# Competition for Visibility: When do (FX) Signal Providers employ Lotteries?

**Julian Schneider[a*] and Andreas Oehler[b]**

*This version: May 2021*

**Abstract**
We argue that certain currency pairs, similar to stocks, are perceived and employed as gambling opportunities. We define currency pairs with extreme positive daily returns as lotteries. By analyzing data from a popular foreign exchange focused social trading platform, we provide empirical evidence of a U-shaped relationship between previous relative trader performance and the traded lottery share: Traders with bad performance and traders with good performance, in comparison to their peers, are more prone to gamble, i.e. trade a higher monthly share of lotteries. Regarding both sides of the relative performance spectrum, we link our results to well-documented behavioral phenomena. Furthermore, we relate our results to remuneration design features common to social trading, where only outperformers gain visibility and may become eligible for receiving compensation form the platform vendor. In consequence, especially signal providers at the lower end of the performance spectrum are incentivised to gamble; after (repeatedly) performing poorly, traders might be willing to take gambles for a small chance to get a declining account back on track.

JEL Classification: G11, G40, G41

Key Words: Foreign Exchange Trading, Gambling, Social Trading

[a] Department of Finance, Bamberg University, Bamberg, Germany.
[b] Full Professor and Chair of Finance, Bamberg University, Bamberg, Germany.
* Address correspondence to Julian Schneider, Chair of Finance, Bamberg University, Kaerntenstrasse 7, 96052 Bamberg, Phone: (+49) 951-863-2686, Fax: (+49) 951-863-2538, e-mail: julian.schneider@uni-bamberg.de.
All remaining errors are our own.

# Competition for Visibility: When do (FX) Signal Providers employ Lotteries?

**Abstract**
We argue that certain currency pairs, similar to stocks, are perceived and employed as gambling opportunities. We define currency pairs with extreme positive daily returns as lotteries. By analyzing data from a popular foreign exchange focused social trading platform, we provide empirical evidence of a U-shaped relationship between previous relative trader performance and the traded lottery share: Traders with bad performance and traders with good performance, in comparison to their peers, are more prone to gamble, i.e. trade a higher monthly share of lotteries. Regarding both sides of the relative performance spectrum, we link our results to well-documented behavioral phenomena. Furthermore, we relate our results to remuneration design features common to social trading, where only outperformers gain visibility and may become eligible for receiving compensation form the platform vendor. In consequence, especially signal providers at the lower end of the performance spectrum are incentivised to gamble; after (repeatedly) performing poorly, traders might be willing to take gambles for a small chance to get a declining account back on track.

JEL Classification: G11, G12

Key Words: Foreign Exchange Trading, Gambling, Social Trading

## *1 Introduction*

On social trading platforms individual traders (so-called signal providers) publish their investment decisions as well as their corresponding returns – based on this information, individual investors (so-called signal followers) can choose to copy their trading signals[1] (Oehler, Horn, & Wendt, 2016). As there are no specific qualification requirements to become a signal provider, it is very simple to open an account. In addition, most platform vendors enable signal providers to simultaneously operate several accounts which may easily be closed and replaced. Regarding the publication of trading signals, signal providers may choose to trade with virtual money, hence conducted transactions are not executed within real-world signal provider portfolios, i.e. signal providers are not directly exposed to their generated profits and losses.[2]

In the context of social trading, Pelster and Breitmayer (2019) argue that signal providers receiving attention (from signal followers) increase their trading activity due to increased levels of excitement (Taffler, 2018). Nevertheless, it seems reasonable to assume that most signal providers (at least partly) establish and continue operating their social trading accounts with the intention to generate income by receiving remuneration from the social trading platform. When assuming that signal providers try to maximize remuneration, social trading platforms, by default, create a certain incentive structure: In order to get access to remuneration, signal providers need to build a sufficient base of signal followers. To attract the attention of such followers, signal providers need to become visible, i.e. obtain a top position on the platform composed selection lists. As almost all sorting criteria incorporate relative performance (see *Section 3.4*), signal providers need to yield results which are superior to the majority of their peers. Considering the limited capacity of private investors (signal followers) to perceive and process information, signal providers have to compete for visibility. In this regard, social trading platforms indirectly impose tournament incentives (Kirchler, Linder, & Weitzel, 2018) as a certain ranking is required to attract the attention of potential followers which, in turn, is a prerequisite for receiving compensation.

The competition for visibility established by social trading frameworks may induce behavioral patterns among signal providers which aim at catapulting a corresponding account to the top of the lists presented to signal followers. In this context, we assess the factors which induce signal providers to gamble. Focusing on relative performance measures, we analyze when signal providers tend to trade lotteries, i.e. speculate on the small probability to generate a major return.[3]

---

[1] Depending on the social trading platform, copying signals may relate to replicating signal provider returns via exchange-traded certificates (e.g. *wikifolio*; *www.wikifolio.com*) or replicating trades via automatic order execution (e.g. *ZuluTrade*; *www.ZuluTrade.com*).

[2] On the *ZuluTrade* platform signal providers can choose whether they want to trade with virtual money (referred to as *Demo* accounts), or actually execute the trades corresponding to their published signals via an online broker (referred to as *Live* or *Real* accounts). With regard to the *wikifolio* platform, signal providers trade with virtual money by default.

[3] In foreign exchange trading, the employed leverage – and thus the corresponding risk – can be set for each transaction individually. However, when deciding to copy a signal provider, signal followers individually chose the leverage which is

Within the present paper, we focus on *ZuluTrade*, an international social trading platform primarily offering foreign exchange trading. As the foreign exchange market offers substantially fewer feasible choices in comparison to international equity markets, signal providers may be able to assess the full range of available investment opportunities. The selection range of a foreign exchange focused social trading platform is unlikely to stress the cognitive capacity of traders, therefore gambling opportunities, i.e. investments involving lottery-like payoffs (Bali et al., 2011; Kumar, 2009), may be easily identified.

In addition, due to the complex nature of currency price developments, we argue that the foreign exchange market exhibits particularly speculative qualities which offer a convenient framework for gambling.

Motivated by Bali et al.'s (2011) approach, we define lottery currency pairs using extreme daily exchange rate price movements. Applying a comprehensive dataset comprising signal provider trading data from the *ZuluTrade* social trading platform, we provide empirical evidence for a quadratic relationship between relative signal provider performance and the traded share of lotteries. Our results suggest that signal providers with comparatively good and signal providers with comparatively bad past performance trade a higher share of lottery currency pairs. The results are robust to several applied performance measures as well as the respective definition of lottery-like currency pairs.

We link results to previous research in behavioral finance. Assessing absolute gains and losses (rather than relative performance), Thaler and Johnson (1990) describe a similar behavioral pattern labeled as the *break-even effect*. The *break-even effect* states that, in the presence of prior losses, individuals are willing to accept gambles, especially when presented with the opportunity to entirely make up for incurred losses. We argue that after exhibiting poor performance in comparison to their peers, signal providers might be induced to take gambles. Underperforming accounts are unlikely to generate (or maintain) followers. As followers are needed to be eligible for compensation, signal providers might employ lotteries, speculating on an unlikely, but nonetheless possible, large gain which will bring the account back on track.

At the other side of the spectrum, signal providers with relatively good past performance are subject to different mechanisms. Signal providers managing accounts outperforming peers face a substantial downside. When the performance of an account with a sound track record deteriorates, signal followers are likely to cease the relationship. As followers are mandatory in order to receive funds from the platform, signal providers may lose their eligibility for remuneration when entered gambles fail.

---

used to copy corresponding published signals. As the profit generated for signal followers is one of the main performance measures and consequently sorting criteria for signal providers, engaging in a lottery transaction has a different effect than simply increasing leverage.

Yet, there are factors which may induce signal providers to enter lottery trades when a corresponding account has outperformed its peers. The increased share of traded lotteries by good performing signal providers may be related to the well-documented connection between overconfidence and risk taking (Barber & Odean, 2001; Broihanne, Merli, & Roger, 2014; De Long, Shleifer, Summers, & Waldmann, 1991; Odean, 1999). In the context of social trading, Czaja and Röder (2020) provide evidence for overconfidence due to biased self-enhancement. When experiencing a surge in overconfidence caused by good relative past performance (Gervais & Odean, 2001; Odean, 1999; Statman, Thorley, & Vorkink, 2006), signal providers might be inclined to take more risk and thus trade lotteries more frequently.

Pelster and Breitmayer (2019) provide evidence that signal providers receiving attention from peers – attention being in turn triggered by past performance – increase their risk appetite. Outperforming peers builds up a signal provider's follower base, i.e. increases the attention received by followers. Hence, the increased share of traded lotteries may be related to the attention-driven surge in signal provider risk appetite.

Finally, the set-up of the social trading platform's compensation scheme may impact the lottery trading behavior of signal providers at the upper end of the relative performance spectrum. As established, signal providers must first outperform their peers in order to attract followers and, subsequently, generate profits with issued trading signals in order to receive compensation from the social trading platform. After a desirable follower base has been built through outperforming peers, the direct appeal of receiving compensation might motivate signal providers to invest a proportion of their funds in lotteries. When compensation seems within reach, lottery return characteristics, particularly positive skewness, may appear explicitly appealing.

Our study makes several contributions to the existing literature. First, we add to the growing research on financial market gambling by arguing that certain currency pairs may be perceived and employed as lotteries. Second, we link behavioral patterns in social trading to existing research in behavioral finance and add to a more comprehensive understanding of motives and aggregated outcomes in an information rich and interactive digital environment – previously labeled as scopic regime (Gemayel & Preda, 2018a, 2018b). Finally, we provide insights on how design features common to social trading may induce signal providers to gamble which, in turn, triggers gambling for signal followers. Signal followers should be conscious of those effects to appropriately assess the risk associated with investments in social trading. Platform operators should carefully consider potential incentives – and consequential behavioral modifications – when introducing or adjusting design features.

The rest of the paper is structured as follows. In *Section 2* we provide a short review on literature concerning gambling on financial markets, social trading, and associated relevant behavioral phenomena. *Section 3* describes the employed data and the applied methodological approach.

Subsequently, in *Section 4* we present and discuss our obtained results. In *Section 5* we conduct and describe robustness tests regarding our main results. *Section 6* concludes.

## *2 Literature Review*

So far, research on gambling on financial markets focuses on stocks (Bali et al., 2011; Kumar, 2009) and options (Félix, Kräussl, & Stork, 2019). Currency pairs have, to our knowledge, not been directly assessed as potential gambling opportunities. Due to the speculative nature of foreign exchange trading, analyzing gambling behavior with regard to currency pairs may be particularly interesting.

Regarding neoclassical finance theory, where risk is the only factor that is priced (Sharpe, 1964) and informational advantages are (almost) non-existent (Fama, 1970), the only reason for individuals to buy an asset is to include its particular risk into their portfolios. However, the behavior of real-world investors has been shown to differ substantially from what is predicted by neoclassical models (Oehler, 1995; Thaler, 2016, 2018). As individuals are subject to hardly controllable factors like personality characteristics (Oehler, Wendt, Wedlich, & Horn, 2018), emotions (Taffler, 2018), risk perception (Oehler & Wedlich, 2018), and varying degrees of financial literacy (Oehler, Horn, Wendt, Reisch, & Walker, 2018), as well as limited capabilities to perceive and process information (Kahneman, 1973), neoclassical finance is a useful benchmark for – and not an exact image of – reality. Taking a more behavioral approach (Hirshleifer, 2015; Statman, 2014; Thaler, 2016, 2018), investors may buy assets – in particularly stocks – because they believe in a corresponding company's business model and speculate on a favorable future price development. In the context of foreign exchange trading, the economic rationale to buy and sell currency pairs is a lot more complex (Allen & Taylor, 1990) and may be very difficult to comprehend for non-professional investors. Furthermore, in comparison to international equity markets, foreign exchange trading comprises a rather limited selection of investment opportunities. Considering those factors, analyzing investor behavior regarding currency pairs with extreme daily returns – in the present paper, following Bali et al. (2011), defined as lotteries – promises to add a novel component to existing literature on financial market gambling.

In social trading, all transactions conducted by signal providers, as well as the resulting profits and losses, can be retrace by all other platform users Oehler et al. (2016). Thus, social trading offers a population of majorily private traders to publicly display their investing abilities, a feature formerly reserved to professional asset managers. Given its transparent nature and the almost non-existing requirements for private individuals to become signal providers, social trading offers a convenient frameworkt for studying foreign exchange gambling behavior.

Social trading signal providers compete for visibility which, in turn, enables them to build a follower base (Pelster & Breitmayer, 2019; Röder & Walter, 2019). By convincing signal followers to copy their transactions, signal providers become eligible for compensation. The peculiarities of a social trading platform's corresponding compensation scheme are likely to have a substantial impact on signal provider behavior.

Serval behavioral phenomena have been assessed within the innovative and transparent framework established by social trading. Oehler et al. (2016) argue that signal followers display herding behavior by using social trading as an investment alternative. Followingly, Gemayel and Preda (2018b) provide evidence that excess and perpetual herding behavior is produced through the framework of social trading. Glaser and Risius (2018), Pelster and Hofmann (2018) and Gemayel and Preda (2018a) assess the disposition effect (Shefrin & Statman, 1985) with regard to signal providers on social trading platforms. There is empirical evidence that the disposition effect increases with the number of signal followers tailing a signal provider (Pelster & Hofmann, 2018) as well as the respective entrusted capital (Glaser & Risius, 2018), i.e. attention and visibility impact trading behavior. On the other hand, Gemayel and Preda (2018a) argue that signal providers exhibit a weaker disposition effect compared to traders in a traditional setting. Further evidence for the relation between visibility and trading behavior is provided by Pelster and Breitmayer (2019), who suggest that signal providers receiving attention from peers exhibit a surge in trading activity and are more prone to take risks. Overconfidence – a behavioral phenomenon which has been shown to have a major impact on investor decisions (Barber & Odean, 2001; Odean, 1998, 1999) – is assessed by Czaja and Röder (2020) with regard to signal providers in social trading. In their analysis, Czaja and Röder (2020) provide empirical evidence that signal providers in social trading become overconfident through biased self-enhancement.[4]

Motivated by the particular incentive structures in social trading, as well as by the already documented behavioral patterns (Glaser & Risius, 2018), we assess the factors which induce signal providers to trade lotteries. It is well-established that individuals make decisions with regard to a reference point (Thaler, 2016, 2018; Tversky & Kahneman, 1974). Regarding the transparent framework established by social trading, the low entrance barriers for traders, and the resulting competition for visibility, relative past signal provider performance may potentially have a major impact on trading decisions. Hence, within our analysis, we we focus on a variety of relative past performance measures as corresponding explanatory variables.

[4] Further research on social trading is provided by Berger, Wenzel, and Wohlgemuth (2018), Dorfleitner et al. (2018), Jin, Zhu, and Huang (2019), Kromidha and Li (2019), Lambert, Ostrovsky, and Panov (2018), Lee and Ma (2018), Reith, Fischer, and Lis (2019), and Wohlgemuth, Berger, and Wenzel (2016).

### *3 Data and Methodology*

*3.1 ZuluTrade Platform and Signal Provider Data*

Transaction data is directly obtained from the *ZuluTrade* platform. Data for all accounts that can be grasped via the platform's search function is collected. This approach leads to a substantial survivorship bias as accounts which can no longer be found by using the platform's search function – indicating abandonment or inactivity – are not included in the dataset. Each account's front page, however, displays all further accounts that have been operated by the corresponding signal provider, even after trading activity has ceased. Data on individual accounts may be downloaded even if the account no longer appears when using the search function. We go through all obtained accounts in our dataset, gathering information on which accounts correspond to one signal provider. Furthermore, accounts which had not been collected via the search function in the initial download, are added to the dataset. After dropping accounts with insufficient data (activity for less than six months and less than 20 transactions), the resulting dataset contains 3,936 accounts which correspond to 2,652 signal providers. In total, 5,048,626 round trips (or 10,097,252 single trades) are considered. The first transactions are conducted as early as October 2008. We include data until the end of January 2021 for the following analyses.[5]

As data for accounts corresponding to signal providers which are now longer active on the platform is not available, survivorship bias has been reduced but could not be erased. It is reasonable to assume that there are numerous signal providers who have completely disappeared from the platform. As there is no apparent reason for signal providers to cease activities when exhibiting good performance in comparison to their peers, these traders had likely been located at the lower end of the performance spectrum, at least towards the end of their involvement. This is further addressed when discussing the empirical results in *Section 4*.

Signal followers on the *ZuluTrade* platform can choose between operating a *Demo* account, or a *Real* (or *Live*) account. *Demo* accounts are purely virtual, their objective is to simulate signal follower investments and resulting returns under realistic conditions without using real capital. Signal followers can choose from a wide spectrum of signal provider accounts[6]; signal provider trading performance (including the entire transaction history) is accessible on the *ZuluTrade* platform. In addition, signal followers can perform manual trades. When using a *Real* account, all transactions – initiated by tailed signal providers or manually conducted by the respective signal follower – are executed via a preselected broker account linked to the *ZuluTrade* platform.

---

[5] Signal provider trading data is provided in the form of completed round trips, i.e. opening and closing information for each distinct position – including relevant profitability indicators – are jointly issued. In the following, we use the term trade to refer to a singular action, i.e. the opening or closing of a position.

[6] In addition to single signal provider tailing, *ZuluTrade* offers so-called *Trader Combos*, i.e. preselected copy-trading portfolios intended to facilitate the diversification process.

Similarly, as in the case of signal followers, signal providers are asked to choose between a *Real* and a *Demo* account; both account types are eligible for signal follower copying and may create revenue for the corresponding signal provider. When creating an account, signal providers must select a trading platform. *ZuluTrade*'s in-house trading platform is labeled *ZuluTrade+*, which provides platform users with a trading station interface including technical charts as well as a variety of trading indicators.[7] The *ZuluTrade+* platform enables signal providers to engage in algorithmic trading via an integrated coding application called *ZuluScripts*. In addition, via the *ZuluTrading API* (Application Programming Interface), signal providers may submit trading requests by using their own custom programs.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Round Trips:*** | 5,048,626 | | | | | | | | | |
| ***Trades:*** | 10,097,252 | | | | | | | | | |
| ***Accounts:*** | 3,936 | | | | | | | | | |
| ***Traders:*** | 2,652 | | | | | | | | | |
| | $D1$ | $D2$ | $D3$ | $D4$ | $D5$ | $D6$ | $D7$ | $D8$ | $D9$ | $D10$ |
| ***Round Trips*** | | | | | | | | | | |
| Total by account | 59.53 | 133.53 | 212.06 | 314.13 | 454.76 | 641.92 | 901.83 | 1,229.87 | 2,103.78 | 6,720.13 |
| ***Trades*** | | | | | | | | | | |
| Total by account | 119.07 | 267.06 | 424.13 | 628.27 | 909.53 | 1,283.84 | 1,803.66 | 2,599.71 | 4,207.57 | 13,440.26 |
| Ø by account / month | 12.26 | 24.81 | 37.03 | 49.62 | 65.54 | 85.32 | 114.32 | 158.42 | 237.72 | 682.82 |
| ***Holding Period in Hours*** | | | | | | | | | | |
| All round trips | .12 | .59 | 1.43 | 2.98 | 5.85 | 11.81 | 22.75 | 53.35 | 123.72 | 821.62 |
| Ø by account | 5.86 | 16.99 | 29.02 | 43.94 | 60.87 | 83.82 | 114.53 | 161.29 | 258.31 | 691.52 |
| ***Standard Lots*** | | | | | | | | | | |
| All round trips | .01 | .01 | .01 | .02 | .05 | .10 | .85 | .85 | .85 | 1,008.15 |
| Ø by account | .01 | .01 | .02 | .05 | .09 | .14 | .32 | .77 | 1.07 | 3,045.40 |
| ***Account Age in Days*** | | | | | | | | | | |
| Ø account age | 156.15 | 192.71 | 235.26 | 287.16 | 352.77 | 468.25 | 620.12 | 863.45 | 1,327.52 | 2,250.20 |
| ***Win Ratio*** | | | | | | | | | | |
| Total by account | .40 | .54 | .61 | .67 | .71 | .76 | .80 | .85 | .90 | .96 |
| ***Profit*** | | | | | | | | | | |
| All round trips | -12,581.66 | -11.99 | -.60 | .56 | 1.49 | 3.52 | 9.13 | 34.06 | 149.32 | 17,565.90 |
| Total by account | -6,158.39 | -592.12 | -16.39 | 57.12 | 359.94 | 1,263.52 | 2,673.38 | 11,566.58 | 22,510.13 | 150,524.30 |
| Ø by account / round trip | -1,534.87 | -3.34 | -.22 | .37 | 1.10 | 2.58 | 6.69 | 20.82 | 72.41 | 23,015.19 |
| Ø by account / month | -2,668.47 | -15.38 | -2.04 | -.05 | .91 | 2.54 | 6.65 | 21.11 | 81.73 | 19,330.81 |
| ***Profit Pips*** | | | | | | | | | | |
| All round trips | -351.24 | -26.23 | -1.58 | 3.89 | 7.43 | 11.85 | 18.98 | 30.64 | 55.87 | 456.72 |
| Total by account | -903.50 | 91.50 | 699.50 | 1,146.70 | 2,468.30 | 3,987.30 | 8,212.20 | 10935.40 | 23,930.10 | 673,088.80 |
| Ø by account / round trip | -42.61 | .50 | 1.91 | 3.63 | 6.01 | 9.10 | 14.05 | 22.53 | 43.04 | 266.91 |
| Ø by account / month | -101.98 | -11.45 | -1.24 | 2.12 | 5.07 | 9.10 | 15.97 | 27.49 | 53.05 | 334.48 |

**Table°I: Signal Provider Trading Data**

*Notes:* The table above displays summary statistics regarding signal provider trading data on the *ZuluTrade* platform, covering a period from October 2008 to January 2021. The data is listed according to deciles ($D1$ to $D10$). The term round trip refers to completed transactions (opening and closing of one position). The term trader refers to a social trading signal provider on the *ZuluTrade* platform. It is important to note that one signal provider may operate several signal provider accounts.

When deciding to follow a signal provider, signal followers have to make certain decisions regarding the execution of copied trades within their account. In this context, the amount the signal follower is

[7] As an alternative to *ZuluTrade+*, signal providers may link their account to an external *MetaTrader 4* (*MT4*) platform – followingly, all trades executed in the *MT4* account are copied to the corresponding *ZuluTrade* account.

willing to entrust to the signal provider, i.e. the funds which are used to execute the tailed trades, is selected. For the execution of trading signals, signal providers can choose between *Fixed* (each trade is executed using a selected lot number / size) and *Pro-Rata* (each trade is executed proportionally using a selected percentage). Furthermore, signal providers can recommend default options which signal followers may select to copy all trades with 1 micro lot (*Fixed*) / a 100 percent ratio (*Pro-Rata*) and a leverage of 100:1. Those preset amounts are adjusted in accordance with the *Indicative Leverage*[8] ratio chosen by each signal follower when creating a *ZuluTrade* account.

Summary statistics regarding signal provider trading data are displayed in Table°I.

*3.2 Traded Currency Pairs and Assets*

In comparison to other social trading platforms where signal providers can choose from a large variety of tradable assets, the selection on *ZuluTrade* is rather limited. Taking into account all traded assets in the dataset obtained from the *ZuluTrade* platform leads to a compilation of 86 (regular) currency pairs, six currency pairs where the base currency is a crypto currency, six currency pairs where base and quote currency are crypto currencies, ten commodities (traded in USD or EUR), 15 indices, 19 stocks, and one future (traded in EUR). All traded assets, as well as the corresponding number of transactions (round trips), are displayed in the appendix in Table°A.

Currency pairs where no crypto currency is involved make up for 94.84 percent of all round trips. The single most traded currency pair is EUR/USD, accounting for 28.41 percent of all currency transactions. The next most frequently traded currency pairs are GBP/USD, GBP/JPY, USD/JPY, and USD/CAD, which respectively make up for 13.81 percent, 6.59 percent, 5.38 percent, and 4.69 percent of all currency transactions in the composed dataset.[9]

As previously mentioned, *ZuluTrade* platform users operating *Real* (or *Live*) accounts have to select a broker to carry out their orders. Depending on the broker, currency pairs may be traded via the interbank market (straight-through processing or no dealing desk execution model), or via CFDs directly issued by the corresponding broker. All other assets, including crypto currencies, are traded via CFDs.

Each currency pair and each asset can be bought or sold, i.e. it is possible to take a long as well as a short position, allowing for 286 distinct tradable options.[10]

[8] The *Indicative Leverage*, which is individually selected by signal followers, is employed by the *ZuluTrade* platform to calculate account specific statistics and indications; the figure may differ from the actual leverage inherent to the respective account.

[9] All abbreviations relating to currencies are displayed and described in in the appendix in Table°A.

[10] The included tradeable assets refer to all transactions in the composed dataset which dates back to 2008. Depending on the selected broker, the asset selection for *ZuluTrade* platform users might be much more limited. For example, the first trade in the dataset involving a crypto currency is conducted in 2017.

*3.3 Signal Provider Compensation*

On the *ZuluTrade* platform, signal provider compensation depends on the account type of their corresponding *Real* investors. When opening an account, signal followers may choose between *Volume Based* and *Profit Sharing* signal provider compensation. In the case of the *Volume Based* compensation scheme – the corresponding accounts are also labeled *Classic Accounts* – signal providers earn 0.5 pips per standard lot for each round trip executed in a *Real* Investor's account. On the other hand, the *Profit Sharing* compensation scheme remunerates signal providers for generating profits for signal followers which exceed a previously set high watermark.[11] In detail, signal providers are credited a 20 percent performance fee when gaining a monthly profit (above a previously set high watermark) for signal followers using *Real* accounts. Reflecting the maximum profit generated by a signal provider since it has been added to a signal follower's portfolio, high watermarks are (re)calculated at the first calendar day of each month.

Followingly, 50 percent of the charged performance fee is directly credited to the signal provider's account. Regarding the remaining 50 percent, the proceeding depends on the funds deposited in the respective signal provider's so-called *Reserve Bucket* (followingly reserves). Each signal provider holds distinct reserves for all of his followers operating *Profit Sharing* accounts. Assuming that there are sufficient reserves, the remaining share of the performance fee is hereof released and credited; similarly, 50 percent of the current period's performance fee are credited to the associated reserves. In case of periods with net trading losses, there are no performance fees for signal followers. However, the corresponding signal provider's reserves are reduced by 25 percent of the generated losses. For generated profits which are below the prevailing high watermark, referred to as *Recovering Losses Period*, no performance fee is charged. Regarding these cases, 25 percent of the generated profit is added to the signal provider's reserves.

Regarding US *ZuluTrade* platform users, different compensation rules apply. Signal providers receive a fixed subscription fee of 21 USD for each *Real* US-based signal follower tailing their signals. In turn, US-based signal providers receive a fixed subscription fee of 21 USD for each *Real* investor copying their trades.[12]

Furthermore, different rules apply for *Real* signal followers based in Japan; in these cases, signal providers are compensated with 0.3 pips per executed standard lot. Japanese residents may operate a signal provider account, however, due to country-specific restrictions, their trading activity will not generate any revenues.

---

[11] When operating a *Profit Sharing* account, signal followers are charged with a 25 percent performance fee. It is important to note that signal followers are charged with performance fees relating to the individual amounts generated by the different signal providers of their choosing – as a result, undifferentiated signal follower profits are not employable for calculating performance fees. Furthermore, irrespective of the performance obtained through the selected signal providers, signal followers holding *Profit Sharing* accounts are charged a monthly *Subscription Fee* of 30 USD.

[12] Corresponding fees are calculated on a pro-rata basis.

The EU regulative framework imposes further restrictions on signal providers to be eligible for EU-based signal followers.[13] Only the top 1,000 signal providers can be followed by EU investors. In order to be eligible for copying, signal providers have to meet the following three criteria: The maximum drawdown can't exceed 30 percent of their total profit, the trading time must exceed twelve weeks, and the profit per trade must be greater than three pips on average.

Signal providers can open and simultaneously administer up to ten trader accounts with the same registration email address. Thus, signal providers may simultaneously pursue a variety of different strategies.[14]

### *3.4 Sorting Criteria for Signal Providers*

When browsing for signal providers, *ZuluTrade* initially lists a preselection of 20 striking traders (labeled *Top Traders*), which are evenly distributed among the following five categories: *New and Upcoming*, *Winning Last Week (Live)*[15], *Multiple Instruments Strategies*, and *Highest AUM – Amount Following*[16]. Only when selecting the tab captioned *All Traders*, the full range of available signal providers is displayed.

While all traders are displayed by default, platform users are provided with a shortcut option which limits the listing to signal providers using *Real* accounts. The main sorting criterion for signal providers on the *ZuluTrade* platform is called *ZuluRank*. As stated by *ZuluTrade*, sorting signal provider accounts according to *ZuluRank* facilitates the signal follower search process by filtering out feasible trading strategies which provide robust trading results. The *ZuluRank* sorting criterion incorporates the parameters *Maturity* (weeks of trading), *Exposure* (open positions at the same time), *Drawdown* (rather volatility of the signal provider's trading account than actual drawdown), and *Performance* (combination of various not specified performance measurement approaches, inter alia, involving earned pips). An exact definition of the stated parameters as well as the *ZuluRank* calculation approach is not provided by the *ZuluTrade* platform. There are eight further default sorting criteria: *Winning today*, *Winning last week*, *Winning last month*, *Winning last 3 months*, *Winning last 6 months*, *Winning last year*, *Winning* (covering the overall timeframe of the account), and *Trading Cryptos* (covering one month by default). Within each sorting criterion, traders are sorted by *Live Investors Profit*, i.e. the nominal profit generated for signal followers using *Real* accounts. Other options for arranging signal providers include *ROI* (return on investment), *Investors*

---

[13] For EU residents, *ZuluTrade* is operated by *Triple A Experts SA*, a Greek investment services company authorized and supervised by the *Hellenic Capital Markets Commission* (*HCMC*). The *HCMC* is a member of the *European Securities and Markets Authority* (*ESMA*), operating within the applying regulative framework.

[14] Each trader account displays pointers to corresponding accounts operated by the same signal provider.

[15] On the *ZuluTrade* platform, *Winning* relates to the nominal amount a signal provider has generated for signal followers using *Real* accounts.

[16] *ZuluTrade* defines the *Amount Following* as the invested funds of *Real* investors copying a signal provider's transactions.

(number of *Real* and *Demo* investors following the respective signal provider), *Pips* (total profit in pips), *Trades* (number of trades), *Avg Pips* (average number of pips earned per trade), *Winning Trades* (percentage of winning trades), *Maximum Drawdown* (difference in pips between the highest and the lowest point), *Weeks* (number of weeks trading), and *Amount Following* (sum of invested funds of *Real* investors). It is possible for (potential) signal followers to make a variety of further specifications regarding the initially provided sorting criteria. Furthermore, customized new sorting criteria can be created (see *Section 3.1*).

Unsuccessful accounts which have been closed, either due to a loss of interest by their corresponding signal provider (e.g. failure to gain *Real* investors) or the depletion of available funds, are not displayed on the *ZuluTrade* platform.

### *3.5 Definition of Lottery-like Assets*

Our definition of lottery-like assets is motivated by Bali et al. (2011) who argue that investors exhibit a preference for stocks with extreme positive daily returns during the previous month as they resemble lottery-like payoffs. Stocks with extreme past daily returns tend to underperform their peers. However, they are more likely to exhibit an extreme daily return in the following months (Bali et al., 2011).

| ***Panel°A*: Characteristics Based on Daily Returns** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $P10$ | $P25$ | $P75$ | $P90$ | $Mean$ | $TVol_{t-1}$ | $TSkew_{t-1}$ | $TVol_{t-6}^{t-1}$ | $TSkew_{t-6}^{t-1}$ |
| ***All Assets in Dataset*** | | | | | | | | | |
| All Assets | -1.10 | -.44 | .46 | 1.14 | .04 | 1.08 | 3.24 | 1.11 | 6.54 |
| Currencies | -.77 | -.35 | .35 | .79 | .03 | .71 | 2.25 | .73 | 6.61 |
| Crypto Currencies | -5.27 | -2.41 | 1.79 | 5.47 | .15 | 5.47 | 40.27 | 5.56 | 129.30 |
| Crypto Currency/Fiat Money | -5.63 | -2.35 | 2.01 | 5.87 | .03 | 5.10 | 16.33 | 5.44 | 75.87 |
| Crypto Currency/Crypto Currency | -4.97 | -2.44 | 1.64 | 5.15 | .24 | 5.83 | 64.46 | 5.68 | 182.92 |
| Commodities | -1.89 | -.76 | .85 | 1.93 | .05 | 1.70 | -.98 | 1.78 | 2.53 |
| Indices | -1.52 | -.62 | .73 | 1.54 | .03 | 1.27 | .24 | 1.32 | -12.81 |
| Stocks | -2.09 | -.83 | .96 | 2.17 | .08 | 1.90 | 9.08 | 1.96 | 11.02 |
| ***Assets sorted into Lottery*** | | | | | | | | | |
| Lottery | -3.01 | -1.23 | 1.24 | 3.00 | .17 | 3.40 | 48.95 | 3.16 | 52.46 |
| Other | -.93 | -.39 | .42 | .98 | .02 | .79 | -2.60 | .86 | .78 |

**Table°II: Summary Statistics Assets**

*Notes:* The table displays return characteristics for all assets included in our dataset, the distinct asset categories, as well as the subcategory of assets classified as lotteries, covering an observation period from January 2000 to December 2020. Time series data for crypto currencies is obtained starting in early 2014. Based on daily returns (*Panel°A*), monthly returns (*Panel°B*), and equally weighted monthly returns by category (*Panel°C*), we report the 10th ($P10$), 25th ($P25$), 75th ($P75$), and 90th ($P90$) percentile, as well as mean values ($Mean$). Furthermore, in *Panel°A,* we report total volatility and total skewness, for all assets in the dataset and by category, calculated based on daily returns over the previous month ($TVol_{t-1}$ / $TSkew_{t-1}$) and over the previous six months ($TVol_{t-6}^{t-1}$ / $TSkew_{t-6}^{t-1}$). Each month, assets are sorted based on their maximum daily return of the previous month; assets with the most extreme single positive daily returns (highest decile) are categorized as lotteries (Bali et al., 2011). Crypto currencies are by default categorized as lotteries (not included into the sorting procedure). Remaining assets are denoted as others. Return characteristics are displayed in percent; accordingly, skewness has been multiplied by a factor of $100$.

We argue that, similar to stocks, currency pairs exhibiting extreme positive daily returns in the previous months are perceived as lotteries by investors. When faced with a variety of investable currencies, signal providers with gambling intentions might look for currency pairs exhibiting extreme daily price movements.[17] In this context, signal providers may speculate on another major positive price movement – value appreciation of base currency or value depreciation of quote currency – by taking a long position in the respective currency pair. Alternatively, signal providers may speculate on a reversal of the price movement – value depreciation of base currency or value appreciation of quote currency – by taking a short position.

| ***Panel°B*: Characteristics Based on Monthly Returns** | | | | | |
|---|---|---|---|---|---|
| | $P10$ | $P25$ | $P75$ | $P90$ | $Mean$ |
| ***All Assets in Dataset*** | | | | | |
| All Assets | -4.87 | -1.98 | 2.50 | 5.85 | .50 |
| Currencies | -3.48 | -1.64 | 1.72 | 3.72 | .14 |
| Crypto Currencies | -32.30 | -20.36 | 14.37 | 41.10 | 3.15 |
| Crypto Currency/Fiat Money | -34.00 | -19.41 | 17.89 | 35.24 | 1.25 |
| Crypto Currency/Crypto Currency | -28.85 | -20.80 | 8.96 | 45.63 | 5.07 |
| Commodities | -8.80 | -3.81 | 5.44 | 10.71 | .93 |
| Indices | -6.56 | -2.55 | 4.19 | 7.41 | .68 |
| Stocks | -8.69 | -3.52 | 6.06 | 11.70 | 1.54 |
| ***Assets sorted into Lottery*** | | | | | |
| Lottery | -14.19 | -6.02 | 7.64 | 16.60 | 2.24 |
| Other | -4.14 | -1.79 | 2.24 | 4.85 | .28 |
| ***Panel°C*: Characteristics Based on Mean Monthly Returns** | | | | | |
| | $P10$ | $P25$ | $P75$ | $P90$ | $Mean$ |
| ***All Assets in Dataset*** | | | | | |
| All Assets | -1.35 | -.44 | 1.41 | 2.12 | .51 |
| Currencies | -.69 | -.31 | .52 | .91 | .14 |
| Crypto Currencies | -23.30 | -10.12 | 9.38 | 33.24 | 8.63 |
| Crypto Currency/Fiat Money | -29.83 | -14.70 | 14.17 | 27.90 | -.83 |
| Crypto Currency/Crypto Currency | -28.06 | -19.43 | 17.94 | 49.93 | 12.73 |
| Commodities | 5.05 | -2.38 | 4.23 | 7.09 | .93 |
| Indices | -5.23 | -2.04 | 3.78 | 6.15 | .64 |
| Stocks | -5.86 | -1.53 | 4.94 | 8.11 | 1.49 |
| ***Assets sorted into Lottery*** | | | | | |
| Lottery | -5.66 | -2.26 | 5.79 | 9.50 | 2.15 |
| Other | -1.00 | -.22 | .96 | 1.42 | .27 |

**Table°II – *Continued***

Based on Bali et al. (2011), we use daily exchange rates to calculated the maximum daily return for each currency pair and each month included in our dataset.[18] Accordingly, we employ daily prices for commodities included in the dataset to compose maximum daily returns; regarding equity indices and individual equities, the *Thomson Reuters Datastream Return Index* (in USD) is applied.

[17] There is a comprehensive body of literature which links extreme daily price movements of a respective currency (currency crashes / currency crisis) to speculative attacks (Krugman (1979); Connolly (1986); Rotemberg and Krugman (1991); Eichengreen, Rose, Wyplosz, Dumas, and Weber (1995)) as well as a wide variety of political and economic factors (Balima (2020); Chiu and Willett (2009); Frankel and Rose (1996); Leblang and Satyanath (2006, 2008); Obstfeld (1996); Steinberg, Koesel, and Thompson (2015)). This paper, however, does not cover the underlying causes for occurring extreme currency price movements.

[18] Daily exchange rates for currency pairs in our dataset are obtained from the respective base currency's (or in some cases the quote currency's) national central bank. Provided that neither the base currency's nor the quote currency's national central bank issues sufficient daily time series data, we derive the required exchange rates by applying corresponding EUR rates obtained from the *European Central Bank*.

Subsequently, we form monthly decile portfolios based on the maximum daily return of the previous month ($t - 1$). Assets assigned to the highest decile portfolio are defined as lotteries. For categorizing lotteries, corresponding assets are included one month prior to their initial trade in the composed dataset.[19]

Currency pairs involving at least one crypto currency are only traded in about 0.28 percent of all transactions in the dataset. Crypto currency price trends might be fundamentally different to those of regular currencies and thus harder to predict. Therefore, crypto currency pairs might be unsuitable for most applied trading strategies, making them a rather specific choice for signal providers. Taking into account their associated extreme price movements (Chimienti, Kochanska, and Pinna (2019), Giudici, Milne, and Vinogradov (2020)), in the context of our analysis, crypto currencies are by default categorized as lottery-like.

Summary statistics with regard to all assets included in the dataset, as well as the subcategory of sorted lotteries, are displayed in Table°II.

### *3.6 Regression Model*

#### *3.6.1 Selection of Main Independent Variables*

As described in *Section 3.3*, signal providers are subject to a sophisticated compensation scheme depending on the account type (and location) of their corresponding *Real* investors. In essence, signal providers are compensated when managing to obtain a number of *Real* investors copying the signals of one of their corresponding accounts.

The incentive system stemming from the signal provider compensation scheme (see *Section 3.3*) and the signal provider ranking criteria (see *Section 3.4*) may be summarized as follows: In order to be eligible for compensation, signal providers need *Real* investors to subscribe to their account and copy their respective trading signals.

It is well documented that (retail) investors suffer from cognitive and temporal limits when perceiving and processing information. Therefore, when making investment decisions, investors focus on alternatives which have caught their attention (Barber & Odean, 2008; Odean, 1999). In the context of selectable assets and their corresponding list positioning, Jacobs and Hillert (2016) argue that stocks being placed at the top of an alphabetically ordered list experience a boost in visibility which has a positive impact on corresponding trading activity and liquidity. In social trading, to generate new followers, signal providers have to be visible – i.e. generate attention – which is achieved by obtaining a top position on the selection lists presented to signal followers.

[19] The first crypto currency in our dataset is traded in November 2017. Individual equities are not traded until the very end of the observation period.

On *ZuluTrade*, as is customary on social trading platforms, almost all sorting criteria relate to past signal provider performance (see *Section 3.4*). Thus, we base the main independent variables for our analysis on past win ratios as well as past net profits to broadly mirror signal provider trading merit. Each account is considered separately.

More precisely, we apply the win ratio of account $i$ covering the previous month ($t-1$):

$$Win_{i,t-1} = \frac{NWin_{i,t-1}}{NClose_{i,t-1}},$$

$NWin_{i,t-1}$ depicts the number of closed positions where a positive net profit could be attained, $NClose_{i,t-1}$ depicts the total number of closed positions. To model account performance over a more comprehensive time horizon, we compute the average win ratio over the previous six months ($t-6$ to $t-1$):

$$\overline{Win}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Win_{i,t-n}}{6}.$$

We further employ the monthly net profit of the previous month as signal provider account performance measure:

$$Profit_{i,t-1} = \sum_{n=1}^{m} SProfit_{i,t-1}^{n},$$

computed as the sum of individual profits and losses ($SProfit_{i,t-1}^{n}$) from completed round trips. Accordingly, to model performance over a more comprehensive time horizon, the average monthly profit over the previous six months is computed:

$$\overline{Profit}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Profit_{i,t-n}}{6}.$$

Followingly, we employ each performance measure to generate monthly deciles. Using the respective deciles as thresholds, each account-month observation is then assigned a number from 1 to 10, indicating the according relative monthly performance ranking with regard to the different performance measures. The variables referring to relative past performance based on win ratios are depicted as

$$RWin_{i,t-1} \quad / \quad R\overline{Win}_{i,t-6}^{t-1},$$

while the variables reflecting relative past performance based on net profits are represented by

$$RProfit_{i,t-1} \quad / \quad R\overline{Profit}_{i,t-6}^{t-1}.$$

All variables included in the regression analyses are displayed and described in the appendix in Table°B.

*3.6.2 Number Transactions*

We start by assessing the relationship between the monthly number of conducted trades and the relative past performance indicators described in *Section 3.6.1*. The according dependent variable, the number of conducted trades (opening or closing of positions) of signal provider $i$ in month $t$, is depicted as follows:

$$Num_{i,t}.$$

Since the dependent variable is positively skewed, we apply the natural logarithm to all signal provider account-month observations in our dataset:

$$RNum_{i,t} = \ln\left(1 + Num_{i,t}\right).$$

The resulting baseline regression model is as follows:

$$RNum_{i,t} = \alpha + \beta_1 \times IV_{i,t} + \beta_2 \times Lots_{i,t} + \beta_3 \times Open_{i,t} + \beta_4 \times Long_{i,t} + \beta_5 \times Age_{i,t} + \beta_6 \times Crypto_{i,t} + \beta_7 \times Commodity_{i,t} + \beta_8 \times Index_{i,t} + \varepsilon.$$

$IV_{i,t}$ represents the relevant independent variable, which respectively reflects signal provider win ratios ($RWin_{i,t-1}$ / $R\overline{Win}_{i,t-6}^{t-1}$) and profits ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$). We include a variety of control variables: $Lots_{i,t}$ represents the average lot size (in standard lots) traded by signal provider account $i$ in month $t$, $Open_{i,t}$ reflects the ratio of trades opened to trades conducted (opened and closed) by signal provider account $i$ in month $t$, $Long_{i,t}$ reflects the ratio of trades involving long positions to trades conducted (long and short) by signal provider account $i$ in month $t$, $Age_{i,t}$ is the current age (measured in months) of signal provider account $i$ in month $t$, and $Crypto_{i,t}$, $Commodity_{i,t}$, and $Index_{i,t}$ depict dummy variables taking the value of 1 when a crypto currency, commodity, or index is traded in signal provider account $i$ in month $t$. All variables are displayed and described in the appendix in Table°B.

Regarding the initial results from the regression analysis, we do not report a consistent relationship between past relative win ratios and the number of conducted trades. On the other hand, the relationship between past relative profits and the number of conducted trades seems to be significantly positive.

To get further insights, we include the squares of the respective win ratio variables into the regression analysis. The obtained results suggest a statistically significant inverted U-shaped (quadratic) relationship between attained relative win ratios and conducted trades. Although the newly attained regression outputs do not clarify the impact of relative performance on subsequent trading frequency, they point out peculiarities of the relation between the conducted number of trades and realized win ratios. Whereas trading frequency may be impacted by numerous factors, signal providers are unlikely to completely change their habits over a short period of time.

Followingly, signal provider accounts displaying relatively low (high) trading frequency in month $t-1$ can be assumed to display relatively low (high) trading frequency in month $t$. Moreover, accounts with generally low trading frequencies are more likely to be placed at the very top or the very bottom of the win ratio spectrum: For instance, if only one position is closed in month $t$, the corresponding account $i$ will either have a win ratio of $1$ or $0$. Accordingly, accounts with less trades are more likely to be assigned to either the top or the bottom win ratio deciles, explaining the inverted U-shaped relation obtain through the regression analysis.

We therefore adjust the relative win ratio variable as follows:

$$RWinAdj_{i,t-1} = (RWin_{i,t-1} + RNWin_{i,t-1})/2,$$

$$R\overline{Win}Adj_{i,t-6}^{t-1} = (R\overline{Win}_{i,t-6}^{t-1} + R\overline{NWin}_{i,t-6}^{t-1})/2,$$

where $RNWin_{i,t-1}$ / $R\overline{NWin}_{i,t-6}^{t-1}$ reflect the ranking of signal provider account $i$ with regard to the number of positions closed at a net profit in month $t-1$ / the average monthly number of positions closed at a net profit from months $t-6$ to $t-1$. The ranking is expressed in a number from $1$ to $10$; monthly deciles covering all accounts in the dataset are employed as threshold values.

When applying the adjusted win ratio as independent variable, the corresponding coefficients are significantly positive in all regression specifications. Results are displayed in the appendix in Table°B.

To sum up, we report a statistically significant positive relationship between the applied relative performance measures and the conducted number of trades.[20] Although we do not directly observe the number of investors copying a corresponding signal provider account, it is reasonable to assume that good relative peer performance will increase followers. Pelster and Breitmayer (2019) and Röder and Walter (2019) provide evidence that signal followers mainly use past performance as decisive factor when allocating funds. In the context of our analysis, favorable win ratios and net profits – in comparison to peers – are likely to boost account attractiveness and, thus, result in a greater number of investors copying signals.

The effect is amplified by the platforms ranking scheme. Outperforming peers with regard to attained win ratios and generated net profits will earn a corresponding signal provider account a favorable position on the selection lists provided by the *ZuluTrade* platform (see *Section 3.4*). Thus, visibility is increased, which in turn leads to more followers.

Our obtained results are in line with Pelster and Breitmayer (2019), who provide evidence that receiving attention (from signal followers) increases signal provider trading activity due to increased levels of excitement (Dorn & Sengmueller, 2009; Taffler, 2018). The enhanced excitement which is

[20] Including a dependent variable based on profit pips rather than based on profits leads to similar results.

caused by additional followers may encourage signal providers to be more active, i.e. increase their trading activity (Pelster & Breitmayer, 2019).

Furthermore, performing well relative to peers, might additionally boost signal provider overconfidence which causes a surge in trading activity (Gervais & Odean, 2001; Odean, 1999; Statman et al., 2006).

*3.6.3 Main Analysis: Relative lottery transactions*

In our main analysis, we assess the impact of the previously described relative past performance indicators (see *Section 3.6.1*) on the monthly share of lottery-like trades (see *Section 3.5*). We employ the share of lottery-like assets traded by signal provider account $i$ in month $t$ as dependent variable:

$$Lottery_{i,t}^{max} = \frac{LotteryNum_{i,t}^{max}}{Num_{i,t}},$$

where $LotteryNum_{i,t}^{max}$ is the number of trades of signal provider $i$ in month $t$ involving lottery assets. Since the dependent variable $Lottery_{i,t}^{max}$ is positively skewed, we conduct the following transformation using the natural logarithm:

$$RLottery_{i,t}^{max} = \ln{(1 + Lottery_{i,t}^{max})}.$$

As a considerable number of account-month observations do not involve lottery-like assets, the variable $RLottery_{i,t}^{max}$ frequently takes the value of zero. By adding the constant 1 to the initial variable before applying the natural logarithm, we assure that account-month observations where no lottery-asset is traded can be kept in the dataset. The baseline regression model is as follows:

$$RLottery_{i,t}^{max} = \alpha + \beta_1 \times IV_{i,t} + \beta_2 \times Lots_{i,t} + \beta_3 \times Open_{i,t} + \beta_4 \times Long_{i,t} + \beta_5 \times Age_{i,t} + \beta_6 \times Commodity_{i,t} + \beta_7 \times Index_{i,t} + \beta_8 \times RNum_{i,t} + \varepsilon.$$

As in the regression analysis in the previous section, $IV_{i,t}$ represents the independent variable of interest which, in turn, reflects signal provider win ratios and profits. All variables are displayed and described in the appendix in Table°B.

The dependent variable reflecting the share of lottery-like trades is only defined for account-month observations where at least one trade is conducted. Average trading frequency is high; when sorting accounts into deciles based on the average number of monthly trades, accounts within the lowest decile conduct, on average, more than twelve trades per month (see Table°I). Thus, it is rarely the case that not at least one monthly trade is conducted within any of the included signal provider accounts.

## *4 Results and Discussion*

The initial results obtained from applying the regression model depicted in *Section 3.6.3* do not indicate a significant relation between the composed relative performance measures and the share of conducted lottery trades, the assessed dependent variable.

As results in regard to the analyzed coherence are of limited informative value, we include squared terms of the employed relative performance measures to obtain a more comprehensive picture. Panel regression results including squared terms are displayed in Table°III.

Including squared terms indicates a steady statistically significant relationship between the variables measuring relative past performance and the traded lottery share. Within all specifications, the regression analysis yields statistically significant coefficients for the past performance variables and their corresponding squared terms – the signs of the considered coefficients indicate a U-shaped relationship. When relative performance is based on net profits ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$), the magnitude of the obtained coefficients is slightly higher than for relative performance based on win ratios ($RWin_{i,t-1}$ / $R\overline{Win}_{i,t-6}^{t-1}$).

We further introduce a variable reflecting relative past performance jointly based on win rations and net profits:

$$RComb_{i,t-1} = (RWin_{i,t-1} + RProfit_{i,t-1})/2,$$

$$R\overline{Comb}_{i,t-6}^{t-1} = (R\overline{Win}_{i,t-6}^{t-1} + R\overline{Profit}_{i,t-6}^{t-1})/2.$$

Respectively including the joint variables as well as their corresponding squared terms in the regression model yields roughly similar results; the considered coefficients are statistically significant at the permil-level.

Applying adjusted win ratios (see *Section 3.6.3*) composed over the previous month ($RWinAdj_{i,t-1}$) as well as the corresponding squared terms leads to results similar to those obtained by the previous regressions. When relative performance is based on adjusted win ratios composed over the previous six months ($R\overline{Win}Adj_{i,t-6}^{t-1}$), hpwever, we do no longer document a statistically significant effect.

To sum up, our results indicate a quadratic relationship between the primarily examined independent variables, relative win ratios and relative profits, and the traded lottery share of a signal provider account. The interpretation is as follows: Signal providers exhibiting relatively bad past performance – win ratios and profits assigned to the bottom deciles – and signal providers exhibiting relatively good past performance – win ratios and profits assigned to the top deciles – seem to trade a higher share of lotteries.

Our results are related to two behavioral effects initially documented by Thaler and Johnson (1990). Based on the framework introduced by Kahneman and Tversky’s (1979) prospect theory where decisions are made in regard to a reference point, Thaler and Johnson (1990) provide evidence that prior gains and losses have a major impact on risk-taking behavior. More specifically, Thaler and Johnson (1990) describe two behavioral patterns labeled as *house money* and *break-even effect*.

The *break-even effect* states that, in the presence of prior losses, individuals are willing to accept (high-risk) "gambles which offer the prospect of changing the sign of the status of the current account" (Thaler & Johnson, 1990, p. 658), making up for incurred losses entirely. Labeled as *gambling for resurrection*, similar risk-taking patterns have been described with regard to banks experiencing financial distress (Bruche & Llobet, 2014; Jean-Charles Rochet, 2008)[21] and firms biding for procurement contracts (Calveras, Ganuza, & Hauk, 2004)[22].

Regarding the *house money effect*, Thaler and Johnson (1990) state that: "After a gain, subsequent losses that are smaller than the original gain can be integrated with the prior gain, mitigating the influence of loss aversion and facilitating risk-seeking.". In the context of horse race betting, a distinct setting for gambles, Suhonen and Saastamoinen (2018) provide empirical evidence for the *house money effect* – considering the described design features of the analyzed social trading platform as well as the reported results, it seems reasonable to assume that signal providers (under certain circumstances) show similar behavioral patterns to participants in traditional gambling games.

It is important to note that Thaler and Johnson (1990) refer to absolute performance, i.e. gains and losses with regard to a previously set reference point, while our variables capture the relative performance of signal provider accounts. Nonetheless, when computing relative performance based on net profits, the resulting variable is a sound indicator for absolute performance. Only in 0.4 percent of all account-month observations, a net loss is incurred when the ranking variable reflecting relative profit of the previous month ($RProfit_{i,t-1}$) takes a value of $5$; when taking a value of $6$, there is not a single account-month observation exhibiting a net loss. While still being a reasonable proxy for absolute performance, high (relative) win ratios do not automatically translate into monthly net profits. Notwithstanding, when the variable composed with regard to win ratios of the previous month ($RWin_{i,t-1}$) takes a value of $8$, more than 98 percent of account-month observations yield a net profit.

Signal providers are subject to different mechanisms which may help to explain the documented quadratic relation between the share of traded lotteries and the applied relative past performance measures.

[21] Rochet (2008) provides evidence that insolvent banks may continue to invest – even in the face of negative expected net present values – for a small chance of recovery. Bruche and Llobet (2014) argue that insolvent banks have an incentive to continue lending to insolvent borrowers: The realization of losses is avoided while the (small) chance for a recovery of the insolvent borrowers remains.

[22] Calveras et al. (2004) provide evidence that due to limited liability, firms experiencing financial distress have an incentive to bid for procurement contracts more aggressively, i.e. undercut their competitors.

Regarding the lower end of the relative performance spectrum, signal providers are faced with considerable incentives to take more risk or, as assessed in this paper, gambles. In the context of social trading, signal providers compete for visibility. Underperforming accounts are unlikely to generate (or maintain) followers which can potentially be lost. As followers are needed to be eligible for compensation, signal providers might employ lotteries, speculating on an unlikely, but nonetheless possible, large gain which will bring the account back on track. This effect is further supported by literature on tournament incentives (Kirchler et al., 2018). As a certain ranking is required to attract the attention of followers – which, in turn, is a prerequisite for receiving compensation – social trading platforms indirectly impose tournament incentives. When compensation is rank-dependent, underperformers have been shown to take significantly more risk. This effect might be further facilitated by certain platform design features common to social trading. *ZuluTrade* enables platform users to simultaneously operate up to ten signal provider accounts. Accounts either involve signals which are triggered by actual trades (*Live* or *Real* accounts) executed via an online broker or, alternatively, transmitted signals relate to purely virtual transactions (*Demo* accounts) withour affectting real-world signal provider portfolios. When operating a variety of accounts and / or when operating *Demo* accounts where no real-world funds are at risk, signal providers might not experience major costs when abandoning or closing poorly performing accounts which show little prospects of becoming profitable.

Considering the limited downside risk for underperforming accounts, taking gambles may appear as a compelling option. When gambling fails, signal providers might simple turn their focus to accounts with better prospects.

In addition, signal providers might be subject to the gambler's fallacy (Tversky & Kahneman, 1974): After having executed several transactions with unfavorable outcomes, signal providers might erroneously believe that future trades are more likely to yield desirable results. Thus, lotteries are traded due to the overestimation of desirable outcomes, e.g. the reoccurence of an extreme daily price movment in the anticipated direction.

While signal providers administering an account at the lower end of the performance spectrum have little to lose, signal providers managing accounts outperforming peers face a substantial downside. When accounts which have previously outperformed their peers drop, signal followers are likely to cease the relationship, especially when losses are realized. As followers are mandatory in order to receive funds from the platform (see *Section 3.3*), signal providers may lose their eligibility for remuneration when accepted gambling trades fail. Yet, there are factors which may induce signal providers to enter lottery trades when a corresponding account has outperformed its peers.

In the context of social trading, Pelster and Breitmayer (2019) provide evidence that signal providers receiving attention from peers – attention being in turn triggered by (relative) past performance –

increase their risk appetite. Thus, the share of traded lotteries may be increased after (continuously) outperforming peers.

Furthermore, the observed results might be explained by the well-documented relationship between overconfidence and risk taking (Barber & Odean, 2001; Broihanne et al., 2014; De Long et al., 1991; Odean, 1999). Regarding social trading, Czaja and Röder (2020) provide evidence that signal providers become overconfident due to biased self-enhancement. When experiencing a surge in overconfidence due to good (relative) past performance (Gervais & Odean, 2001; Odean, 1999; Statman et al., 2006), signal providers might be inclined to take more risk and thus increase the share of traded lotteries. Moreover, overconfident traders tend to overestimate the precision of their information (Benos, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998; Odean, 1998; 1999). Followingly, signal providers might assume that they are capable of correctly timing subsequent major price movements – another extreme positive daily return or a corresponding reversal – and consequentially trade more lotteries.

Finally, it is important to point out that performing well relative to peers does not inevitably result in (substantial) compensation for signal providers. Signal providers must first outperform their peers in order to attract followers and subsequently generated profits with issued trading signals (see *Section 3.3*). After having gained a certain number of followers through outperforming peers, the direct incentive of receiving compensation might drive signal providers to take gambles. When compensation appears to be within reach, signal providers may perceive lottery return characteristics, particularly positive skewness, as explicitly appealing. Considering the discussed downside risk, signal providers may only invest a proportion of their funds in lotteries – motivated by the upside potential – and otherwise conduct less risky trades.

Although we take considerable efforts to reduce the survivorship bias in our dataset, we are not able to collect data for accounts corresponding to signal providers who have completely disappeared from the platform. As there is no sound reason why signal providers should lose interest and disappear from the platform when (consistently) outperforming peers, we assume that the majority of the unobserved accounts were located at the lower end of the performance spectrum. In line with previously made arguments, those signal providers would have had an incentive to take gambles at the end of the lifecycle of a corresponding account. Regarding the lower end of the performance spectrum, including such accounts might have potentially increased the magnitude of the documented effect.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Panel°A*: Relative Performance Measured over Previous Month** | | | | | | | | | | | | | | | |
| *α* | .0309*** | .0309*** | .0315*** | .0343*** | .0350*** | .0430*** | .0430*** | .0429*** | .0364*** | .0373*** | .0449*** | .0449*** | .0454*** | .0371*** | .0382*** |
| | (3.84) | (3.61) | (14.03) | (12.83) | (13.42) | (5.42) | (4.76) | (18.80) | (13.54) | (14.17) | (5.10) | (4.51) | (18.49) | (13.05) | (13.66) |
| $RWin_{i,t-1}$ | -.0067*** | -.0067*** | -.0064*** | -.0032*** | -.0034*** | | | | | | | | | | |
| | (-2.84) | (-2.74) | (-8.54) | (-3.82) | (-4.06) | | | | | | | | | | |
| $(RWin_{i,t-1})^2$ | .0007*** | .0007*** | .0006*** | .0003*** | .0003*** | | | | | | | | | | |
| | (2.82) | (2.66) | (8.50) | (3.44) | (3.45) | | | | | | | | | | |
| $RProfit_{i,t-1}$ | | | | | | -.0097*** | -.0097*** | -.0095*** | -.0040*** | -.0044*** | | | | | |
| | | | | | | (-5.36) | (-4.66) | (-15.84) | (-5.40) | (-6.13) | | | | | |
| $(RProfit_{i,t-1})^2$ | | | | | | .0010*** | .0010*** | .0010*** | .0004*** | .0004*** | | | | | |
| | | | | | | (5.57) | (4.78) | (17.72) | (5.84) | (6.53) | | | | | |
| $RComb_{i,t-1}$ | | | | | | | | | | | -.0130*** | -.0130*** | -.0127*** | -.0046*** | -.0050*** |
| | | | | | | | | | | | (-5.09) | (-4.39) | (-16.60) | (-5.13) | (-5.68) |
| $(RComb_{i,t-1})^2$ | | | | | | | | | | | .0013*** | .0013*** | .0013*** | .0004*** | .0005*** |
| | | | | | | | | | | | (5.06) | (4.31) | (17.69) | (5.04) | (5.45) |
| $Lots_{i,t}$ | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (4.34) | (4.41) | (9.43) | (8.47) | (8.31) | (1.34) | (1.35) | (5.98) | (4.70) | (4.75) | (4.28) | (4.34) | (9.39) | (8.50) | (8.34) |
| $Age_{i,t}$ | -.0000 | -.0000 | -.0000* | -.0003*** | -.0003*** | -.0001*** | -.0001** | -.0001*** | -.0004*** | -.0003*** | -.0001** | -.0001** | -.0001*** | -.0003*** | -.0003*** |
| | (-.90) | (-.79) | (-1.78) | (-13.06) | (-12.51) | (-2.67) | (-2.54) | (-6.40) | (-14.01) | (-13.56) | (-2.31) | (-2.18) | (-5.48) | (-13.52) | (-13.06) |
| $Open_{i,t}$ | .0104 | .0104 | .0031 | .0043 | .0044 | .0093 | .0093 | .0026 | .0058** | .0059** | .0110 | .0110 | .0038 | .0043 | .0045* |
| | (1.06) | (1.08) | (1.20) | (1.61) | (1.64) | (1.05) | (1.09) | (1.03) | (2.32) | (2.36) | (1.12) | (1.15) | (1.45) | (1.64) | (1.68) |
| $Long_{i,t}$ | .0111** | .0111* | .0131*** | .0077*** | .0081*** | .0096** | .0096* | .0120*** | .0068*** | .0072*** | .0103** | .0103* | .0124*** | .0077*** | .0080*** |
| | (2.59) | (1.96) | (10.38) | (5.33) | (5.68) | (2.27) | (1.78) | (9.65) | (4.81) | (5.17) | (2.45) | (1.87) | (9.81) | (5.30) | (5.66) |
| $Commodity_{i,t}$ | .0602*** | .0602*** | .0589*** | .0562*** | .0575*** | .0587*** | .0587*** | .0573*** | .0571*** | .0585*** | .0591*** | .0591*** | .0578*** | .0562*** | .0575*** |
| | (6.05) | (5.90) | (46.75) | (31.61) | (34.01) | (5.90) | (5.76) | (45.86) | (32.56) | (35.01) | (5.97) | (5.83) | (45.91) | (31.59) | (33.98) |
| $Index_{i,t}$ | .0889*** | .0889*** | .0922*** | .0590*** | .0702*** | .0881*** | .0881*** | .0914*** | .0593*** | .0703*** | .0891*** | .0891*** | .0924*** | .0591*** | .0703*** |
| | (4.08) | (4.06) | (45.35) | (18.84) | (25.05) | (4.03) | (4.01) | (45.12) | (19.00) | (25.14) | (4.10) | (4.08) | (45.53) | (18.84) | (25.09) |
| $RNum_{i,t}$ | -.0030*** | -.0030*** | -.0027*** | -.0020*** | -.0023*** | -.0043*** | -.0043*** | -.0039*** | -.0026*** | -.0029*** | -.0033*** | -.0033*** | -.0030*** | -.0021*** | -.0024*** |
| | (-3.13) | (-2.80) | (-9.92) | (-5.27) | (-6.30) | (-4.95) | (-4.52) | (-14.78) | (-6.97) | (-8.19) | (-3.73) | (-3.37) | (-11.25) | (-5.56) | (-6.64) |
| $R^2$ | .0720 | .0720 | .1499 | .2133 | .1856 | .0737 | .0737 | .1508 | .2089 | .1813 | .0751 | .0751 | .1529 | .2135 | .1857 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes |

## Table°III: Monthly Relative Lottery Trades

*Notes:* The table above displays panel regression estimates obtained by applying the regression model in *Section 3.6.3*. In each regression, the share of lottery-like trades of signal provider account $i$ in month $t$ ($RLottery_{i,t}^{max}$) is set as dependent variable. *Panel°A* reports the results relating to the relative performance variables – win ratio ($RWin_{i,t-1}$), net profit ($RProfit_{i,t-1}$), and the combined term ($RComb_{i,t-1}$) – measured over the previous month. In *Panel°B*, relative performance variables ($R\overline{Win}_{i,t-6}^{t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$ / $R\overline{Comb}_{i,t-6}^{t-1}$) are computed over the previous six months. In specification (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specification (2), (7), and (12) standard errors are clustered by month and signal provider (Petersen, 2009). Specifications (3), (8), and (13) include time fixed effects. Fixed effects on the portfolio-level, i.e. for each signal provider account, are included in specifications (4), (9), and (14). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5), (10), and (15). All employed variables are displayed and described in the appendix Table°B. Trading data is obtained directly from the *ZuluTrade* platform, covering the period from October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| *Panel°B*: **Relative Performance Measured over Previous Six Months** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| $\alpha$ | .0302*** | .0302*** | .0311*** | .0370*** | .0382*** | .0512*** | .0512*** | .0512*** | .0377*** | .0392*** | .0492*** | .0492*** | .0493*** | .0430*** | .0432*** |
| | (4.18) | (3.89) | (14.06) | (12.63) | (13.61) | (5.96) | (5.05) | (22.28) | (13.59) | (14.52) | (5.76) | (5.00) | (19.34) | (13.80) | (14.34) |
| $R\overline{Win}_{i,t-6}^{t-1}$ | -.0051*** | -.0051*** | -.0051*** | -.0039*** | -.0038*** | | | | | | | | | | |
| | (-4.10) | (-3.62) | (-8.73) | (-4.67) | (-4.85) | | | | | | | | | | |
| $(R\overline{Win}_{i,t-6}^{t-1})^2$ | .0005*** | .0005*** | .0005*** | .0003*** | .0003*** | | | | | | | | | | |
| | (3.63) | (3.17) | (8.75) | (4.30) | (3.91) | | | | | | | | | | |
| $R\overline{Profit}_{i,t-6}^{t-1}$ | | | | | | -.0132*** | -.0132*** | -.0130*** | -.0036*** | -.0042*** | | | | | |
| | | | | | | (-6.10) | (-4.77) | (-21.42) | (-4.34) | (-5.40) | | | | | |
| $(R\overline{Profit}_{i,t-6}^{t-1})^2$ | | | | | | .0012*** | .0012*** | .0012*** | .0003*** | .0003*** | | | | | |
| | | | | | | (6.17) | (4.83) | (22.51) | (3.37) | (4.30) | | | | | |
| $R\overline{Comb}_{i,t-6}^{t-1}$ | | | | | | | | | | | -.0133*** | -.0133*** | -.0129*** | -.0056*** | -.0053*** |
| | | | | | | | | | | | (-5.94) | (-4.93) | (-17.36) | (-5.97) | (-5.92) |
| $(R\overline{Comb}_{i,t-6}^{t-1})^2$ | | | | | | | | | | | .0012*** | .0012*** | .0012*** | .0004*** | .0004*** |
| | | | | | | | | | | | (5.31) | (4.42) | (18.06) | (4.97) | (4.54) |
| $Lots_{i,t}$ | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (4.37) | (4.44) | (9.36) | (8.43) | (8.26) | (1.32) | (1.33) | (5.73) | (4.59) | (4.65) | (4.33) | (4.40) | (9.13) | (8.38) | (8.21) |
| $Age_{i,t}$ | -.0000 | -.0000 | -.0000* | -.0003*** | -.0003*** | -.0002*** | -.0002*** | -.0001*** | -.0003*** | -.0003*** | -.0001* | -.0001 | -.0001*** | -.0003*** | -.0003*** |
| | (-.61) | (-.53) | (-1.04) | (-12.95) | (-12.43) | (-3.12) | (-3.01) | (-7.88) | (-13.24) | (-12.90) | (-1.77) | (-1.58) | (-3.77) | (-13.28) | (-12.72) |
| $Open_{i,t}$ | .0097 | .0097 | .0025 | .0041 | .0042 | .0103 | .0103 | .0036 | .0061** | .0062** | .0099 | .0099 | .0028 | .0043 | .0043 |
| | (.99) | (1.01) | (.97) | (1.56) | (1.58) | (1.17) | (1.22) | (1.44) | (2.44) | (2.46) | (1.03) | (1.05) | (1.09) | (1.61) | (1.63) |
| $Long_{i,t}$ | .0111*** | .0111** | .0132*** | .0077*** | .0081*** | .0091** | .0091* | .0115*** | .0067*** | .0071*** | .0106** | .0106* | .0127*** | .0076*** | .0080*** |
| | (2.61) | (1.98) | (10.41) | (5.36) | (5.69) | (2.19) | (1.72) | (9.25) | (4.74) | (5.07) | (2.55) | (1.95) | (10.06) | (5.29) | (5.61) |
| $Commodity_{i,t}$ | .0602*** | .0602*** | .0589*** | .0564*** | .0577*** | .0575*** | .0575*** | .0560*** | .0570*** | .0584*** | .0592*** | .0592*** | .0578*** | .0562*** | .0575*** |
| | (6.05) | (5.91) | (46.74) | (31.71) | (34.10) | (5.84) | (5.71) | (44.77) | (32.48) | (34.91) | (6.04) | (5.90) | (45.94) | (31.64) | (34.02) |
| $Index_{i,t}$ | .0885*** | .0885*** | .0918*** | .0590*** | .0700*** | .0881*** | .0881*** | .0914*** | .0595*** | .0707*** | .0888*** | .0888*** | .0921*** | .0589*** | .0702*** |
| | (4.06) | (4.05) | (45.11) | (18.82) | (24.98) | (4.04) | (4.03) | (45.16) | (19.06) | (25.29) | (4.09) | (4.08) | (45.36) | (18.81) | (25.07) |
| $RNum_{i,t}$ | -.0033*** | -.0033*** | -.0029*** | -.0021*** | -.0024*** | -.0040*** | -.0040*** | -.0036*** | -.0023*** | -.0026*** | -.0033*** | -.0033*** | -.0029*** | -.0020*** | -.0023*** |
| | (-3.97) | (-3.56) | (-10.91) | (-5.62) | (-6.69) | (-4.51) | (-4.17) | (-13.81) | (-6.09) | (-7.18) | (-3.88) | (-3.52) | (-11.11) | (-5.45) | (-6.46) |
| $R^2$ | .0719 | .0719 | .1499 | .2134 | .1857 | .0756 | .0756 | .1526 | .2089 | .1814 | .0752 | .0752 | .1530 | .2137 | .1860 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes |

**Table°III – *Continued***

## *5 Robustness*

*5.1 Robustness regarding Independent Variables*

First, we test the robustness of our results by exchanging the previously applied independent variables relating to past relative net profits ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$). Since net profits depend on the traded lot size (and thus the applied leverage), profit pips gained per transaction might be a preferred indication of signal provider skill. Thus, we employ the net gain in profit pips of the previous month as signal provider trading performance measure:

$$Pips_{i,t-1} = \sum_{n=1}^{m} SPips_{i,t-1}^{n},$$

computed as the sum of individual gains and losses in profit pips ($SPips_{i,t-1}^{n}$) from completed round trips. As before, to model signal provider trading performance over a more comprehensive time horizon, average monthly profit pips over the previous six months are computed:

$$\overline{Pips}_{i,t-6}^{t-1} = \frac{\sum_{n=1}^{6} Pips_{i,t-n}}{6}.$$

Similar to the approach described in *Section 3.6.1*, we employ the computed performance measures to generate monthly deciles. Using deciles as thresholds, each account-month observation is assigned a number from $1$ to $10$, indicating its according relative monthly performance ranking. The corresponding variables referring to relative past performance based on profit pips are depicted as follows:

$$RPips_{i,t-1} \quad / \quad R\overline{Pips}_{i,t-6}^{t-1}.$$

We employ the regression model described in *Section 3.6.3*. The corresponding results are displayed in Table°IV.

The obtained results are very similar to those described in Table°III where net profits are employ as the respective performance measure. There is consistent empirical evidence for a quadratic relationship between past relative profit pips and the traded lottery share.

*5.2 Robustness regarding lottery definition*

Second, we test the robustness of our results by applying a different lottery definition. Once again following Bali et al. (2011), we form decile portfolios based on an average comprising the five highest daily returns of the previous month. Accordingly, as describes in *Section 3.5*, assets in the highest monthly decile portfolio are defined as lotteries. Crypto currencies are by default categorized as lottery-like.

The corresponding dependent variable is defined as follows:

$$Lottery_{i,t}^{max5} = \frac{LotteryNum_{i,t}^{max5}}{Num_{i,t}},$$

where $LotteryNum_{i,t}^{max5}$ is the number of lottery trades conducted within signal provider account $i$ in month $t$. As the variable is positively skewed, we apply the natural logarithm:

$$RLottery_{i,t}^{max5} = \ln\left(1 + Lottery_{i,t}^{max5}\right).$$

The regression model described in *Section 3.6.3* is applied; results are displayed in Table°V.

| ***Panel°A*: Relative Performance Measured over Previous Month** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\alpha$ | .0424*** | .0424*** | .0423*** | .0375*** | .0385*** | .0413*** | .0413*** | .0421*** | .0389*** | .0395*** |
| | (4.96) | (4.25) | (18.42) | (14.39) | (14.98) | (4.39) | (3.78) | (17.08) | (13.82) | (14.27) |
| $RPips_{i,t-1}$ | -.0089*** | -.0089*** | -.0087*** | -.0045*** | -.0049*** | | | | | |
| | (-4.15) | (-3.43) | (-14.37) | (-6.43) | (-7.05) | | | | | |
| $(RPips_{i,t-1})^2$ | .0009*** | .0009*** | .0008*** | .0004*** | .0005*** | | | | | |
| | (4.13) | (3.33) | (15.21) | (6.64) | (7.15) | | | | | |
| $RComb_{i,t-1}$ | | | | | | -.0104*** | -.0104*** | -.0103*** | -.0054*** | -.0055*** |
| | | | | | | (-3.57) | (-2.93) | (-13.51) | (-6.28) | (-6.48) |
| $(RComb_{i,t-1})^2$ | | | | | | .0011*** | .0011*** | .0010*** | .0005*** | .0005*** |
| | | | | | | (3.62) | (2.89) | (13.96) | (6.16) | (6.17) |
| $Lots_{i,t}$ | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (1.35) | (1.36) | (6.07) | (4.65) | (4.71) | (4.35) | (4.41) | (9.53) | (8.49) | (8.32) |
| $Age_{i,t}$ | -.0001 | -.0001 | -.0000*** | -.0003*** | -.0003*** | -.0001 | -.0001 | -.0000*** | -.0003*** | -.0003*** |
| | (-1.39) | (-1.28) | (-2.68) | (-13.41) | (-12.88) | (-1.31) | (-1.20) | (-2.67) | (-13.37) | (-12.85) |
| $Open_{i,t}$ | .0112 | .0112 | .0045* | .0063** | .0065** | .0120 | .0120 | .0047* | .0045* | .0046* |
| | (1.25) | (1.29) | (1.79) | (2.51) | (2.56) | (1.20) | (1.24) | (1.81) | (1.68) | (1.73) |
| $Long_{i,t}$ | .0107** | .0107** | .0131*** | .0069*** | .0073*** | .0113*** | .0113** | .0133*** | .0077*** | .0081*** |
| | (2.52) | (1.99) | (10.53) | (4.86) | (5.23) | (2.64) | (2.02) | (10.55) | (5.35) | (5.71) |
| $Commodity_{i,t}$ | .0564*** | .0564*** | .0550*** | .0563*** | .0575*** | .0585*** | .0585*** | .0572*** | .0558*** | .0571*** |
| | (5.47) | (5.30) | (43.16) | (31.98) | (34.25) | (5.79) | (5.62) | (45.20) | (31.35) | (33.71) |
| $Index_{i,t}$ | .0888*** | .0888*** | .0921*** | .0594*** | .0703*** | .0891*** | .0891*** | .0924*** | .0591*** | .0703*** |
| | (4.06) | (4.04) | (45.44) | (19.03) | (25.16) | (4.09) | (4.07) | (45.50) | (18.87) | (25.10) |
| $RNum_{i,t}$ | -.0048*** | -.0048*** | -.0044*** | -.0027*** | -.0030*** | -.0039*** | -.0039*** | -.0035*** | -.0022*** | -.0024*** |
| | (-6.43) | (-5.60) | (-15.98) | (-7.06) | (-8.26) | (-4.56) | (-4.05) | (-13.23) | (-5.73) | (-6.80) |
| $R^2$ | .0723 | .0723 | .1493 | .2090 | .1813 | .0734 | .0734 | .1514 | .2136 | .1858 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes |

**Table°IV: Monthly Relative Lottery Trades – Robustness regarding Independent Variables**

*Notes:* The table above displays panel regression estimates obtained by applying the regression model in *Section 3.6.3*. In each regression, the share of lottery-like trades of signal provider account $i$ in month $t$ ($RLottery_{i,t}^{max}$) is set as dependent variable. *Panel°A* reports the results relating to the relative performance variables – profit pips ($RPips_{i,t-1}$) and a term combining the profit pips and the win ratio metrics ($RComb_{i,t-1}$) – measured over the previous month. In *Panel°B*, relative performance variables ($R\overline{Pips}_{i,t-6}^{t-1}$ / $R\overline{Comb}_{i,t-6}^{t-1}$) are computed over the previous six months. In specification (1) and (6) t-statistics correspond to month and signal provider account-clustered standard errors; in specification (2) and (7) standard errors are clustered by month and signal provider (Petersen, 2009). Specifications (3) and (8) include time fixed effects. Fixed effects on the portfolio-level, i.e. for each signal provider account, are included in specifications (4) and (9). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5) and (10). All employed variables are displayed and described in the appendix Table°B. Trading data is obtained directly from the *ZuluTrade* platform, covering the period from October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| *Panel°B*: Relative Performance Measured over Previous Six Months | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| α | .0460*** | .0460*** | .0460*** | .0376*** | .0387*** | .0385*** | .0385*** | .0390*** | .0363*** | .0366*** |
| | (5.35) | (4.44) | (20.05) | (14.01) | (14.78) | (4.62) | (3.97) | (15.32) | (11.76) | (12.27) |
| $R\overline{Pips}_{i,t-6}^{t-1}$ | -.0102*** | -.0102*** | -.0101*** | -.0039*** | -.0043*** | | | | | |
| | (-4.53) | (-3.43) | (-16.66) | (-5.03) | (-5.74) | | | | | |
| $(R\overline{Pips}_{i,t-6}^{t-1})^2$ | .0009*** | .0009*** | .0009*** | .0003*** | .0003*** | | | | | |
| | (4.48) | (3.32) | (16.58) | (4.28) | (4.71) | | | | | |
| $R\overline{Comb}_{i,t-6}^{t-1}$ | | | | | | -.0077*** | -.0077*** | -.0075*** | -.0027*** | -.0023** |
| | | | | | | (-4.01) | (-3.19) | (-10.14) | (-2.86) | (-2.60) |
| $(R\overline{Comb}_{i,t-6}^{t-1})^2$ | | | | | | .0007*** | .0007*** | .0007*** | .0002* | .0001 |
| | | | | | | (3.99) | (3.03) | (9.97) | (1.90) | (1.16) |
| $Lots_{i,t}$ | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (1.36) | (1.37) | (6.04) | (4.60) | (4.66) | (4.30) | (4.35) | (9.42) | (8.43) | (8.25) |
| $Age_{i,t}$ | -.0001* | -.0001* | -.0001*** | -.0003*** | -.0003*** | -.0000 | -.0000 | -.0000* | -.0003*** | -.0003*** |
| | (-1.80) | (-1.69) | (-3.65) | (-13.51) | (-13.00) | (-.98) | (-.87) | (-1.88) | (-13.09) | (-12.62) |
| $Open_{i,t}$ | .0110 | .0110 | .0043* | .0062** | .0062** | .0106 | .0106 | .0034 | .0041 | .0042 |
| | (1.24) | (1.28) | (1.72) | (2.46) | (2.46) | (1.08) | (1.10) | (1.32) | (1.56) | (1.57) |
| $Long_{i,t}$ | .0107** | .0107** | .0131*** | .0067*** | .0071*** | .0114*** | .0114*** | .0135*** | .0076*** | .0079*** |
| | (2.53) | (2.00) | (10.57) | (4.74) | (5.09) | (2.68) | (2.05) | (10.66) | (5.28) | (5.59) |
| $Commodity_{i,t}$ | .0563*** | .0563*** | .0549*** | .0568*** | .0580*** | .0596*** | .0596*** | .0582*** | .0563*** | .0577*** |
| | (5.47) | (5.29) | (42.95) | (32.26) | (34.57) | (5.97) | (5.81) | (46.12) | (31.67) | (34.10) |
| $Index_{i,t}$ | .0887*** | .0887*** | .0920*** | .0596*** | .0707*** | .0886*** | .0886*** | .0919*** | .0591*** | .0703*** |
| | (4.06) | (4.04) | (45.41) | (19.10) | (25.31) | (4.07) | (4.05) | (45.20) | (18.84) | (25.10) |
| $RNum_{i,t}$ | -.0044*** | -.0044*** | -.0040*** | -.0023*** | -.0026*** | -.0036*** | -.0036*** | -.0033*** | -.0021*** | -.0023*** |
| | (-5.62) | (-4.98) | (-14.75) | (-6.17) | (-7.13) | (-4.11) | (-3.65) | (-12.43) | (-5.50) | (-6.39) |
| $R^2$ | .0728 | .0728 | .1498 | .2089 | .1813 | .0723 | .0723 | .1502 | .2134 | .1857 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes |

**Table°IV – *Continued***

Applying an alternative lottery definition yields results that are very similar to those of the previous regression analyses. There is consistent empirical evidence for a quadratic relationship between past relative performance – measured in win ratios ($RWin_{i,t-1}$ / $R\overline{Win}_{i,t-6}^{t-1}$) and net profits ($RProfit_{i,t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$) – and the traded lottery share.

## *6 Conclusion*

On social trading platforms, signal providers may easily open accounts without having to meet qualification requirements. As social trading platforms allow signal providers to simultaneously operate several accounts and furthermore offer trading with virtual money, the costs of closing an unsuccessful or declining account are rather limited. When facing the relatively narrow selection of the foreign exchange market, we argue that signal providers may be inclined to trade currency pairs with extreme past returns due to their own limited downside risk. Using panel regression analyses, we provide empirical evidence of a quadratic relationship between previous relative trader account performance and the traded lottery share: Signal providers with bad relative performance and signal providers with good relative performance – in comparison to their peers – trade a higher monthly share of lotteries. Our results are in line with previous research in behavioral finance (Broihanne et al., 2014; De Long et al., 1991; Odean, 1999) as well as with research in the relatively nouvelle area of social trading (Czaja & Röder, 2020).

As competition among signal providers is fierce, only few manage to obtain a top position on the platform composed selection lists which, in turn, attracts the attention of followers. Since an adequate follower base is required in order to become eligible for compensation, signal providers managing a poorly performing account might be inclined to take gambles as a potentially last chance to get to the top. Those signal providers may perceive currency pairs exhibiting extreme daily returns as adequate gambling options and, thus, allocate their resources accordingly. Signal providers who previously outperformed their peers face the downside of losing followers as well as their obtained positioning when gambling trades fail. However, factors like overconfidence as well as the direct incentive to receive (extensive) remuneration may induce those signal providers to conduct lottery transactions.

| ***Panel°A*: Relative Performance Measured over Previous Month** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| $\alpha$ | .0349*** | .0349*** | .0362*** | .0361*** | .0378*** | .0429*** | .0429*** | .0436*** | .0337*** | .0358*** | .0447*** | .0447*** | .0456*** | .0354*** | .0372*** |
| | (5.33) | (5.07) | (17.20) | (15.08) | (16.14) | (6.61) | (5.58) | (20.20) | (13.89) | (14.99) | (6.36) | (5.58) | (19.78) | (13.87) | (14.80) |
| $RWin_{i,t-1}$ | -.0063*** | -.0063*** | -.0064*** | -.0024*** | -.0027*** | | | | | | | | | | |
| | (-3.56) | (-3.31) | (-9.18) | (-3.24) | (-3.59) | | | | | | | | | | |
| $(RWin_{i,t-1})^2$ | .0007*** | .0007*** | .0007*** | .0002*** | .0002*** | | | | | | | | | | |
| | (3.71) | (3.37) | (9.62) | (2.94) | (3.10) | | | | | | | | | | |
| $RProfit_{i,t-1}$ | | | | | | -.0077*** | -.0077*** | -.0076*** | -.0017** | -.0021*** | | | | | |
| | | | | | | (-5.81) | (-4.80) | (-13.29) | (-2.47) | (-3.21) | | | | | |
| $(RProfit_{i,t-1})^2$ | | | | | | .0008*** | .0008*** | .0008*** | .0002*** | .0002*** | | | | | |
| | | | | | | (6.40) | (5.02) | (15.70) | (2.94) | (3.70) | | | | | |
| $RComb_{i,t-1}$ | | | | | | | | | | | -.0107*** | -.0107*** | -.0105*** | -.0021*** | -.0025*** |
| | | | | | | | | | | | (-5.31) | (-4.53) | (-14.55) | (-2.69) | (-3.15) |
| $(RComb_{i,t-1})^2$ | | | | | | | | | | | .0011*** | .0011*** | .0011*** | .0002*** | .0002*** |
| | | | | | | | | | | | (5.41) | (4.49) | (16.26) | (2.76) | (3.15) |
| $Lots_{i,t}$ | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (6.22) | (6.39) | (10.99) | (10.82) | (10.49) | (1.58) | (1.59) | (6.85) | (5.71) | (5.72) | (6.12) | (6.29) | (10.96) | (10.84) | (10.51) |
| $Age_{i,t}$ | -.0001* | -.0001 | -.0001*** | -.0003*** | -.0003*** | -.0001*** | -.0001*** | -.0001*** | -.0003*** | -.0003*** | -.0001*** | -.0001*** | -.0001*** | -.0003*** | -.0003*** |
| | (-1.79) | (-1.51) | (-3.18) | (-13.38) | (-14.01) | (-4.00) | (-3.45) | (-7.68) | (-13.64) | (-14.29) | (-3.49) | (-3.04) | (-6.61) | (-13.48) | (-14.18) |
| $Open_{i,t}$ | -.0038 | -.0038 | -.0083*** | -.0127*** | -.0123*** | -.0028 | -.0028 | -.0072*** | -.0088*** | -.0087*** | -.0034 | -.0034 | -.0079*** | -.0127*** | -.0124*** |
| | (-.39) | (-.41) | (-3.39) | (-5.34) | (-5.18) | (-.28) | (-.29) | (-3.09) | (-3.89) | (-3.79) | (-.36) | (-.37) | (-3.24) | (-5.36) | (-5.19) |
| $Long_{i,t}$ | .0042 | .0042 | .0053*** | .0006 | .0014 | .0038 | .0038 | .0050*** | .0001 | .0008 | .0035 | .0035 | .0047*** | .0006 | .0014 |
| | (.96) | (.68) | (4.50) | (.45) | (1.13) | (.88) | (.64) | (4.30) | (.05) | (.60) | (.82) | (.58) | (3.93) | (.44) | (1.12) |
| $Commodity_{i,t}$ | .0656*** | .0656*** | .0655*** | .0581*** | .0605*** | .0644*** | .0644*** | .0642*** | .0583*** | .0608*** | .0647*** | .0647*** | .0645*** | .0581*** | .0605*** |
| | (6.00) | (5.89) | (55.42) | (36.47) | (39.80) | (5.88) | (5.78) | (54.33) | (36.73) | (40.11) | (5.93) | (5.83) | (54.65) | (36.48) | (39.80) |
| $Index_{i,t}$ | .1003*** | .1003*** | .1036*** | .0637*** | .0795*** | .1000*** | .1000*** | .1031*** | .0649*** | .0799*** | .1006*** | .1006*** | .1038*** | .0637*** | .0796*** |
| | (5.19) | (5.16) | (54.30) | (22.70) | (31.59) | (5.16) | (5.12) | (53.80) | (22.98) | (31.50) | (5.21) | (5.18) | (54.53) | (22.69) | (31.62) |
| $RNum_{i,t}$ | -.0031*** | -.0031*** | -.0031*** | -.0013*** | -.0019*** | -.0046*** | -.0046*** | -.0045*** | -.0018*** | -.0024*** | -.0035*** | -.0035*** | -.0035*** | -.0014*** | -.0020*** |
| | (-4.03) | (-3.42) | (-12.12) | (-3.85) | (-5.72) | (-5.55) | (-4.94) | (-18.25) | (-5.37) | (-7.46) | (-4.69) | (-4.08) | (-14.08) | (-4.20) | (-6.15) |
| $R^2$ | .1001 | .1001 | .1300 | .2658 | .2359 | .0999 | .0999 | .1298 | .2588 | .2297 | .1028 | .1028 | .1327 | .2657 | .2358 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes |

**Table°V: Monthly Relative Lottery Trades – Robustness regarding Lottery Definition**

*Notes:* The table above displays regression estimates obtained by applying the regression model in *Section 3.6.3*; the share of lottery-like trades as defined in *Section 5.2* is set as dependent variable ($RLottery_{i,t}^{max5}$). *Panel°A* reports the results relating to the relative performance variables – win ratio ($RWin_{i,t-1}$), net profit ($RProfit_{i,t-1}$), and the combined term ($RComb_{i,t-1}$) – measured over the previous month. In *Panel°B*, relative performance variables ($R\overline{Win}_{i,t-6}^{t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$ / $R\overline{Comb}_{i,t-6}^{t-1}$) are computed over the previous six months. In specification (1), (6), and (11), t-statistics correspond to month and signal provider account-clustered standard errors; in specification (2), (7), and (12) standard errors are clustered by month and signal provider (Petersen, 2009). Specifications (3), (8), and (13) include time fixed effects. Fixed effects on the portfolio-level, i.e. for each signal provider account, are included in specifications (4), (9), and (14). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5), (10), and (15). All employed variables are displayed and described in the appendix Table°B. Trading data is obtained directly from the *ZuluTrade* platform, covering the period from October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Panel°B*: Relative Performance Measured over Previous Six Months** | | | | | | | | | | | | | | | |
| $\alpha$ | .0346*** | .0346*** | .0356*** | .0398*** | .0412*** | .0539*** | .0539*** | .0546*** | .0388*** | .0410*** | .0496*** | .0496*** | .0493*** | .0406*** | .0412*** |
| | (5.45) | (5.16) | (17.15) | (15.16) | (16.36) | (7.46) | (6.00) | (25.12) | (15.48) | (16.75) | (6.64) | (5.96) | (20.60) | (14.56) | (15.23) |
| $R\overline{Win}_{i,t-6}^{t-1}$ | -.0051*** | -.0051*** | -.0050*** | -.0037*** | -.0034*** | | | | | | | | | | |
| | (-3.97) | (-3.49) | (-9.06) | (-4.93) | (-4.79) | | | | | | | | | | |
| $(R\overline{Win}_{i,t-6}^{t-1})^2$ | .0005*** | .0005*** | .0005*** | .0003*** | .0002*** | | | | | | | | | | |
| | (3.90) | (3.49) | (9.61) | (4.60) | (3.95) | | | | | | | | | | |
| $R\overline{Profit}_{i,t-6}^{t-1}$ | | | | | | -.0126*** | -.0126*** | -.0125*** | -.0032*** | -.0036*** | | | | | |
| | | | | | | (-6.48) | (-4.82) | (-21.69) | (-4.30) | (-5.11) | | | | | |
| $(R\overline{Profit}_{i,t-6}^{t-1})^2$ | | | | | | .0012*** | .0012*** | .0012*** | .0003*** | .0003*** | | | | | |
| | | | | | | (6.62) | (4.94) | (23.69) | (3.56) | (4.27) | | | | | |
| $R\overline{Comb}_{i,t-6}^{t-1}$ | | | | | | | | | | | -.0116*** | -.0116*** | -.0109*** | -.0033*** | -.0028*** |
| | | | | | | | | | | | (-5.52) | (-4.95) | (-15.65) | (-3.95) | (-3.51) |
| $(R\overline{Comb}_{i,t-6}^{t-1})^2$ | | | | | | | | | | | .0011*** | .0011*** | .0011*** | .0002*** | .0002** |
| | | | | | | | | | | | (5.24) | (4.63) | (17.06) | (3.12) | (2.35) |
| $Lots_{i,t}$ | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000 | .0000 | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** | .0000*** |
| | (6.36) | (6.57) | (10.92) | (10.78) | (10.44) | (1.55) | (1.56) | (6.59) | (5.63) | (5.65) | (6.48) | (6.72) | (10.70) | (10.75) | (10.43) |
| $Age_{i,t}$ | -.0000 | -.0000 | -.0000** | -.0003*** | -.0003*** | -.0002*** | -.0002*** | -.0002*** | -.0003*** | -.0003*** | -.0001*** | -.0001*** | -.0001** | -.0003*** | -.0003*** |
| | (-1.36) | (-1.13) | (-2.26) | (-13.32) | (-13.95) | (-4.76) | (-4.10) | (-9.96) | (-13.60) | (-14.26) | (-2.66) | (-2.24) | (-4.92) | (-13.45) | (-14.02) |
| $Open_{i,t}$ | -.0044 | -.0044 | -.0088*** | -.0128*** | -.0125*** | -.0015 | -.0015 | -.0059** | -.0085*** | -.0083*** | -.0043 | -.0043 | -.0086*** | -.0127*** | -.0124*** |
| | (-.46) | (-.48) | (-3.61) | (-5.37) | (-5.22) | (-.15) | (-.16) | (-2.53) | (-3.74) | (-3.65) | (-.45) | (-.47) | (-3.51) | (-5.35) | (-5.21) |
| $Long_{i,t}$ | .0042 | .0042 | .0054*** | .0006 | .0015 | .0032 | .0032 | .0044*** | -.0000 | .0007 | .0037 | .0037 | .0049*** | .0005 | .0014 |
| | (.97) | (.69) | (4.53) | (.48) | (1.14) | (.74) | (.54) | (3.74) | (-.02) | (.52) | (.88) | (.63) | (4.16) | (.41) | (1.07) |
| $Commodity_{i,t}$ | .0657*** | .0657*** | .0655*** | .0582*** | .0606*** | .0627*** | .0627*** | .0626*** | .0582*** | .0607*** | .0647*** | .0647*** | .0645*** | .0581*** | .0605*** |
| | (6.00) | (5.90) | (55.43) | (36.56) | (39.89) | (5.79) | (5.68) | (52.91) | (36.64) | (40.00) | (5.96) | (5.86) | (54.65) | (36.49) | (39.80) |
| $Index_{i,t}$ | .0999*** | .0999*** | .1032*** | .0637*** | .0793*** | .0998*** | .0998*** | .1030*** | .0650*** | .0801*** | .1004*** | .1004*** | .1036*** | .0636*** | .0795*** |
| | (5.18) | (5.15) | (54.06) | (22.69) | (31.52) | (5.17) | (5.13) | (53.81) | (23.02) | (31.61) | (5.22) | (5.19) | (54.40) | (22.67) | (31.61) |
| $RNum_{i,t}$ | -.0033*** | -.0033*** | -.0033*** | -.0014*** | -.0019*** | -.0044*** | -.0044*** | -.0043*** | -.0016*** | -.0022*** | -.0034*** | -.0034*** | -.0034*** | -.0014*** | -.0019*** |
| | (-4.74) | (-4.11) | (-13.27) | (-4.11) | (-6.04) | (-5.30) | (-4.80) | (-17.62) | (-4.77) | (-6.75) | (-4.76) | (-4.18) | (-13.84) | (-4.02) | (-5.92) |
| $R^2$ | .1001 | .1001 | .1300 | .2659 | .2360 | .1032 | .1032 | .1330 | .2568 | .2299 | .1032 | .1032 | .1328 | .2659 | .2361 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes | No | No | No | No | Yes |

**Table°V – *Continued***

## *References*


Allen, H., & Taylor, M. P. (1990). Charts, Noise and Fundamentals in the London Foreign Exchange Market. *The Economic Journal*, *100*(400), 49. https://doi.org/10.2307/2234183

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014

Balima, H. W. (2020). Coups d'état and the foreign exchange market. *The World Economy*, *43*(7), 1928–1950. https://doi.org/10.1111/twec.12905

Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics*, *116*(1), 261–292. https://doi.org/10.1162/003355301556400

Barber, B. M., & Odean, T. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, *21*(2), 785–818. https://doi.org/10.1093/rfs/hhm079

Benos, A. V. (1998). Aggressiveness and survival of overconfident traders. *Journal of Financial Markets*, *1*(3-4), 353–383. https://doi.org/10.1016/S1386-4181(97)00010-4

Berger, E. S.C., Wenzel, M., & Wohlgemuth, V. (2018). Imitation-related performance outcomes in social trading: A configurational approach. *Journal of Business Research*, *89*, 322–327. https://doi.org/10.1016/j.jbusres.2017.12.016

Broihanne, M. H., Merli, M., & Roger, P. (2014). Overconfidence, risk perception and the risk-taking behavior of finance professionals. *Finance Research Letters*, *11*(2), 64–73. https://doi.org/10.1016/j.frl.2013.11.002

Bruche, M., & Llobet, G. (2014). Preventing Zombie Lending. *The Review of Financial Studies*, *27*(3), 923–956. Retrieved from http://www.jstor.org/stable/24465697

Calveras, A., Ganuza, J.-J., & Hauk, E. (2004). Wild Bids. Gambling for Resurrection in Procurement Contracts. *Journal of Regulatory Economics*, *26*(1), 41–68. https://doi.org/10.1023/B:REGE.0000028013.76488.44

Chimienti, M. T., Kochanska, U., & Pinna, A. (2019). Understanding the crypto-asset phenomenon, its risks and measurement issues. *Economic Bulletin*. (5), 100–122.

Chiu, E. M. P., & Willett, T. D. (2009). The Interactions of Strength of Governments and Alternative Exchange Rate Regimes in Avoiding Currency Crises. *International Studies Quarterly*, *53*(4), 1001–1025. https://doi.org/10.1111/j.1468-2478.2009.00566.x

Connolly, M. (1986). The speculative attack on the peso and the real exchange rate: Argentina, 1979–1981. *Journal of International Money and Finance*, *5*, S117-S130. https://doi.org/10.1016/0261-5606(86)90025-2

Czaja, D., & Röder, F. (2020). Self-attribution bias and overconfidence among nonprofessional traders. *The Quarterly Review of Economics and Finance.* Advance online publication. https://doi.org/10.1016/j.qref.2020.02.003

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, *53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1991). The Survival of Noise Traders in Financial Markets. *The Journal of Business*, *64*(1), 1–19. https://doi.org/10.1086/296523

Dorfleitner, G., Fischer, L., Lung, C., Willmertinger, P., Stang, N., & Dietrich, N. (2018). To follow or not to follow – An empirical analysis of the returns of actors on social trading platforms. *The Quarterly Review of Economics and Finance*, *70*, 160–171. https://doi.org/10.1016/j.qref.2018.04.009

Dorn, D., & Sengmueller, P. (2009). Trading as Entertainment? *Management Science*, *55*(4), 591–603. Retrieved from www.jstor.org/stable/40539172

Eichengreen, B., Rose, A. K., Wyplosz, C., Dumas, B., & Weber, A. (1995). Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks. *Economic Policy*, *10*(21), 249. https://doi.org/10.2307/1344591

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Félix, L., Kräussl, R., & Stork, P. (2019). Single Stock Call Options as Lottery Tickets: Overpricing and Investor Sentiment. *Journal of Behavioral Finance*, *20*(4), 385–407. https://doi.org/10.1080/15427560.2018.1511792

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. *Journal of International Economics*, *41*(3-4), 351–366. https://doi.org/10.1016/S0022-1996(96)01441-9

Gemayel, R., & Preda, A. (2018a). Does a scopic regime erode the disposition effect? Evidence from a social trading platform. *Journal of Economic Behavior & Organization*, *154*, 175–190. https://doi.org/10.1016/j.jebo.2018.08.014

Gemayel, R., & Preda, A. (2018b). Does a scopic regime produce conformism? Herding behavior among trade leaders on social trading platforms. *The European Journal of Finance*, *24*(14), 1144–1175. https://doi.org/10.1080/1351847X.2017.1405832

Gervais, S., & Odean, T. (2001). Learning to Be Overconfident. *Review of Financial Studies*, *14*(1), 1–27. https://doi.org/10.1093/rfs/14.1.1

Giudici, G., Milne, A., & Vinogradov, D. (2020). Cryptocurrencies: market analysis and perspectives. *Journal of Industrial and Business Economics*, *47*(1), 1–18. https://doi.org/10.1007/s40812-019-00138-6

Glaser, F., & Risius, M. (2018). Effects of Transparency: Analyzing Social Biases on Trader Performance in Social Trading. *Journal of Information Technology*, *33*(1), 19–30. https://doi.org/10.1057/s41265-016-0028-0

Hirshleifer, D. (2015). Behavioral Finance. *Annual Review of Financial Economics*, *7*(1), 133–159. https://doi.org/10.1146/annurev-financial-092214-043752

Jacobs, H., & Hillert, A. (2016). Alphabetic Bias, Investor Recognition, and Trading Behavior. *Review of Finance*, *20*(2), 693–723. https://doi.org/10.1093/rof/rfv060

Jean-Charles Rochet (2008). Why Are There So Many Banking Crises?: The Politics and Policy of Bank Regulation. In J.-C. Rochet (Ed.), *Why are there so many banking crises?: The politics and policy of bank regulation*. Princeton, NJ: Princeton University Press.

Jin, X., Zhu, Y., & Huang, Y. S. (2019). Losing by learning? A study of social trading platform. *Finance Research Letters*, *28*, 171–179. https://doi.org/10.1016/j.frl.2018.04.017

Kahneman, D. (1973). *Attention and effort*. *Prentice Hall series in experimental psychology*. Englewood Cliffs: Prentice Hall.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–291. https://doi.org/10.2307/1914185

Kirchler, M., Linder, F., & Weitzel, U. (2018). Rankings and Risk-Taking in the Finance Industry. *The Journal of Finance*, *73*(5), 2271–2302. https://doi.org/10.1111/jofi.12701

Kromidha, E., & Li, M. C. (2019). Determinants of leadership in online social trading: A signaling theory perspective. *Journal of Business Research*, *97*, 184–197. https://doi.org/10.1016/j.jbusres.2019.01.004

Krugman, P. (1979). A Model of Balance-of-Payments Crises. *Journal of Money, Credit and Banking*, *11*(3), 311. https://doi.org/10.2307/1991793

Kumar, A. (2009). Who Gambles in the Stock Market? *The Journal of Finance*, *64*(4), 1889–1933. https://doi.org/10.1111/j.1540-6261.2009.01483.x

Lambert, N. S., Ostrovsky, M., & Panov, M. (2018). Strategic Trading in Informationally Complex Environments. *Econometrica*, *86*(4), 1119–1157. https://doi.org/10.3982/ECTA12635

Leblang, D., & Satyanath, S. (2006). Institutions, Expectations, and Currency Crises. *International Organization*, *60*(01). https://doi.org/10.1017/S0020818306060073

Leblang, D., & Satyanath, S. (2008). Politically generated uncertainty and currency crises: Theory, tests, and forecasts. *Journal of International Money and Finance*, *27*(3), 480–497. https://doi.org/10.1016/j.jimonfin.2008.01.006

Lee, W., & Ma, Q. (2018). Discovering Expert Traders on Social Trading Services. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *22*(2), 224–235. https://doi.org/10.20965/jaciii.2018.p0224

Obstfeld, M. (1996). Models of currency crises with self-fulfilling features. *European Economic Review*, *40*(3-5), 1037–1047. https://doi.org/10.1016/0014-2921(95)00111-5

Odean, T. (1998). Volume, Volatility, Price, and Profit When All Traders Are Above Average. *The Journal of Finance*, *53*(6), 1887–1934. https://doi.org/10.1111/0022-1082.00078

Odean, T. (1999). Do Investors Trade Too Much? *American Economic Review*, *89*(5), 1279–1298. https://doi.org/10.1257/aer.89.5.1279

Oehler, A. (1995). *Die Erklärung des Verhaltens privater Anleger: Theoretischer Ansatz und empirische Analysen*. Zugl.: Hagen, Fernuniv., Habil-Schr., 1994. *Betriebswirtschaftliche Abhandlungen: N.F., 100*. Stuttgart: Schäffer-Poeschel.

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. https://doi.org/10.1016/j.irfa.2016.05.007

Oehler, A., Horn, M., Wendt, S., Reisch, L. A., & Walker, T. J. (2018). Young Adults and Their Finances: An International Comparative Study on Applied Financial Literacy. *Economic Notes*, *47*(2-3), 305–330. https://doi.org/10.1111/ecno.12110

Oehler, A., & Wedlich, F. (2018). The relationship of extraversion and neuroticism with risk attitude, risk perception, and return expectations. *Journal of Neuroscience, Psychology, and Economics*, *11*(2), 63–92. https://doi.org/10.1037/npe0000088

Oehler, A., Wendt, S., Wedlich, F., & Horn, M. (2018). Investors' Personality Influences Investment Decisions: Experimental Evidence on Extraversion and Neuroticism. *Journal of Behavioral Finance*, *19*(1), 30–48. https://doi.org/10.1080/15427560.2017.1366495

Pelster, M., & Breitmayer, B. (2019). Attracting attention from peers: Excitement in social trading. *Journal of Economic Behavior & Organization*, *161*, 158–179. https://doi.org/10.1016/j.jebo.2019.03.010

Pelster, M., & Hofmann, A. (2018). About the fear of reputational loss: Social trading and the disposition effect. *Journal of Banking & Finance*, *94*, 75–88. https://doi.org/10.1016/j.jbankfin.2018.07.003

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, *22*(1), 435–480. Retrieved from www.jstor.org/stable/40056916

Reith, R., Fischer, M., & Lis, B. (2019). Explaining the intention to use social trading platforms: an empirical investigation. *Journal of Business Economics*, *50*, 179. https://doi.org/10.1007/s11573-019-00961-2

Rochet, J.-C. (Ed.) (2008). *Why are there so many banking crises?: The politics and policy of bank regulation*. Princeton, NJ: Princeton University Press. https://doi.org/10.2307/j.ctt7sxbq

Röder, F., & Walter, A. (2019). What Drives Investment Flows into Social Trading Portfolios? *The Journal of Financial Research*, *42*(2), 383–411. https://doi.org/10.1111/jfir.12174

Rotemberg, J. J., & Krugman, P. (1991). Speculative Attacks on Target Zones. In P. Krugman & M. Miller (Eds.), *Exchange Rate Targets and Currency Bands*. Cambridge: Cambridge University Press.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

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. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65–73. https://doi.org/10.1016/j.bir.2014.03.001

Statman, M., Thorley, S., & Vorkink, K. (2006). Investor Overconfidence and Trading Volume. *Review of Financial Studies*, *19*(4), 1531–1565. https://doi.org/10.1093/rfs/hhj032

Steinberg, D. A., Koesel, K. J., & Thompson, N. W. (2015). Political Regimes and Currency Crises. *Economics & Politics*, *27*(3), 337–361. https://doi.org/10.1111/ecpo.12060

Suhonen, N., & Saastamoinen, J. (2018). How Do Prior Gains and Losses Affect Subsequent Risk Taking? New Evidence from Individual-Level Horse Race Bets. *Management Science*, *64*(6), 2797–2808. https://doi.org/10.1287/mnsc.2016.2679

Taffler, R. (2018). Emotional finance: investment and the unconscious. *The European Journal of Finance*, *24*(7-8), 630–653. https://doi.org/10.1080/1351847X.2017.1369445

Thaler, R. H. (2016). Behavioral Economics: Past, Present, and Future. *American Economic Review*, *106*(7), 1577–1600. https://doi.org/10.1257/aer.106.7.1577

Thaler, R. H. (2018). From Cashews to Nudges: The Evolution of Behavioral Economics. *American Economic Review*, *108*(6), 1265–1287. https://doi.org/10.1257/aer.108.6.1265

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science*, *36*(6), 643–660. Retrieved from http://www.jstor.org/stable/2631898

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science (New York, N.Y.)*, *185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

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. https://doi.org/10.1016/j.jbusres.2016.04.061

## Table°A: Traded Assets *ZuluTrade* Platform

| Symbol | Meaning | Source | Round Trips | Buy | Sell |
|---|---|---|---|---|---|
| ***Currencies*** | | | | | |
| AUD/CAD | Australian Dollar/Canadian Dollar | Reserve Bank of Australia | 71,179 | 34,359 | 36,820 |
| AUD/CHF | Australian Dollar/Swiss Franc | Reserve Bank of Australia | 29,229 | 15,859 | 13,370 |
| AUD/DKK | Australian Dollar/Danish Krone | Danmarks Nationalbank | 3 | 2 | 1 |
| AUD/JPY | Australian Dollar/Japanese Yen | Reserve Bank of Australia | 56,759 | 25,571 | 31,188 |
| AUD/NOK | Australian Dollar/Norwegian Krone | Norges Bank | 1 | 1 | 0 |
| AUD/NZD | Australian Dollar/New Zealand Dollar | Reserve Bank of Australia | 56,378 | 29,173 | 27,205 |
| AUD/PLN | Australian Dollar/Polish Zloty | Narodowy Bank Polski | 5 | 4 | 1 |
| AUD/SGD | Australian Dollar/Singapore Dollar | Reserve Bank of Australia | 2,345 | 1,128 | 1,217 |
| AUD/USD | Australian Dollar/US Dollar | Reserve Bank of Australia | 190,766 | 85,529 | 105,237 |
| AUD/ZAR | Australian Dollar/South African Rand | South African Reserve Bank | 4 | 1 | 3 |
| CAD/CHF | Canadian Dollar/Swiss Franc | European Central Bank | 24,818 | 12,869 | 11,949 |
| CAD/JPY | Canadian Dollar/Japanese Yen | European Central Bank | 37,244 | 18,119 | 19,125 |
| CAD/MXN | Canadian Dollar/Mexican Peso | European Central Bank | 1 | 0 | 1 |
| CHF/HUF | Swiss Franc/Hungarian Forint | Central Bank of Hungary | 2 | 1 | 1 |
| CHF/JPY | Swiss Franc/Japanese Yen | European Central Bank | 41,763 | 18,787 | 22,976 |
| CHF/NOK | Swiss Franc/Norwegian Krone | Norges Bank | 7 | 5 | 2 |
| CHF/PLN | Swiss Franc/Polish Zloty | Narodowy Bank Polski | 1 | 1 | 0 |
| CHF/SEK | Swiss Franc/Swedish Krona | Sveriges Riksbank | 10 | 3 | 7 |
| CHF/SGD | Swiss Franc/Singapore Dollar | Monetary Authority of Singapore/ European Central Bank | 475 | 165 | 310 |
| CHF/ZAR | Swiss Franc/South African Rand | South African Reserve Bank | 2 | 1 | 1 |
| EUR/AUD | Euro/Australian Dollar | European Central Bank | 113,777 | 51,536 | 62,241 |
| EUR/CAD | Euro/Canadian Dollar | European Central Bank | 73,146 | 34,068 | 39,078 |
| EUR/CHF | Euro/Swiss Franc | European Central Bank | 80,974 | 40,550 | 40,424 |
| EUR/CZK | Euro/Czech Koruna | European Central Bank | 77 | 48 | 29 |
| EUR/DKK | Euro/Danish Krone | European Central Bank | 186 | 167 | 19 |
| EUR/GBP | Euro/Pound Sterling | European Central Bank | 120,039 | 51,607 | 68,432 |
| EUR/HKD | Euro/Hong Kong Dollar | European Central Bank | 180 | 95 | 85 |
| EUR/HUF | Euro/Hungarian Forint | European Central Bank | 59 | 47 | 12 |
| EUR/JPY | Euro/Japanese Yen | European Central Bank | 177,219 | 82,039 | 95,180 |
| EUR/MXN | Euro/Mexican Peso | European Central Bank | 17 | 4 | 13 |
| EUR/NOK | Euro/Norwegian Krone | European Central Bank | 2,940 | 843 | 2,097 |
| EUR/NZD | Euro/New Zealand Dollar | European Central Bank | 64,351 | 29,940 | 34,411 |
| EUR/PLN | Euro/Polish Zloty | European Central Bank | 54 | 19 | 35 |
| EUR/RUB | Euro/Russian Ruble | European Central Bank | 2 | 2 | 0 |
| EUR/SEK | Euro/Swedish Krona | European Central Bank | 1,760 | 942 | 818 |
| EUR/SGD | Euro/Singapore Dollar | European Central Bank | 4,054 | 1,836 | 2,218 |
| EUR/TRY | Euro/Turkish Lira | European Central Bank | 753 | 226 | 527 |
| EUR/USD | Euro/US Dollar | European Central Bank | 1,360,249 | 673,899 | 686,350 |
| EUR/ZAR | Euro/South African Rand | European Central Bank | 383 | 79 | 304 |
| GBP/AUD | Pound Sterling/Australian Dollar | Bank of England | 129,847 | 54,985 | 74,862 |
| GBP/CAD | Pound Sterling/Canadian Dollar | Bank of England | 74,965 | 36,256 | 38,709 |
| GBP/CHF | Pound Sterling/Swiss Franc | Bank of England | 58,694 | 31,627 | 27,067 |
| GBP/DKK | Pound Sterling/Danish Krone | Bank of England | 6 | 6 | 0 |
| GBP/HKD | Pound Sterling/Hong Kong Dollar | Bank of England | 2 | 2 | 0 |
| GBP/JPY | Pound Sterling/Japanese Yen | Bank of England | 315,527 | 160,767 | 154,760 |
| GBP/MXN | Pound Sterling/Mexican Peso | European Central Bank | 1 | 0 | 1 |
| GBP/NOK | Pound Sterling/Norwegian Krone | Bank of England | 89 | 14 | 75 |
| GBP/NZD | Pound Sterling/New Zealand Dollar | Bank of England | 115,421 | 59,397 | 56,024 |
| GBP/PLN | Pound Sterling/Polish Zloty | Bank of England/European Central Bank | 14 | 14 | 0 |
| GBP/SEK | Pound Sterling/Swedish Krona | Bank of England | 159 | 103 | 56 |
| GBP/SGD | Pound Sterling/Singapore Dollar | Bank of England | 719 | 329 | 390 |
| GBP/TRY | Pound Sterling/Turkish Lira | Bank of England/ Central Bank of the Republic of Turkey | 1 | 0 | 1 |
| GBP/USD | Pound Sterling/US Dollar | Bank of England | 661,469 | 347,548 | 313,921 |
| GBP/ZAR | Pound Sterling/South African Rand | Bank of England | 1 | 1 | 0 |

*Notes:* The table above displays all assets which have been traded by signal providers in the obtained dataset. For each asset, the respective applied source of price data as well as the number of corresponding transactions is displayed. Asset categories include currencies, crypto currencies, commodities, indices, stocks, and others.

## Table°A – *Continued*

| Symbol | Meaning | Source | Round Trips | Buy | Sell |
|---|---|---|---|---|---|
| ***Currencies*** | | | | | |
| HKD/JPY | Hong Kong Dollar/Japanese Yen | European Central Bank | 8 | 4 | 4 |
| HUF/JPY | Hungarian Forint/Japanese Yen | Central Bank of Hungary | 20 | 11 | 9 |
| MXN/JPY | Mexican Peso/Japanese Yen | European Central Bank | 1 | 1 | 0 |
| NOK/JPY | Norwegian Krone/Japanese Yen | Norges Bank | 48 | 31 | 17 |
| NOK/SEK | Norwegian Krone/Swedish Krona | Norges Bank | 26 | 17 | 9 |
| NZD/CAD | New Zealand Dollar/Canadian Dollar | Reserve Bank of New Zealand | 47,477 | 22,034 | 25,443 |
| NZD/CHF | New Zealand Dollar/Swiss Franc | Reserve Bank of New Zealand/ European Central Bank | 16,109 | 8,710 | 7,399 |
| NZD/JPY | New Zealand Dollar/Japanese Yen | Reserve Bank of New Zealand | 33,936 | 17,416 | 16,520 |
| NZD/SGD | New Zealand Dollar/Singapore Dollar | Reserve Bank of New Zealand | 1 | 0 | 1 |
| NZD/USD | New Zealand Dollar/US Dollar | Reserve Bank of New Zealand | 102,538 | 51,091 | 51,447 |
| SEK/JPY | Swedish Krona/Japanese Yen | Sveriges Riksbank | 40 | 25 | 15 |
| SGD/JPY | Singapore Dollar/Japanese Yen | Singapore Monetary Authority/ European Central Bank | 602 | 293 | 309 |
| TRY/JPY | Turkish Lira/Japanese Yen | Central Bank of the Republic of Turkey | 1,023 | 860 | 163 |
| USD/BRL | US Dollar/Brazilian Real | Federal Reserve Bank | 20 | 0 | 20 |
| USD/CAD | US Dollar/Canadian Dollar | Federal Reserve Bank | 224,554 | 104,029 | 120,525 |
| USD/CHF | US Dollar/Swiss Franc | Federal Reserve Bank | 133,022 | 68,814 | 64,208 |
| USD/CNH | US Dollar/Chinese Yuan Renminbi | investing.com | 5,506 | 2,469 | 3,037 |
| USD/CZK | US Dollar/Czech Koruna | Czech National Bank | 38 | 17 | 21 |
| USD/DKK | US Dollar/Danish Krone | Federal Reserve Bank | 172 | 89 | 83 |
| USD/HKD | US Dollar/Hong Kong Dollar | Federal Reserve Bank | 62 | 47 | 15 |
| USD/HUF | US Dollar/Hungarian Forint | Central Bank of Hungary | 259 | 114 | 145 |
| USD/ILS | US Dollar/Israeli New Shekel | Bank of Israel | 574 | 533 | 41 |
| USD/JPY | US Dollar/Japanese Yen | Federal Reserve Bank | 257,676 | 129,785 | 127,891 |
| USD/MXN | US Dollar/Mexican Peso | Federal Reserve Bank | 42,258 | 18,414 | 23,844 |
| USD/NOK | US Dollar/Norwegian Krone | Federal Reserve Bank | 15,858 | 6,963 | 8,895 |
| USD/PLN | US Dollar/Polish Zloty | Narodowy Bank Polski | 96 | 51 | 45 |
| USD/RUB | US Dollar/Russian Ruble | Bank of Russia | 321 | 64 | 257 |
| USD/SEK | US Dollar/Swedish Krona | Federal Reserve Bank | 4,641 | 2,398 | 2,243 |
| USD/SGD | US Dollar/Singapore Dollar | Federal Reserve Bank | 2,948 | 1,130 | 1,818 |
| USD/TRY | US Dollar/Turkish Lira | Central Bank of the Republic of Turkey | 2,863 | 1,212 | 1,651 |
| USD/ZAR | US Dollar/South African Rand | South African Reserve Bank | 25,927 | 7,898 | 18,029 |
| ZAR/JPY | South African Rand/Japanese Yen | South African Reserve Bank | 1,457 | 1,336 | 121 |
| HKD/JPY | Hong Kong Dollar/Japanese Yen | European Central Bank | 8 | 4 | 4 |
| HUF/JPY | Hungarian Forint/Japanese Yen | Central Bank of Hungary | 20 | 11 | 9 |
| MXN/JPY | Mexican Peso/Japanese Yen | European Central Bank | 1 | 1 | 0 |
| NOK/JPY | Norwegian Krone/Japanese Yen | Norges Bank | 48 | 31 | 17 |
| NOK/SEK | Norwegian Krone/Swedish Krona | Norges Bank | 26 | 17 | 9 |
| NZD/CAD | New Zealand Dollar/Canadian Dollar | Reserve Bank of New Zealand | 47,477 | 22,034 | 25,443 |
| NZD/CHF | New Zealand Dollar/Swiss Franc | Reserve Bank of New Zealand/ European Central Bank | 16,109 | 8,710 | 7,399 |
| NZD/JPY | New Zealand Dollar/Japanese Yen | Reserve Bank of New Zealand | 33,936 | 17,416 | 16,520 |
| NZD/SGD | New Zealand Dollar/Singapore Dollar | Reserve Bank of New Zealand | 1 | 0 | 1 |
| NZD/USD | New Zealand Dollar/US Dollar | Reserve Bank of New Zealand | 102,538 | 51,091 | 51,447 |
| SEK/JPY | Swedish Krona/Japanese Yen | Sveriges Riksbank | 40 | 25 | 15 |
| SGD/JPY | Singapore Dollar/Japanese Yen | Singapore Monetary Authority/ European Central Bank | 602 | 293 | 309 |
| TRY/JPY | Turkish Lira/Japanese Yen | Central Bank of the Republic of Turkey | 1,023 | 860 | 163 |
| USD/BRL | US Dollar/Brazilian Real | Federal Reserve Bank | 20 | 0 | 20 |
| USD/CAD | US Dollar/Canadian Dollar | Federal Reserve Bank | 224,554 | 104,029 | 120,525 |
| USD/CHF | US Dollar/Swiss Franc | Federal Reserve Bank | 133,022 | 68,814 | 64,208 |
| USD/CNH | US Dollar/Chinese Yuan Renminbi | investing.com | 5,506 | 2,469 | 3,037 |
| USD/CZK | US Dollar/Czech Koruna | Czech National Bank | 38 | 17 | 21 |
| USD/DKK | US Dollar/Danish Krone | Federal Reserve Bank | 172 | 89 | 83 |
| USD/HKD | US Dollar/Hong Kong Dollar | Federal Reserve Bank | 62 | 47 | 15 |
| USD/HUF | US Dollar/Hungarian Forint | Central Bank of Hungary | 259 | 114 | 145 |
| USD/ILS | US Dollar/Israeli New Shekel | Bank of Israel | 574 | 533 | 41 |

## Table°A – *Continued*

| Symbol | Meaning | Source | Round Trips | Buy | Sell |
|---|---|---|---|---|---|
| ***Crypto Currencies*** | | | | | |
| ADA/BTC | Cardano/Bitcoin | investing.com | 3 | 2 | 1 |
| BCH/USD | Bitcoin Cash/US Dollar | Thomson Reuters Datastream | 110 | 65 | 45 |
| BTC/EUR | Bitcoin/Euro | Thomson Reuters Datastream | 1 | 1 | 0 |
| BTC/USD | Bitcoin/US Dollar | Thomson Reuters Datastream | 13,407 | 10,029 | 3,378 |
| DASH/BTC | Dash/Bitcoin | investing.com | 7 | 4 | 3 |
| EOS/BTC | EOS/Bitcoin | investing.com | 17 | 6 | 11 |
| ETC/BTC | Ethereum Classic/Bitcoin | investing.com | 16 | 8 | 8 |
| ETH/USD | Ethereum/US Dollar | Thomson Reuters Datastream | 235 | 185 | 50 |
| LTC/USD | Litecoin/US Dollar | Thomson Reuters Datastream | 245 | 153 | 92 |
| NEO/BTC | Neo/Bitcoin | investing.com | 6 | 3 | 3 |
| XLM/BTC | Stellar/Bitcoin | investing.com | 2 | 0 | 2 |
| XRP/USD | XRP/US Dollar | Thomson Reuters Datastream | 163 | 129 | 34 |
| ***Commodities*** | | | | | |
| Copper/USD | Copper/US Dollar | Thomson Reuters Datastream | 1,216 | 604 | 612 |
| XAG/EUR | Silver/Euro | Thomson Reuters Datastream | 46 | 38 | 8 |
| XAG/USD | Silver/US Dollar | Thomson Reuters Datastream | 6,328 | 5,309 | 1,019 |
| XAU/EUR | Gold/Euro | Thomson Reuters Datastream | 443 | 173 | 270 |
| XAU/USD | Gold/US Dollar | Thomson Reuters Datastream | 143,214 | 74,184 | 69,030 |
| XBR/USD | Brent Crude Oil/US Dollar | Thomson Reuters Datastream | 7,171 | 5,590 | 1,581 |
| XNG/USD | Natural Gas/US Dollar | Thomson Reuters Datastream | 912 | 570 | 342 |
| XPT/USD | Platin/US Dollar | Thomson Reuters Datastream | 1 | 0 | 1 |
| XTI/USD | West Texas Intermediate Crude Oil/US Dollar | Thomson Reuters Datastream | 10,547 | 6,214 | 4,333 |
| SOY/USD | Soya Beans/USD | Thomson Reuters Datastream | 1 | 1 | 0 |
| ***Indices*** | | | | | |
| ASX 200 | Australian Stock Index | Thomson Reuters Datastream | 718 | 388 | 330 |
| CAC 40 | French Stock Index | Thomson Reuters Datastream | 1,249 | 823 | 426 |
| DAX 30 | German Stock Index | Thomson Reuters Datastream | 22,187 | 13,800 | 8,387 |
| Dow Jones | US Stock Index | Thomson Reuters Datastream | 18,338 | 9,093 | 9,245 |
| Euro Stoxx 50 | European Stock Index | Thomson Reuters Datastream | 595 | 392 | 203 |
| FTSE 100 | British Stock Index | Thomson Reuters Datastream | 2,232 | 1,394 | 838 |
| FTSE China A50 | Chinese Stock Index | Thomson Reuters Datastream | 112 | 87 | 25 |
| FTSE MIB | Italian Stock Index | Thomson Reuters Datastream | 59 | 30 | 29 |
| HSI | Hong Kong Stock Index | Thomson Reuters Datastream | 51 | 32 | 19 |
| IBEX 35 | Spanish Stock Index | Thomson Reuters Datastream | 829 | 507 | 322 |
| NASDAQ-100 | US Stock Index | Thomson Reuters Datastream | 11,311 | 6,611 | 4,700 |
| Nikkei 225 | Japanese Stock Index | Thomson Reuters Datastream | 1,595 | 671 | 924 |
| Russell 2000 | US Stock Index | Thomson Reuters Datastream | 2 | 0 | 2 |
| S&P 500 | US Stock Index | Thomson Reuters Datastream | 16,465 | 7,811 | 8,654 |
| SMI | Swiss Stock Index | Thomson Reuters Datastream | 28 | 24 | 4 |
| ***Stocks*** | | | | | |
| @AAL | American Airlines Group | Thomson Reuters Datastream | 4 | 4 | 0 |
| @AAPL | Apple | Thomson Reuters Datastream | 5 | 4 | 1 |
| @AMZN | Amazon | Thomson Reuters Datastream | 11 | 8 | 3 |
| U:BA | Boeing | Thomson Reuters Datastream | 1 | 1 | 0 |
| U:CRM | Salesforce | Thomson Reuters Datastream | 2 | 2 | 0 |
| U:CVX | Chevron | Thomson Reuters Datastream | 2 | 2 | 0 |
| @EBAY | EBAY | Thomson Reuters Datastream | 2 | 2 | 0 |
| @FB | Facebook | Thomson Reuters Datastream | 1 | 0 | 1 |
| @GILD | Gilead Sciences | Thomson Reuters Datastream | 2 | 2 | 0 |
| @GOOGL | Alphabet | Thomson Reuters Datastream | 13 | 7 | 6 |
| U:KO | Coca Cola | Thomson Reuters Datastream | 1 | 1 | 0 |
| @MSFT | Microsoft | Thomson Reuters Datastream | 1 | 1 | 0 |
| @NFLX | Netflix | Thomson Reuters Datastream | 5 | 5 | 0 |
| U:PFE | Pfizer | Thomson Reuters Datastream | 1 | 1 | 0 |
| U:T | AT&T | Thomson Reuters Datastream | 1 | 1 | 0 |
| @TSLA | Tesla | Thomson Reuters Datastream | 5 | 3 | 2 |
| U:WMT | Walmart | Thomson Reuters Datastream | 2 | 2 | 0 |
| U:XOM | ExxonMobile | Thomson Reuters Datastream | 7 | 6 | 1 |

## Table°A – *Continued*

| Symbol | Meaning | Source | Round Trips | Buy | Sell |
|---|---|---|---|---|---|
| ***Others*** | | | | | |
| @QQQ | Invesco QQQ Trust | Thomson Reuters Datastream | 3 | 2 | 1 |
| Bund/EUR | Euro-Bund-Future | Thomson Reuters Datastream | 479 | 225 | 254 |
| ***Unidentified*** | | | | | |
| NA | NA | NA | 8 | 4 | 4 |

### Table°B: Variables employed in Regression Analyses

| Variable | Description |
|---|---|
| ***Independent Variables and Components Panel Regression Analyses*** | |
| $N_{i,t-1}$ | Number of positions closed within signal provider account $i$ in month $t-1$. |
| $NWin_{i,t-1}$ | Number of positions closed within signal provider account $i$ in month $t-1$ with a net profit. |
| $Win_{i,t-1}$ | Win ratio monthly; share of positions closed within signal provider account $i$ in month $t-1$ where a net profit is gained. |
| $\overline{Win}_{i,t-6}^{t-1}$ | Average win ratio; average monthly share of positions closed within signal provider account $i$ where a net profit is gained, covering months $t-1$ to $t-6$. |
| $SProfit_{i,t-1}^{n}$ | Profit round trip; net profit / loss obtained within signal provider account $i$ through closing position $n$ in month $t-1$. |
| $Profit_{i,t-1}$ | Profit monthly; sum of net profits / losses obtained within signal provider account $i$ in month $t-1$. |
| $SPips_{i,t-1}^{n}$ | Profit pips round trip; profit pips gained / lost within signal provider account $i$ through closing positon $n$ in month $t-1$. |
| $Pips_{i,t-1}$ | Profit pips monthly; sum of gained / lost profit pips obtained within signal provider account $i$ in month $t-1$. |
| $R\overline{Profit}_{i,t-6}^{t-1}$ | Average profit; average monthly net profit / loss obtained within signal provider account $i$, covering months $t-6$ to $t-1$. |
| $RWin_{i,t-1}$ | Win ratio variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to the obtained monthly win ratio in month $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the win ratios of all signal provider accounts in the dataset are employed as threshold values. |
| $R\overline{Win}_{i,t-6}^{t-1}$ | Average win ratio variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to obtained average of monthly win ratios, covering months $t-6$ to $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the win ratios of all signal provider accounts in the dataset are employed as threshold values. |
| $RProfit_{i,t-1}$ | Profit variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to the obtained monthly net profit / loss in month $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the profits of all signal provider accounts in the dataset are employed as threshold values. |
| $R\overline{Profit}_{i,t-6}^{t-1}$ | Average profit variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to obtained average monthly net profit / loss, covering months $t-6$ to $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the profits of all signal provider accounts in the dataset are employed as threshold values. |
| $RPips_{i,t-1}$ | Profit pips variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to the obtained monthly profit pips in month $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the profit pips balances of all signal provider accounts in the dataset are employed as threshold values. |
| $R\overline{Pips}_{i,t-6}^{t-1}$ | Average profit pips variable as applied in the regression analyses; ranking of signal provider account $i$ with regard to obtained average of monthly profits pips, covering months $t-6$ to $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the profits pips balances of all signal provider accounts in the dataset are employed as threshold values. |
| $RNWin_{i,t-1}$ | Ranking of signal provider account $i$ with regard to the number of positions closed in month $t-1$ with a net profit. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the number of closed positions with a net profit of all signal providers in the dataset are employed as threshold values. |
| $R\overline{NWin}_{i,t-6}^{t-1}$ | Ranking of signal provider account $i$ with regard to obtained average of the monthly number of positions closed with a net profit, covering months $t-6$ to $t-1$. The ranking is expressed in a number from $1$ to $10$. Monthly deciles covering the number of closed positions with a net profit of all signal provider accounts in the dataset are employed as threshold values. |

*Notes:* The table above displays all variables employed in the regression analyses described in *Section 3.6*.

**Table°B – *Continued***

| Variable | Description |
|---|---|
| ***Independent Variables and Components Panel Regression Analyses*** | |
| $RWinAdj_{i,t-1}$ | Adjusted win ratio; mean of win ratio ($RWin_{i,t-1}$) and ranking variable corresponding to the number of positions closed with a net profit ($RNWin_{i,t-1}$). |
| $R\overline{Win}Adj_{i,t-6}^{t-1}$ | Average adjusted win ratio; mean of average win ratio ($R\overline{Win}_{i,t-6}^{t-1}$) and ranking variable corresponding to the average number of positions closed with a net profit ($R\overline{NWin}_{i,t-6}^{t-1}$). |
| $RComb_{i,t-1}$ | Combined relative performance variable; mean of win ratio ($RWin_{i,t-1}$) and profit ($RProfit_{i,t-1}$) / profit pips ($RPips_{i,t-1}$) variable. |
| $R\overline{Comb}_{i,t-6}^{t-1}$ | Average combined relative performance variable; mean of average win ratio ($R\overline{Win}_{i,t-6}^{t-1}$) and average profit ($R\overline{Profit}_{i,t-6}^{t-1}$) / profit pips ($R\overline{Pips}_{i,t-6}^{t-1}$) variable. |
| $IV_{i,t}$ | Stand-in for independent performance variable reflecting win ratios / profits / profit pips. |
| ***Independent Control Variables Panel Regression Analyses*** | |
| $Lots_{i,t}$ | Average lot size (in standard lots) traded within signal provider account $i$ in month $t$. |
| $Open_{i,t}$ | Share of opened positions to all conducted trades (opened and closed positions) within signal provider account $i$ in month $t$. |
| $Long_{i,t}$ | Share of entered long positions to all conducted trades (long and short) within signal provider account $i$ in month $t$. |
| $Age_{i,t}$ | Current age (measured in months) of signal provider account $i$ in month $t$. |
| $Crypto_{i,t}$ | Dummy variable; equals 1 if a crypto currency (base and/or quote currency) is traded within signal provider account $i$ in month $t$. |
| $Commodity_{i,t}$ | Dummy variable; equals 1 if a commodity is traded within signal provider account $i$ in month $t$. |
| $Index_{i,t}$ | Dummy variable; equals 1 if an index is traded by signal provider $i$ in month $t$. |
| ***Dependent Variables and Components Panel Regression Analyses*** | |
| $Num_{i,t}$ | Number of trades (opened and closed positions) conducted within signal provider account $i$ in month $t$. |
| $RNum_{i,t}$ | Number of conducted trades within signal provider account $i$ in month $t$ as employed in the regression analysis; obtained by adding the constant 1 to the number of trades and then applying the natural logarithm. |
| $LotteryNum_{i,t}^{max}$ | Number of lottery trades (opened and closed positions) conducted within signal provider account $i$ in month $t$. Lottery-like assets are defined according to Bali et al. (2011): Stocks are sorted into monthly decile portfolios based on the single highest daily return in month $t-1$. Assets in the highest decile portfolio ($max$) are categorized as lottery-like. |
| $LotteryNum_{i,t}^{max5}$ | Robustness: Number of lottery trades (opened and closed positions) conducted within signal provider account $i$ in month $t$. Lottery-like assets are defined according to Bali et al. (2011): Stocks are sorted into monthly decile portfolios based on an average value calculated as the mean of the five single highest returns in month $t-1$. Assets in the highest decile portfolio are categorized as lottery-like. |
| $Lottery_{i,t}^{max}$ | Share of lottery trades to all trades conducted within signal provider account $i$ in month $t$. |
| $Lottery_{i,t}^{max5}$ | Robustness: Share of lottery trades to all trades conducted within signal provider account $i$ in month $t$. |
| $RLottery_{i,t}^{max}$ | Share of lottery trades within signal provider account $i$ in month $t$ as employed in the regression analysis; obtained by adding the constant 1 to the traded lottery share and then applying the natural logarithm. |
| $RLottery_{i,t}^{max5}$ | Robustness: Share of lottery trades within signal provider account $i$ in month $t$ as employed in the regression analysis; obtained by adding the constant 1 to the traded lottery share and then applying the natural logarithm. |

**Table°C: Monthly Number Trades**

| ***Panel°A*: Relative Performance Measured over Previous Month** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\alpha$ | 2.032*** | 2.032*** | 2.023*** | 2.712*** | 2.545*** | 3.398*** | 3.398*** | 3.386*** | 3.504*** | 3.443*** |
| | (20.71) | (18.30) | (87.33) | (132.17) | (122.86) | (30.66) | (27.01) | (149.82) | (196.66) | (187.55) |
| $RWinAdj_{i,t-1}$ | .307*** | .307*** | .307*** | .186*** | .213*** | | | | | |
| | (45.94) | (32.94) | (131.12) | (78.27) | (89.83) | | | | | |
| $RProfit_{i,t-1}$ | | | | | | .054*** | .054*** | .054*** | .040*** | .046*** |
| | | | | | | (11.02) | (8.58) | (29.26) | (26.66) | (29.56) |
| $Lots_{i,t}$ | -.000** | -.000** | -.000* | .000 | .000 | -.000*** | -.000*** | -.000*** | .000 | .000 |
| | (-2.55) | (-2.48) | (-1.90) | (1.63) | (1.56) | (-5.53) | (-5.51) | (-2.62) | (1.60) | (1.33) |
| $Open_{i,t}$ | .958*** | .958*** | .962*** | .953*** | .952*** | 1.113*** | 1.113*** | 1.131*** | .968*** | .997*** |
| | (5.45) | (5.11) | (28.98) | (36.59) | (35.68) | (5.94) | (5.59) | (32.18) | (37.79) | (37.47) |
| $Long_{i,t}$ | -.207*** | -.207*** | -.212*** | -.160*** | -.157*** | -.311*** | -.311*** | -.317*** | -.200*** | -.206*** |
| | (-3.93) | (-3.26) | (-13.13) | (-11.19) | (-10.85) | (-5.17) | (-4.02) | (-17.96) | (-13.64) | (-13.78) |
| $Age_{i,t}$ | -.008*** | -.008*** | -.008*** | -.012*** | -.010*** | -.012*** | -.012*** | -.011*** | -.014*** | -.012*** |
| | (-8.55) | (-6.25) | (-35.02) | (-49.00) | (-42.72) | (-10.08) | (-7.51) | (-45.95) | (-55.43) | (-48.88) |
| $Crypto_{i,t}$ | .164* | .164 | .185*** | .272*** | .305*** | .216* | .216 | .236*** | .250*** | .280*** |
| | (1.69) | (1.61) | (3.50) | (5.35) | (6.07) | (1.68) | (1.47) | (4.05) | (4.79) | (5.37) |
| $Commodity_{i,t}$ | .301*** | .301*** | .303*** | .511*** | .428*** | .311*** | .311*** | .312*** | .563*** | .473*** |
| | (5.73) | (4.46) | (18.81) | (29.19) | (25.02) | (5.27) | (4.19) | (17.58) | (31.28) | (26.62) |
| $Index_{i,t}$ | .231*** | .231*** | .237*** | .391*** | .281*** | .167* | .167* | .168*** | .433*** | .287*** |
| | (3.42) | (3.02) | (9.05) | (12.59) | (9.87) | (1.94) | (1.70) | (5.79) | (13.46) | (9.61) |
| $R^2$ | .2327 | .2327 | .2430 | .5802 | .5444 | .0627 | .0627 | .0725 | .5498 | .5006 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes |

*Notes:* The table above displays panel regression estimates obtained by applying the regression model in *Section 3.6.2*. In each regression, the number of conducted trades (opening or closing of positions) of signal provider account $i$ in month $t$ ($RNum_{i,t}$) is set as dependent variable. *Panel°A* reports the results relating to the relative performance variables – win ratio ($RWinAdj_{i,t-1}$) and net profit ($RProfit_{i,t-1}$) – measured over the previous month. In *Panel°B*, relative performance variables ($R\overline{WinAdj}_{i,t-6}^{t-1}$ / $R\overline{Profit}_{i,t-6}^{t-1}$) are computed over the previous six months. In specification (1) and (6), t-statistics correspond to month and signal provider account-clustered standard errors; in specification (2) and (7), standard errors are clustered by month and signal provider (Petersen, 2009). Specifications (3) and (8) include time fixed effects. Fixed effects on the portfolio-level, i.e. for each signal provider account, are included in specifications (4) and (9). Trader-level fixed effects, i.e. for each identified signal provider, are included in specifications (5) and (10). All employed variables are displayed and described in the appendix Table°B. Data is obtained directly from the *ZuluTrade* platform, covering the period from October 2008 to January 2021. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table°C – *Continued***

| *Panel°B*: Relative Performance Measured over Previous Six Months | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| $\alpha$ | 2.133*** | 2.133*** | 2.118*** | 2.704*** | 2.464*** | 3.481*** | 3.481*** | 3.468*** | 3.517*** | 3.454*** |
| | (19.75) | (16.83) | (87.62) | (109.25) | (102.37) | (29.72) | (25.31) | (150.75) | (188.94) | (180.98) |
| $R\overline{WinAdj}_{i,t-6}^{t-1}$ | .266*** | .266*** | .266*** | .175*** | .212*** | | | | | |
| | (36.69) | (23.85) | (113.83) | (54.09) | (70.15) | | | | | |
| $R\overline{Profit}_{i,t-6}^{t-1}$ | | | | | | .034*** | .034*** | .034*** | .034*** | .039*** |
| | | | | | | (5.48) | (3.82) | (18.29) | (20.30) | (23.40) |
| $Lots_{i,t}$ | -.000** | -.000** | -.000* | .000 | .000 | -.000*** | -.000*** | -.000*** | .000 | .000 |
| | (-2.09) | (-2.03) | (-1.86) | (1.60) | (1.56) | (-5.80) | (-5.68) | (-2.73) | (1.56) | (1.30) |
| $Open_{i,t}$ | 1.120*** | 1.120*** | 1.130*** | 1.031*** | 1.040*** | 1.153*** | 1.153*** | 1.171*** | .996*** | 1.028*** |
| | (6.02) | (5.64) | (33.23) | (38.76) | (38.18) | (6.10) | (5.76) | (33.24) | (38.81) | (38.58) |
| $Long_{i,t}$ | -.220*** | -.220*** | -.225*** | -.173*** | -.167*** | -.310*** | -.310*** | -.317*** | -.199*** | -.204*** |
| | (-3.87) | (-3.18) | (-13.57) | (-11.80) | (-11.35) | (-5.11) | (-3.99) | (-17.85) | (-13.53) | (-13.62) |
| $Age_{i,t}$ | -.008*** | -.008*** | -.008*** | -.012*** | -.010*** | -.011*** | -.011*** | -.011*** | -.014*** | -.012*** |
| | (-8.23) | (-6.02) | (-33.71) | (-47.03) | (-40.47) | (-9.68) | (-7.23) | (-44.14) | (-54.34) | (-47.62) |
| $Crypto_{i,t}$ | .129 | .129 | .150*** | .306*** | .359*** | .247* | .247 | .267*** | .282*** | .323*** |
| | (1.36) | (1.35) | (2.76) | (5.88) | (7.00) | (1.84) | (1.59) | (4.58) | (5.39) | (6.17) |
| $Commodity_{i,t}$ | .306*** | .306*** | .308*** | .523*** | .438*** | .311*** | .311*** | .312*** | .565*** | .475*** |
| | (5.61) | (4.37) | (18.62) | (29.15) | (25.04) | (5.27) | (4.20) | (17.48) | (31.35) | (26.68) |
| $Index_{i,t}$ | .252*** | .252*** | .258*** | .410*** | .304*** | .167* | .167* | .169*** | .440*** | .290*** |
| | (3.55) | (3.20) | (9.59) | (12.92) | (10.44) | (1.93) | (1.68) | (5.80) | (13.65) | (9.68) |
| $R^2$ | .1938 | .1938 | .2043 | .5608 | .5246 | .0559 | .0559 | .0658 | .5478 | .4983 |
| Time Fixed Effects | No | No | Yes | No | No | No | No | Yes | No | No |
| Portfolio Fixed Effects | No | No | No | Yes | No | No | No | No | Yes | No |
| Trader Fixed Effects | No | No | No | No | Yes | No | No | No | No | Yes |