Journal of Business Research 97 (2019) 184–197

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Determinants of leadership in online social trading: A signaling theory perspective

Endrit Kromidha[a,*], Matthew C. Li[b]

[a] University of Birmingham, Birmingham Business School, Birmingham B15 2TT, UK
[b] Royal Holloway University of London, School of Management, Egham TW20 0EX, UK

ARTICLE INFO

Keywords:
Social trading
Networks
Leadership
Signaling theory
Investing
Digital platforms

ABSTRACT

Online social trading offers an opportunity for less-experienced individuals or firms to follow top traders by mimicking their behavior, but little is known about the determinants of leadership that shape such relationships. To study this, we build on signaling theory using fixed-effect panel least squares estimations to analyze 250 top traders in a network of around 1100 traders; we examine their trader credentials, volume of trades, performance, and risk signals. Contrary to our initial expectations, findings show that trader credentials are more important than performance, volume, or risk signals, but there are significant differences between virtual and real money traders. This study proposes a network signaling theory approach by linking it to herd behavior and the disposition effect. Our findings can have practical implications not only for top traders, followers, and social trading platform managers but also for policy-makers and regulators of such investment instruments.

1. Introduction

Much innovation has occurred in investment trading platforms during the last decades as a result of better technologies and smarter information systems. Starting with portfolio optimization in the 1950s, the rise of high-frequency trading in the 2000s, and more recently algorithm developments, trading now requires a new financial regulatory framework for the Digital Age (Kirilenko & Lo, 2013). Collaborative consumption has recently emerged as a peer-to-peer activity of exchanging goods and services through online community platforms fueled by sustainability, the enjoyment of shared activities and economic gains (Hamari, Sjöklint, & Ukkonen, 2016). Online social trading is a form of collaborative consumption facilitated by a platform and community where traders can automatically and simultaneously copy the decisions of traders they trust (Wohlgemuth, Berger, & Wenzel, 2016). This comes as an alternative to traditional settings. Research shows that individual traders acting alone perform poorly compared to securities firms and banks (Kamesaka, Nofsinger, & Kawakita, 2003), but online social trading allows inexperienced investors to improve their returns by imitating the investment decisions of those they perceive as more experienced (Pentland, 2013). A key assumption is that top traders lead by making their investment decisions available to those following them (Oehler, Horn, & Wendt, 2016). Imitation, in this case, is a risk-mitigation strategy for inexperienced social traders (Berger, Wenzel, & Wohlgemuth, 2018). We have a clear perspective on how traders use signals to establish trust, but we need to focus more on determinants of signaling leadership in the network that could condition how those less experienced decide to follow or leave a top trader.

A recent review of leadership theories identifies ten emerging approaches, and two are directly related to this study: leadership in teams and decision groups, and leader and follower cognitions (Meuser et al., 2016). The first theme related to team decision-making in organizations seems to capture more attention in management studies (Cullen-Lester & Yammarino, 2016). A review of collectivistic leadership approaches introduces the 'we' in a broader sense by highlighting five key areas: team, network, shared, complexity, and collective leadership (Yammarino, Salas, Serban, Shirreffs, & Shuffler, 2012). Relational leadership theory expands the idea of leadership beyond organizational boundaries, presented as an embedded approach to common relationally-responsive dialogue and practices of leaders being morally accountable to others they connect with (Cunliffe & Eriksen, 2011). Tests with agent-based simulations point at collective intelligence as an important feature of collective decision-making and leadership (McHugh et al., 2016). These studies discuss the concept of collective leadership in the context of informal team relationships and social capital, but online social trading is less social and more individualistic, rational and calculative in nature. Therefore, in this study, we prefer to use the term network leadership to highlight the more detached and

* Corresponding author.
E-mail addresses: E.Kromidha@bham.ac.uk (E. Kromidha), Matthew.Li@rhul.ac.uk (M.C. Li).

https://doi.org/10.1016/j.jbusres.2019.01.004
Received 31 March 2018; Received in revised form 4 January 2019; Accepted 5 January 2019

transactional nature of relationships in peer-to-peer environments such as online social trading platforms.

In our analysis of online social trading, we use signaling theory (Connelly, Certo, Ireland, & Reutzel, 2011) to have a better understanding of network leadership considering the importance of shared and perceived information in collective leadership mentioned earlier. Signaling theory has traditionally been used to explain information asymmetry effects on investment decision-making and relationships, so it can be related to online social trading. What is different in our context is the fact that both top traders and followers are similar in nature and disclose the same information on the platform. In doing so, each party can generate gains. In our case of Ayondo.com, for example, actual payment rewards are granted by the platform for being a top trader based on the number of followers. On the other hand, improved monetary investment returns are available for real money followers when copying a highly competent top trader. Hence, signals transmitted by top traders play an essential role in this environment. What differentiates top traders from followers according to the definition in the Ayondo platform is how they use their profiles and trading information, with top traders using it as signals to attract followers (Ayondo, 2018b). In addition, there is almost no transaction cost in terms of money and time for switching between top traders, becoming one, or changing between virtual or real money trading. This makes the network very dynamic and different from previous applications of signaling theory. Further, it allows us to study determinants of leadership through daily high-frequency data by capturing changes in the number of followers joining or leaving for each top trader.

Current research on social trading signals is related to trust (Carlos Roca, José García, & José de la Vega, 2009; Wohlgemuth et al., 2016). Wohlgemuth et al. (2016) argue that trust established between top traders and their followers is the result of two key groups of signals: affect-based signals and cognition-based signals. In their qualitative study, affect-based signals entail traders' personal information and trading history, whereas cognition-based signals are conditioned by the number of profitable trades, investment returns, maximum drawdown, and the risk level. Conversely, Lee and Ma (2015) in a quantitative study propose three measures when deciding whom to follow in social trading services: performance, risk, and consistency. The qualitative approach adapted by Wohlgemuth et al. (2016) tends to focus more on the relational aspect of social trading, while the quantitative approach adapted by Lee and Ma (2015) tries to make an assessment of the more formal and measurable social trading characteristics. We converge these views by proposing a conceptual framework to study network leadership consisting of four key determinants of online social trading along the affect-based and cognition-based continuum of signals: trader credentials, volume, performance, and risk. The signals for each determinant are investigated quantitatively through four hypotheses discussed in the next section.

Our methodological and empirical framework for studying network leadership in online social trading offers a balanced quantitative approach to analyze trader credentials, the volume of trades, performance, and risk, and it could be relevant for both research and practice. We also aim to contribute by controlling for differences between real and virtual traders and accounting for joiners and leavers. This should also inform policy-makers working on regulatory practices and the intermediary role of online trading platforms for protecting inexperienced traders. Overall, this study aims to make a theoretical, methodological and empirical contribution by exploring the research question: **What determinants affect leadership in online social trading**?

This paper is structured as follows. In the next section, we introduce signaling theory that aims to describe behavior when two parties have access to different information (Connelly et al., 2011), such as top traders and trading followers. This is followed by the methodology, where we explain the application of fixed-effect panel least squares estimations for our models. We use high-frequency data extracted daily from Ayondo.com, an online social trading platform that allows traders to follow each other and facilities mimicking trading behavior. Finally, we present a discussion of our findings, conclusions, and directions for future research.

2. Signaling theory and network leadership

The core idea of signaling theory is that signalers are insiders who have access to information and knowledge not available to receivers who are outsiders (Connelly et al., 2011). Signaling theory has traditionally been used to explain how new ventures seeking external finance and having more information about their business try to communicate this and connect with external funders seeking profitable investment opportunities (Connelly et al., 2011). In investment and finance, signaling theory is used for understanding the valuation of new firms seeking external financing in the case of initial public offering (Michaely & Shaw, 1994) or venture capital investments (Busenitz, Fiet, & Moesel, 2001; Busenitz, Fiet, & Moesel, 2005). The link between signaling theory and investment markets suggests that participation and convertibility features of stock can reduce information asymmetry between the venture and potential investors (Arcot, 2014; Elitzur & Gavious, 2003). In the online social trading platform Ayondo, top traders are defined as those who publish trading signals, and followers as those who follow trading signals of top traders (Ayondo, 2018b). This implies that the signaling and decision-making processes between top traders and their followers participating in a network of peers are similar to those in investment markets. Therefore, signaling theory could be used to explain how trust in leadership competence is established.

Signaling theory accepts a changing environment between members and the signals they share in a network over time. For example, new venture teams aim to project signals of value, commitment, and competence to their potential investors in the early funding stages, but this does not seem to have any significant relationship with long-term outcomes (Busenitz et al., 2005). Association signals are also necessary in the context of networks and stakeholders when setting premiums and initial public offering targets (Reuer, Tong, & Wu, 2012). In industrial networks, new entrants should consider the trade-off between conformity and innovation due to institutional forces or limited shared resources and market opportunities (Boone, Wezel, & van Witteloostuijn, 2013). Empirical findings from a study of 251 small firms, on the other hand, highlight the need to consider a network approach in understanding the mechanisms of performance enhancement and entrepreneurial orientation (Jiang, Liu, Fey, & Jiang, 2018). However, in the case of online social trading, participants can perfectly mimic each other's' behavior without any detriment to outcomes. On the contrary, larger networks can help top traders profit more as a reward/commission. This also suggests that leadership in online social trading networks is dynamic, as the position and relationships between traders can change often.

Signals, especially for investments, can be categorized as rational, focused on the performance indicators of the ventures, and relational, focused on personal characteristics and connections (Moss, Neubaum, & Meyskens, 2015). Comparative research in this direction is limited, but for example, in equity crowdfunding networks, retaining equity and information about risk signals can increase the probability of funding success, while social capital and intellectual capital have little or no impact (Ahlers, Cumming, Günther, & Schweizer, 2015). Reward-based crowdfunding research, on the other hand, reveals a different picture about social capital signals whereby e-words of mouth, introductory text, videos and "Like" counts (Bi, Liu, & Usman, 2017) as well as social media shares, social network size, comments updates (Kromidha & Robson, 2016) seem to be positively related to successful funding. In the context of online social trading, prospect theory, which shares some similarities with signaling theory, has been used to explain that people can be more risk-seeking toward losses and more risk-averse toward gains, but at the same time, they are more sensitive to losses than gains (Liu, Nacher, Ochiai, Martino, & Altshuler, 2014). However, separating the human from the irrational is not an easy task, especially in networks, so signaling theory would require a refined approach in the context of online social trading.

Even though leadership is considered a mature field of study (Hunt & Dodge, 2000), its intersections with the business networks and investment literature remain limited. Network leadership is another aspect, besides network effects, that signaling theory has not addressed sufficiently, but it is essential to understanding how top traders emerge and why others decide to follow or leave them. On an organizational level, research on small business leaders shows how their inspirational personality signals can help them lead more competitively and enable an innovative environment around them (Dunne, Aaron, McDowell, Urban, & Geho, 2016). On an inter-organizational level, research on venture capital alliance networks shows how new firms assuming leadership roles and managing their position between networks can send important strategic signals (Ozmel, Reuer, & Gulati, 2013). A social network analysis of leadership in virtual collaboration settings such as social software systems, chat-rooms or virtual worlds suggests that the most effective emergent leaders are those who assume a mediating, rather than directing or monitoring roles in virtual network interactions (Sutanto, Tan, Battistini, & Phang, 2011). In our study, top traders mediate market and network forces to make decisions that are signaled back, influencing relationships and their own leadership position over time.

Transactional digital platforms present excellent opportunities to study and advance network leadership theory in inter-organizational settings. In online social trading platforms like Ayondo in this study traders create opportunities by collaborating. Followers can follow up to five top traders and benefit from their experience to exploit new investment opportunities (Ayondo, 2018a). Top traders benefit by either a long-term, performance-based remuneration model or by a short-term, volume-based remuneration model, depending on the profit they help followers generate (Ayondo, 2018c). A theory aiming to explain this environment should be able to give insights on information flows, communication signals, and perceptions that influence network leadership and trading behavior for investment opportunities. Building on these premises, we argue that signaling theory can be applied to gain a better understanding of leadership in online social trading networks.

3. Derivation of hypotheses

3.1. Trader credentials (TRDC)

First, we start with a general overview of top traders' credentials. Research shows that some common characteristics for top traders are their drive, leadership motivation, honesty, integrity, self-confidence, cognitive ability, and knowledge of the business, but the evidence for traits such as charisma, creativity, and flexibility is not that clear (Kirkpatick & Locke, 1991). Beyond personality (De Vries, 1977), research on investors and leadership traits reveals mixed findings when looking at their personality, demographics, environmental fit, and cognitive framing (Vecchio, 2003). Therefore, it is difficult to generalize based on these findings.

Traders do not seem to have a defined personality profile, and research suggests that anyone could perform trading tasks well after proper training (Lo, Repin, & Steenbarger, 2005). However, research acknowledges the importance of aggressiveness, survival drive, and overconfidence to generate higher profits through first-mover advantage (Benos, 1998). A study of a large pool of Finnish traders confirms that investors who are overconfident and more prone to sensation-seeking trade more frequently (Grinblatt & Keloharju, 2009). High-IQ Finnish investors, on the other hand, are more rational but also more aggressive about tax-loss trading, displaying superior market timing, stock-picking, and trade execution skills (Grinblatt, Keloharju, & Linnainmaa, 2012). Personal characteristics seem to play an important role in investment trading, leading to different approaches.

A fundamental problem related to traders' personalities and credentials is the disposition effect, described as a type of irrational behavior whereby investors sell securities that have increased in price and keep assets that have dropped in value instead (Weber & Camerer, 1998). In the group environment of an online trading platform, the situation is even more complex, and the disposition effect can multiply as members are more exposed to each other. Heimer (2016) confirms that traders' connectivity to a network and its social effect nearly doubles their disposition effect. Access to the network can offer more opportunities for connections, allowing members to influence but also be influenced to become a top trader or a follower.

Another problem can be herd behavior (Shang, Chen, & Chen, 2013), described as the tendency of people to mimic and follow the rational or irrational behavior of groups, even in transparent and order-driven trading markets. Identifying the role top traders play in this environment is not easy due to the complexity and inconclusive results of previous studies on individual traits. In addition, research on trading dealers shows that those that are relatively central in a network are characterized by relatively lower and less dispersed spreads compared to peripheral dealers (Hollifield, Neklyudov, & Spatt, 2017), indicating a preference for a risk-averse and reliable behavior. Nevertheless, previous research acknowledges the importance of individual credentials in general, and we intend to investigate them by looking at the independent variables of Career, Membership, Experience, and Popularity defined in Table 1 to analyze the following hypothesis.

Table 1
Description of variables used in regressions.

Group	Variable	Description
	Followers	Number of followers on the day
TRDC	*Career*	Institutional or Professional = 1, otherwise = 0
	Membership	Membership in months
	Experience	Number of years in trading
	Popular	Popularity among followers yes = 1, otherwise = 0
VOLUME	*Trades_Month*	Number of trades per month
	Number_of_Trades	Amount of trades placed since the trader's registration
PERFORMANCE	*Winning_Trades*	Percentage of all trades that were closed with in profit
	Winning_Months	Distribution of months since registration in which the trader generated profit
	Performance_CurrentMonth	Profit/Loss (P/L) of the current month
	Performance_CurrentYear	P/L of the current year
	Performance_Past	Composite index based on trader's P/L: since start, 1 year, 6 months, 3 months
RISK	*Risk_Trader*	Composite index based on trader's risk profile that includes information of: MAR ratio, maximum draw down, Shape ratio, value at risk, volatility, risk score
	Risk_German30	Composite index based on German DAX 30 that includes information of: MAR ratio, maximum draw down, Shape ratio, value at risk, volatility
	Risk_US500	Composite index based on US S&P 500 that includes information of: MAR ratio, maximum draw down, Shape ratio, value at risk, volatility

Hypothesis 1. H1: Leadership in an online trading network is positively related to individual credential signals of top traders.

3.2. Volume

The volume of trades is expected to send important signals in financial markets. A theory of trading volume suggests that market agents frequently revise their position in the market, and abnormal trading volumes do not necessarily imply disagreement but can be related to divergent prior expectations, causing markets not to clear immediately (Karpoff, 1986). Also indirectly, online search data on trading intensity could be used to reliably predict abnormal stock returns and trading volumes (Joseph, Babajide Wintoki, & Zhang, 2011). This shows the dual effect of herd behavior (Shang et al., 2013) on trading volume, both in terms of positioning of traders close to each other and group acceptance of market information.

Research shows that information linkages and signals among traders are positively related to their trading volume (Colla & Mele, 2009). In the stock market, price signals lead option volumes, but for certain types of options, volume signals can also lead stock price changes (Easley, O'Hara, & Srinivas, 1998). In these markets, higher trading volume is often related to overconfidence, resulting in more volatile and risky behavior but also higher profits than rational trading due to an unconscious “first-mover advantage” (Benos, 1998). Volume seems related to knowledge and information signals, but also a degree of irrational behavior related to the disposition effect and the herding effect with both institutional investors (Nofsinger & Sias, 1999) and information-based trading (Zhou & Lai, 2009). In online social trading, volume is co-created by the interaction of followers with top traders, their decisions and incentives to benefit from having many followers or following prominent top traders.

Signaling theory would suggest that the volume of trades sends positive signals about the investment opportunities and the trader's commitment to trading. The herding effect in the network could multiply such signals, and we would assume that a consistent, frequent trader of relatively large volumes could attract a larger number of followers. To examine the impact of volume on trader positioning, we look at Trades Month and Number of Trades defined in Table 1 to investigate the following hypothesis:

Hypothesis 2. H2: Leadership in an online trading network is positively related to the volume of trade signals of top traders.

3.3. Performance

Performance has many definitions in finance and management literature (Admati & Ross, 1985), but in this study, we focus on accounting profit and loss and the extent of wining trades to capture followers' response to top traders' performance. Research has shown that as a result of the disposition effect, investors are reluctant to realize losses quickly, often selling winning investments that continue to outperform the losers they keep in hope of their recovery (Garvey & Murphy, 2004; Odean, 1998; Shefrin & Statman, 1985). Hartzmark (2014) also highlights the rank effect in investment performance by citing the situation when entire portfolios are examined; traders are shown to prefer to sell extreme winning or extreme losing positions and maintain what appears to be more stable. Taken together, this means that performance signals should be interpreted in the context of both external signals and traders' investment strategies.

It appears that trading in online networks outperforms individual trading due to the social influence and wisdom of crowds, although top traders' reputation and trustworthiness are not entirely determined by their performance (Pan, Altshuler, & Pentland, 2012). This is further compounded by the irrationality of the disposition effect (Weber & Camerer, 1998) and its multiplication by herd behavior (Shang et al., 2013), which will affect followers' ability to perceive and interpret top traders' signals. Notwithstanding these probable complications, since we are looking at information from an online investment trading network, we logically assume that trading performance is a significant factor that draws the attention of followers whose main objective is to obtain high investment returns. To maintain a clear and direct focus on the correlation between leadership and performance, a positive relationship is expected. To investigate more in this direction, we look at Winning Trades, Winning Months Performance Current Month, Performance Current Year, and Performance Past defined in Table 1 to explore the following hypothesis:

Hypothesis 3. H3: Leadership in an online trading network is positively related to performance signals of top traders.

3.4. Risk

Trading and gambling seem to share structural characteristics related to sensation-seeking (Grall-Bronnec et al., 2017) and risk-taking propensity (Markiewicz & Weber, 2013). Also, in financial markets noise is often mistaken for information, resulting in incorrect decisions, uncertainty and, consequently, risk (Black, 1986; Trueman, 1988). Since not all demand changes are rational, “noise traders” can still generate profits by following a more aggressive trend of chasing strategy regardless of higher risks (Shleifer & Summers, 1990). In social trading, top traders' performance is not always a good indicator of their competence, especially in times of risk and uncertainty (Pan et al., 2012). However, traders can learn to understand and translate useful signals or noise better over time (Banerjee & Green, 2015) to manage risk.

Online social trading networks and platforms can help individuals that manage their money online make better financial decisions by providing more peer or aggregated crowd information for better risk management (Zhao, Fu, Zhang, Zhao, & Duh, 2015). The disposition effect, i.e., the tendency of traders to forgo loss realization in favor of gain realization, seems to be lower in an online social trading environment due to higher transparency and the sense of being observed (Lukas, Eshraghi, & Danbolt, 2017). Traders' disposition effect seems to be affected by the attention they receive from their followers who believe in the traders' strategy (Glaser & Risius, 2016). This shows that traders influence each other's perception of risk in the network, something that could help us understand followers' perception of top traders and the associated risk in an online social trading platform.

Consistency in providing information in a virtual investment community is considered useful to make less risky and more profitable decisions, but not satisfactory due to members' herding tendency (Shang et al., 2013). Although sentiment plays an important role among followers initially, research shows that larger investors do not rely on social interaction as much as small investors do when making decisions (Ammann & Schaub, 2016). Despite growing literature on financial interconnections, our knowledge of how the network structure is related to risk remains limited (Cohen-Cole, Kirilenko, & Patacchini, 2014). Assuming a risk-averse preference for our sample traders, we aim to establish whether and how risk serves as a determinant of a top trader in the trading platform. In this study, we intend to contribute in this direction using three composite risk index variables: Risk Trader, Risk German30, and Risk US500 (defined in Table 1), to explore the following hypothesis:

Hypothesis 4. H4: Leadership in an online trading network is negatively related to risk signals of top traders.

3.5. Virtual versus real money traders

Online social trading platforms offer the opportunity to use virtual money. Such digital currency that has no real value, but can be used for practicing purse, allows traders to familiarize themselves with the digital platform, the online social trading environment, gain experience and learn without the risk of making any loss before investing real money. This can have serious implications similar to digitally-facilitated gambling where playing for fun as skill-building and even socializing activity can lead to gambling for money (Kristiansen, 2016). There is no research on the behavior of virtual and real money traders, so this study intends to contribute in this direction.

Introducing new technologies and innovations does not always have a positive effect on trading. For example, research on 1607 investors who switched from phone-based to online trading in the 1990s shows that the change caused them to trade more actively, more speculatively, and less profitably due to overconfidence, self-attribution bias, and the illusion of knowledge and control (Barber & Odean, 2002). In this study, we control for virtual versus real money trading to have a better understanding of the signals transmitted by these two groups and examine their impacts on network leadership.

4. Research design

4.1. Data source, sample composition, and descriptive statistics

All data are collected from an online social trading platform, Ayondo.com, which allows global traders to trade in the German and US securities markets. Other well-known platforms are eToro and Zulutrade. We chose Ayondo because it provides detailed information about the traders, uses a transparent and user-friendly interface for displaying this information, and has a clear focus on two of the largest securities markets, which would help us attain consistent results.

The traders' profiles are available and open to the general public. Additionally, we secured the platform's approval to use this information for this study. The data was collected using web scraping, referring to the automatic software-assisted extraction of information from a website instead of copying it manually (Vargiu & Urru, 2012). The number of traders on the platform varied each day, but it was around 1100 on average at the time of this study. We extracted detailed information from the top 250 traders using 30 variables to address our research question. High-frequency daily observations were made for 35 consecutive days: 2 March 2017 to 5 April 2017, representative of a period of normal trading activity when we had daily access to the publicly available data. For the sample period, we analyze 250 cross-sections and 8750 panel observations. Descriptive statistics of most of the variables used in the estimations are shown in Table 2. It can be seen that *Number_of_Trades* is the variable with the largest fluctuations in its values, whereas *Winning_Trades* and *Winning_Months* are close to each other. Out of the three risk indicators, *Risk_Trader* is the most volatile index also with the largest mean; in contrast, the other two indicators share similar distributions.

4.2. Composite index construction and classification of signal groups

We started our investigation with original data of 30 variables. To reduce the dimension of our study and minimize the problem of multicollinearity among some of the variables, through the use of composite indexes, the final set of independent variables used in our regressions is condensed to 15. Some of the original variables which share high levels of similar quality regarding measurement and attributes are used in the construction of composite indexes which suitably reflect their information content. The procedure we apply to this variable transformation involves: 1) running principal components analysis (PCA) on the relevant raw data; 2) collecting the loadings of the first principal component; 3) using the loadings to compute a composite index (Cox, 1972; Vyas & Kumaranayake, 2006). This process is used in the production of four new variables: *Performance_Past*, *Risk_Trader*, *Risk_ German30*, and *Risk_US500*. Further descriptions of the four variables are presented in Table 1.

It is reasonable to assume that when deciding to follow a particular trader, given the information available on the trading platform, a potential follower can assess the trader's competence through four key signal groups: TRADER CREDENTIALS (TRDC), VOLUME, PERFORMANCE, and RISK. Henceforth, the four signal groups will be presented in capital letters, with individual variables shown in italic. The TRDC group contains the four variables representing a trader's general background, which include intensity of trading knowledge, i.e., whether he/she is a popular professional or institutional trader or otherwise, membership duration, and experience of trading in months. In the VOLUME group, the amount and number of trades a trader executed are utilized, whereas, the PERFORMANCE group encompasses variables that highlight the profit and loss a trader achieved during a specific time horizon. Finally, the RISK profile of a trader is revealed through three risk indexes that are measured at the trader, German30, and US500 levels.

The four hypotheses introduced in the previous section are examined through four sets of independent variable groups: TRDC, VOLUME, PERFORMANCE, and RISK signals across the affect-based and cognition-based continuum dimensions (Lee & Ma, 2015; Wohlgemuth et al., 2016). Our dependent variable is LEADERSHIP, examined through the relationship between the independent variables and the number of followers, leavers, or joiners. We control for virtual versus real money traders to identify any differences between the two groups. Fig. 1 provides a graphical representation of our conceptual model, with further details explained in the following section.

4.3. Methodology

For the investigation of how our four signal groups play a role in a follower's decision in choosing a leader and to account for possible unobserved heterogeneity across traders, fixed effects panel least

Table 2
Descriptive statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
Followers	46.01	3.00	1422.00	1.00	160.90	8750
Membership	14.41	13.06	96.41	0.01	12.36	8750
Experience	2.62	4.00	5.00	0.00	2.30	8750
Trades_Month	51.16	27.53	513.13	0.50	70.13	8750
Number_of_Trades	631.93	282.00	11,853.00	1.00	1241.41	8750
Winning_Trades	0.72	0.72	1.00	0.00	0.20	8750
Winning_Months	0.61	0.62	1.00	0.00	0.24	8750
Performance_Past	0.16	0.08	1.98	−0.36	0.33	8750
Performance_CurrentYear	0.10	0.04	1.83	−0.36	0.25	8750
Perofrmance_CurrentMonth	0.00	0.00	0.38	−0.35	0.05	8750
Risk_Trader	0.70	0.67	1.51	0.14	0.32	8750
Risk_German30	0.05	0.04	0.11	0.00	0.03	8750
Risk_US500	0.04	0.03	0.08	−0.01	0.02	8750

Sample period: 3/02/2017 to 4/05/2017. Variables that carry binary numbers are not reported.

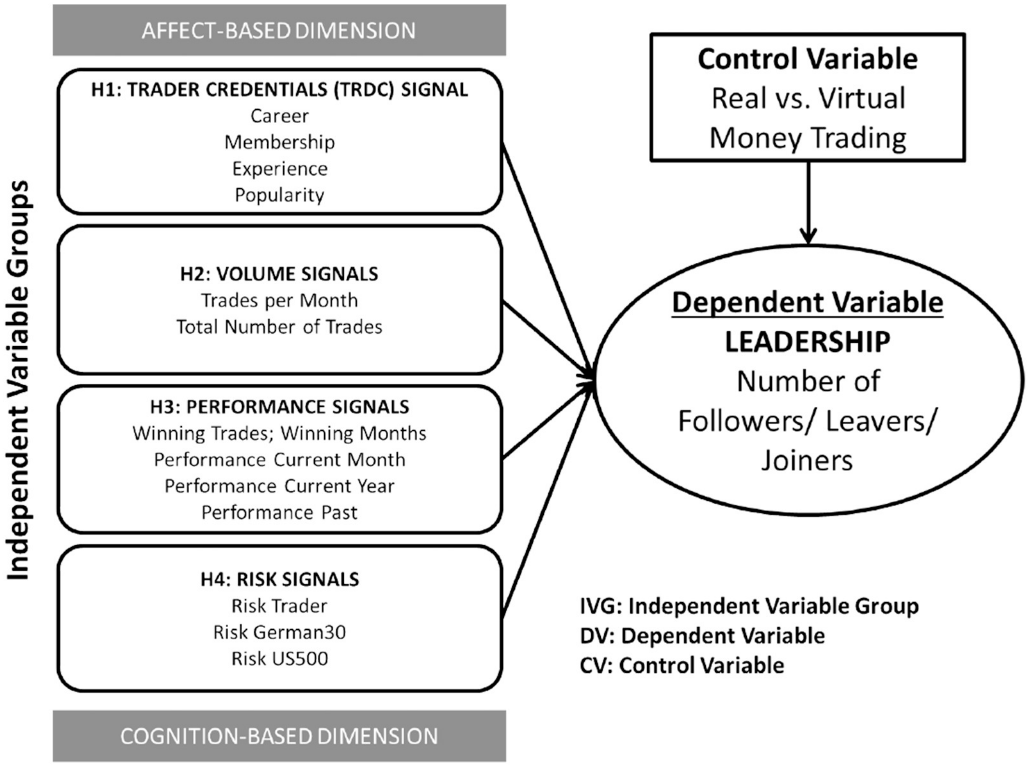

Fig. 1. A signaling theory model of network leadership determinants in online social trading.

squares estimations (Bartels, 2008) are applied to five models. To control for the possible influence of time trends on the hypothesized causal relationships, period/day fixed effects are also used in the regressions.

Baseline model

$$\begin{aligned} Followers_{i,t} = {} & \alpha_0 + \alpha_1 Career_{i,t} + \alpha_2 Membership_{i,t} + \alpha_3 Experience_{i,t} + \alpha_4 Popular_{i,t} \\ & + \alpha_5 Trades\_Month_{i,t} + \alpha_6 Number\_of\_Trades_{i,t} \\ & + \alpha_7 Winning\_Trades_{i,t} + \alpha_8 Winning\_Months_{i,t} \\ & + \alpha_9 Performance\_CurrentMonth_{i,t} \\ & + \alpha_{10} Performance\_CurrentYear_{i,t} + \alpha_{11} Performance\_Past_{i,t} \\ & + \alpha_{12} Risk\_Trader_{i,t} + \alpha_{13} Risk\_German30_{i,t} \alpha_{14} Risk\_US500_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Eq. (1) shows the hypothesized relationship at the club level for the top 250 traders, with i indexing the 250 traders, and t indexing the 35 days under investigation. The dependent variable *Followers* is the total number of followers of trader i on day t. The 13 independent variables represent the four signal groups with their corresponding coefficients and hypotheses (TRDC: α_1 to α_4 (H1), VOLUME: α_5 to α_6 (H2), PERFORMANCE: α_7 to α_{11} (H3), and RISK: α_{12} to α_{14} (H4)), and $\varepsilon_{i,t}$ is the idiosyncratic error term. We predict that coefficients α_1 to α_{11} will be positive. That is, in general, followers react positively to a trader with well-established personal credentials who regularly trades with good results. However, according to the risk-averse preference assumption, negative coefficients (α_{12} to α_{14}) on RISK are anticipated.

The baseline model studies the reactions of all followers to our four signal groups. However, the involvement of these followers in this trading club varies according to whether they are virtual traders or real traders. Virtual traders operate with a fictitious account with no real money changes hand, while transactions of real traders entail the inflow and outflow of money. Because of this vital distinction, we are interested in discovering whether it impacts on our baseline model differently. We partition the overall sample according to the two trader categories and re-estimate Eq. (1).

4.3.1. Modeling for leavers and joiners

The independent variable *Followers* in Eq. (1) is measured at levels and gives a general picture of the relationship between club followers and the four signal groups in a static setting. To add dynamics to our investigation, we extend our study by examining the movements of these followers over time through the use of Eqs. (2) and (3). We first capture followers' movements by computing the change in followers from day t to day t-1 ($Followers_t - Followers_{t-1}$). Then, when the change is a negative number, i.e., the total number of a trader's followers has decreased, we consider it as a case of *Leavers*. Alternatively, a positive change serves as an observation of *Joiners*. We ignore those with zeros since they provide no additional information to our investigation. Upon collection of the required observations, we utilize the following two equations to explore their statistical relationship with the independent variables.

$$\begin{aligned} Leavers = {} & \beta_0 + \beta_1 Number\_of\_PreviousLeavers_{i,t} + \beta_2 Popular_{i,t} + \beta_3 Trades\_Month_{i,t} \\ & + \beta_4 Number\_of\_Trades_{i,t} + \beta_5 Winning\_Trades_{i,t} \\ & + \beta_6 Winning\_Months_{i,t} \\ & + \beta_7 Performance\_CurrentMonth_{i,t} \\ & + \beta_8 Performance\_CurrentYear_{i,t} + \beta_9 Performance\_Past_{i,t} \\ & + \beta_{10} Risk\_Trader_{i,t} + \beta_{11} Risk\_German30_{i,t} + \beta_{12} Risk\_US500_{i,t} + \mu_{i,t} \end{aligned} \tag{2}$$

$$\begin{aligned} Joiners = {} & \chi_0 + \chi_1 Number\_of\_PreviousJoiners_{i,t} + \chi_2 Popular_{i,t} + \chi_3 Trades\_Month_{i,t} \\ & + \chi_4 Number\_of\_Trades_{i,t} + \chi_5 Winning\_Trades_{i,t} \\ & + \chi_6 Winning\_Months_{i,t} \\ & + \chi_7 Performance\_CurrentMonth_{i,t} \\ & + \chi_8 Performance\_CurrentYear_{i,t} + \chi_9 Performance\_Past_{i,t} \\ & + \chi_{10} Risk\_Trader_{i,t} + \chi_{11} Risk\_German30_{i,t} + \chi_{12} Risk\_US500_{i,t} + \delta_{i,t} \end{aligned} \tag{3}$$

Eqs. (2) and (3) share many independent variables in their estimations. Moreover, while preserving the VOLUME, PERFORMANCE, and RISK groups, the variables employed are similar to those of Eq. (1) with two modifications. First, we include a lag dependent variable, *Number_of_PreviousLeaver/Joiners*. Its inclusion explores whether current followers are affected by the number of previous followers' movements. That is to test the existence of herd behavior (Banerjee, 1992) among our samples, a human attribute which can be described as the tendency of traders to mimic the actions of others. Second, we only retain one variable (*Popular*) from the TRDC group, because a trader's popularity can change daily, but it is unlikely that considerable changes in the other three variables (*Career*, *Membership*, *Experience*) materialize over a short horizon. We predict that both VOLUME and PERFORMANCE will have a positive impact on followers to stay with a trader, i.e., followers will join a trader who has high trading volume and good investment performance, while the opposite holds for followers who decide to leave a trader. Again, due to the risk-averse preference assumption among followers, their relationship with RISK remains negative.

5. Empirical results

5.1. Baseline model results

Overall in this paper, we evaluate our empirical results through two approaches. First, we study the statistical significance of the independent variables both individually and according to their groupings. Second, we investigate the importance of individual variable groups through group-stepwise regressions by excluding a group from the regression and examining changes in the sum squared residuals (ΔSSR), which functions as an indicator of its contribution to the model. We expect that a relatively small change in *SSR* implies the absence of this group will not alter our estimation substantially, and vice versa.

Table 3 presents our regression results of the baseline model – Eq. (1) – for all 250 traders by using *Followers* as the dependent variable. The majority of the estimated statistically significant coefficients have the expected positive sign, especially the TRDC and VOLUME groups. According to Column (1), in the TRDC group, three (*Career*, *Experience*, *Popular*) out of four variables proved to be statistically significant, whereas only one in the VOLUME group variable, *Trades_Month*, is significant. The PERFORMANCE group results show that *Performance_CurrentYear* and *Performance_Past* are the two variables that contain explanatory power for the number of followers. The RISK group results offer us an interesting picture of how followers react to risk. Our findings show that while followers respond negatively to risk as measured by *Risk_Trader* and *Risk_US500*, i.e., they dislike a high-risk trader under these two classes, the opposite occurs for *Risk_German30*. In terms of our hypothesis testing, these results generally suggest that we cannot reject all four hypotheses.

Columns (2) to (5) of Table 3 present our group-stepwise regression results. These findings are comparable to those of Column (1). The majority of statistically significant coefficients maintain their influences on our model with minor changes. Indeed, looking at the estimated coefficients ΔSSR and Adjusted R^2, with an increase in estimation error of 219.24%, we see that followers consider TRDC the most important signal when choosing a leader, and this signal is followed by PERFORMANCE, VOLUME, and RISK. Overall, we cannot reject the statistical relationships implied in our four hypotheses.

5.2. Virtual versus real money traders

To produce a full picture of how followers' trading status affects the

Table 3
Regression results of Eq. (1) - All traders. Dependent variable: Followers.

	(1)	(2)	(3)	(4)	(5)
	All	W/o TRDC	W/o VOLUME	W/o PERFORMANCE	W/o RISK
Intercept	14.995	−5.016	8.267	10.846	−14.516
	(1.165)	(−0.152)	(0.584)	(1.042)	(−1.294)
Career	**21.135*****		**20.223*****	**27.937*****	**29.217*****
	(2.857)		−2.842	−3.646	(3.976)
Membership	0.042		−0.335	0.089	**0.367****
	(0.154)		(−0.685)	−0.328	(2.006)
Experience	**3.638****		**3.565****	**4.099*****	**4.145*****
	(2.480)		−2.355	−2.922	(2.796)
Popular	**709.180*****		**706.222*****	**719.323*****	**704.951*****
	(5.588)		(5.495)	(5.666)	(5.522)
Trades_Month	**0.308*****	0.157		**0.332*****	**0.256****
	(2.708)	(1.108)		(2.650)	(2.262)
Number_of_Trades	−0.012	**0.029*****		−0.011	−0.010
	(−1.249)	(2.900)		(−1.157)	(−1.056)
Winning_Trades	−14.183	−25.707	5.522		−10.980
	(−0.847)	(−0.636)	(0.310)		(−0.658)
Winning_Months	5.134	**60.504*****	1.243		9.561
	(0.642)	−3.388	(0.147)		(1.144)
Performance_CurrentMonth	42.325	−56.370	71.737		50.889
	(0.994)	(−0.784)	(1.541)		(1.212)
Performance_CurrentYear	**−137.399*****	**−374.459*****	**−131.576*****		**−137.777*****
	(−3.103)	(−5.118)	(−2.873)		(−3.120)
Performance_Past	**122.481*****	**288.616*****	**127.294*****		**115.897*****
	(4.699)	(4.824)	(4.412)		(4.584)
Risk_Trader	**−31.653*****	**−34.492***	**−20.107***	**−33.084*****	
	(−3.174)	(−1.925)	(−1.875)	(−3.235)	
Risk_German30	**599.359****	**1283.815***	**417.739***	152.739	
	(2.110)	(1.908)	(1.667)	(0.516)	
Risk_US500	**−775.370***	1474.094	−492.967	−144.171	
	(−1.938)	(−1.638)	(−1.353)	(−0.333)	
Adj. R^2	0.741	0.175	0.734	0.733	0.738
ΔSSR (%)	n/a	+219.24%	+2.82%	+3.16%	+1.38%
N	8750	8750	8750	8750	8750

t-Statistics are in parentheses. Significant statistics are in bold.
***, ** and * denote significance levels of 1%, 5% and 10% respectively.

Table 4
Regression results of Eq. (1) - Virtual vs Real traders.

	Virtual traders with dependent variable: *Followers*					Real traders with dependent variable: *Followers*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All	W/o TRDC	W/o VOLUME	W/o PERFORMANCE	W/o RISK	All	W/o TRDC	W/o VOLUME	W/o PERFORMANCE	W/o RISK
Intercept	2.668	**4.692***	2.826	**15.693*****	**−12.756*****	25.447	−15.764	6.978	4.391	−8.317
	(1.314)	(1.855)	(1.383)	(4.562)	(−3.739)	(0.860)	(−0.271)	(0.204)	(0.220)	(−0.345)
Career	**14.625****		**14.766****	**26.135*****	**15.958****	**26.354****		**23.904***	**34.057****	**29.458*****
	(2.409)		(2.490)	(3.153)	(2.492)	(1.900)		(1.655)	(2.432)	(2.694)
Membership	0.101		0.093	0.011	**0.166*****	1.518		**2.138****	**2.218****	0.426
	(0.755)		(0.633)	(0.074)	(2.730)	(1.501)		(2.316)	(2.298)	(0.955)
Experience	**1.049****		**1.019****	**1.606*****	**1.244*****	**5.305***		5.238	**5.999***	**5.851***
	(2.554)		(2.499)	(3.520)	(3.396)	(1.659)		(1.540)	(1.836)	(1.811)
Popular	**365.362*****		**359.699*****	**358.384*****	**344.411*****	**681.701*****		**700.984*****	**726.914*****	**673.923*****
	(33.493)		(33.396)	(26.404)	(24.934)	(5.734)		(5.641)	(5.838)	(5.600)
Trades_Month	−0.001	**−0.335*****		0.014	**−0.053*****	**0.151****	0.056		**0.264*****	0.108
	(−0.051)	(−6.117)		(0.666)	(−4.311)	(2.042)	(0.304)		(2.611)	(1.426)
Number_of_Trades	−0.001	**0.032*****		0.000	**0.003*****	**0.018****	**0.043***		0.016	**0.019****
	(−0.344)	(6.399)		(0.252)	(3.248)	(1.966)	(1.655)		(1.540)	(2.122)
Winning_Trades	**12.285*****	**20.881*****	**11.993*****		**11.905*****	−28.995	−30.414	0.713		−25.535
	(3.924)	(5.362)	(3.357)		(3.336)	(−0.837)	(−0.401)	−0.021		(−0.817)
Winning_Months	2.974	**11.183*****	3.062		**5.647****	−20.384	−12.046	−33.724		−11.071
	(1.203)	−3.55	(1.229)		(1.975)	(−1.015)	(−0.443)	(−1.613)		(−0.598)
Performance_CurrentMonth	13.836	21.892	13.377		17.111	−71.822	**−469.339****	−18.819		−47.08
	(0.982)	(1.530)	(0.889)		(1.179)	(−0.683)	(−1.921)	(−0.181)		(−0.469)
Performance_CurrentYear	**−108.510*****	**−132.835*****	**−109.137*****		**−110.603*****	−44.068	−292.561	−100.461		−47.736
	(−3.956)	(−4.325)	(−4.014)		(−3.803)	(−0.430)	(−1.651)	(−1.048)		(−0.481)
Performance_Past	**81.047*****	**86.374*****	**80.826*****		**78.171*****	**296.648*****	**889.604*****	**353.320*****		**296.246*****
	(4.826)	(4.572)	(4.865)		(4.691)	(5.393)	(4.465)	(5.038)		(6.335)
Risk_Trader	**−17.130*****	**−14.714*****	**−17.267*****	**−20.808*****		−20.140	11.969	−2.258	**−31.258***	
	(−3.813)	(−2.547)	(−4.209)	(−3.547)		(−1.051)	(0.438)	(−0.105)	(−1.744)	
Risk_German30	**490.100*****	83.053	**487.553*****	205.918		138.782	**3602.567****	126.811	**−1196.236****	
	(2.835)	(0.547)	(3.049)	(1.308)		(0.267)	(2.473)	(0.239)	(−2.225)	
Risk_US500	**−730.029*****	**−363.021****	**−726.363*****	**−275.093****		−927.550	**−4282.985****	−847.841	727.786	
	(−4.222)	(−2.104)	(−4.475)	(−2.201)		(−1.116)	(−2.032)	(−0.981)	(0.892)	
Adj. R^2	0.692	0.575	0.692	0.635	0.678	0.784	0.319	0.769	0.766	0.783
ΔSSR (%)	n/a	+38.25%	+0.03%	+18.65%	+4.63%	n/a	+215.84%	+7.06%	+8.58%	+0.89%
N	4443	4443	4443	4443	4443	4307	4307	4307	4307	4307

t-Statistics are in parentheses. Significant statistics are in bold. ***, ** and * denote significance levels of 1%, 5% and 10% respectively.

Table 5
Regression results of Eq. (2) and Eq. (3).

	Dependent variable: *Leavers*						Dependent variable: *Joiners*					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	W/o previous leavers	W/o popular	W/o VOLUME	W/o PERFORMANCE	W/o RISK	All	W/o previous joiners	W/o popular	W/o VOLUME	W/o PERFORMANCE	W/O RISK
Intercept	−1.228	−1.516	−0.172	−1.213	**−1.707*****	−0.989	**1.013***	**1.558*****	−0.019	0.329	**1.079*****	**0.751***
	(−0.905)	(−1.139)	(−0.129)	(−0.890)	(−3.138)	(−1.148)	(1.891)	(2.776)	(−0.032)	(0.463)	(3.114)	(1.662)
Number_of_PreviousLeavers	**0.139*****		**0.183*****	**0.139*****	**0.142*****	**0.138*****	**0.339*****		**0.406*****	**0.355*****	**0.346*****	**0.336*****
	(4.035)		(5.323)	(4.068)	(5.047)	(3.996)	(9.920)		(9.680)	(9.777)	(9.089)	(9.643)
Popular	**−4.199*****	**−5.162*****		**−4.168*****	**−4.728*****	**−4.109*****	**1.934*****	**3.542*****		**2.042*****	**1.854****	**1.821*****
	(−4.080)	(−3.585)		(−4.287)	(−4.615)	(−3.943)	(2.639)	(2.830)		(2.680)	(2.480)	(2.691)
Trades_Month	0.000	0.001	−0.002		0.001	−0.001	**0.009*****	**0.011*****	**0.008*****		**0.010*****	**0.010*****
	(−0.055)	(0.175)	(−0.557)		(0.204)	(−0.270)	(3.061)	(2.853)	(2.686)		(3.205)	(3.433)
Number_of_Trades	0.000	0.000	0.000		0.000	0.000	**−0.0002***	**−0.0003***	0.000		**−0.0002****	**−0.0003****
	(0.116)	(0.054)	(−0.443)		(0.040)	(0.344)	(−1.709)	(−1.948)	(−0.845)		(−2.042)	(−2.511)
Winning_Trades	1.518	1.004	1.427	1.504		1.279	−0.514	−0.953	0.006	0.035		−0.485
	(1.007)	(0.746)	(1.029)	−1.042		(0.961)	(−0.697)	(−0.976)	(0.008)	−0.047		(−0.617)
Winning_Months	**−2.621*****	**−1.798*****	**−3.377*****	**−2.635*****		**−2.327*****	0.357	1.198	0.734	0.200		0.972
	(−2.847)	(−2.589)	(−2.972)	(−2.906)		(−2.781)	(0.593)	(1.501)	(1.109)	−0.356		(1.498)
Performance_CurrentMonth	**12.569***	**10.479****	**18.611****	**12.617***		**13.118***	**4.697****	4.930	**4.268***	**7.308****		2.668
	(1.877)	(1.970)	(2.188)	(1.951)		(1.858)	(1.963)	(1.623)	(1.819)	(2.504)		(1.379)
Performance_CurrentYear	2.608	1.808	4.107	2.564		2.141	**2.851****	2.179	**3.017****	**2.260***		**2.538***
	(0.754)	(0.494)	(1.239)	(0.723)		(0.593)	(2.097)	(1.094)	(1.968)	(1.747)		(1.830)
Performance_Past	−2.018	−1.872	−3.126	−1.990		−2.060	−0.932	−0.526	−1.106	−0.193		**−1.086***
	(−0.981)	(−0.928)	(−1.609)	(−0.980)		(−1.020)	(−1.337)	(−0.538)	(−1.507)	(−0.312)		(−1.661)
Risk_Trader	−0.407	−0.331	−0.778	−0.416	−0.392		**−0.663***	−0.515	−0.300	−0.312	−0.475	
	(−0.614)	(−0.460)	(−1.013)	(−0.595)	(−0.558)		(−1.899)	(−1.031)	(−0.895)	(−0.744)	(−1.446)	
Risk_German30	−1.363	23.500	**−56.029****	0.103	**43.752***		**−32.516***	−20.958	−23.727	**−63.025*****	−17.521	
	(−0.055)	(0.844)	(−2.095)	(0.004)	(1.905)		(−1.917)	(−0.971)	(−1.286)	(−3.309)	(−1.139)	
Risk_US500	14.485	−26.250	**83.503***	12.749	**−62.054***		**59.096****	32.905	**51.647***	**112.481*****	29.646	
	(0.334)	(−0.621)	(1.781)	(0.302)	(1.676)		(2.034)	(0.901)	(1.693)	(2.968)	(1.174)	
Adj. R^2	0.132	0.120	0.095	0.135	0.128	0.135	0.347	0.253	0.316	0.328	0.338	0.342
ΔSSR (%)	n/a	+8.30%	+4.40%	0.00%	+1.25%	+0.11%	n/a	+34.60%	+4.60%	+3.18%	+2.00%	+1.18%
N	842	842	842	842	842	842	915	915	915	915	915	915

t-Statistics are in parentheses. Significant statistics are in bold. ***, ** and * denote significance levels of 1%, 5% and 10% respectively.

Table 6
Summary of hypothesis testing outcome.

Hypothesis	Type of traders				
	All	Virtual	Real	Leavers	Joiners
H1	Cannot reject	Cannot reject	Cannot reject	Cannot reject	Cannot reject
H2	Cannot reject	Reject	Cannot reject	Reject	Cannot reject
H3	Cannot reject	Cannot reject	Cannot reject	Cannot reject	Cannot reject
H4	Cannot reject	Cannot reject	Reject	Reject	Cannot reject

various degrees of reaction to these signals, we divide our full sample into two subsamples, real and virtual traders, and regress our baseline model of Eq. (1) accordingly.

5.2.1. Virtual traders

Table 4, Columns 1 to 5 exhibit our findings; we notice that the pattern of statistically significant coefficient appearance is similar to Table 3. Column (1) displays the estimation results when all virtual traders are included in the regression. The three variables (*Career*, *Experience*, *Popular*) in the TRDC group continue to play a significant role in our model, however, VOLUME shows no explanatory power for *Followers*. In the PERFORMANCE group, in addition to *Performance_CurrentYear*, *Performance_Past*, *Winning_Trades* is another statistically significant factor in our model. All risk-related variables are shown to be significant, and although *Risk_German30* maintains its unexpected positive relationship with traders, its function as a set of essential signals cannot be disregarded. These findings support the rejection of H2, while we cannot reject H1, H3, and H4.

We re-estimate our baseline model following the procedure of variable exclusion. The results of this process are presented in Columns (2) to (5) of Table 4. We observe that the stability of those statistically significant coefficients is maintained with no change in predicted signs and limited variations in their magnitude. From ΔSSR, we observe that although the rate of change in the estimation residuals decreased to +38.25% from +219.24% in Table 3, TRDC remains our most important signal, followed by PERFORMANCE, RISK, and VOLUME. Both ΔSSR (+0.03%) and *Adj.* R^2 (0.692) in Column (3) tell us that removal of the VOLUME group has little impact on our baseline model.

5.2.2. Real traders

Table 4, Columns 6 to 10 show the estimation results when only real traders are included in the sample. For the TRDC group, three variables (*Career*, *Experience*, *Popular*) are statistically significant with the predicted positive sign. However, compared to the virtual trader regression, in Column 6, two VOLUME variables (*Trades_Month*, *Number_of_Trades*), previously shown to provide no explanatory power to *Followers*, become statistically significant. In the PERFORMANCE group, only *Performance_Past* serves as a useful signal to followers, whereas, the statistical significance of all estimated coefficients of the RISK group is absent. Synthesizing the overall findings of this type of traders, we cannot reject H1, H2, and H3, but have to reject H4. Hence, compared to virtual traders, a slightly different set of results is generated.

Regarding the group-stepwise regression results, it is apparent that the TRDC group leads in its position as the key signal with the highest ΔSSR of +215.84%. Following that, from Columns (8) to (10), we can see that the other signal groups can be placed in the order of PERFORMANCE, VOLUME, and RISK.

5.3. Leavers versus joiners

The estimation of our basic baseline model offers a general picture of how followers assess the four groups of trader dispositions in identifying top traders. To add robustness to our model and discussion, we further estimate the changes in the number of followers by categorizing them as either *Leavers* or *Joiners*. Panel least squares multiple regression is first applied to Eqs. (2) and (3), then followed by group-stepwise regressions, and their results are shown in Table 5.

5.3.1. Leavers

Table 5, Columns 1 to 6, display the estimation outcomes of Eq. (2) when *Leavers* serves as the dependent variable. Column (1) shows that *Leavers* is statistically and positively affected by *Number_of_PreviousLeavers*, and negatively by *Popular*. Within the PERFORMANCE group, the estimated coefficients of both *Winning_Months* and *Performance_CurrentMonth* are statistically significant. However, the negative estimated coefficient of *Winning_Months* is consistent with our expectation, i.e., followers leave because the trader has fewer winning months. Again, it is not surprising to see followers leaving a trader who has fallen in popularity. These estimation results, which are the weakest hypothesis testing findings we have obtained thus far, suggest that we cannot reject H1 and H3. Nonetheless, we do not have enough evidence to support the cases of H2 and H4.

Group-stepwise regression results are presented in Columns (2) to (6) of Table 5. Most of the statistically significant coefficients in Column (1) preserve their status except for the case of RISK. This group shows an erratic occurrence and explanatory power toward *Leavers*. Upon inspection of ΔSSR of these five columns, it is clear that the most important signal used by a follower in becoming a leaver is *Number_of_PreviousLeavers*, which is then followed by the other GROUPS/variable in the order of *Popular*, PERFORMANCE, RISK, and finally, VOLUME.

5.3.2. Joiners

Regression results for our *Joiners* sample are shown in Table 5, Columns 7 to 12. Figures in Column (7) highlight the statistical

Table 7
Ranking of independent variable or group significance.

Estimation model	GROUP/*variable* ranking				
	1	2	3	4	5
Eq. (1) - All traders. Dependent variable: *Followers*	TRDC	PERFORMANCE	VOLUME	RISK	
Eq. (1) - Virtual traders. Dependent variable: *Followers*	TRDC	PERFORMANCE	RISK	VOLUME	
Eq. (1) - Real traders. Dependent variable: *Followers*	TRDC	PERFORMANCE	VOLUME	RISK	
Eq. (2). Dependent variable: *Leavers*	*Number_of_PreviousLeavers*	*Popular*	PERFORMANCE	RISK	VOLUME
Eq. (3). Dependent variable: *Joiners*	*Number_of_PreviousJoiners*	*Popular*	VOLUME	PERFORMANCE	RISK

importance of signals/variables that followers take into consideration when joining a trader. They include *Number_of_PreviousJoiners*, *Popular*, *Trades_Month*, *Number_of_Trades*, *Performance_CurrentMonth*, *Performance_CurrentYear*, plus all three risk indicators. As expected, *Joiners* positively react to *Number_of_PreviousLeavers*, *Popular*, *Trades_Month*, and the two current performance variables. Nevertheless, our findings demonstrate that the dependent variable *Joiners* is statistically and negatively affected by RISK, except when *Risk_US500* increases, a greater number of followers will join the trader. Relatively speaking, the empirical results we collected for the *Joiners* estimation indicate that we cannot reject our four hypotheses H1, H2, H3, and H4.

The group-stepwise regression results are depicted in Columns (8) to (12). With the support of the ΔSSR statistics, we identify the order of significance of our independent variables/GROUPS as 1. *Number_of_PreviousJoiners*; 2. *Popular*; 3. VOLUME; 4. PERFORMANCE; 5. RISK.

Looking at the results of Table 5, the most striking finding comes from the VOLUME group of variables. While VOLUME serves no value as a signal of trader competence for followers to depart from a trader, when it comes to deciding whether a follower should become a joiner of a new trader, this group plays a role in the decision. The distinctive characteristics possessed by *Leavers* and *Joiners* are highlighted in our overall findings.

To present a succinct picture of our overall results, Table 6 displays a summary of our hypothesis testing outcomes, and Table 7 highlights the importance of trader credentials and the existence of herd behavior in our models.

6. Discussion and conclusions

Our analysis starts with a general understanding of collaborative leadership (Yammarino et al., 2012) and relational leadership (Cunliffe & Eriksen, 2011) to explain the network dynamics of online social trading. We adapt signaling theory (Connelly et al., 2011) traditionally used to explain the effects of information asymmetry between entrepreneurs and investors for interpreting the relationship between top traders and followers in this study. This builds on what we know about online social trading and trust (Carlos Roca et al., 2009; Wohlgemuth et al., 2016), imitation-related performance (Berger et al., 2018), and open signals by top traders to their followers (Oehler et al., 2016). Informed by the work of Wohlgemuth et al. (2016) and Lee and Ma (2015), we focus on trader credentials, trading volume, performance, and risk signals across the affect-based and cognition-based continuum. Advancing signaling theory in the direction of network leadership, we argue that trust established between top traders and their followers depends on these four determining signals, so we examined them in detail.

We started our investigation by exploring how followers choose a leader in online social trading. We expected that financial factors such as performance and risk signals would play a dominant role compared to personal credentials and volume signals. However, our findings failed to substantiate this assumption. In fact, our estimation results of failing to reject H1 and H3 in all different types of traders show that followed by performance, a trader's personal credentials serve as the most valuable signal about trader competence.

The volume of trades had a positive impact on followers as predicted, but only in relationship to trades per month and not regarding the overall volume of trades since registration. Our findings reconfirm the relationship between information signals among traders and their closely-monitored trading volume (Colla & Mele, 2009), This shows a rational side of the herd behavior (Shang et al., 2013) whereby trading volume signals serve as a controlling mechanism in the network.

Performance has the predicted positive impact on followers as indicated in Table 3; however, an unanticipated negative coefficient of current year performance (α_{11}) is observed. This relation implies that followers view a trader's good performance during the current year negatively. This contradicts our expectation and might suggest that followers are attracted by a trader's past performance but show concerns about a trader with good trading results during the current year. According to Hartzmark (1991) and Cornell (2009), investment performance is affected by a combination of luck and skill. While luck is serendipity, skill is relatively permanent. Agreeing with their remarks, we can interpret our empirical results as evidence to support the case that followers value a trader's skill through observations made of past performance while discounting current performance as an occurrence of luck which might not repeat. As Cornell (2009) succinctly puts it, "An investment manager who is skillful this year presumably will be skillful next year. An investment manager who was lucky this year is no more likely to be lucky next year than any other manager".

Our findings on risk show the importance of network affinity signals and leadership. We observe that frequently followers exhibit risk-averse behavior toward *Risk_Trader* and *Risk_US500* statistics but become more risk-loving when *Risk_German30* increases. While the risk-averse cases are expected, we suggest two probable explanations for our *Risk_German30* result. First, it could be because most of our traders hold investment portfolios linked to German financial instruments. As such, they react to German market risk in a positive and empathetic manner. Secondly, as elucidated in Keysar, Hayakawa, and An (2012), during the decision-making process, when choices are presented in a foreign tongue, the framing effect disappears and, as such, biases are also reduced. Based on their finding, we maintain that when our traders participate in securities investments outside their home country and a foreign language is involved, they are more risk-averse and cautious about their investments. Unlike when investing in German market portfolios, which entails a shorter geographic and emotional distance, a lesser degree of deliberate thinking is required, and hence, a more risk-loving attitude is exhibited. The association between the degree of risk-aversion and geographic/emotional distance is an interesting and relevant topic that deserves future research to explain the phenomenon.

All four signal groups of TRADERS CREDENTIALS, VOLUME, PERFORMANCE, and RISK exhibit explanatory power to the formation of network leadership in online social trading, but with varied degrees of significance. However, we detect two notable cases when comparing virtual and real money traders. First, for the virtual and real trader subsamples, a trader's personal credentials, which are represented by the TRDC group variables, have consistently shown to be the most valuable signal for followers to identify top traders. Second, whereas followers consider real traders' trading volume pattern as a more important factor than risk profile, the opposite applies to virtual traders. These observations inform us that in addition to testing the statistical importance of the hypothesized relationships, our empirical estimation approach quantifies the contribution of individual signals, and hence, a clear representation of how followers assess these signals is offered.

When followers observe an increase in the number of leavers in the previous period, the number of followers leaving a ranked trader increases during the current period. Another interesting aspect we observe is that joiners seem to care about a trader's trading volume, but it is not a factor leavers consider when quitting a trader. We can understand the herd behavior effect on our current followers when deciding to cease following a trader if others have left. Likewise, it is not surprising to see that a currently well-performing popular trader with an increasing number of followers is likely to attract new joiners.

Also, the direction of the relationship between *Followers* and RISK is negative if risk-averse preference is assumed. Our results indicate that both risk-averse and risk-loving attitudes are embedded within our samples. These findings better explain the apparent risk-averse behavior of those central to an investment network (Hollifield et al., 2017) as a result of differences and contradicting perceptions of signals being offset by each other. Both joiners and leavers exhibit a comparable high degree of herd behavior. That is, they mimic what other followers did in the previous period. This supports previous research which suggests that building a reputation for honesty is important (Hartman-Glaser, 2017), but irrational disposition effect (Weber & Camerer, 1998) and herd behavior (Shang et al., 2013) cannot be avoided as contradicting signals and forces coexist in a network. According to our study, this holds true for real and virtual traders alike.

We make a theoretical contribution by proposing a network leadership approach to understand the dynamics online social trading. Due to the more calculative, individualistic and profit-oriented nature of online social trading relationships, this is relatively different from current theoretical constructs on collaborative leadership (Yammarino et al., 2012) and relational leadership (Cunliffe & Eriksen, 2011). Our contribution is informed by signaling theory (Connelly et al., 2011) based on the analysis of followers joining or leaving top traders. Previous applications of signaling theory distinguish between two groups: signalers with inside information and outsiders (Connelly et al., 2011) or firms and potential investors in the case of initial public offerings (Michaely & Shaw, 1994) and venture capital (Busenitz et al., 2001; Busenitz et al., 2005). We utilize signaling theory in an environment meditated by a digital platform where all members have the same attributes as traders and investors but can take interchanging positions of becoming top traders or followers. This study expands the ideas of signaling theory in network leadership by evidencing its relationship to the herd behavior (Banerjee, 1992) and the disposition effect (Glaser & Risius, 2016; Heimer, 2016; Lukas et al., 2017). Our results suggest that for followers, placing trust in someone with a strong career and professional background in investment trading is the most pertinent factor. This finding highlights personal credentials as the key determinant of leadership in online social trading. Indeed, a trader's popularity offers followers further reassurance of their choice. This finding is consistent with existing research on networks of financial intermediaries and their role in reducing local bias for cross-border venture capital investments (Jääskeläinen & Maula, 2014). In addition, our study confirms the importance of traders' connectivity to each other. The relative irrelevance of risk signals in the network provides empirical evidence to justify the link between irrational disposition effect and herd behavior as a consequence of group relationships.

Network leadership as a signaling theory construct in our study is marked by top traders' central role in two moments: the joining of followers informed by their popularity and trading volume, and the leaving of followers informed by their popularity and performance. This finding expands the application of signaling theory by suggesting that social elements such as credentials and popularity are essential to establish a relationship, but these are constantly assessed and reassessed in network environments. Volume signals associated with "more" seem to be important to establish relationships, but performance signals associated with "better" seem important to maintain such relationships. This adds a longitudinal dimension to signaling theory related to information and knowledge sharing for adaptation, learning and group improvements in network environments.

Regarding methodology, we begin our investigation with a baseline model that targets the testing of our four hypotheses related to credentials, volume, performance, and risk. We then add a robust dimension to our examinations by further categorizing our sample into virtual versus real traders. Leavers versus joiners are then analyzed by applying fixed effects panel least squares estimations (Bartels, 2008) and composite indexes (Cox, 1972; Vyas & Kumaranayake, 2006). Besides producing a comprehensive study of the subject matter, the subsampling approach confirms the stability of the baseline model results. Considering the vast amount of information about online business, further research could benefit from similar high-frequency data analysis and studies. Our research perspective is consistent with signaling theory, we contribute positively to classify determinants of network leadership signals, and highlight the importance of herd behavior and disposition effect in this regard.

The key lessons for policy-makers from this study are related to the lower importance of risk and volume determinants of leadership in online social trading. Our study confirms what previous research has found about trading and gambling sharing structural characteristics related to sensation-seeking (Grall-Bronnec et al., 2017) and risk-taking propensity (Markiewicz & Weber, 2013). In the new and generally unregulated environment of digital platforms for investments, potentially speculative forms of network leadership for entrepreneurial activities deserve more attention.

For practitioners in online social trading, followers need to adapt a rational approach when deciding whom to follow. Top traders should be more aware of the personal credentials they need to project when seeking to build an extensive network of followers. Our findings confirm the presence of human irrationality in online social trading and what previous research suggests about people being more risk-seeking toward losses, more risk-averse toward gains, but also more sensitive to losses than to gains (Liu et al., 2014). Our robust model about leavers and joiners only captures the element of timing in making such strategic decisions. Learning and gaining experience over a longer period or the conversion process from virtual traders to real traders could also have significant implications on how certain traders emerge to become top traders.

7. Limitations and directions for future research

This study makes a significant contribution by introducing a network leadership approach to signaling theory, evidencing the link between leadership signals, herd behavior, and disposition effect in network environments. The importance of individual credentials, followed by performance and whether other traders join or leave, compared to more rational volume and risk determinants indicates the largely human and, in cases, irrational nature of investments markets. We propose a conceptual and empirical link between leadership, finance and digital platforms, but this is only a starting point to explain the complex network relationships formed as the three fields converge.

In the specific context of this study more research is needed to investigate the timely performance of top traders, joiners or leavers and members' ability to admit loses. This could be done by looking beyond trust (Wohlgemuth et al., 2016), automated performance imitation (Berger et al., 2018), and signals (Oehler et al., 2016) by taking a systems approach to look at innovative entrepreneurial responses and opportunities arising from better analytical skills and network leadership expertise. The key intermediary role of online trading and entrepreneurship platforms deserves more attention. With the existence of imperfect information, our results show that an individual's credentials play a major part in conveying information about his/her competence, which serves as a key element of trust. Such behavior, however, could create opportunities for speculation and exploitation that need to be observed and investigated more closely. Firms can certainly benefit from our results by focusing their efforts on the development of a robust firm-level competence profile that reflects its unique characteristics. Regulators, on the other hand, could reflect on these findings to have a better understanding of potential risks and vulnerabilities in new digital network trading environments.

References

Admati, A. R., & Ross, S. A. (1985). Measuring investment performance in a rational expectations equilibrium model. *Journal of Business, 58*(1), 1–26.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice, 39*(4), 955–980.
Ammann, M., & Schaub, N. (2016). *Social interaction and investing: Evidence from an online social trading network*. St. Gallen, Switzerland: Swiss Institute of Banking and Finance, University of St. Gallen.
Arcot, S. (2014). Participating convertible preferred stock in venture capital exits. *Journal of Business Venturing, 29*(1), 72–87.
Ayondo (2018a). Experience the new Ayondo. Retrieved from https://www.ayondo.com/en/new-ayondo.
Ayondo (2018b). Social trading - registration. Retrieved from https://www.ayondo.com/en/registration.
Ayondo (2018c). Top traders - how it works. Retrieved from https://www.ayondo.com/en/social/top-trader/how-it-works.
Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107*(3), 797–817.
Banerjee, S., & Green, B. (2015). Signal or noise? Uncertainty and learning about whether other traders are informed. *Journal of Financial Economics, 117*(2), 398–423.
Barber, B. M., & Odean, T. (2002). Online investors: Do the slow die first? *The Review of Financial Studies, 15*(2), 455–488.
Bartels, B. (2008). Beyond "fixed versus random effects": A framework for improving substantive and statistical analysis of panel, time-series cross-sectional, and multilevel data. *25th annual summer conference of the society for political methodology*. *43*.
Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets, 1*(3), 353–383.
Berger, E. S., Wenzel, M., & Wohlgemuth, V. (2018). Imitation-related performance outcomes in social trading: A configurational approach. *Journal of Business Research, 89*, 322–327.
Bi, S., Liu, Z., & Usman, K. (2017). The influence of online information on investing decisions of reward-based crowdfunding. *Journal of Business Research, 71*(2), 10–18.
Black, F. (1986). Noise. *The Journal of Finance, 41*(3), 528–543.
Boone, C., Wezel, F. C., & van Witteloostuijn, A. (2013). Joining the pack or going solo? A dynamic theory of new firm positioning. *Journal of Business Venturing, 28*(4), 511–527.
Busenitz, L., Fiet, J., & Moesel, D. (2001). Signaling theory and new venture evaluations. *Babson-Kaufman research conference*.
Busenitz, L. W., Fiet, J. O., & Moesel, D. D. (2005). Signaling in venture capitalist—New venture team funding decisions: Does it indicate long-term venture outcomes? *Entrepreneurship Theory and Practice, 29*(1), 1–12.
Carlos Roca, J., José García, J., & José de la Vega, J. (2009). The importance of perceived trust, security and privacy in online trading systems. *Information Management & Computer Security, 17*(2), 96–113.
Cohen-Cole, E., Kirilenko, A., & Patacchini, E. (2014). Trading networks and liquidity provision. *Journal of Financial Economics, 113*(2), 235–251.
Colla, P., & Mele, A. (2009). Information linkages and correlated trading. *The Review of Financial Studies, 23*(1), 203–246.
Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management, 37*(1), 39–67.
Cornell, B. (2009). Luck, skill and investment performance. *Journal of Portfolio Management, 35*(2), 131–134.
Cox, D. R. (1972). The analysis of multivariate binary data. *Applied Statistics, 21*(2), 113–120.
Cullen-Lester, K. L., & Yammarino, F. J. (2016). Collective and network approaches to leadership: Special issue introduction. *The Leadership Quarterly, 27*(Special Issue), 173–180.
Cunliffe, A. L., & Eriksen, M. (2011). Relational leadership. *Human Relations, 64*(11), 1425–1449.
De Vries, M. (1977). The entrepreneurial personality: A person at the crossroads. *Journal of Management Studies, 14*(1), 34–57.
Dunne, T. C., Aaron, J. R., McDowell, W. C., Urban, D. J., & Geho, P. R. (2016). The impact of leadership on small business innovativeness. *Journal of Business Research, 69*(11), 4876–4881.
Easley, D., O'hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance, 53*(2), 431–465.
Elitzur, R., & Gavious, A. (2003). Contracting, signaling, and moral hazard: A model of entrepreneurs, 'angels,' and venture capitalists. *Journal of Business Venturing, 18*(6), 709–725.
Garvey, R., & Murphy, A. (2004). Are professional traders too slow to realize their losses? *Financial Analysts Journal, 60*(4), 35–43.
Glaser, F., & Risius, M. (2016). Effects of transparency: Analyzing social biases on trader performance in social trading. *Journal of Information Technology,* 1–12. https://doi.org/10.1057/s41265-016-0028-0.
Grall-Bronnec, M., Sauvaget, A., Boutin, C., Bulteau, S., Jiménez-Murcia, S., Fernández-Aranda, F., ... Caillon, J. (2017). Excessive trading, a gambling disorder in its own right? A case study on a French disordered gamblers cohort. *Addictive Behaviors, 64*, 340–348.
Grinblatt, M., & Keloharju, M. (2009). Sensation seeking, overconfidence, and trading activity. *The Journal of Finance, 64*(2), 549–578.
Grinblatt, M., Keloharju, M., & Linnainmaa, J. T. (2012). IQ, trading behavior, and performance. *Journal of Financial Economics, 104*(2), 339–362.
Hamari, J., Sjöklint, M., & Ukkonen, A. (2016). The sharing economy: Why people participate in collaborative consumption. *Journal of the Association for Information Science and Technology, 67*(9), 2047–2059.
Hartman-Glaser, B. (2017). Reputation and signaling in asset sales. *Journal of Financial Economics, 125*(2), 245–265.
Hartzmark, M. L. (1991). Luck versus forecast ability: Determinants of trader performance in futures markets. *The Journal of Business, 64*(1), 49–74.
Hartzmark, S. M. (2014). The worst, the best, ignoring all the rest: The rank effect and trading behavior. *The Review of Financial Studies, 28*(4), 1024–1059.
Heimer, R. Z. (2016). Peer pressure: Social interaction and the disposition effect. *The Review of Financial Studies, 29*(11), 3177–3209.
Hollifield, B., Neklyudov, A., & Spatt, C. (2017). Bid-ask spreads, trading networks, and the pricing of securitizations. *The Review of Financial Studies, 30*(9), 3048–3085.
Hunt, J. G., & Dodge, G. E. (2000). Leadership déjà vu all over again. *The Leadership Quarterly, 11*(4), 435–458.
Jääskeläinen, M., & Maula, M. (2014). Do networks of financial intermediaries help reduce local bias? Evidence from cross-border venture capital exits. *Journal of Business Venturing, 29*(5), 704–721.
Jiang, X., Liu, H., Fey, C., & Jiang, F. (2018). Entrepreneurial orientation, network resource acquisition, and firm performance: A network approach. *Journal of Business Research, 87*(6), 46–57.
Joseph, K., Babajide Wintoki, M., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting, 27*(4), 1116–1127.
Kamesaka, A., Nofsinger, J. R., & Kawakita, H. (2003). Investment patterns and performance of investor groups in Japan. *Pacific-Basin Finance Journal, 11*(1), 1–22.
Karpoff, J. M. (1986). A theory of trading volume. *The Journal of Finance, 41*(5), 1069–1087.
Keysar, B., Hayakawa, S. L., & An, S. G. (2012). The foreign-language effect: Thinking in a foreign tongue reduces decision biases. *Psychological Science, 23*(6), 661–668.
Kirilenko, A. A., & Lo, A. W. (2013). Moore's law versus murphy's law: Algorithmic trading and its discontents. *The Journal of Economic Perspectives, 27*(2), 51–72.
Kirkpatick, S. A., & Locke, E. A. (1991). Leadership: Do traits matter? *The Executive, 5*(2), 48–60.
Kristiansen, S. (2016). From playing for fun to gambling for money: A qualitative longitudinal study of simulated digital gambling among danish adolescents. *16th international conference on gambling and risk-taking, June 6–10, 2016. Las Vegas, Nevada*.
Kromidha, E., & Robson, P. (2016). Social identity and signalling success factors in online crowdfunding. *Entrepreneurship and Regional Development, 28*(9–10), 605–629.
Lee, W., & Ma, Q. (2015). Whom to follow on social trading services? A system to support discovering expert traders. *Tenth International Conference on Digital Information Management (ICDIM)* (pp. 188–193). .
Liu, Y., Nacher, J. C., Ochiai, T., Martino, M., & Altshuler, Y. (2014). Prospect theory for online financial trading. *PLoS One, 9*(10), e109458.
Lo, A. W., Repin, D. V., & Steenbarger, B. N. (2005). Fear and greed in financial markets: A clinical study of day-traders. *American Economic Review, 95*(2), 352–359.
Lukas, M. F., Eshraghi, A., & Danbolt, J. (2017). The disposition effect in social trading: Influence of transparency on investment decisions. Available at SSRN https://ssrn.com/abstract=2975086.
Markiewicz, Ł., & Weber, E. U. (2013). DOSPERT's gambling risk-taking propensity scale predicts excessive stock trading. *Journal of Behavioral Finance, 14*(1), 65–78.
McHugh, K. A., Yammarino, F. J., Dionne, S. D., Serban, A., Sayama, H., & Chatterjee, S. (2016). Collective decision making, leadership, and collective intelligence: Tests with agent-based simulations and a field study. *The Leadership Quarterly, 27*(2), 218–241.
Meuser, J. D., Gardner, W. L., Dinh, J. E., Hu, J., Liden, R. C., & Lord, R. G. (2016). A network analysis of leadership theory: The infancy of integration. *Journal of Management, 42*(5), 1374–1403.
Michaely, R., & Shaw, W. H. (1994). The pricing of initial public offerings: Tests of adverse-selection and signaling theories. *Review of Financial Studies, 7*(2), 279–319.
Moss, T. W., Neubaum, D. O., & Meyskens, M. (2015). The effect of virtuous and entrepreneurial orientations on microfinance lending and repayment: A signaling theory perspective. *Entrepreneurship Theory and Practice, 39*(1), 27–52.
Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance, 54*(6), 2263–2295.
Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance, 53*(5), 1775–1798.
Oehler, A., Horn, M., & Wendt, S. (2016). Benefits from social trading? Empirical evidence for certificates on wikifolios. *International Review of Financial Analysis, 46*, 202–210.
Ozmel, U., Reuer, J. J., & Gulati, R. (2013). Signals across multiple networks: How venture capital and alliance networks affect interorganizational collaboration. *Academy of Management Journal, 56*(3), 852–866.
Pan, W., Altshuler, Y., & Pentland, A. (2012). Decoding social influence and the wisdom of the crowd in financial trading network. *Privacy, Security, Risk and Trust (PASSAT) international conference on social computing (SocialCom)* (pp. 203–209). .
Pentland, A. S. (2013). Beyond the echo chamber. *Harvard Business Review, 91*(11), 1–7.
Reuer, J. J., Tong, T. W., & Wu, C. (2012). A signaling theory of acquisition premiums: Evidence from IPO targets. *Academy of Management Journal, 55*(3), 667–683.
Shang, R., Chen, Y., & Chen, C. (2013). The social and objective value of information in virtual investment communities. *Online Information Review, 37*(4), 498–517.
Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance, 40*(3), 777–790.
Shleifer, A., & Summers, L. H. (1990). The noise trader approach to finance. *The Journal of Economic Perspectives, 4*(2), 19–33.
Sutanto, J., Tan, C. H., Battistini, B., & Phang, C. W. (2011). Emergent leadership in virtual collaboration settings: A social network analysis approach. *Long Range Planning, 44*(5-6), 421–439.

Trueman, B. (1988). A theory of noise trading in securities markets. *The Journal of Finance, 43*(1), 83–95.
Vargiu, E., & Urru, M. (2012). Exploiting web scraping in a collaborative filtering-based approach to web advertising. *Artificial Intelligence Research, 2*(1), 44–54.
Vecchio, R. P. (2003). Entrepreneurship and leadership: Common trends and common threads. *Human Resource Management Review, 13*(2), 303–327.
Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning, 21*(6), 459–468.
Weber, M., & Camerer, C. F. (1998). The disposition effect in securities trading: An experimental analysis. *Journal of Economic Behavior & Organization, 33*(2), 167–184.
Wohlgemuth, V., Berger, E. S. C., & Wenzel, M. (2016). More than just financial performance: Trusting investors in social trading. *Journal of Business Research, 69*(11), 4970–4974.
Yammarino, F. J., Salas, E., Serban, A., Shirreffs, K., & Shuffler, M. L. (2012). Collectivistic leadership approaches: Putting the "we" in leadership science and practice. *Industrial and Organizational Psychology, 5*(4), 382–402.
Zhao, J. C., Fu, W. T., Zhang, H., Zhao, S., & Duh, H. (2015, February). To risk or not to risk?: Improving financial risk taking of older adults by online social information. *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing* (pp. 95–104). ACM.
Zhou, R. T., & Lai, R. N. (2009). Herding and information based trading. *Journal of Empirical Finance, 16*(3), 388–393.

Endrit Kromidha is a Senior Lecturer in Entrepreneurship and Innovation at the University of Birmingham. His research looks at entrepreneurship financing, collaborative innovation, social entrepreneurship and public sector digital innovation systems. Endrit has published in a number of business, management, entrepreneurship and e-government journals and h is particularly interested on the use of digital platforms for entrepreneurship, access to finance and development.

Matthew C. Li is a Lecturer in Business Economics at Royal Holloway, University of London and a Fellow of the British Higher Education Academy. He received his PhD in Economics from Trinity College, University of Dublin and is currently the Director of the Accounting, Finance and Economics Undergraduate Programme. Dr. Li has published on international financial market regulations, bond yields, and financial crisis analysis as well as property market movements. His expertise is on theoretical and quantitative empirical research involving time series or panel data in the areas of behavioral economics, behavioral finance, and property market volatility.