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Abstract

Social trading platforms are considered to be amongst the major innovations in online trading. The purpose of this article is to analyze the trading activity of traders on social trading networks by taking a behavioral approach. We investigate the factors that influence the irrational part of trading activity derived from the key characteristics of these platforms, i.e. those dealing with social interaction. Our investigation utilizes an extensive set of trading data from two major platforms in Germany to study the trading behavior. We apply a fixed effects two-stage least squares approach to quantify the relationship between trading activity and performance and define overconfidence as the part of trading activity that is irrationally motivated and results in negative returns. Our results provide evidence for the negative relationship between overconfidence and return on social trading platforms. The article finds that the number of followers and some platform-specific features significantly affect the trading behavior of the traders. We contribute to literature by exploring how the novel social interaction characteristics of online trading impact trading activity by giving rise to a new dimension of overconfidence. In addition, we evidence that the different frameworks of the platforms motivate heterogenous behavioral responses by the signalers. Finally, we refine existing studies by applying a distinct methodology for modeling overconfidence.

JEL classification: G14 · G20 · G41

Keywords: Social trading platforms, overconfidence, social interaction, individual trading behavior, behavioral finance

1 Introduction

Social trading is considered to be one of the major innovations in online trading. Since 2007 an increasing number of platforms offering social trading services has entered the market. These platforms incorporate social network characteristics in online trading. They distinguish themselves from classic trading by providing the possibility of so-called *mirror trading*, which allows users to copy and automatically execute investment strategies of other traders, referred to as *signalers, signal providers* or *trade leaders.* This feature adds a new perspective to the classic principal-agent relationship between investors (*followers*) and fund managers (signalers), as investors can follow their trade leaders and monitor the performances of these in real-time. Information transparency, reduced costs for users and the participation of professionals and media companies have led to an increased level of acceptance of social trading (Glaser and Risius, 2016; Dorfleitner et al., 2017). Social trading, hence, created a new type of market place that adds a new facet to trading by enabling social interaction between signalers and followers for example through

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the communication of trading strategies and the possibility of rating the signalers. This social dimension implies a novel set of determinants of trading behavior. In this paper we study whether trade leaders on two leading social trading platforms in Germany are affected by the social network aspects and exhibit a behavioral bias known as *overconfidence*. In particular, we investigate the irrational factors that influence trading activity derived from the social network characteristics of these platforms, i.e. the number of followers as well as the rating and compensation framework.

The contribution of this paper is twofold. First, we add to the existing literature by investigating the influence of social network features on the trading behavior of signal providers on social trading platforms. To the best of our knowledge, we are the first to explore how these novel social interaction characteristics of online trading impact trading activity by giving rise to a new dimension of overconfidence. Second, by assessing two heterogenous platforms we generate new insights into the influence of the platform design on individual behavior.

Social trading platforms have aroused researchers' interest as they provide accessibility of an extensive amount of information and trading data to their users. Due to the fact that social interaction can be observed in real-time, they constitute a valuable environment for studying investor behavior. The hitherto best researched platform is eToro, which is also the global market leader. Empirical studies of eToro find, on average, negative returns between 2010 and 2012 (Pan et al., 2012). Dorfleitner et al. (2018) provide empirical evidence showing that only complex trading strategies tailored to platform characteristics are able to provide positive returns (see also Oehler et al., 2016). According to Neumann (2014), the disposition and loss aversion effect explain the return characteristics of social trading returns (see also Liu et al., 2014; Heimer, 2016). Glaser and Risius (2016) observe that the trader's exposure to the disposition effect depends on behavioral and interaction features (see also Pelster and Hofmann, 2017). Contrary to this, Gemayel (2016) indicates that improved information transparency weakens the disposition effect (see also Lukas et al., 2017).

Pan et al. (2012) and Gemayel (2016) provide evidence for a certain level of wisdom of the crowd regarding the followers selecting the right signalers and for a herding behavior of signalers with respect to replicating the strategies of their competitors. Pan et al. (2012) show that investors are influenced by social dynamics such as the number of followers and do not select trade leaders rationally based on performance indicators (see also Röder and Walter, 2019; Kromidha and Li, 2019). Lee and Ma (2015) establish a model to help investors improve the selection of signalers.Wohlgemuth et al. (2016) indicate that both the affect-based and cognition-based signals raise the probability of followers copying their strategies. Ammann and Schaub (2016) find that superior past performance induces increased, positive communication, which, in turn, attracts followers. We extend the findings of Dorfleitner et al. (2018) regarding the negative relationship between high trading activity and social trading returns by analyzing the factors that motivate the irrational part of trading activity of signalers. This article contributes to the stream of literature on overconfidence in a social setting (Bénabou and Tirole, 2002; Pentland, 2013; Proeger and Meub, 2014). Contrary to Proeger and Meub (2014), our study is based on actual trading data from two trading platforms. We emphasize the importance of the platform design and the followers for the behavior of trade leaders.

We apply a two-stage least squares model to overcome the endogeneity of trading activity and to quantify the relationship between trading activity and performance. To this end, we implement an instrumental variable approach endogenizing the trading volume in the first stage. We define overconfidence as the part of trading activity that is irrationally motivated and results in negative returns. Our investigation utilizes an extensive set of trading data from the platforms Ayondo and Wikifolio to study the trading behavior of trade leaders in the observation period from October 2015 to May 2016.

The empirical analysis of the trading activity of signalers on social trading platforms provides new insights.

First, we find that overconfident traders on social trading platforms impair their performance through excessive trading, which is consistent with prior research. Second, we show that the social network aspects of these platforms, in particular the number of followers and the ranking of the traders, exhibit a positive relationship with the degree of overconfidence. Third, our findings suggest that the specific incentive schemes of the platforms have diverse impacts. While the incentive scheme on Ayondo includes means that appear to reduce the degree of overconfidence, the Wikifolio reward system does not reveal such an effect. Consequently, our results are not only relevant for traders and investors but also for the operators of social trading platforms.

The remainder of the paper is structured as follows: First, we provide a description of social trading platforms. Building on related literature we derive the hypotheses followed by a description of the data. We subsequently outline our empirical approach in the Section 4. We present the results, analyze the differences across the platforms and discuss their theoretical and practical implications in the Section 5. Section 6 concludes and identifies areas for further research.

2 Description of the social trading platforms utilized in the analysis

As digitization and social media have entered the financial sector and affected traditional business models, so-called *fintechs* have arisen providing financial services through the application of modern technology (Mackenzie, 2015; Dorfleitner et al., 2017). Social trading platforms combine classic online trading tools with the features of social networks (Neumann, 2014). The design of the platforms enables investors to communicate with each other and to contemplate, scrutinize and copy investment strategies of traders in the network (Pentland, 2013; Liu et al., 2014; Dorfleitner et al., 2017; Gemayel, 2016). The replication of trades in real-time is the distinguishing feature of social trading and provides individuals with the opportunity to profit from more proficient traders, who are compensated for sharing their investment ideas based on performance fees (Pentland, 2013; Doering et al., 2015; Ammann and Schaub, 2016). Although followers do not transfer capital to the signal provider's accounts, the latter de facto act as portfolio managers (Doering et al., 2015, p. 1). Profile pages of signalers display information on the trading strategy, key figures on risk and performance, and social media characteristics such as the number of followers and the ranking (Lee and Ma, 2015; Ammann and Schaub, 2016). Social trading platforms monitor signalers and, depending on the business model, charge users fees, for example spreads or order costs (Neumann, 2014; Doering et al., 2015; Dorfleitner et al., 2017).

This study focuses on Ayondo and Wikifolio since both only allow followers mirror trading and do not provide the option to copy single trades. Both platforms attract heterogenous types of traders based on the differences in the platform design. On Wikifolio, trade leaders (private and professional investors and media companies[1]) create trading strategies by choosing from an investment universe of more than 250,000 shares, exchange traded products, and leveraged products in order to profit from the price development of foreign exchange or commodities (Wikifolio, 2016). After meeting certain criteria, these so-called *wikifolios* become tradable as open-ended index certificates (Dorfleitner et al., 2018). Followers can thereby participate in the performance of the wikifolio (Wikifolio, 2016). Signalers on Ayondo implement their strategies by trading with contracts for difference (CFDs). Buyers of CFDs trade on margins and participate in the changes of the value of the underlying disproportionally (Neumann, 2014). Investors are given the opportunity to invest in up to five traders via CFDs (Ayondo, 2016). Leveraged products especially find favor with social trading because they facilitate the execution of mirror trading (Doering et al., 2015; Dorfleitner et al., 2017). The high flexibility in terms of contract sizes allows for a fractional mapping

[1]Media companies and financial market magazines such as Börse Online or AnlegerPlus publish their trading strategies on Wikifolio.

and ensures an exact proportionality between the signal provider's and followers' accounts (Doering et al., 2015, p.7). While traders on Ayondo can only publish one trading strategy each, signalers on Wikifolio can open several wikifolios. Wikifolio applies a high-water mark (HWM) remuneration scheme, whereas Ayondo compensates its signalers based on the created trading volume and their rating contingent on risk-adjusted performance (Doering et al., 2015). The composition of the ranking constitutes one of the major differences between the platforms. On Ayondo five different career levels (*Level*) are available, which also serve as the basis for the signaler's compensation. The criteria for promotion comprise trading activity and performance figures. To mitigate excessive risk taking, the maximum drawdown (*MDD*) is set to 25% on every level, leading to a demotion from the current level to the basic level in case of exceeding the limit and making promotions in the future impossible (Ayondo, 2016). Wikifolio pursues a different approach and ranks its traders based on *Wikifolio points* that are calculated on a daily basis conditioned to risk, activity, performance, and capital criteria (Wikifolio, 2016). As the HWM compensation principle is already implemented to minimize agency problems, the ranking mechanism appears to be less stringent, allowing signalers to move up and down in the grading scale at any given time.

3 Theory and hypotheses

In the following, we build on the existing literature to derive three hypotheses regarding the factors influencing trading behavior on social trading platforms. Hereby, we also account for the different rating and incentivizing features of Ayondo and Wikifolio.

Platform design and expectable rational trading behavior A rational signal provider can be characterized by a behavior that maximizes their profits. The compensation strategies of both platforms consist of different elements, which can influence trading behavior. In the case of Ayondo, the trade leader's profits depend directly on the trading volume accountable to him or her, which is created by the number of followers and the degree of his or her trading intensity. This quantity is multiplied by his or her respective level, ranging from 1 to 5 and representing the rating of the trader by Ayondo (Ayondo, 2016). By linking compensation to trading volume, signalers are provided with the incentive to trade in any situation, but with different levels of intensity. At the start of their careers, signalers attempt to establish a sound track record aimed at attracting followers, while not having much to lose. Consequently, signalers will be enticed into trading more, given a smaller number of followers and a lower level (Neumann, 2014). If a signaler advances in the rating system and more followers copy his or her strategy, the signal provider will be able to adapt his or her behavior by reducing his or her trading intensity as he or she profits proportionally from the more followers and the higher level. Higher levels, though, entail the risk of losing more, as the expulsion from the current level to the entry level has strong adverse effects on the rating (due to the irreversibility of the drop) and number of investors. This risk is amplified by the limitation of publishing only one trading strategy. Finally, there is a greater probability of being relegated from the current level due to not meeting the performance criteria because increased trading activity scales down returns by means of transactions costs (Dorfleitner et al., 2018). The strict requirements of the ranking system regarding the maximum drawdown and the risk-adjusted performance support this expected behavior.

There are several major differences on the Wikifolio platform. First, trade leaders receive a performance premium, that partially depends on the capital invested in the signaler's strategy, but only in the case that a new HWM is achieved (Wikifolio, 2016). The option-like character of this compensation can – depending on the time horizon of the trader – induce traders to undertake more risky projects in order to increase the probability of achieving the HWM (Carpenter, 2000; Panageas and Westerfield, 2009).

Due to the fact that a minimum of 10,000 EUR must be invested in the wikifolio certificate in order to become eligible for remuneration, signalers can be expected to behave similarly to traders on Ayondo in their early career stage, by seeking the attraction of followers. Once they have an investable portfolio, trade leaders focus rationally on their performance in order to surpass the HWM while aiming at growing capital inflows, which will, in turn, increase their profits. Contrary to Ayondo, neither trading activity nor the rating have a direct impact on the profits of a signal provider. Trading volume, though, partly affects the quantity of Wikifolio points. There is no general incentive to trade more or less in the case of having acquired a certain level of Wikifolio points and following capital. Trade leaders are expected to rationally maintain their trading intensity when moving up in the Wikifolio score, and to exhibit higher levels of volatility. The lack of strict risk and maximum drawdown requirements as well as of penalties in the event of not meeting these criteria supports this expected behavior. Finally, the anticipated behavior of traders, which is similar to that of option holders, is further amplified by the possibility of opening several wikifolios. Signalers are assumed to pursue various trading strategies with different levels of risk until they have created one wikifolio with a broad investor base and good performance. Summarizing, unlike on Ayondo there is no mechanism that incentivizes the traders to trade more on lower promotion levels and to trade less on higher ones.

Popularity and the signaler's trading behavior Thus far, behavioral finance studies have concentrated on the behavior of investors. However, social interaction can alter the traders' conduct as investors learn through observing the behavior of others (Barber and Odean, 2001b; Baker and Nofsinger, 2002; Duflo and Saez, 2002; Seasholes, 2010; Hirshleifer, 2015). The social network features on both platforms give rise to new aspects of social interaction in trading, which have the ability to influence overconfidence. These include, among others, the number of followers that presents an indicator for the popularity of signalers. Kim and Lee (2011) provide proof of the fact that the number of friends on Facebook serves as an affirmation and boost of self-worth. The endeavor to be positively perceived by others can induce overconfidence (Dowling and Lucey, 2010; Burks et al., 2013). Pentland (2013) shows that the confidence of individuals increases when they realize that others pursue strategies akin to their investment ideas. He elaborates by stating that, in the case of limited sources of information, traders consequently face the risk of becoming overconfident. Individuals who are contingent upon self-serving attribution bias, tend to credit past success to their skills and in doing so become more overconfident (Barber and Odean, 2001a; Gervais and Odean, 2001; Hirshleifer, 2001; Puetz and Ruenzi, 2011; Hirshleifer, 2015). As a trade leader cannot directly influence the number of followers or capital invested in his or her trading strategy, the success of the trade leader is partly measured by the ability to entice followers (Doering et al., 2015). Rational signalers who consider the mutual impacts on their profits would, given a certain number of followers, behave in a way as to maintain their performance level and the number of followers. However, all considered, we hypothesize that the popularity of a signaler's strategy is perceived as being a confirmation of his or her skills and thus connected with his or her tendency to trade more. Such a type of irrational behavior is a clear indication of (more) overconfidence.

Hypothesis 1 *The popularity of a trading strategy among followers is positively related with increased trading activity.*

Overconfidence and a trader's return Extensive research has been conducted into the relationship between trading activity and performance. Contrary to rational traders, the overconfident overestimate their expected gains and, hence, trade excessively, resulting in diminished returns compared with benchmarks (Bondt and Thaler, 1995; Daniel et al., 1998; Barber and Odean, 2000; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009). Increased transaction costs for inordinate trading and the lower proficiency levels of the traders can therefore explain the reduced returns of overconfident traders (Barber and Odean, 1999; Shefrin, 2002; Merkle and Weber, 2011; Hirshleifer, 2015). Barber and Odean (2002) show that this relationship is particularly prevalent in online trading due to mitigated market frictions. The enhanced availability of information even augments overconfidence by contributing to the illusion of knowledge and control (Barber and Odean, 2001b; Baker and Nofsinger, 2002; Tsai et al., 2008; Abreu and Mendes, 2012). In the case of Ayondo and Wikifolio, one could argue that the increased trading activity is fostered through the setup of the platforms' compensation rather than being a sign of overconfidence. However, rational trade leaders will take into account that excessive trading entailing negative performance can lead to the loss of followers, capital and rating, and, ultimately, profits. What is more, technical aspects such as the trading strategy or the portfolio composition account for a certain level of trading activity.[2] In addition, trade leaders may see their trading activity as an opportunity to signal their competency and trustworthiness and, hence, adjust their trading behavior accordingly (Burks et al., 2013; Proeger and Meub, 2014; Wohlgemuth et al., 2016). With knowledge of the implied transaction costs, this rational signaling strategy should still be profitable, though. Consequently, taking into account all rational factors, we argue that excessive trading activity which is stimulated by irrational factors e.g. increased popularity is connected with negative returns (after transaction costs).

Hypothesis 2 *The increased trading activity due to higher popularity reduces a trader's return.*

Our second hypothesis is, hence, contingent on the first hypothesis. Consequently, only if we find evidence for both hypotheses we have a clear indication of overconfidence, since we define overconfidence as the part of trading activity induced by irrational factors and resulting in negative returns.

Influence of the platform-specific rating and incentivizing methodologies Since social trading platforms prominently display the rating of each signaler, trade leaders strive for good positions in the platform's league table in order to attract new investments (Cheng, 2007; Jin et al., 2016; Gortner and van der Weele, 2019). Both platforms under review reinforce this behavior by suggesting the ranking as one of the key investment criterion, with the result that the predefined search for portfolios in the investigation period has been based on levels and Wikifolio points respectively. A more elaborate analysis of the investment opportunities taking into account risk and performance measures requires additional efforts by the followers. Dowling and Lucey (2010) show that ambitious settings fostering competition among individuals nurture a biased self-attribution (see also Eshraghi and Taffler, 2012; Simon and Heimer, 2015). The social ranking theory contributes by explaining in which way good performances compared with the social environment nourish the signaler's self-perception and result in higher confidence and risk taking (Gilbert et al., 1996; Baker and Nofsinger, 2002). While several studies argue that the scarcity of information in competitive fields augments overconfidence, the immediate feedback on social trading platforms can reduce biased self-attribution as true abilities are revealed (Jin et al., 2016; Heimer, 2016; Gortner and van der Weele, 2019). Moreover, changes in the rating of signalers can be regarded as being a mechanism to supervise signalers and minimize the probability of adverse selection (Neumann, 2014; Glaser and Risius, 2016). In general, we expect that a positive rating (higher levels on Ayondo and more Wikifolio points on Wikifolio) tends to support overconfidence. However, the platform-specific rating and incentive frameworks can influence the way signalers react. The strict limits concerning the maximum drawdown and performance requirements on Ayondo can reduce the overconfidence of trade leaders and might lead to more rational behavior. Signalers do not wish to risk an expulsion to the base level, in particular if they have already achieved a higher position. Not having the option to open a new portfolio emphasizes the effect. Since Wikifolio points are calculated on a daily basis allowing signalers to move up

[2]A trader may, for instance, pursue a strategy close to that of an arbitrageur between an stock index future and the underlying index, forcing him or her to trade a lot. If carried out rationally, though, the strategy should still be so profitable that at least the accruing transactions costs are earned and no negative expected returns emerge as a result from the strategy. However, the generally higher level of trading activity must be accounted for as it is not an expression of overconfidence.

and down the grading scale at any time, we expect that, contrary to Ayondo, the Wikifolio rating scheme will rather foster overconfident behavior. The platform has also not implemented rebalancing measures such as risk limiting mechanisms, which could reduce irrational trading activity. This effect is reinforced by the option of opening several wikifolios.

Hypothesis 3 *The platform-specific rating and incentive features influence the trading activity in a different manner.*

4 Data and methodology

4.1 Data

We use a comprehensive data set that enables us to measure the relationship between financial activities and social interaction on two major social trading platforms in Germany. The setting of the platforms offers the possibility to simultaneously observe trading activity and individual behavior.

Both platforms publish historical time series of individual trading and performance data on their websites. We downloaded individual daily trading data from Ayondo and Wikifolio during the observation period of November 2015 to May 2016. The dataset includes all portfolios created on Ayondo ever since April 2009 and all portfolios created on Wikifolio ever since September 2011. Furthermore, we manually collected additional information on social interaction such as the number of followers or Wikifolio points on a weekly basis. The dataset employed is similar to but more comprehensive than the dataset utilized by Dorfleitner et al. (2018).

Since the platforms are open to everyone and entry prerequisites are loose, the customer base includes both novices and experts. We adjust the data set by excluding both the demo and inactive accounts to reduce possible biases. Some deficient observations on Ayondo with a maximum drawdown exceeding 100% are deleted. With respect to Wikifolio, we concentrate on the wikifolios that are published and eligible for investment. Finally, we arrive at a data set containing 15,654 weekly performance observations of 1,284 signalers on Ayondo and 106,634 weekly return observations of 4,504 wikifolios of 2,716 signalers on Wikifolio. While some portfolios were created during the observation period, others existed previously, sometimes for months or years. Consequently, the dataset also features traders who do not have any investors yet. Our data do not suffer from survivorship bias, as both the successful and less successful portfolios are retained in the dataset. The platforms disclose information on the trading and social activity of each signaler starting from the beginning of their membership. While Ayondo supplies extensive metric data, Wikifolio provides an insight into quality indicators such as the relationship between risk and return, the traded instruments, and trading style, by using so-called *tags* to categorize wikifolios. We therefore expect – due to disparities in the availability of information as well as in the platform design – Ayondo and Wikifolio to attract different trader and investor groups. Additionally, we assume that the likelihood of errors in the data points is minimal since platform operators advertise the transparency of information and high data quality.

To quantify the returns we follow the platforms, which display the figure *Total performance* as the main performance indicator of trading strategies measuring the performance of the signal provider since the creation of the portfolio to the corresponding day. Weekly performance (*Return*) is calculated based on the relative difference in *Total performance* between the week under consideration and the previous one. To avoid spurious results due to weekend effects, we construct our performance variable on the interval between one Wednesday and the next. Since daily performance figures are not retrievable for every single portfolio, we interpolate performance data on Ayondo and search externally for corresponding prices for wikifolios[3]. Note that the variable *Return* already accounts for transaction costs[4]. As suggested by Hypothesis 1, we include the popularity of a signaler – measured by the numbers of followers or net cash flows respectively (Sirri and Tufano, 1998). Apart from this we consider the ranking of trade leaders to investigate Hypothesis 3. We measure the current *Level* of a trader on Ayondo as well as $Wikifolio\,points$ at the end of one week. In order to control for the effects of the market on returns, we include $Benchmark\,returns$, obtained from Yahoo Finance. We follow a similar approach to Sharpe (1992) and apply asset-specific benchmarks. We account for the focus on trading with (CFDs on) stocks and indices and utilize the return of the MSCI World index in Euro. Moreover, the variable $Volatility$ enters the model to measure risk exposure on performance. By adding lagged returns we account for the past success of signalers. Finally, platform-specific risk and performance key figures as well as social interaction variables i.e. the number of comments published in a week enter the regression. Table 1 and 2 provide a detailed description of all explanatory variables as well as additional control variables.

INSERT TABLE 1 AND 2 HERE

4.2 Descriptive statistics

Ayondo Table 3 provides descriptive statistics for our sample of 882 signalers on Ayondo in the observation period. As a consequence of trading with CFDs and the disproportional effect of price changes on performance the weekly returns exhibit large variations. We account for the skewness of the return distribution and winsorize weekly returns at the 1% and 99% levels leading to a minimum of −913.11% and a maximum of 703.64%. The resulting average return amounts to −8.4%. In comparison, the mean weekly benchmark performance is −0.33%. We conclude that, on average, signalers underperform the benchmark. Regarding the hypotheses-related variable trades, we observe an average of 18 trades per week. Some traders, though, appear to trade intensively, resulting in a maximum of 839 trades within one week. The risk measure maximum drawdown adds to the presumption of extremely risky trading on Ayondo with a mean of 19.7% and a maximum value of 99.87%. With respect to popularity, signalers have an average of 31 followers. We interpret the skewed distribution as an indicator for herding as investors merely appear to concentrate on a few signalers. An advanced skill level of a trader should be reflected through a higher career level. In fact, the mean of 1.7 suggests that signalers stay in the region of the first and second level. One explanation for this result could be the return of a trader to the initial level in the case of exceeding the maximum drawdown.

INSERT TABLE 3 HERE

Wikifolio Table 4 presents the descriptive statistics for the Wikifolio sample comprised of 4,370 wikifolios among 2,670 signalers in the sample period. To begin with, the distribution of returns is skewed to the right as in the case of Ayondo. However, as trading instruments are not restricted to CFDs, the leverage effect in returns is reduced. Nonetheless, a minimum of −19.03% and a maximum of 13.33% is achieved after winsorizing returns at the 1% and 99% levels. Signalers on Wikifolio generate, on average, weekly returns of −0.12%. In comparison, the weekly performance of the benchmark ranges from −6.4% to 4.8% with a mean of −0.07%. Consequently, the traders on Wikifolio appear to perform better than those on Ayondo, although they still underperform the MSCI World Index. The volatility in returns exhibits a mean of 0.0206 and a standard deviation of 0.0709. The positive skewness indicates extreme outliers.

[3]Interpolated values account for less than 1% of Ayondo performance data.

[4]While Ayondo incorporates transaction costs in the CFD spreads, transaction costs on Wikifolio are a part of the replication strategy in the certificates and thus also already contained in the certificate prices.

We observe an average trading activity of 5.4 trades per week. Consistent with the results on Ayondo, a few signalers appear to trade extensively. The higher level in trading activity on Ayondo compared with Wikifolio can be partially explained by the fact that Ayondo applies a volume-based performance model. Concerning the popularity of wikifolios, the mean net capital change amounts to 110.947 Euro. While the most successful wikifolio has thus far experienced a maximum of 19,421 Euro worth of net cash inflows, the least favourable wikifolio experienced net cash flows of $-14{,}853$ Euro. Based on certain criteria, trading strategies are awarded with Wikifolio points, that are spread between 0 and 8,514 with an average value of 317. Table 5 provides insights into the relative frequency of the binary variables.

INSERT TABLE 4 AND 5 HERE

4.3 Methodology

Due to the two-dimensional structure of the data, we perform panel regressions to study our hypotheses. We apply an approach similar to that of Jin et al. (2016) to quantify the relationship between weekly performance (*Return*) and the trading activity (*Trades*). Since only negative returns after transaction costs following increased trading activity initiated by irrational factors are a clear identification of overconfidence, our model considers benchmark return, volatility, and platform-specific variables describing the characteristics of the trading strategies. We follow Gervais and Odean (2001) and Glaser and Weber (2010) and assume that overconfidence is not constant over time as it may be subject to fluctuations conditioned by events that occur within the course of social trading. In light of the skewed distribution of $Trades$ and $Followers$ we logarithmically transform the variables. Since this method is inappropriate for $Net\,capital\,change$, we instead winsorize it at the 1% and 99% level to account for extreme outliers.

Traders differ in unobservable personal traits such as trading ability or the level of overconfidence and are subject to the incentives imposed by the platform. Furthermore, the trading strategy has an impact on the signaler's general performance, risk taking and trading activity. All these factors give rise to possible endogeneity issues (Heimer, 2016; Glaser and Risius, 2016; Dorfleitner et al., 2018). We therefore employ fixed effects to account for the endogeneity arising from personal characteristics of traders as well as from differences in trading strategies (Hausman and Taylor, 1981). In order to analyze the factors that influence overconfidence and the traders' returns, we implement a two-stage least squares (2SLS) model with fixed effects in both stages. We include rational determinants of trading activity as control variables in the estimation of overconfidence proxied by the part of trading activity that is induced by irrational factors. Besides tackling the endogeneity issue, the instrumental variable (IV) method provides the opportunity to measure the rational and the irrational influences on trading activity in a dynamic setting. In doing so, we distinguish ourselves from existing overconfidence models.

When establishing our conceptual model, we build on behavioral finance literature in order to analyze the irrational factors affecting overconfidence. To begin with, we include lagged variables of the number of followers and net change in invested capital, respectively, as well as the previous rating as instruments to investigate our hypotheses. We account for the different behavioral patterns induced by the platform-specific features by including further variables. Ayondo's incentive and rating system is designed with the objective to mitigate excessive risk taking by the traders by imposing a limit on the maximum drawdown. Therefore, the lagged values of the maximum drawdown are added as instrumental variables. In addition, as overconfidence is associated with a higher inclination towards risk (Odean, 1998; Cheng, 2007), we thereby analyze whether this holds for signalers on Ayondo. Considering the fact that past success may stimulate a trader's confidence (Barber and Odean, 2001b; Statman et al., 2006; O'Connell and Teo, 2009; Dowling and Lucey, 2010; Puetz and Ruenzi, 2011; Hirshleifer, 2015), we incorporate past performance, the lagged trades-won ratio on Ayondo as well as performance related *tags* on Wikifolio as IVs. Finally, we investigate whether the overconfidence of the traders on Ayondo changes over time, based on the experience of the trader (Gervais and Odean, 2001; Glaser and Weber, 2010).

In view of the technical factors influencing trading activity and returns[5], we include lagged variables of leverage and short ratio on Ayondo as well as different Wikifolio *tags* following Dorfleitner et al. (2018). Since traders on Wikifolio can comment on their trading activities, we also include the variable *Comments* in our model to factor in the social network characteristics (Dorfleitner et al., 2018). We account for the relationship between diversification and trading activity by encompassing the lagged Herfindahl-Hirschmann index for Ayondo and the tag *Diversified* for Wikifolio. We also establish the variable *Heavy trader* as control variable in the Wikifolio model.

As a result, the regression models for Ayondo and Wikifolio manifest the following structure, where i represents the signaler and t denotes the time dimension. The terms $\varepsilon_{i,t}$ and $\varphi_{i,t}$ constitute the error terms in the instrumental and reduced form equation respectively.

The **Ayondo 2SLS model** is represented by:

$$\begin{aligned}\log(1+Trades)_{i,t} = {} & \pi_1 \log(1+Follower)_{i,t-1} + \pi_2\, Level_{i,t-1} + \pi_3\, TWR_{i,t-1} \\ & + \pi_4\, MDD_{i,t-1} + \pi_5\, Experience_{i,t-1} + \phi_1\, Benchmark_{i,t} + \phi_2\, Volatility_{i,t-1} \\ & + \phi_3\, Return_{i,t-1} + \phi_4\, Leverage_{i,t-1} + \phi_5\, Short_{i,t-1} + \phi_6\, HHI_{i,t-1} \\ & + \phi_7\, Week_t + \eta_i + \varphi_{i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}Return_{i,t} = {} & \gamma_1\, Benchmark_{i,t} + \gamma_2\, Volatility_{i,t-1} + \gamma_3\, Return_{i,t-1} + \gamma_4\, Leverage_{i,t-1} \\ & + \gamma_5\, Short_{i,t-1} + \gamma_6\, HHI_{i,t-1} + \gamma_7\, Week_t + \beta_1 \log(1+Trades)_{i,t} + \upsilon_i + \varepsilon_{i,t}\end{aligned} \tag{2}$$

while the **Wikifolio 2SLS model** can be expressed as:

$$\begin{aligned}\log(1+Trades)_{i,t} = {} & \pi_1 \log(1+Net\,capital\,change)_{i,t-1} + \pi_2\, WF\,points_{i,t-1} \\ & + \pi_3\, Money\,manager_{i,t-1} + \phi_1\, Benchmark_{i,t} + \phi_2\, Volatility_{i,t-1} \\ & + \phi_3\, Return_{i,t-1} + \phi_4\, Comments_{i,t} + \phi_5\, Heavy_{i,t-1} + \phi_6\, Performance_{i,t-1} \\ & + \phi_7\, Bestseller_{i,t-1} + \phi_8\, Diversified_{i,t-1} + \phi_9\, Week_t + \eta_i + \varphi_{i,t}\end{aligned} \tag{3}$$

$$\begin{aligned}Return_{i,t} = {} & \gamma_1\, Benchmark_{i,t} + \gamma_2\, Volatility_{i,t-1} + \gamma_3\, Return_{i,t-1} + \gamma_4\, Comments_{i,t} + \gamma_5\, Heavy_{i,t-1} \\ & + \gamma_6\, Performance_{i,t-1} + \gamma_7\, Bestseller_{i,t-1} + \gamma_8\, Diversified_{i,t-1} + \gamma_9\, Week_t \\ & + \beta_1 \log(1+Trades)_{i,t} + \upsilon_i + \varepsilon_{i,t}\end{aligned} \tag{4}$$

We use clustered standard errors at the signaler level and include the time variable *Week* to control for the effects of time-series trends. Due to the fact that OLS estimates are likely to be more precise than IV estimates, we check whether the application of the IV approach biases our results. The Hansen's J statistic and endogeneity tests confirm that the econometric estimation procedure satisfies the conditions for efficiently estimating the effect of overconfidence on performance (Hansen and Singleton, 1982; James H. Stock and Motohiro Yogo, 2005; Kleibergen and Paap, 2006; Baum et al., 2007).

[5]In comparison to other research such as the study of Oehler et al. (2016), we do not take the approach of applying factor models to analyze returns, but instead base our analysis on the panel data structure and thus follow a rather Fama-MacBeth style approach. By accounting for market returns we implicitly use a beta of 1. In addition, as we consider various influencing factors of returns we do not consider it fruitful to implement additional risk factors.

5 Results

In this section, we explore the relationship between performance and trading behavior on Ayondo and Wikifolio. We analyze the factors that influence overconfidence with respect to our hypotheses and perform robustness checks. Finally, we discuss the differences between both platforms.

5.1 Ayondo

Table 6 represents the 2SLS regression results with *Return* as the dependent variable. With respect to the hypothesis-related variable *Level*, regression 1 includes dummy variables for the different career levels, while regression 2 utilizes the continuous variable $Level_{i,t\text{-}1}$. To begin with, the auxiliary regression 1 provides an insight into the validity of the instruments for overconfidence (*log(1+Trades)*). As suggested by hypothesis 1, the coefficient of the number of followers is positively significant at the 5% level. This result indicates that popularity amongst investors stimulates the overconfidence of traders in their abilities leading to an increase in trading activity. It needs to be noted that this finding is novel, since the development of social trading platforms has introduced the social dimension of followers. In addition, this information is made immediately available to the trade leaders and is able to influence their behavior in this way. Regarding hypothesis 3, we find that the platform-specific ranking and incentive scheme significantly affects trading behavior. The coefficients of the career levels 3 and 4 on Ayondo are positively significant at the 10% level. However, the coefficient is insignificant for the highest level 5. The remuneration model of Ayondo follows a volume-based approach directly aligning the signaler's compensation to his or her position in the platform ranking and the trading volume generated. Due to the fact that traders at a higher level profit proportionally from more followers and the higher level, we interpret this finding as being an indication of the fact that rational traders adapt their trading behavior accordingly. However, the positive, significant coefficient demonstrates that higher positions in the league table tend to nourish the signaler's self-perception and nurture his or her overconfidence, leading to increased trading activity. The insignificant coefficient of *Level 5* can be explained by the fact that this career level entails the risk of losing the most due to the irreversible drop to the entry level. The risk is further amplified by increased trading activity, which, in turn, reduces returns by means of transaction costs. The negative and significant effect of maximum drawdown on overconfidence can be explained by the fact that this figure constitutes one of the main criteria for the assignment of the career level. Since exceeding the limited MDD of 25% will result in an expulsion from the current level back to the initial position, the maximum drawdown serves as a monitor for the level of risk taking. Therefore, the measure maximum drawdown reduces the signalers' propensity towards overconfidence. Looking at the combined effect of Level and MDD shows that the impact of the risk requirement exceeds the positive effect of the rating on overconfidence, leading to a joined negative effect of the ranking and incentive system. Concluding, our results suggest that the ranking system on Ayondo is constructed in a way that mitigates overconfident behavior by making the traders more rational.[6]

INSERT TABLE 6 HERE

The positive development of the trades-won ratio predicts that the signaler will be more greatly exposed to increased trading activity following past success. The coefficient of experience is negatively correlated with overconfidence. With respect to the rational and trading-strategy-related factors affecting trading activity, we find that high leverage ratios, representing the trader's inclination towards risk, have an

[6] If we additionally control for the interaction of *Level 1* and an MDD exceeding 25% (regression not reported here), we observe an insignificant coefficient. Thus, there is no support for the view that those traders that are not anymore subject to the risk limits trade more excessively.

insignificant impact on trading activity. Traders whose strategies comprise fewer asset classes appear to trade less extensively as compared with signalers who focus on a variety of instruments in their portfolios. Additionally, the portfolio's performance in the previous week is positively significant. Lastly, the week dummies exhibit significant negative coefficients implying that traders reduce trading activity over time.

Finally, when analyzing the second stage regression 2, we find that the results support our hypothesis 2, being that the trader's performance is adversely affected by overconfidence. The negative and highly significant coefficient of trading activity suggests that overconfident signalers, whose behavior is affected by irrational factors, diminish their returns by trading too much. The interesting aspect in this finding is the fact that overconfidence is still present after controlling for several technical aspects affecting trading activity such as the portfolio concentration, past returns and their volatility as well as the portfolio's strategy. The irrational part of trading intensity can thus be explained by the social interaction dimensions of followers and the rating and incentive scheme. Regarding the benchmark return, we find a negative relationship between the development of the return of the MSCI World Index and a trader's performance, indicating a tendency amongst signalers to short the market. We assume that the insignificant coefficients can be partly explained by the fact that a large part of the return variation due to the weekly market variations is captured by the time dummy. Moreover, we discover a significant negative relationship between past and current performance. Contrary to expectations, the results demonstrate an insignificant risk-reward-relationship. What is more, the leverage and short ratio do not significantly affect social trading returns, while the effect of the portfolio composition is significantly negative. With respect to time series trends, we in fact observe a significant negative coefficient, indicating that signalers impair their performance over time.

5.2 Wikifolio

The results of the 2SLS regression with *Return* as the dependent variable are reported in Table 7. The first column shows the regressions containing the hypotheses-related variables *Net capital change*, *WF Points* and *Money manager*. In the second regression the main model is extended by the instrumental variables *Loyal* and *Frequently*. Starting with the first stage regression 3, we assess the validity of our instruments. In line with hypothesis 1, the net capital change positively and significantly affects the degree of overconfidence. These results indicate that subsequent to fund inflows, signalers become more overconfident and trade more actively. The information on the popularity of a trader is displayed prominently and can therefore impact a signaler's behavior. As expected, we find that the ranking system on Wikifolio significantly influences overconfidence, thereby confirming hypothesis 3. Just like on Ayondo, the coefficient of Wikifolio points is positive. This finding implies that a promotion in the league table nourishes the signal provider's self-perception and fosters his or her overconfidence. Contrary to Ayondo, the Wikifolio ranking does not impose a strict restriction on the further progress of the signalers. Since Wikifolio follows the HWM-compensation approach, the incentive system appears to encourage excessive trading activity. The option to open several wikifolios simultaneously adds to this expected behavior. Therefore, we conjecture that the setup of the ranking and incentive system induces overconfident investors to continue in the same manner, as setbacks do not have an educational character and means with a countervailing effect are not in place. In the next step, we examine whether quality tags that indicate the popularity of a wikifolio move overconfidence. We observe a significant positive effect of the reward *Money manager* and a slightly positive effect of the tag *Loyal investors* on overconfidence.

INSERT TABLE 7 HERE

With respect to the effect of rational and trading-strategy-related factors on trading activity the results demonstrate a negative significant relationship between benchmark returns and trading activity. Trade leaders appear to decrease their trading intensity following positive benchmark performances. Contrary to Ayondo, past performance exhibits negative coefficients significant at the 10% level. Besides, we find a negative, yet insignificant correlation between past volatility and trading activity. The number of comments are not significantly related to trading activity. Wikifolio grants portfolios with awards based on quality indicators, the relationship between risk and return, traded instruments and trading style. Among these the tag *Heavy trader* exhibits a positive and significant coefficient, implying the persistence of high trading activity. As is the case with Ayondo, we provide empirical evidence of the positive relationship between past success in terms of risk-return-ratios and trading activity, which is displayed by the significant coefficient of the tag *High performance*. Interestingly, we find that if a wikifolio has been amongst the 25 most frequently purchased strategies within the last two weeks (*Bestseller*), it has a positive, albeit insignificant, effect on trading activity. Finally, trade leaders appear to reduce their trading activity over time – as in the case of Ayondo.

The results from the second stage regression 4 add weight to hypothesis 2. The negative and significant coefficient of overconfidence proves that excessive trading by overconfident signalers on Wikifolio reduces returns. We show that after accounting for the rational factors affecting trading activity, namely benchmark returns and volatility of returns as well as the wikifolio characteristics, overconfidence leads to increased trading activity. We provide evidence of the fact that the irrational part of trading intensity can, thus, be explained through the social interaction features of followers and the rating and incentive scheme. When taking into account that we already control for the tag *Heavy trader*, we show that overconfidence is existent beyond this. Contrary to Ayondo, the benchmark return has a positive and significant coefficient. There appears to be evidence of the fact that traders on Wikifolio tend to go long in the market. What is more, past returns have a significant positive relationship with current returns. According to our results, volatility has an insignificant negative effect on performance. Furthermore, since the number of posted comments implies a decrease in social trading returns we assume that experts are more reluctant to communicate their trading strategies. Regarding the wikifolio tags, we do not observe significant effects on social trading returns. Interestingly, the tag *Heavy trader* significantly positively affects a trader's return. Finally, the results indicate that signalers on Wikifolio also impair their performance over time.

5.3 Robustness checks

We conduct a series of robustness checks by establishing model variations and calculating the regressions with different subsamples.

Subsample regressions Lastly, traders on Wikifolio decide, at the beginning of their career, whether or not they wish to make use of leveraged products. We account for the high affinity to risk of overconfident traders and analyze overconfidence of those signalers that include leveraged products in their wikifolios (Odean, 1998). In this setting, we can confirm all three hypotheses. We observe that the coefficients of the hypotheses related variables *Net capital change* and *WF points* slightly increase in size (see Table 7 models 3–4). However, one has to keep in mind that the traders do not actually have to trade this type of securities during the observation period. One could argue that our results are biased towards extremely active traders. We thus form subsamples by focusing on the active traders who traded in the previous week (see Table 6 models 3–4 and Table 7 models 5–6). We observe almost identical results for the active subsample compared to the original sample in the case of Ayondo. The main difference lies in the insignificance of the coefficient of *Level 3*. When considering the Wikifolio subsample of active traders, the coefficients of the hypotheses related variables increase slightly in size, while the effect of trading activity on returns is slightly reduced. The effects of past returns and the tag *Heavy trader* become insignificant.

Model variations We follow Dorfleitner et al. (2018) and use the performance of the German stock index (DAX 30) as an alternative measure of benchmark performance to capture possible market and timing effects. In addition, we use USD/EUR return as a benchmark for Ayondo due to the extensive use of forex trading. For both platforms, our results provide evidence for our hypotheses (see Table 6 models 5–8 and Table 7 models 7–8). Finally, we winsorize the number of comments at the 1% and 99% level to incorporate the skewness of the distribution. Due to the marginal differences in comparison to the main models, we do not report the results here. Altogether, our results substantiate that our indication of overconfidence, namely the irrational part of trading activity, instrumented by a set of variables to account for several dimensions of overconfidence and resulting in negative returns, is a predictive factor for performance and appropriately accounts for endogeneity.

6 Conclusion

To date, extensive research has indicated that investors are subject to behavioral and social biases. In this article we analyze aspects of trading behavior on two major social trading platforms in Germany, namely Ayondo and Wikifolio. In particular, we investigate the factors influencing the overconfidence contingent on social interaction features. In contrast to existing overconfidence studies, our data stem from a world external to the laboratory setting. To the best of our knowledge, we are the first to explore how these novel dimensions of online trading impact on overconfidence. We apply a fixed effects two-stage least squares approach to resolve endogeneity issues and confirm our results following a series of robustness checks. By using an exclusive dataset from two leading social trading platforms, we gain insights into the influence of the heterogenous business models. We sustain novel and, to some extent, surprising conclusions.

Above all, we add to behavioral finance research by providing evidence of the negative relationship between overconfidence, proxied by the irrational part of trading activity, and social trading returns in this innovative online trading environment. The negative returns after transaction costs indicate that the increased trading intensity triggered by irrational factors can actually be unequivocally identified as overconfidence. Considering the magnitude of the effect, we find that the coefficient of the endogenous variable is larger in absolute value on Ayondo than on Wikifolio. The difference in trading activity on both platforms could account for this finding. As proven by the IV estimation, there are various irrational factors on the platforms that are significantly related to overconfidence. The signaler's popularity, either measured by the number of followers or the net change in invested capital, reveals itself to be a significant driver of irrational behavior on both platforms. Hence, we conclude that the overconfidence of the traders increases when they receive more attention from the network, as they attribute capital inflows to their abilities. This finding is particularly intriguing as the business model of the platforms is geared to attracting followers.The benefits for investors of investing in sophisticated traders are, to some extent, reduced by the inverse effect of a growing quantity of followers on the overconfidence of signalers. We identify that the platform-specific ranking and incentive system is a significant driver of overconfidence. In general, we find that the rating system nurtures the trade leader's overconfidence. A clear difference is evidenced by the strict risk limits and drop out consequences on Ayondo, which have a significant countervailing effect on excessive trading. On the contrary, the HWM remuneration approach on Wikifolio combined with less prohibitive measures regarding the progression in the rating do not mitigate overconfident behavior. Moreover, we provide insights into the relationship of several factors such as risk, experience and past success with the degree of overconfidence. Taken together, the different frameworks of the platforms motivate heterogenous behavioral responses by the signalers.

Our findings are relevant from both a theoretical and a practical perspective. On the one hand, platform operators aim to attract successful traders, who will in turn entice followers, consequently increasing the operators' revenues. On the other hand, we have proven that the social feedback characteristics can lead to more pronounced overconfidence compared with the standard market setting. Since the overconfident traders experience reduced returns, they may deter prospective customers from joining the platform. Specifically, the more restrictive rating system can be of an advantage for platforms in guiding trader behavior. Even more so, platform operators should be aware of how the monitoring mechanisms and incentives of the platform affect their business models. Investors can refer to our findings when choosing the platform that matches their preferences. Due to the fact that the return of investors is equally affected by the performance of the underlying assets and the behavior of the trader, gaining greater insight into the behavior of signalers can help followers in forming their portfolios.

A limitation of our research lies in the fact that due to lack of data availability, only a few control variables can be used in assessing overconfidence on Wikifolio. The incorporation of additional metric variables would allow us to capture supplementary factors. To improve the generalizability of our findings, future research could investigate additional platforms that differ in products offered, incentive systems, interaction mechanisms, specifically since we demonstrate that the different platform designs shape the behavior of the traders. Summarizing, we expect increasing digitization combined with changes in the regulatory environment to affect the development of social trading platforms. In conclusion, our article contributes to an improved understanding of the phenomenon of social trading.

Table 1: Definition of the explanatory variables on Ayondo

Data sources: Own calculations based on data from Ayondo and Yahoo Finance. Description of variables following Ayondo (2016).

Variable	**Meaning**	**Description**
$Return_{\mathrm{i,t}}$	Weekly return	Performance of a trader's portfolio in week t, calculated as being the ratio of the weekly net total performance to the previous week's total performance
$Benchmark_{\mathrm{i,t}}$	Benchmark return	Weekly return of the MSCI World Index (in Euro)
$Volatility_{\mathrm{i,t}}$	Volatility	Volatility of daily returns over the last 4 weeks
$Trades_{\mathrm{i,t}}$	Trades per week	Number of trades a trader executed in week t
$TWR_{\mathrm{i,t}}$	Trades-won ratio	Ratio of all previous trades that have been closed with a winning position
$Follower_{\mathrm{i,t}}$	Number of followers	Number of followers following a trader's portfolio measured on a weekly basis
$MDD_{\mathrm{i,t}}$	Maximum drawdown	Maximum drawdown a trader has ever experienced since the beginning of the observation period
$Leverage_{\mathrm{i,t}}$	Leverage ratio	Average leverage of all trades during the previous week
$Short_{\mathrm{i,t}}$	Short ratio	Ratio of securities that have been shortened during the previous week
$HHI_{\mathrm{i,t}}$	Herfindahl-Hirschmann index	Sum of squared portfolio allocations to a specific asset class according to Hoffmann and Shefrin (2011)
$Level_{\mathrm{i,t}}$	Career level	Career level of the trader in categorical values ranging from 1 to 5 (Street Trader, Advanced, Professional, Risk-adjusted, Institutional)
$Experience_{\mathrm{i,t}}$	Experience	Trading experience of the trader in categorical values ranging from 0 to 6 (0 years, 0-1, 1-2, 2-5, 5-10, more than 10 years)
$Week\,dummy_{\mathrm{t}}$	Week	Binary, time identifying variable indicating the week of measurement

Table 2: Definition of the explanatory variables on Wikifolio

Data sources: Own calculations based on data from Wikifolio and Yahoo Finance. Description of variables following Wikifolio (2016).

Variable	Meaning	Description
Metric variables		
$Return_{i,t}$	Weekly return	Performance of a trader's portfolio in week t, calculated as being the ratio of the weekly net total performance to the previous week's total performance
$Benchmark_{i,t}$	Benchmark return	Weekly return of the MSCI World Index (in Euro)
$Volatility_{i,t}$	Volatility	Volatility of daily returns over the last 4 weeks
$Trades_{i,t}$	Trades per week	Number of trades a trader executed in week t, measured in multiples of 5
$Net\,capital\,change_{i,t}$	Net change in invested capital	Difference between the total capital invested in the current and in the previous week accounting for capital changes following positive returns
$Comments_{i,t}$	Number of comments	Number of published comments by the trader in week t, measured in multiples of 5
$WF\,points_{i,t}$	Wikifolio points	Wikifolio points of the trader in the respective week
$Week\,dummy_{t}$	Week	Time identifying variable indicating the week of measurement
Wikifolio tags (binary variables)		
$Money\_manager_{i,t}$	Good money manager	Good money managers accomplished a mean monthly return exceeding 0.3% during a time interval of 6-24 months, while at the same time experiencing losses above 20% of the portfolio value. In addition, the trader executed more than 35 trades.
$Loyal_{i,t}$	Loyal investors	More than 15 buy orders have been placed on the wikifolio during the preceding 24 months. In addition, the ratio of sale transactions to total transactions is below 35%.
$Frequently_{i,t}$	Frequently bought	The difference in the number of purchase requests and sale requests since the emission of the index certificate is higher than 25.
$Heavy\,trader_{i,t}$	Heavy trader	Within the last 49 days, at least 7 times the aggregated portfolio value has been turned around by the trader.
$Performance_{i,t}$	High performance	The portfolio with the status "published" or "investable" achieved a performance of more than 40% in the preceding 12 months and a mean return of more than 4% in the last 6 months.
$Bestseller_{i,t}$	Bestseller	The index certificate on the wikifolio has been purchased more often than sold within the last two weeks. Furthermore, it is amongst the 25 most highly purchased wikifolios on the platform during the past 14 days.
$Diversified_{i,t}$	Actively diversified	These types of wikifolios have invested in at least 10 different securities in the last 6 weeks, of which none comprise for more than one fifth of the portfolio value.
$Leveraged_{i,t}$	Trades leveraged products	The wikifolio can include structured products.

Table 3: Descriptive statistics Ayondo

Notes: Descriptive statistics of the Ayondo dataset consisting of 9,522 observations of 882 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains means and standard deviations (STD) of the variables. Min./Max. refer to the minimum/maximum values of the variables. The variables are defined in Table 1.

Variable	N	Min.	Mean	Max.	SD
$Return_{\mathrm{i,t}}$	9,365	−9.1311	−0.0840	7.0364	1.5544
$Benchmark_{\mathrm{i,t}}$	9,365	−0.0629	−0.0033	0.0477	0.0290
$Benchmark\_USD/EUR_{\mathrm{i,t}}$	9,365	−0.0289	−0.0007	0.0247	0.0134
$Benchmark\_DAX_{\mathrm{i,t}}$	9,365	−0.0623	0.0046	0.0606	0.0338
$Volatility_{\mathrm{i,t}}$	9,365	0.0107	2.1661	1,664.6800	24.6133
$Trades_{\mathrm{i,t}}$	9,365	0.0000	17.7368	839.0000	37.1474
$log(1 + Trades)_{\mathrm{i,t}}$	9,365	0.0000	2.0682	6.7334	1.2905
$Follower_{\mathrm{i,t}}$	9,365	0.0000	30.9247	2,165.0000	191.4300
$log(1 + Follower)_{\mathrm{i,t}}$	9,365	0.0000	0.9679	7.8876	1.5015
$Level_{\mathrm{i,t}}$	9,365	1.0000	1.6711	5.0000	1.0319
$MDD_{\mathrm{i,t}}$	9,365	0.0000	19.7061	99.8760	24.3581
$TWR_{\mathrm{i,t}}$	9,365	0.0000	0.6209	1.0000	0.3426
$Leverage_{\mathrm{i,t}}$	9,365	0.8000	23.5187	200.0000	37.8622
$Short_{\mathrm{i,t}}$	9,365	0.0000	0.4277	1.0000	0.3490
$HHI_{\mathrm{i,t}}$	9,365	0.0000	0.8982	1.0000	0.2023
$Experience_{\mathrm{i,t}}$	9,365	0.0000	1.7923	5.0000	2.2120

Table 4: Descriptive statistics Wikifolio

Notes: Descriptive statistics of the Wikifolio dataset consisting of 87,128 observations of 4,370 wikifolios of 2,670 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains means and standard deviations (STD) of the variables. Min./Max. refer to the minimum/maximum values of the variables. The variables are defined in Table 2.

Variable	N	Min.	Mean	Max.	SD
$Return_{i,t}$	87,031	−0.1903	−0.0012	0.1333	0.0396
$Benchmark_{i,t}$	87,031	−0.0643	−0.0007	0.0483	0.0279
$Benchmark\_DAX_{i,t}$	87,031	−0.0832	−0.0013	0.0467	0.0316
$Volatility_{i,t}$	87,031	0.0000	0.0206	7.1166	0.0709
$Trades_{i,t}$	87,031	0.0000	5.4017	1,265.0000	26.3591
$log(1 + Trades)_{i,t}$	87,031	0.0000	0.6110	7.1436	1.1750
$Net\,capital\,change_{i,t}$	87,031	−14,853.0000	110.9747	19,421.0000	3,014.0000
$WF\,points_{i,t}$	87,031	0.0000	317.3683	8,514.0000	690.5921
$Comments_{i,t}$	87,031	0.0000	43.8605	2,275.0000	109.1601

Table 5: Descriptive statistics of binary variables on Wikifolio

Notes: Descriptive statistics of the Wikifolio dataset consisting of 87,128 observations of 4,370 wikifolios of 2,670 signalers for the observation period from November 13th 2015 to May 20th 2016. This table contains absolute and relative frequencies of the binary variables. *Relative frequency of the variable *Leverage* refers to the overall dataset. The variables are defined in Table 2.

Variable	Obs.	Rel. Frequency
$Money\,manager_{i,t}$	8,307	9.53
$Loyal_{i,t}$	5,197	5.96
$Frequently_{i,t}$	4,665	5.35
$Heavy_{i,t}$	5,738	6.59
$Performance_{i,t}$	481	0.55
$Bestseller_{i,t}$	476	0.55
$Diversified_{i,t}$	34,499	39.60
$Leverage_{i,t}$	22,477	0.28*

Table 6: 2SLS regression of $Return_{i,t}$ on trading activity – Ayondo

Notes: This table presents the results of a two-stage least squares fixed effects regression estimating the relationship between $Return_{i,t}$ and trading activity ($(log(1+Trades)_{i,t}$), instrumented by a set of instrumental variables on Ayondo. $Return_{i,t}$ is winsorized at the 1% and 99% level. While model 1 uses dummy variables for the different *Levels*, model 2 utilizes *Level* as a continuous variable to measure the effect of rating on trading activity. Models 3 to 4 constitute robustness checks and focus on a subsample of active signalers who have been trading in the previous week. Models 5 to 6 and models 7 to 8 use USD/EUR returns and DAX returns respectively as market returns to investigate the robustness of the regression results. Table 1 provides detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered at the signaler level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	2	3	4	5	6	7	8
First stage regression: estimation of the endogenous variable $log(1+Trades)_{i,t}$								
$log(1+Follower)_{i,t-1}$	0.0618**	0.0624**	0.0504*	0.0512**	0.0618**	0.0624**	0.0618**	0.0624**
	(0.0276)	(0.0258)	(0.0278)	(0.0258)	(0.0276)	(0.0258)	(0.0276)	(0.0258)
$Level\_2_{i,t-1}$	0.0852		0.0670		0.0852		0.0852	
	(0.0566)		(0.0579)		(0.0566)		(0.0566)	
$Level\_3_{i,t-1}$	0.170**		0.142		0.170**		0.170**	
	(0.0855)		(0.0894)		(0.0855)		(0.0855)	
$Level\_4_{i,t-1}$	0.225*		0.240*		0.225*		0.225*	
	(0.122)		(0.127)		(0.122)		(0.122)	
$Level\_5_{i,t-1}$	0.170		0.177		0.170		0.170	
	(0.235)		(0.202)		(0.235)		(0.235)	
$Level_{i,t-1}$		0.0779**		0.0713*		0.0779**		0.0779**
		(0.0373)		(0.0390)		(0.0373)		(0.0373)
$MDD_{i,t-1}$	−0.016***	−0.016***	−0.015***	−0.015***	−0.016***	−0.016***	−0.016***	−0.016***
	(0.0029)	(0.0029)	(0.0030)	(0.0030)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
$TWR_{i,t-1}$	0.368***	0.368***	0.375***	0.375***	0.368***	0.368***	0.368***	0.368***
	(0.0412)	(0.0412)	(0.0465)	(0.0464)	(0.0412)	(0.0412)	(0.0412)	(0.0412)
$Experience_{i,t-1}$	−0.0004	−0.0005	−0.0003	−0.0003	−0.0004	−0.0005	−0.0004	−0.0005
	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
$Benchmark_{i,t-1}$	−0.501	−0.492	−0.515	−0.510				
	(1.683)	(1.684)	(1.787)	(1.789)				
$Benchmark\_USD/EUR_{i,t-1}$					−5.101	−5.008		
					(17.13)	(17.14)		
$Benchmark\_DAX_{i,t-1}$							−1.166	−1.144
							(3.915)	(3.916)
$Volatility_{i,t-1}$	−0.0004	−0.0005	−0.0001	−0.0001	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
$Return_{i,t-1}$	0.0107*	0.0106*	0.0104	0.0104	0.0107*	0.0106*	0.0107*	0.0106*
	(0.0062)	(0.0062)	(0.0064)	(0.0064)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
$Leverage_{i,t-1}$	0.0013	0.0013	0.0007	0.0008	0.0013	0.0013	0.0013	0.0013
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
$Short_{i,t-1}$	0.0193	0.0186	−0.0226	−0.0239	0.0193	0.0186	0.0193	0.0186
	(0.0356)	(0.0357)	(0.0406)	(0.0407)	(0.0356)	(0.0357)	(0.0356)	(0.0357)
$HHI_{i,t-1}$	−0.483***	−0.482***	−0.429***	−0.430***	−0.483***	−0.482***	−0.483***	−0.482***
	(0.0758)	(0.0759)	(0.0751)	(0.0750)	(0.0758)	(0.0759)	(0.0758)	(0.0759)
Week dummy	yes	yes	yes	yes	yes	yes	yes	yes
Second stage regression: estimation of the exogenous variable $Return_{i,t}$ with $log(1+Trades)_{i,t}$ instrumented								
$log(1+Trades)_{i,t}$	−0.806***	−0.806***	−0.801***	−0.796***	−0.806***	−0.806***	−0.806***	−0.806***
	(0.131)	(0.132)	(0.149)	(0.150)	(0.131)	(0.132)	(0.131)	(0.132)
$Benchmark_{i,t-1}$	−4.574	−4.574	−4.335	−4.331				
	(2.830)	(2.830)	(3.063)	(3.059)				
$Benchmark\_USD/EUR_{i,t-1}$					−46.56	−46.56		
					(28.80)	(28.81)		
$Benchmark\_DAX_{i,t-1}$							−10.64	−10.64
							(6.581)	(6.582)
$Volatility_{i,t-1}$	−0.0002	−0.0002	-9.95×10^{-5}	-9.90×10^{-5}	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Return_{i,t-1}$	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***	−0.081***
	(0.0138)	(0.0138)	(0.0147)	(0.0147)	(0.0138)	(0.0138)	(0.0138)	(0.0138)
$Leverage_{i,t-1}$	0.0025	0.0025	0.0018	0.0018	0.0025	0.0025	0.0025	0.0025
	(0.0019)	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
$Short_{i,t-1}$	0.0074	0.0074	−0.0003	−0.0002	0.0074	0.0074	0.0074	0.0074
	(0.0615)	(0.0615)	(0.0700)	(0.0700)	(0.0615)	(0.0615)	(0.0615)	(0.0615)
$HHI_{i,t-1}$	−0.438***	−0.439***	−0.424***	−0.422***	−0.438***	−0.439***	−0.438***	−0.439***
	(0.138)	(0.138)	(0.145)	(0.145)	(0.138)	(0.138)	(0.138)	(0.138)
Week dummy	yes	yes	yes	yes	yes	yes	yes	yes
Hansen J statistic	5.39	3.65	8.03	6.49	5.39	3.65	5.39	3.65
$p-value$	0.61	0.45	0.33	0.17	0.61	0.45	0.61	0.46
Endogeneity test	51.77	48.57	39.89	35.87	51.77	48.57	51.77	48.57
$p-value$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	9,365	9,365	8,327	8,327	9,365	9,365	9,365	9,365
Number of signalers	882	882	810	810	882	882	882	882

Table 7: 2SLS regression of $Return_{i,t}$ on trading activity – Wikifolio

Notes: This table presents the results of a two-stage least squares fixed effects regression estimating the relationship between $Return_{i,t}$ and trading activity ($log(1 + Trades)_{i,t}$), instrumented by a set of instrumental variables on Wikifolio. $Return_{i,t}$ is winsorized at the 1% and 99% level and $Net\,capital\,change_{i,t}$ is calculated following Sirri and Tufano (1998). Model 1 represents the core model and is extended by additional social interaction variables in model 2. Models 3 to 4 and models 5 to 6 constitute robustness checks and focus on a subsample of wikifolios trading leveraged products and a subsample of active traders who have been trading in the previous week, respectively. Models 7 to 8 use DAX returns as market return to investigate the robustness of the regression results. Table 2 provides detailed descriptions of all variables used throughout the study. The standard errors (in parentheses) are clustered at the signaler level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	1	2	3	4	5	6	7	8
First stage regression: estimation of the endogenous variable $log(1+Trades)_{i,t}$								
$Net\,capital\,change_{i,t-1}$	6.70×10^{-6}***	6.66×10^{-6}***	1.04×10^{-5}***	1.03×10^{-5}***	8.20×10^{-6}***	8.15×10^{-6}***	6.70×10^{-6}***	6.66×10^{-6}***
	(1.23×10^{-6})	(1.23×10^{-6})	(2.13×10^{-6})	(2.12×10^{-6})	(1.80×10^{-6})	(1.79×10^{-6})	(1.23×10^{-6})	(1.23×10^{-6})
$WF\,points_{i,t-1}$	5.00×10^{-5}***	5.05×10^{-5}***	0.0001***	0.0001***	6.14×10^{-5}***	6.21×10^{-5}***	5.00×10^{-5}***	5.05×10^{-5}***
	(1.19×10^{-5})	(1.19×10^{-5})	(3.08×10^{-5})	(3.13×10^{-5})	(1.98×10^{-5})	(1.98×10^{-5})	(1.19×10^{-5})	(1.19×10^{-5})
$Money\,manager_{i,t-1}$	0.0650**	0.0641**	0.113	0.112	0.0738	0.0742	0.0650**	0.0641**
	(0.0271)	(0.0271)	(0.0715)	(0.0708)	(0.0581)	(0.0583)	(0.0271)	(0.0271)
$Loyal_{i,t-1}$		0.0996*		0.157		0.0009		0.0996*
		(0.0604)		(0.0968)		(0.0751)		(0.0604)
$Frequently_{i,t-1}$		−0.0896		−0.168		−0.0408		−0.0896
		(0.110)		(0.181)		(0.131)		(0.110)
$Benchmark_{i,t-1}$	−3.280***	−3.275***	−5.044***	−5.029***	−9.127***	−9.122***		
	(0.725)	(0.725)	(1.515)	(1.516)	(2.902)	(2.902)		
$Benchmark\_DAX_{i,t-1}$							0.224	0.212
							(1.707)	(1.707)
$Volatility_{i,t-1}$	−0.0543	−0.0552	−0.0610	−0.0625	−0.0934	−0.0933	−0.0543	−0.0552
	(0.0458)	(0.0455)	(0.0472)	(0.0468)	(0.0714)	(0.0712)	(0.0458)	(0.0455)
$Return_{i,t-1}$	−0.197*	−0.196*	−0.145	−0.143	0.150	0.147	−0.197*	−0.196*
	(0.110)	(0.110)	(0.159)	(0.159)	(0.222)	(0.222)	(0.110)	(0.110)
$Comments_{i,t}$	0.0008	0.0008	-6.84×10^{-5}	-1.53×10^{-5}	0.0007	0.0007	0.0008	0.0008
	(0.0008)	(0.0008)	(0.0013)	(0.0013)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
$Heavy_{i,t-1}$	0.256***	0.256***	0.293***	0.294***	0.0539	0.0544	0.256***	0.256***
	(0.0387)	(0.0386)	(0.0536)	(0.0532)	(0.0535)	(0.0535)	(0.0387)	(0.0386)
$Performance_{i,t-1}$	0.377***	0.373***	0.427***	0.416***	0.352***	0.350***	0.377***	0.373***
	(0.0807)	(0.0797)	(0.110)	(0.107)	(0.105)	(0.104)	(0.0807)	(0.0797)
$Bestseller_{i,t-1}$	0.107	0.0987	0.115	0.104	0.117	0.126	0.107	0.0987
	(0.0891)	(0.0878)	(0.146)	(0.149)	(0.112)	(0.112)	(0.0891)	(0.0878)
$Diversified_{i,t-1}$	0.0135	0.0137	0.0535	0.0547	0.0440	0.0442	0.0135	0.0137
	(0.0233)	(0.0233)	(0.0490)	(0.0490)	(0.0531)	(0.0531)	(0.0233)	(0.0233)
$Week\,dummy$	yes	yes	yes	yes	yes	yes	yes	yes
Second stage regression: estimation of the exogenous variable $Return_{i,t}$ with $log(1+Trades)_{i,t}$ instrumented								
$log(1+Trades)_{i,t}$	−0.0366***	−0.0320***	−0.0339***	−0.0266***	−0.0274***	−0.0256***	−0.0366***	−0.0320***
	(0.0070)	(0.0070)	(0.0089)	(0.0091)	(0.0088)	(0.0086)	(0.0070)	(0.0070)
$Benchmark_{i,t-1}$	0.496***	0.511***	0.222*	0.260**	−0.250	−0.234		
	(0.0478)	(0.0460)	(0.119)	(0.116)	(0.179)	(0.175)		
$Benchmark\_DAX_{i,t-1}$							0.262***	0.262***
							(0.102)	(0.0980)
$Volatility_{i,t-1}$	−0.0059	−0.0056	−0.0072	−0.0067	−0.0011	−0.0009	−0.0059	−0.0056
	(0.0053)	(0.0052)	(0.0055)	(0.0053)	(0.0035)	(0.0034)	(0.0053)	(0.0052)
$Return_{i,t-1}$	0.0256***	0.0270***	0.0159	0.0181	0.00198	0.00202	0.0255***	0.0269***
	(0.0100	(0.0098)	(0.0147)	(0.0142)	(0.0207)	(0.0206)	(0.0100)	(0.0098)
$Comments_{i,t}$	-3.33×10^{-5}	-3.83×10^{-5}	-9.28×10^{-5}	-9.57×10^{-5}*	-4.18×10^{-5}	-4.36×10^{-5}	-3.31×10^{-5}	-3.82×10^{-5}
	(3.62×10^{-5})	(3.33×10^{-5})	(6.31×10^{-5})	(5.60×10^{-5})	(3.79×10^{-5})	(3.67×10^{-5})	(3.62×10^{-5})	(3.33×10^{-5})
$Heavy_{i,t-1}$	0.0084***	0.0072***	0.0103**	0.0082**	0.0013	0.0012	0.0083***	0.0072***
	(0.0027)	(0.0027)	(0.0041)	(0.0041)	(0.0026)	(0.0026)	(0.0027)	(0.0027)
$Performance_{i,t-1}$	−0.0016	−0.0034	0.0035	1.59×10^{-5}	−0.0006	−0.0013	−0.0016	−0.0034
	(0.0061)	(0.0058)	(0.0082)	(0.0078)	(0.0080)	(0.0078)	(0.0061)	(0.0058)
$Bestseller_{i,t-1}$	−0.0077	−0.0086*	−0.0179**	−0.0196**	−0.0142*	−0.0147*	−0.0077	−0.0086*
	(0.0052)	(0.0050)	(0.0091)	(0.0089)	(0.0076)	(0.0076)	(0.0052)	(0.0050)
$Diversified_{i,t-1}$	0.0005	0.0005	0.0021	0.0017	0.0014	0.0014	0.0005	0.0005
	(0.0010)	(0.0009)	(0.0020)	(0.0018)	(0.0020)	(0.0020)	(0.0010)	(0.0009)
$Week\,dummy$	yes	yes	yes	yes	yes	yes	yes	yes
Hansen J statistic	1.80	7.24	0.42	6.89	1.52	3.09	1.80	7.22
$p-value$	0.41	0.12	0.81	0.14	0.47	0.54	0.41	0.12
Endogeneity test	106.35	100.37	28.99	24.96	22.09	22.41	106.13	100.19
$p-value$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	87,031	87,031	22,435	22,435	13,097	13,097	87,031	87,031
Number of wikifolios	4,370	4,370	1,181	1,181	1,461	1,461	4,370	4,370
Number of signalers	2,670	2,670	970	970	1,144	1,144	2,670	2,670

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