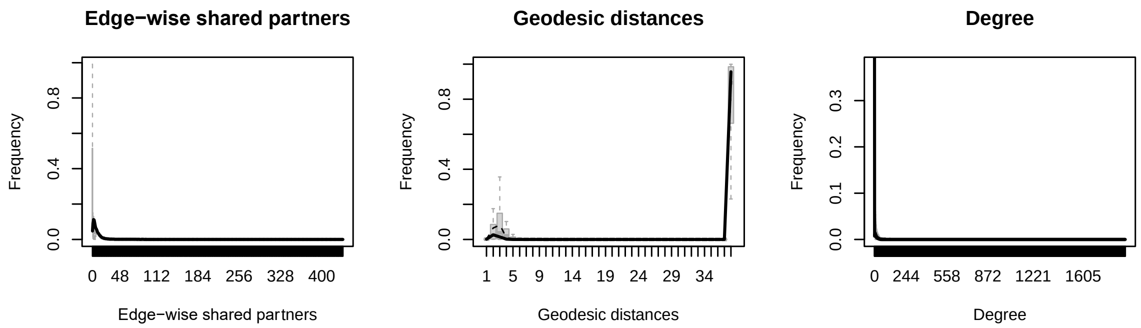
Appendix 4. Goodness-of-fit

We assess the validity of our models using a goodness-of-fit approach, as outlined by Leifeld, Cranmer, & Desmarais (2018). For every time step, we generate 50 networks using the estimated model parameters found in Table 3, sub-test (7), and juxtapose these with the observed networks. As illustrated below, our models exhibit strong congruence in terms of edge-wise shared partners, geodesic distances, and degree distributions. Consequently, we can affirm the reliability and validity of our estimates with confidence.

Panel A. Goodness-of-fit for Link Sent



Panel B. Goodness-of-fit for Link Received



Appendix 5. Link Requests with Centrality by Month

Drawing from our baseline model presented in Table 3, we account for social profile, centrality and network topology with results detailed in Panels A through F with TERGM. The control variables remain consistent with those in Table 3. Our findings demonstrate consistent robustness, even when factoring in potential biases stemming from centrality and network topology. *, **, *** means coefficients are in 90%, 95%, 99% confidence interval without zero inside respectively. (Bootstrapping sample size: 1000)

Panel C: Control with Centrality (Sent)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary variables	Better return	0.455***		0.668***	0.668***	0.664***	0.668***	0.664***
	Worse return		0.325***	0.584***	0.584***	0.574***	0.582***	0.572***
	Return				0.000	-0.006	0.000	-0.006
	Max daily return					0.033**		0.033**
	Min daily return					0.002		0.002
	Max transaction return						0.000	0.000
	Min transaction return						0.000	0.000
Centrality	In degree	-0.264***	-0.251***	-0.266***	-0.266***	-0.265***	-0.266***	-0.265***
	Out degree	0.449***	0.439***	0.446***	0.446***	0.446***	0.446***	0.445***
Control Factors		Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel D: Control with Centrality (Received)		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Primary variables	Better return	0.160***		0.258***	0.258***	0.259***	0.257***	0.259***
	Worse return		0.162***	0.266***	0.266***	0.267***	0.266***	0.267***
	Return				0.000	0.002	0.000	0.002
	Max daily return					-0.013		-0.013
	Min daily return					-0.005		-0.005
	Max transaction return						0.000	0.000
	Min transaction return						0.000	0.000
Centrality	In degree	0.889***	0.891***	0.885***	0.885***	0.885***	0.885***	0.885***
	Out degree	-0.628***	-0.629***	-0.627***	-0.627***	-0.627***	-0.626***	-0.627***
Control Factors		Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 6. Link Requests Identification settings

We undertake a sensitivity analysis by altering the definitions of 'Better' and 'Worse' returns and by adjusting the time intervals for networks with TERGM. In Table 3, 'Better' and 'Worse' returns are gauged by their relative performance compared to the preceding term. Now, only when a return surpasses its predecessor by 5%, 10%, or 20% does it qualify as a 'Better' return, and the opposite holds for 'Worse' returns. These outcomes are illustrated in Panels A2, A3, A4, and Panels B2, B3, B4 of Table 5. Additionally, we furnish estimates on both weekly and quarterly bases (refer to Panels A5, A6, and Panels B5, B6). For reference, Panels A1 and B1 depict the original monthly coefficients from Table 3. The control variables remain consistent with those in Table 3. Our estimations continue to be consistent and significant, reinforcing the robustness of our findings during the sensitivity analysis. *, **, *** means coefficients are in 90%, 95%, 99% confidence interval without zero inside respectively. (Bootstrapping sample size: 1000)

Panel A: Link Sent				(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A1	Monthly	0%	Better return	0.725***		1.062***	1.062***	1.059***	1.067***	1.064***
			Worse return		0.800***	1.133***	1.133***	1.130***	1.133***	1.130***
Panel A2		5%	Better return	0.751***		0.963***	0.963***	0.959***	0.964***	0.959***
			Worse return		0.834***	1.041***	1.040***	1.035***	1.036***	1.031***
Panel A3		10%	Better return	0.705***		0.855***	0.855***	0.848***	0.856***	0.848***
			Worse return		0.755***	0.905***	0.904***	0.896***	0.899***	0.891***
Panel A4		20%	Better return	0.685***		0.795***	0.795***	0.786***	0.796***	0.786***
			Worse return		0.748***	0.855***	0.855***	0.843***	0.848***	0.837***
Panel A5	Weekly	0%	Better return	0.748***		0.924***	0.924***	0.923***	0.937***	0.935***
			Worse return		0.810***	0.986***	0.986***	0.983***	0.992***	0.99***
Panel A6	Quarterly	0%	Better return	0.733**		1.627**	1.628**	1.621**	1.628**	1.622**
			Worse return		0.862**	1.693***	1.69***	1.686***	1.685***	1.681***
	Other		Return				Yes	Yes	Yes	Yes
			Max daily return					Yes		Yes
			Min daily return					Yes		Yes
			Max transaction return						Yes	Yes
			Min transaction return						Yes	Yes
Control Factors				Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Link Received				(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B1	Monthly	0%	Better return	0.463***		0.634***	0.634***	0.634***	0.634***	0.634***
			Worse return		0.312***	0.532***	0.532***	0.533***	0.534***	0.535***
Panel B2		5%	Better return	0.448***		0.536***	0.536***	0.536***	0.535***	0.536***
			Worse return		0.266***	0.396***	0.396***	0.397***	0.399***	0.400***
Panel B3		10%	Better return	0.454***		0.524***	0.524***	0.525***	0.523***	0.524***
			Worse return		0.291***	0.394***	0.394***	0.395***	0.397***	0.398***
Panel B4		20%	Better return	0.454***		0.504***	0.504***	0.504***	0.503***	0.504***
			Worse return		0.284***	0.360***	0.360***	0.361***	0.364***	0.365***
Panel B5	Weekly	0%	Better return	0.340***		0.418***	0.418***	0.418***	0.418***	0.418***
			Worse return		0.291***	0.382***	0.382***	0.383***	0.383***	0.383***
Panel B6	Quarterly	0%	Better return	0.697**		1.255**	1.255**	1.257**	1.254**	1.256**
			Worse return		0.463**	1.069***	1.069***	1.065***	1.071***	1.067***
	Other		Return				Yes	Yes	Yes	Yes
			Max daily return					Yes		Yes
			Min daily return					Yes		Yes
			Max transaction return						Yes	Yes
			Min transaction return						Yes	Yes
Control factors				Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 7. The Impact of Established Social Networks on Investor Performance and Behaviors with Centrality by Month

Similar to Sections 5.2.2, we control both in degree and out degree centrality of investors in networks, marked as C_in and C_out below. Also, we include the number of link requests received. Our results remain robust against these extra controls. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Performance (t+1)				Panel B: Trading frequency (t+1)				Panel C: Asset selection (t+1)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$B_{t-1}\times Ls_t$	0.004* (0.002)				-0.013*** (0.004)				-0.035* (0.019)			
$W_{t-1}\times Ls_t$		-0.001 (0.001)				-0.004 (0.003)				-0.013 (0.013)		
$B_{t-1}\times La_t$			0.017* (0.009)				-0.052*** (0.013)				-0.188*** (0.063)	
$W_{t-1}\times La_t$				-0.004 (0.004)				-0.025** (0.013)				-0.055 (0.043)
C_in	4.588 (6.228)	6.224 (6.273)	4.722 (6.225)	6.218 (6.273)	-15.468* (8.170)	-21.609*** (8.341)	-15.863* (8.160)	-21.648*** (8.334)	10.489 (47.600)	-14.168 (48.138)	8.893 (47.399)	-14.259 (48.107)
C_out	-4.401 (5.497)	-6.305 (5.541)	-4.485 (5.495)	-6.308 (5.543)	13.295** (6.512)	18.149*** (6.594)	13.544** (6.509)	18.125*** (6.586)	15.034 (37.825)	31.476 (38.802)	16.029 (37.718)	31.437 (38.776)
B_{t-1}	Yes		Yes		Yes		Yes		Yes		Yes	
W_{t-1}		Yes		Yes		Yes		Yes		Yes		Yes
Ls_t	Yes	Yes			Yes	Yes			Yes	Yes		
La_t			Yes	Yes			Yes	Yes			Yes	Yes
Received	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pending	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Declined	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Canceled	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Leverage	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Balance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Net deposit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Communication	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mobility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874	59,874
R^2	0.046	0.045	0.046	0.045	0.150	0.137	0.150	0.137	0.369	0.409	0.370	0.409

Appendix 8. The Impact of Established Social Networks on Investor Performance and Behaviors by Week and Quarter

Similar to Sections 5.2.3, we change the time interval from month to week (Panel A) and quarter (Panel B). The control variables remain consistent with those in Table 8. Week/Quarter fix effect and individual fix effect are also applied. Changing the time interval does not alter our results. Standard errors in parentheses are clustered at individual level and ***, **, and * denote significance at p < 0.01, p < 0.05, and p < 0.1, respectively.

	Panel A: Performance (t+1)				Panel B: Trading frequency (t+1)				Panel C: Asset selection (t+1)			
Panel A: Week	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$B_{t-1}\times Ls_t$	0.002**				-0.011***				-0.013			
	(0.001)				(0.004)				(0.019)			
$W_{t-1}\times Ls_t$		-0.001				-0.012***				0.008		
		(0.001)				(0.003)				(0.020)		
$B_{t-1}\times La_t$			0.010**				-0.058***				-0.085	
			(0.005)				(0.012)				(0.074)	
$W_{t-1}\times La_t$				-0.005				-0.061***				-0.006
				(0.006)				(0.015)				(0.076)
B_{t-1}	Yes		Yes		Yes		Yes		Yes		Yes	
W_{t-1}		Yes		Yes		Yes		Yes		Yes		Yes
Ls_t	Yes	Yes			Yes	Yes			Yes	Yes		
La_t			Yes	Yes			Yes	Yes			Yes	Yes
N	250,062	250,062	250,062	250,062	250,062	250,062	250,062	250,062	250,062	250,062	250,062	250,062
R^2	0.002	0.002	0.002	0.002	0.133	0.127	0.133	0.127	0.292	0.311	0.292	0.311
Panel B: Quarter	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$B_{t-1}\times Ls_t$	0.003***				-0.006				-0.024			
	(0.001)				(0.005)				(0.019)			
$W_{t-1}\times Ls_t$		-0.001				-0.001				-0.026*		
		(0.001)				(0.005)				(0.015)		
$B_{t-1}\times La_t$			0.012***				-0.024				-0.107**	
			(0.004)				(0.015)				(0.052)	
$W_{t-1}\times La_t$				-0.003				-0.003				-0.097**
				(0.002)				(0.012)				(0.043)
B_{t-1}	Yes		Yes		Yes		Yes		Yes		Yes	
W_{t-1}		Yes		Yes		Yes		Yes		Yes		Yes
Ls_t	Yes	Yes			Yes	Yes			Yes	Yes		
La_t			Yes	Yes			Yes	Yes			Yes	Yes
N	21,132	21,132	21,132	21,132	21,132	21,132	21,132	21,132	21,132	21,132	21,132	21,132
R^2	0.251	0.237	0.251	0.237	0.331	0.306	0.331	0.306	0.415	0.486	0.415	0.486
Control factors, Week/Quarter FE., Individual FE. for all models in Panel A and B.									Yes			